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Can Technology Overcome Social Disadvantage of School Children's Learning Outcomes? Evidence from a Large-scale Experiment in India

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Abstract

Poor learning outcomes in developing countries are mostly attributed to the low quality of teaching inputs in schools, primarily due to a shortage of adequately trained teachers and rampant teacher absenteeism. Children from socially disadvantaged groups are worst affected, as this lack of resources adds on to the already prevailing discrimination in the classrooms. Computer technology can be used to reduce these deficiencies and provide high quality educational content. We conduct a large scale randomized field experiment among 1823 rural government schools in India, in the state of Karnataka, where satellite-terrestrial technology is used to telecast additional interactive classes. Results show that this intervention has a positive impact on student performance. We find that this technology is non-discriminatory and in fact reduces the educational attainment gap between the socially disadvantaged students and others. In particular, we find that girls from these sections of the society benefit the most from this intervention.

JEL: C93, I28, I25, I29
Keywords: information and communication technology, field experiment, education, computer technology, government policy

1 Introduction

With the second and the third millennium development goals focusing on getting more children to school, enrollment rates have risen substantially in many developing nations. In India, enrollment rate among 6 to 14 year-olds has been over 96% for the past five years (Pratham [2015]). However, the teaching quality and school infrastructure have not kept pace with this increase. The school education systems in many developing countries remain fraught with multiple inadequacies like non-availability of adequately trained teachers, and rampant teacher absenteeism. Chaudhury et al. [2006] report up to 25% absenteeism among teachers in government-run schools in India and further point out that, only 45% of teachers assigned to schools were teaching at any given point.

These inadequacies in the education system are reflected in the below par reading and arithmetic skills of children as reported by many recent surveys. In India, 25% of children enrolled in grade

8 could not read at grade 2 level, and 55% could not do simple tasks of division (Pratham [2015]). Also, in a developing country like India, the socio-economically disadvantaged sections of the society depend heavily on the government services for education and health. Of all the children in the state of Karnataka in India, who enrolled in grade 1 in Academic Year(AY) 2013-14 from the General category, only 19.78% were enrolled in government schools, while this number was 68.38% for children from scheduled castes and 72.28% for children from scheduled tribes. In India, in addition to economic poverty, social disadvantages along the lines of caste and gender remain important concerns. Studies have shown that the socially disadvantaged groups continue to remain at the lower end of the development spectrum regarding educational attainment, employment opportunities and asset ownership (Deshpande [2011]).

Many studies attribute the below par education attainment to the poor performance of government schools. In comparison to the private schools, government schools both across India and in Karnataka, underperform in almost all measures of educational attainment and have been experiencing a consistent decrease in enrollment rates. (Pratham [2015]). We analyze the impact of a large-scale intervention that uses technology to deliver educational content through innovative pedagogy to government schools in rural Karnataka, India.

Several studies have highlighted the importance of quality of teachers and teaching in determining school outcomes. Banerjee et al. [2007] and Muralidharan and Sundararaman [2013] show that the presence of an additional teacher significantly improves learning outcomes. Banerjee et al. [2007] studied a field experiment where an additional teacher from the local community (Balsakhi) was provided to the poorest performing students in government schools in Vadodara and Mumbai. The students who received the intervention showed significant improvement in test scores. Similarly, in an experiment conducted in 100 schools in Andhra Pradesh, India Muralidharan and Sundararaman [2013] show that provision of an additional contract teacher increases pupil to teacher ratio (PTR) and reduces multi-grade classrooms in schools due to better teacher attendance and thus significantly improves student performance.

The pupil-teacher ratio (PTR) in government schools is on average lower than that in the private schools. However, lack of motivation and high level of absenteeism are often cited as reasons for poor performance. Chaudhury et al. [2006] find that incentives like teacher salaries have little or no effect on improving teacher absenteeism. They find that teachers that live in distant towns and have longer commutes to school report higher incidence of absenteeism. Considering the remote location of many government schools in developing countries, providing additional qualified teachers may not be an effective way to improve the quality of teaching inputs and learning outcomes. One of the solutions proposed to address this issue is the use of technology in delivering teaching inputs.

Several attempts to use information and communication technology (ICT) to improve teaching quality and learning outcomes have been made in many countries over the last two decades. However, very few field experiment studies exist to measure the impact of ICT use on attaining better learning outcomes among students. Notably studies by Angrist and Lavy [2002] on the use of computers among fourth and eighth-grade students in Israel for Maths and Hebrew showed no evidence of any improvement in learning achievements. Provision of computers in schools led to higher use of computers but did not necessarily translate into higher test scores. On the other hand Banerjee et al. [2007] find the use of computers have a significant positive impact on maths scores in 55 schools in Vadodara, India. The experiment involved providing children of 4th grade with two hours of shared computer time per week. During this period, the children could play computer games that developed basic competencies in maths. The intervention led to an increase in maths scores by 0.3σ at the end of two years and 0.6σ at the end of three years.

More recently Barrera-Osorio and Linden [2009] study the use of computers through the Colombian "Computers for Education" program and find no impact on student performance in 97 schools in Colombia. Under the program, schools were provided computers with new pedagogical techniques developed by the Universidad de Antioquia. While this increased the use of computers among students and teachers, less than 3-4% of it was for intended use. The impact on maths and Spanish test scores was non-significant. The authors also note that only 42% of teachers from treatment schools had used a computer in class in the week before the survey. Barrera points out that successful use of computers in schools is critically linked to changes in pedagogy. Most programs involving the use of technology fail, primarily because teachers do not have the training or are reluctant to take advantage of the teaching aids that the technology enables. In studies that leave pedagogy to the discretion of the local teacher, it is hard to identify whether the program impact was a result of the use of technology or change in pedagogy or both.

This paper also seeks to contribute to existing literature on caste discrimination. Several studies have pointed towards student-teacher interaction in classrooms as a site for discrimination and its adverse impact on students coming from disadvantaged groups. Technology aided teaching being impersonal, is expected to balance the discriminatory environment that may exist in schools and thus improve the performance of students from socially disadvantaged groups.

A considerable body of literature exists in the developed world on discrimination in classroom interaction between students and teachers. Ehrenberg et al. [1995] use National Educational Longitudinal Survey in 1988 in the USA to show that a teacher-student match on gender, race or ethnicity does not impact student learning. However, it does show a significant impact on the teachers' subjective assessment of the student. Similarly, Dee [2004] use data from the Project STAR randomized experiment to show that same race teacher increased achievement of black and white students in math and reading. Lindahl [2007] using data from schools in Sweden shows that the same gender and ethnic minority group between teacher and student has a positive impact on math scores but not on Swedish and English scores. For India, Hanna and Linden [2012] use an experimental setting and find that teachers discriminate while grading children from 'lower' castes. Analysis of grades assigned by about 120 teachers showed that scores to 'lower' caste students were 0.03 to 0.09 standard deviations lower than for a comparable 'upper' caste student. Using a dataset of 5028 students from 160 rural primary schools in Uttar Pradesh and Bihar, Rawal and Kingdon [2010] show that having a teacher from the same caste/gender group as that of the student enhances student performance. A teacher of the same gender as the student had a positive impact of 0.0361σ, same caste had an impact of 0.0389σ and of same religion had a positive impact of 0.168σ.

While most of these studies focus on either subjective assessments or test scores, the exploratory study among children from 'lower' caste households, by Nambissan et al. [2009] in a village in Jaipur district of Rajasthan in India, outlines the various modes through which discrimination is practiced in schools. Sites of discrimination included division of work in school - children from 'lower' castes are more likely to be assigned the task of sweeping the school whereas children from 'upper' castes are more likely to be assigned the task of serving drinking water. Children mentioned of teachers refusing to accept drinking water from a 'lower' caste child. Treatment in the classroom also was a contentious issue - insults, calling by caste names, neglect and inadequate explanation of the subject were common complaints. Affirmative action programs such as scholarships require these students to identify their caste, often in front of the entire school, thus reinforcing their caste identities among peers and teachers. A study by Hoff and Pandey [2014] uses an experiment to show that priming students about their caste status has a significant effect on their performance. By using the model of frame-dependent self, the study shows that making caste identity public in a mixed group setting leads to a 23% lower performance by 'lower' castes a compared to control setting.

The literature on the use of Information and Communication Technology (ICT) for developmental purposes has been focusing more on economic and political empowerment and has seldom focused on the role of social discrimination in this process. A notable exception has been literature based on developing country experiences on the use of technology. Studies of usage of rural kiosks and ICT based help centres reveal distinct caste based patterns (for instance Best and Maier [2007]; Best and Kumar [2008]). However, several authors have pointed out that technology per se is non-discriminatory and emphasized the fact that corrections in implementation design can easily solve the disadvantages arising out of social discrimination (for instance Kendall and Singh [2012]; Heeks [2010]). In the present paper, we check if the use of technology helps in reducing the unfair disadvantage in the learning environment faced by children from socially disadvantaged groups.

The objective of this paper is to study the impact of a large-scale intervention that uses technology to deliver educational content to government schools in rural Karnataka, India. The intervention that we study packages together, technology and pedagogical improvements and focuses on improving the quality of teaching in rural government schools. Satellite-and-terrestrial technology is used as an enabler to deliver additional interactive classes to the students in English grammar, science, and maths. The topics covered in these classes are part of the syllabus of the schools and thus, act as an additional input. Trained teachers deliver the classes making use of video and animation technology that would otherwise be inaccessible to rural schools. The intervention involves broadcasting the classes live from the studio in Bangalore via an educational satellite of the government of India to treatment schools located in the most backward districts of the state.

A pilot test of the intervention was conducted in AY 2010-11 in Gubbi taluk of Tumkur district in Karnataka, India. After observing significant improvements in the student learning outcomes in the pilot, the Karnataka Education Department decided to expand the intervention to backward areas of the state, in the year 2014-15. We estimate the impact of this intervention using a randomized field experiment that covers 1823 rural government schools spread across 18 economically backward districts of Karnataka, India. Out of 1823, 1000 schools received the treatment while 823 were in the control group.

We find a positive impact on test scores and pass percentages in schools after approximately three months of the intervention. A higher positive effect is noted for science in comparison to that of English and maths. We also find that the students belonging to the weaker sections of the society benefit more from the treatment than those from general category. Interestingly, this trend remains true even when we consider the impact of this intervention on girls belonging to the weaker sections. Baseline data also reveals a disadvantage to students when teachers in the school are predominantly from a different social category. Post-intervention results indicate a weakening of this relation. We also find that the impact is higher for schools performing below the median level in the base year.

The remaining paper is organized as follows - Section 2 discusses the Experiment Design and the context in which the intervention is done, Section 3 covers the estimation and results and Section 4 concludes.

2 The Satellite and Multimedia Interactive Education (SAMIE) Experiment

2.1 Background and Context

Karnataka is among relatively better performing states in India. The state's per capita income in the FY 2013-14 was about 14% higher than the national average (Economic Survey of India, 2014-15). Though the state has been performing better than national averages on many economic indicators, the story of the quality of school education in the state is different.

In 2014 literacy rate in Karnataka was at 75.4%, higher than the national average of 73% (Economic Survey of India, 2014-15). Karnataka also outperformed national averages in school enrollment from 2006 to 2014.[1] Though enrollment rate has increased over time in Karnataka, it still struggles to match up with the national averages in many aspects of quality of education. Of the total grade 2 students surveyed in Karnataka in 2014, 82% did not have reading ability expected of their grade. Though these numbers improve with grades, a high proportion of students still falls behind in their reading and comprehension abilities. Percentage of students in grade 5 who could read grade 2 text, read words and sentences or do division has been consistently lower than national averages (Pratham [2015]). [2] Of the total children enrolled in grade 8, 12.9% of them could not read simple words (national average 12.5%) and 29.4% of them were unable to read grade 2 text (national average 25.4%). Similar trends are also found in arithmetic abilities of students. Of the total children enrolled in grade 8, 35% found it difficult

[1] National enrollment rate in 2014 is 96.7% and that for Karnataka is 98.3% (ASER 2014)

[2] Of the total grade 5 students surveyed in Karnataka in 2014 only 21% (national average of 24%) could read English sentences and only 20% (national average of 26%) could do simple division.

to recognize three-digit numbers (national average 32.8%) and 63% of them could not do simple division problems (national average 53.9%).

Table 1: Learning Levels of % of Children in Class VIII

	Reading Levels					
	Not even letter	Letter	Word	Std I text	Std II text	Total
India	1.8	4.5	6.2	12.8	74.6	100
Karnataka	2.7	3.7	6.5	16.6	70.6	100
	Arithmetic					
	Recognize Numbers			Can Subtract	Can Divide	Total
	None	1-9	10-99			
India	1.3	5.4	26.1	23.2	44.1	100
Karnataka	1.1	2.3	31.2	28.4	37.0	100

1) Source ASER 2014

2) Includes both government and private schools

As per ASER (2014), the number of students opting for private schools in the country and Karnataka has been on the rise. In 2006, 16% (national average of 18.7%) of the total enrollment in the state of Karnataka was attributed to that in private schools which rose to 25.5% (national average of 30.8%) in 2014.

In the Indian context, economic disadvantage is largely aligned with social disadvantage. After more than six decades of independence and two decades of exposure to a globalized market-oriented economy, the stranglehold of centuries old caste system continues. For the purpose of affirmative action, the government has classified more than 3000 *jatis* into four broad categories. The uppermost 'General Category' includes castes that were historically at the top of the social ladder. This group has a dominant presence in most high-ranking government and private sector jobs. The 'Other Backward Castes' (OBC) broadly include the erstwhile artisans in the *jajmani* system and form the middle strata. This group numerically forms the largest segment of the population. The 'Scheduled Castes' (SC) are those who were earlier referred to as 'untouchables' or 'Dalits' or 'Harijans', historically confined to menial work. Lastly, the category of 'Scheduled Tribes' (ST) comprises of tribal population historically living in forests and gradually being integrated into the mainstream development process. The above categorization is a simplified version of the categorization adopted by the government which has several regional variations. However, for the present purpose and for most academic discussions this categorization is sufficient unless one is doing a micro level study. The Caste Development Index calculated by Deshpande [2011] based on National Family and Health Surveys conducted between 1992-93 to 2005-06 shows that all spheres of economic development such as education, asset ownership and employment across the country reflect this social hierarchy.

Specifically in the context of Karnataka school education, there has been a marked shift of higher castes towards private schools, leading to a change in caste composition of government schools. Students from general category comprised of 15.8% of total students enrolled in grade 1 in all schools in Karnataka for AY 2013-14. However, in government schools, they comprised only of 6.1% of total enrollment in grade 1. A perception that the quality of education offered in government schools is inferior to that provided by private schools largely drives the observed disparity. The relationship between socio-economic disadvantage and learning outcomes is also reflected in test scores in the Secondary School Leaving Certificate (SSLC) exam[3]. Students from the SC community have scored lower than general category students by about 15% in the SSLC exams conducted in AY 2013-14 and 2014-15. The gap in scores is as high as 20% in English and maths. The gap between SC and OBC students has been around 12%.[4] Students from ST community have performed marginally better than those from SC community. Providing quality teaching inputs in government schools, therefore, becomes a critical first step towards bridging the socio-economic divide in Indian society.

Many traditional programs and schemes initiated to improve the quality of public schools have had limited success. Increasing acceptance and adoption of Information, and Communication Technology (ICT) has provided a unique opportunity to promote education on a large scale. ICTs have been employed to reach out to a greater number of students, including those to whom education was previously not easily accessible. The problem of teacher absenteeism and the obstacle of geographical distance to obtaining an education has been in many cases surmounted using ICT. ICT also provides students and teachers with innovative tools and educational content to enable and improve teaching and learning. Both central and state governments of India realize the importance of integrating ICT to enhance the quality of education. Many programs like Gyan Darshan, Gyan Vani at the national level and policies of providing computers to schools are expressions of this realization. However, most of these programs and policies that only provide computers to schools have not found significant success in improving test scores as reported by Barrera-Osorio and Linden [2009]. Anecdotal evidence from India suggests that such programs are often badly managed. During field visits for this project, we noticed that in many schools while CPUs were provided in an earlier ICT program, complete working units were rare. The SAMIE (Satellite and Multimedia Interactive Education) program that we study in this paper was envisioned to not only add to computer infrastructure of the classroom but also to use ICT to improve and evolve teaching pedagogy in government schools in rural Karnataka.

Given the limited availability of internet connectivity in remote rural areas, a hybrid technology integrating satellite and terrestrial mode was used to telecast classes. This technology enabled two-way video and audio along with data transfer system by using satellite for the forward path (in broadcasting/multicasting mode) and terrestrial mode for reverse communication, for student interaction. The project was implemented as a Public-Private-Partnership between the Department of Education, Government of Karnataka and the Indian Institute of Manage-

[3]A state-wide examination conducted by the Karnataka Secondary Education Examination Board (KSEEB) in April and October every year. This is mandatory for students completing ten years of schooling to obtain the Secondary Scool Leaving Certificate (SSLC). Students taking the exam for the first time usually take it in the month of April (i.e. end of academic year).

[4]We have not controlled for household or school characteristics while calculating these percentage gaps. Thus, these in some sense reflect the aggregate measure of learning disadvantage faced by children from different communities, a part of which is likely to be on account of factors such as poor economic conditions of their households.

ment, Bangalore (IIMB) Consortium, and funded by the State Department of Education for five years.

The program employed well-trained teachers and research teams with access to a broad range of knowledge resources and expertise in content delivery software. A conceptual diagram of the project is given in figure (1). Teams of teachers would research a topic and develop a lesson plan which is passed on to content developers who would develop multimedia content to accompany the lesson. The classes were delivered by teachers at the government studio in Bangalore and telecast live to the treatment schools across the state.

Classes were delivered to cover syllabus prescribed by Karnataka state education department for English grammar, science, and maths for grades 5th to 10th. Each subject had two classes per week of 40 minutes duration for each grade and were held during the regular school hours. The regular school time allocation for each subject is on an average 5 hours per week. Thus, the SAMIE intervention provides about 25% additional class-time to each subject per week. The schools were instructed to accommodate the time required for the SAMIE classes by taking time from recess and by extending the school day by an hour for the tenth grade. However, some substitution in time allocation may have occurred between subjects at the school level. The medium of instruction of the classes was Kannada, which is the mother tongue of most children in Karnataka. Many do-it-yourself exercises and class assignments were suggested on the topic being covered. Examples and exercises used in the classes were selected so that children from rural areas across the state could relate to them. Every class was followed by an interactive session where students could ask questions to trained moderators. The questions were transmitted over a video chat using broadband connectivity wherever available or through a voice call.

2.2 Sampling, Randomization and Program Description

We focused on selecting schools in the economically backward regions of the State. We used the classification done by the High Power Committee on Redressal of Regional Imbalances (popularly known as the Nanjundappa Committee) to pick 18 districts with the lowest development score. The Nanjundappa Committee Report classifies taluks in Karnataka into 4 categories (Relatively Developed, Backward, More backward and Most Backward) based on various development criteria. For each district, a development index was constructed based on the extent of backwardness of the taluks. 18 backward districts (figure 3) were chosen based on this index, and four taluks were randomly selected from each district. Some of these taluks selected are not necessarily backward taluks in the district. Two taluks out of these were randomly assigned to receive the intervention and two to the control group. Once the taluks were chosen, all government and government-aided schools [5] that satisfy the criteria of having a minimum level of facilities required to run a tele-education class were included in the treatment and control groups. These criteria were - (a) closed classroom in good condition with adequate security for the equipment, (b) working electricity connection and (c) A minimum of 20 students in each class (d) either

[5] Government-aided schools are schools that are public funded and privately managed

availability of existing internet connectivity or feasibility of providing connectivity by the ISP. From the control taluks, 823 schools were included in the control group and 1000 were included in the treatment group.

The technology was selected on the basis of its techno-economic feasibility given the conditions in the remote areas where the schools were located. However, from the experiment design perspective, one of the incidental advantages that the technology offered was control of spill-overs. Unlike distribution of education content using CDs or over public internet websites, it is not possible for schools in the neighborhood to access content provided over a VSAT link. A further control of spillovers was done by taking a taluk as a unit of randomization instead of a school as is the normal practice in such studies. This program is intended to be spread over a 5 year period. Typically rural areas rarely have a single school containing grade 1 to 10. Students from neighboring primary (grades 1 to 4) and upper primary (grades 5 to 8) schools would usually aggregate in a single secondary school (grades 9 and 10) in the locality. A random selection that allocates an upper primary school in a locality to control group and a secondary school in the same locality to treatment group or vise versa would have created high possibilities for spill-overs. Migration across taluks is possible but relatively low.

In this paper, we evaluate the impact of the program on the performance of students and schools in the SSLC exam conducted KSEEB. Among the 1823 schools included in the program, in both treatment and control groups, not all have grades up to 10. Out of the total 1000 treatment schools only 698 schools have secondary section (grades 9 and 10) and only 636 schools have secondary section in the control group. Out of the total 1334 schools that had a secondary section, 1246 schools were identified, using SSLC examination school codes, for this evaluation as some schools did not have students appearing for either 2014 or 2015 exams - 659 receiving the treatment and 587 in the control group.

The school year begins in the first week of June in Karnataka. In the first year of its implementation (AY 2014-15), the SAMIE intervention started in the month of November 2014 and continued until the close of the academic year in February 2015. This evaluation is done on the cohort that was in grade 10 in AY 2014-15 and was exposed to the intervention for about three months. We consider the performance of cohort which was in grade 10 in AY 2013-14 as the baseline for the purpose of this analysis.

3 Data

We take data on enrollment, academic and physical infrastructure for our treatment and control schools from the database of the Karnataka State Department of Education. We use data on teachers from District Information System for Education (DISE) website maintained by National University of Educational Planning and Administration (NUEPA). Student level demographic data and subject-wise scores in the exams conducted in April 2014 and 2015 for control and treatment schools are obtained from KSEEB.

Since the present paper limits the analysis only to performance of students in grade 10 exams, we compare schools with secondary sections from control and treatment groups to check if the two groups are statistically similar. Panel A of table (A1) compares the schools on the basis of enrollment and physical infrastructure. The infrastructure score for each school is computed on the basis of availability of various facilities in the school including those mentioned in the Right to Education Act, 2009. These include facilities such as playground, library, boundary-wall, special ramps and toilet for differently abled students, etc. One point is awarded for each of the facilities. Thus a high score indicates better infrastructure. Panel B compares the schools on characteristics of teachers teaching in secondary section. These include average number of teachers, proportion of female teachers and from various social categories, their academic and professional qualifications. The academic and professional qualification scores are computed for each teacher based on the estimated number of years required to complete the attained qualification. A higher course indicates a higher qualification. [6]

Panel C compares the demographics of the grade 10 students in each school for AY 2013-14 and AY 2014-15 based on gender and social category. In terms of caste composition, the proportion of students from scheduled tribes in the treatment groups is slightly higher in both years. As students from this category have been under-performers in overall state, the treatment group may have a slight disadvantage. Panel D compares average score by students of a school in SSLC 2014 exams i.e. at baseline. The p-values given in column 4 indicate that the schools with grade 10 in control and treatment groups are statistically similar.

4 Estimation and Results

We estimate the impact of the treatment primarily at individual student level and at school level. At individual level, in addition to the overall impact of treatment, we also analyze the impact on various sub-groups of the population such as girls, different caste categories and girls from the socially disadvantaged communities. At school level we also look at the impact of treatment across the distribution of scores.

4.1 Impact of treatment at student level

At the individual student level we estimate a pooled cross section regression on student scores in AY 2013-14 and 2014-15 to check if the difference between control and treatment groups is specifically seen in the intervention year. For this we estimate,

$$Y_{ijt} = \alpha + \beta_1 D_j + \beta_2 Yr_t + \beta_3 D_j * Yr_t + \beta_4 X_i + \epsilon_{ij} \tag{1}$$

where, Y_{ijt} is the SSLC outcome of student i in school j for exams held in time t i.e. April 2014 or 2015 as the case may be. D_j indicates treatment status of the school j and Yr_t is the year dummy that takes value one if the student i has appeared for the exam in 2015 and

[6] The only exception to this rule is Bachelor in Elementary Education. Though this is a Bachelor level course, if the teacher is teaching in secondary section, he/she gets a lower score compared to one with Bachelor in Education.

zero otherwise. The parameter of interest here is β_3. We estimate this equation with and without controlling for school characteristics (X_i). Table (A2) shows the results for estimation of equation (1). Columns 1-3 give results for student scores in English, maths and science respectively without any controls for school characteristics. It can be seen that the treatment effect in AY 2014-15 is positive in English and science but negative in maths. Columns 4-6 includes controls for school characteristics. It can be seen that the treatment effect is robust to addition of controls.

4.1.1 Impact of treatment across various sub-groups

Next we estimate the impact of treatment on various sub-groups of population. We look at groups usually considered as disadvantaged in Indian context such as girls students and students from socially disadvantaged castes i.e. OBC, SC and ST. We do this by addition gender and caste dummies to equation (1) as follows -

$$Y_{ijt} = \alpha + \beta_1 D_j + \beta_2 Yr_t + \beta_3 Z_i + \beta_4 D_j * Z_i + \beta_5 Z_i * Yr_t + \beta_6 D_j * Yr_t + \beta_7 D_j * Yr_t * Z_i + \beta_8 X_i + \epsilon_{ij} \quad (2)$$

where Z_i is an indicator for the specific student sub-group being tested i.e. gender or caste. The above equation (2) can be used to answer a couple of interesting questions. Thus coefficient for Z_i and $D_j * Z_i$ in equation (2) above tells us if the category in question is facing a disadvantage in the base year to begin with. Sum of coefficients for $D_i * Yr_t$ and $D_j * Yr_t * Z_i$ gives the impact of treatment within category Z. eg. If Z indicates gender and $Z = 1$ represents girls, $(\beta_6 + \beta_7) > 0$ would mean that increase in scores of girls in treatment group is greater than that of girls in control group. And finally, $D_j * Yr_t * Z_i$ gives the impact of treatment on gender gap. In all regressions we add district dumies and cluster standard errors at taluk level.

Table (A3) estimates equation (2) for gender. It can be seen that the girls have been performing better than the boys at the base line with a lead of about 2.5 points in each subject. This reversal of gender gap in exam scores has been a feature throughout the State for the last 3 years and is seen in other parts of the country as well. The treatment has helped in reducing the gender gap in favor of boys by 0.3 marks in English and about 0.5 marks in maths and science. Treatment has had a marginally negative impact on the gap between control and treatment girls in all subjects.

Table (A4) does a similar analysis for caste groups. All the socially disadvantaged groups i.e. OBC, SC and ST score less than the general category students at the base-line in all three subjects. The difference is highest among SC and ST students of almost 3.5 marks in all subjects. Difference in scores between all the socially disadvantaged categories and the general category has reduced considerably in AY 2014-15. However, the reduction has been more in control schools than in treatment schools. Comparing the gap within communities between treatment and control group, the SC students in treatment group have benefited from the treatment and the gap between them and their counterparts in control group has increased in favor of treatment group. However that is not the case with ST students. The group of OBC students seem to have benefited only in science while in other subjects the gap remained unchanged.

We can similarly check for other sub-groups of students. One such group of concern would be girls students within socially disadvantaged groups. As pointed above they often are victims of dual discrimination - of caste and gender. in table (A5) to (A8) we check the impact of treatment on girls across different caste groups. We start by estimating equation (2) on a subset of the original data containing only girls with Z indicating the caste of the student. We ask if the treatment benefits girls from disadvantaged castes and helps them in catching up with their counter parts in general category. It can be seen from table (A5) that girls from OBC community do face an initial disadvantage of about 0.7 to one point while girls from SC and ST score low by about 4 to 5 points compared to general category girls. The treatment has a positive impact on scores of girls from SC community in maths and science and from OBC community in science, thus reducing the performance ap between them and the general category girls in these subjects.

In table (A6) we further subset the data on girls into caste groups and estimate equation (1) on these subsets of data. β_3 in this case would compare difference in improvement in performance of girls within communities over the years between control and treatment groups. Thus we see that the girls from SC community have benefited in English and maths and have performed better compared to their counterparts in control group. Similarly, table (A7) subsets the data only by castes and checks for changes in gender gap within castes. This is done by estimating equation (2) on these subsets of data. Here we once again see that girls across communities have been doing better than the boys at the base line. This is indeed a positive development on its own. The advantage to girls at the baseline is minimum in the SC community. Post treatment, it can be seen that the impact of treatment has been positive on girls from SC community and for other communities, boys have benefited more than the girls. In general it can thus be said that gender impact of the treatment has been in favour of groups that starts with an initial disadvantage. This effect across caste groups is as yet weak, though clearly in case of children from SC community the benefit is already seen, though marginal and non-significant. As this evaluation is done only after 3 months of treatment and that too on grade 10 students who are already habituated to certain pedagogical methods, there is room to believe that as children are exposed to the experiment for a longer duration, the impact would be wider (across more sub-groups) and deeper (in terms of amount of change and hence significant).

4.1.2 Possible channels of treatment impact

Clearly, the treatment is making some headway in reducing the gap between performance of the socially disadvantaged students. Student achievement is school tests is determined by a number of factors. These include school quality and environment, socio-economic conditions of the households to which the student belongs, student's learning ability, etc. As mentioned above, the teacher-student interaction in the school is one of the important determinants of student performance. While it is not possible to infer the exact reasons as to why a treatment of this nature which is intended to be non-discriminatory would have a differential impact, however, some pointers can be captured from the data.

One of these is the possible social distance felt by the students from disadvantaged groups with a teacher from a higher caste. We check for the impact of a socio-cultural match between students and teachers in the control and treatment groups by including the proportion of teachers from general category in the respective schools as one of the controls to equation (2) above and also interact this variable with treatment, year and sub-group dummies. Table (A9) shows the differential impact on students from different castes as the proportion of teacher from general category increases. Clearly, at the base line, this has a negative impact on the scores of students from disadvantaged sections. There could be several reasons for this, one of which could be an implicit or explicit neglect or discriminatory treatment as shown by studies cited above. With the tele-education project, the proportion of time students are exposed to a neutral teacher (the teacher on the tele-education screen) increases. Being taught by the teacher who does not give special attention to a select group of students in class could possibly be an encouragement for others to increase their attention levels, thus helping them to improve their performance.

We do a similar exercise for gender difference between the teacher and students. From table (A10) it is seen that at baseline the girls in treatment school have an advantage of between 0.7 to 2.3 points in different subjects with a unit increase in proportion of female teachers. However, the difference is negative when compared at end-line in AY 2014-15. Clearly the treatment has reduced the strength of the match between the gender of local teacher and that of the students. Table (A11) does similar estimation with proportion of male teachers. As expected the effect of higher proportion of male teachers on girls at the base-line is negative in treatment schools. However, this disadvantage to girls due to higher proportion of male teachers is balanced after the intervention.

Technology, being impersonal, has often been criticized to make the teaching and learning process impersonal. However, when personal interactions are discriminatory in nature, use of impersonal mode of technology may be beneficial on those being discriminated against.

4.2 Impact of treatment at school level

For estimating impact at school level, we use school averages of total score, and English, maths and science scores We estimate equation (3) with the difference between 2015 and 2014 school average scores as a dependent variable.

$$Y_{2015i} - Y_{2014i} = \alpha + \beta_1 D_i + \beta_2 Y_{2014i} + \beta_3 X_i + \epsilon_i \tag{3}$$

where $Y_{2015i} - Y_{2014i}$, the outcome variable, is the difference in the average SSLC score of students from school i. D_i is a dummy variable at school level indicating treatment status. X_i are school level controls. The parameter of interest is β_1 indicating the extent of the difference in average score on account of the school receiving treatment. We include the test scores for the April 2014, (Y_{2014i}), in the regression as explanatory variable as the test scores are generally correlated over time. X_i are school level controls. In the first three columns in table (A12) treatment effect is estimated without any controls and is positive in all subjects. The effect is highest in science and marginal in maths. We further include controls for some school level characteristics. Columns 4-6 of table (A12) show that the treatment effect is fairly robust to addition of controls.

The impact of such teaching input based programs is typically different across the cohort. In some programs students in the middle and lower range of initial score benefit more than those in upper range (Banerjee et al. [2007]), while in some other programs the better performing students could derive more benefit thus widening the gap between the better and the poor performers (Glewwe et al. [2009]). Figure (4) clearly shows the shift in school average scores in control and treatment in AY 2013-14 and 2014-15. It is also clear that the treatment effect is more pronounced in the schools around the median of the distribution. We check this in the following manner. We distribute the schools in quartiles based on the average grand total score of the students of the school in exams held in April, 2014. We compare the treatment and control schools in each of these quartiles on their April, 2014 exam scores and find that the control and treatment groups within each quartiles are statistically similar. On these quartile we then estimate equation (1) with only district dummies as controls. The results are shown in table (A13). It can be seen that the lower two quartiles have derived the maximum benefit from the treatment except in all subjects except science.

5 Discussion and Conclusion

The interventions started in November 2014. Typically, the students of grade 10 complete their classes for the academic year and are on a study leave from the end of January. Thus effectively, their exposure of 10th graders to the program in the AY 2014-15 was for a short period of three months. It is not therefore fair to comment on the success or failure of the program solely based on evaluation of grade 10 batch performance in the SSLC results. Nevertheless, the estimated coefficients give some valuable pointers as to the direction of the impact. The regressions give a positive coefficient for the treatment dummy in English and science though the effect size is small. The effect size ranges from 0.4 points in English to 0.6 points in science with three months of treatment.

There are however, two important impacts that are seen. Firstly, the students from lower socio-economic backgrounds are beginning to see benefits from this program. Low performing students, especially when they come from such disadvantaged socio-economic backgrounds cannot afford to purchase additional teaching input in form of private tuitions, additional learning aids, etc. Translation of this disadvantage into educational performance can be clearly quantified from the data. Such students are likely to benefit from an intervention of this nature.

Schools in remote and underdeveloped areas with low academic and physical infrastructure are likely to be at the lower end of performance distribution. An additional input like the SAMIE program is likely to generate relatively higher marginal returns for these schools. This is seen in the quartile regressions. The effect of the treatment is different across subjects and varies slightly across quartiles. The treatment effect seems to peak around the median. As can be seen from table (A13) for all subjects, schools in the 25th to 50th percentile appear to get maximum benefit. Similarly for English and maths, it can be seen that schools from lower percentiles also seem to get the benefit. The positive and significant effect size seen in the quartile regressions for a few quartiles within three months of the intervention looks encouraging.

Thus, overall, while it may still be a bit premature to look for the impact of the intervention, the preliminary results as noted above do show that the impact is in the right direction. Further, the quartile-wise regressions show that the intervention is making an impact among the right strata of the schools i.e. those which are in the middle range of the scoring hierarchy. The impact is positive in schools at the lower end of the distribution, though non-significant. The intervention is designed as an additional teaching input delivered over and above the teaching time allocated for a subject. Its success remains conditional on teaching input and guidance by local teacher. It is likely that in schools at lower end of the distribution, even basic teaching and infrastructure facilities are not present. This may limit the impact of the intervention.

The detailed test results conducted under the project would give far richer data to analyze the impact across grades, gender and socio-economic background of the students. Nevertheless, the present paper shows that the intervention is a step in the right direction.

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Appendix

Table A1: Comparison of Schools with Secondary Section in Controls and Treatment Groups

	Control Mean	Treatment Mean	t-statistic	p-value
Panel A	School Characteristics[a]			
Total Enrolment	211.10	204.78	0.83	0.40
Total Classrooms	5.27	5.45	−1.06	0.29
Working Teachers	8.36	8.32	0.27	0.79
Pupil-Teacher-Ratio	26.30	25.16	1.24	0.22
Pupil-Classroom-Ratio	44.72	40.79	3.31	0.00
Infrastructure Score	7.24	7.32	−1.27	0.20
Panel B	Teachers in Secondary Section			
Number of Teachers	8.78	8.76	0.08	0.94
Number of Female Teachers	2.43	2.42	0.06	0.95
Academic Qualification Score	13.47	13.64	−1.25	0.21
Professional Qualification Score	1.89	1.91	−1.05	0.29
Proportion of Female Teachers	0.26	0.26	0.27	0.78
Proportion of OBC Teachers	0.48	0.50	−1.16	0.25
Proportion of SC Teachers	0.17	0.17	0.26	0.79
Proportion of ST Teachers	0.07	0.07	−0.80	0.43
Panel C	Student Demographics in AY 2013-14- Grade 10			
Proportion of Girls	0.47	0.47	−0.09	0.93
Proportion of OBC	0.44	0.47	−1.42	0.16
Proportion of SC	0.23	0.23	−0.20	0.84
Proportion of ST	0.11	0.13	−3.88	0.00
	Student Demographics in AY 2014-15- Grade 10			
Proportion of Girls	0.47	0.48	−1.29	0.20
Proportion of OBC	0.48	0.49	−0.33	0.74
Proportion of SC	0.24	0.24	−0.10	0.92
Proportion of ST	0.11	0.14	−4.02	0.00
Panel D	SSLC Exam Performance in 2014			
No. of students in grade 10	62.70	62.58	0.05	0.96
No. of students who passed the exam	54.12	54.56	−0.22	0.83
English	47.39	47.65	−0.50	0.62
Maths	45.38	46.13	−1.54	0.12
Science	49.50	49.59	−0.19	0.85
Social Science	60.42	61.06	−1.05	0.29
Total Score	334.04	338.16	−1.42	0.16

[a] For grades 5 to 10

Table A2: Pooled Regression with controls for school infrastructure, student and teacher characteristics

	Dependent variable:					
	English	Maths	Science	English	Maths	Science
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.044	0.707	0.082	0.002	0.692	0.041
	(1.020)	(0.984)	(0.954)	(1.000)	(0.942)	(0.930)
Year(2015)	−7.050***	−1.790**	−5.850***	−7.030***	−1.780**	−5.840***
	(0.920)	(0.871)	(0.863)	(0.921)	(0.870)	(0.867)
Treatment:Year(2015)	0.439	−0.201	0.617	0.431	−0.205	0.619
	(1.280)	(1.340)	(1.320)	(1.280)	(1.340)	(1.320)
Prop. of Girls				−0.029	−0.033*	−0.018
				(0.019)	(0.018)	(0.017)
Prop. of OBC				−0.008	−0.002	−0.010
				(0.010)	(0.010)	(0.009)
Prop. of SC				−0.004	0.001	−0.008
				(0.023)	(0.024)	(0.021)
Prop. of ST				−0.029	−0.015	−0.004
				(0.023)	(0.025)	(0.025)
Infrastructure Score				−0.248	−0.477**	−0.371*
				(0.256)	(0.220)	(0.222)
Teachers' Experience				−0.002	−0.001	−0.010*
				(0.005)	(0.005)	(0.006)
Acad. Qualification Score				−0.244**	−0.133	−0.042
				(0.124)	(0.128)	(0.094)
Prof. Qualification Score				1.780***	2.090**	1.280**
				(0.624)	(0.895)	(0.643)
Prop. Female Teachers				−3.170**	−3.050**	−3.750***
				(1.330)	(1.280)	(1.300)
Prop. OBC Teachers				0.109	0.255	1.050
				(0.989)	(1.040)	(0.708)
Prop. SC Teachers				−2.330	−3.340**	−3.290*
				(2.150)	(1.700)	(1.870)
Prop. ST Teachers				−2.240	−2.510	−3.750
				(2.260)	(1.940)	(2.440)
Constant	48.400***	47.300***	50.000***	53.400***	51.700***	53.800***
	(2.120)	(0.917)	(1.020)	(3.580)	(3.200)	(3.090)
Observations	159,129	159,129	159,129	159,129	159,129	159,129
Note:						*p<0.1; **p<0.05; ***p<0.01

All regressions include district dummies. Figures in brackets are standard errors and are clustered at taluk level

Gender and Caste Differences

Table A3: Gender Difference with School Controls, District Dummies, Taluk Clustering

	Dependent variable:		
	English	Maths	Science
	(1)	(2)	(3)
Treatment	-0.094	-0.024	-0.016
	(0.235)	(0.183)	(0.162)
Year(2015)	-0.717^{***}	-0.189	-0.923^{***}
	(0.142)	(0.121)	(0.122)
Girls	2.590^{***}	2.210^{***}	2.400^{***}
	(0.343)	(0.263)	(0.254)
Treatment:Year(2015)	0.166	0.203	0.253
	(0.226)	(0.189)	(0.169)
Treatment:Girls	0.130	0.097	-0.015
	(0.470)	(0.359)	(0.333)
Year(2015):Girls	0.256	0.130	1.050^{***}
	(0.261)	(0.242)	(0.302)
Treatment:Year(2015):Girls	-0.319	-0.495	-0.490
	(0.386)	(0.329)	(0.367)
Constant	1.410^{***}	0.992^{***}	1.270^{***}
	(0.266)	(0.216)	(0.242)
Note:	*p<0.1; **p<0.05; ***p<0.01		

All regressions include district dummies and controls school characteristics. Figures in brackets are standard errors and are clustered at taluk level.

Table A4: Caste Difference with School Controls, District Dummies, Taluk Clustering

	Dependent variable:		
	English	Maths	Science
	(1)	(2)	(3)
Treatment	0.144	0.310	0.146
	(0.376)	(0.307)	(0.268)
Year(2015)	-1.010^{***}	-0.552^{***}	-0.646^{***}
	(0.189)	(0.125)	(0.157)
OBC	-0.982^{***}	-0.613^{***}	-0.598^{***}
	(0.242)	(0.186)	(0.148)
SC	-3.340^{***}	-3.630^{***}	-3.180^{***}
	(0.381)	(0.346)	(0.261)
ST	-3.740^{***}	-3.450^{***}	-3.310^{***}
	(0.419)	(0.370)	(0.275)
Treatment:Year(2015)	0.152	0.180	0.146
	(0.283)	(0.223)	(0.224)
Treatment:OBC	0.005	-0.243	-0.257
	(0.476)	(0.392)	(0.353)
Treatment:SC	-0.325	-0.345	-0.154
	(0.571)	(0.511)	(0.430)
Treatment:ST	-0.539	-0.542	0.088
	(0.567)	(0.506)	(0.431)
Year(2015):OBC	0.435^{**}	0.425^{**}	0.299^{*}
	(0.219)	(0.193)	(0.158)
Year(2015):SC	0.682^{**}	0.646^{**}	0.167
	(0.300)	(0.275)	(0.289)
Year(2015):ST	1.240^{***}	1.360^{***}	0.918^{**}
	(0.442)	(0.329)	(0.381)
Treatment:Year(2015):OBC	-0.158	-0.239	-0.004
	(0.321)	(0.268)	(0.254)
Treatment:Year(2015):SC	-0.072	-0.052	-0.057
	(0.456)	(0.412)	(0.355)
Treatment:Year(2015):ST	-0.571	-0.821^{*}	-0.893^{*}
	(0.564)	(0.432)	(0.528)
Constant	2.420^{***}	1.980^{***}	2.000^{***}
	(0.381)	(0.298)	(0.265)
Note:	*p<0.1; **p<0.05; ***p<0.01		

All regressions include district dummies and controls school characteristics.
Figures in brackets are standard errors and are clustered at taluk level.

Caste & Gender Gap

Table A5: Performance gap between girls from different caste groups

	Dependent variable:		
	English	Maths	Science
	(1)	(2)	(3)
Treatment	0.020	0.539	0.242
	(0.489)	(0.410)	(0.347)
Year(2015)	-0.763^{**}	-0.191	0.478
	(0.317)	(0.257)	(0.298)
OBC	-1.360^{***}	-0.586	-0.579^{**}
	(0.374)	(0.405)	(0.292)
SC	-5.300^{***}	-5.240^{***}	-4.630^{***}
	(0.408)	(0.473)	(0.355)
ST	-4.950^{***}	-4.040^{***}	-3.880^{***}
	(0.535)	(0.480)	(0.403)
Treatment:Year(2015)	0.127	-0.363	-0.375
	(0.491)	(0.440)	(0.458)
Treatment:OBC	0.252	-0.403	-0.396
	(0.691)	(0.583)	(0.475)
Treatment:SC	0.160	-0.390	-0.074
	(0.711)	(0.634)	(0.547)
Treatment:ST	-0.033	-0.625	0.009
	(0.768)	(0.646)	(0.563)
Year(2015):OBC	0.323	0.033	-0.383
	(0.417)	(0.392)	(0.341)
Year(2015):SC	0.907^{**}	0.555	-0.103
	(0.438)	(0.429)	(0.351)
Year(2015):ST	1.450^{**}	1.180^{**}	0.140
	(0.656)	(0.541)	(0.553)
Treatment:Year(2015):OBC	-0.456	-0.037	0.328
	(0.598)	(0.565)	(0.518)
Treatment:Year(2015):SC	-0.032	0.544	0.106
	(0.672)	(0.627)	(0.521)
Treatment:Year(2015):ST	-1.030	-0.540	-0.542
	(0.837)	(0.783)	(0.832)
Constant	8.590^{***}	6.660^{***}	7.580^{***}
	(1.040)	(0.900)	(0.723)
Observations	74,173	74,173	74,173
R^2	0.243	0.253	0.277
Note:	*p<0.1; **p<0.05; ***p<0.01		

Data used for these regressions include only girls from control and treatment groups. All regressions include district dummies and controls school characteristics. Figures in brackets are standard errors and are clustered at taluk level.

Table A6: Improvement in performance of girls within Castes

	OBC			SC			ST		
Dep. var.:	English	Maths	Science	English	Maths	Science	English	Maths	Science
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.247	0.121	−0.174	0.283	0.161	0.246	0.083	0.065	0.380
	(0.333)	(0.259)	(0.267)	(0.388)	(0.363)	(0.318)	(0.535)	(0.438)	(0.488)
Year(2015)	−0.411*	−0.156	0.139	−0.046	0.351	0.255	0.505	1.010**	0.550
	(0.235)	(0.234)	(0.256)	(0.425)	(0.394)	(0.344)	(0.533)	(0.488)	(0.548)
Treatment:Year(2015)	−0.305	−0.369	−0.033	0.097	0.170	−0.236	−0.922	−0.956*	−0.956
	(0.347)	(0.299)	(0.337)	(0.504)	(0.456)	(0.437)	(0.628)	(0.628)	(0.660)
Constant	5.290***	5.210***	5.620***	5.920***	2.170	5.640***	8.940***	6.270***	5.830**
	(1.520)	(1.160)	(1.180)	(1.970)	(1.800)	(1.540)	(2.980)	(3.080)	(3.050)
Observations	35,656	35,656	35,656	16,100	16,100	16,100	8,768	8,768	8,768
R^2	0.227	0.237	0.262	0.245	0.289	0.291	0.224	0.247	0.263

Note: *p<0.1; **p<0.05; ***p<0.01

Data used for these regressions include only girls from respective caste groups. All regressions include district dummies and controls for school characteristics. Standard errors (in brackets) are clustered at taluk level.

Table A7: Gender gap in performance within Castes

	OBC			SC			ST		
Dep. var.:	English	Maths	Science	English	Maths	Science	English	Maths	Science
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.105	0.091	−0.005	−0.334	−0.073	−0.083	−0.651	−0.340	0.197
	(0.351)	(0.280)	(0.266)	(0.381)	(0.359)	(0.313)	(0.571)	(0.512)	(0.481)
Year(2015)	−0.596***	−0.075	−0.654***	−0.721**	−0.121	−1.250***	−0.350	0.593	−0.121
	(0.228)	(0.203)	(0.199)	(0.338)	(0.293)	(0.307)	(0.442)	(0.428)	(0.398)
Girls	3.180***	2.890***	3.000***	0.331	0.018	0.455	1.250	1.530**	1.740***
	(0.508)	(0.410)	(0.388)	(0.442)	(0.343)	(0.326)	(0.771)	(0.593)	(0.581)
Treatment:Year(2015)	0.234	0.222	0.269	0.030	0.047	0.366	−0.097	−0.454	−0.669
	(0.320)	(0.293)	(0.269)	(0.428)	(0.434)	(0.365)	(0.630)	(0.538)	(0.557)
Treatment:Girls	0.092	−0.041	−0.213	0.528	0.226	0.256	0.821	0.384	0.230
	(0.701)	(0.533)	(0.497)	(0.665)	(0.547)	(0.454)	(0.951)	(0.773)	(0.777)
Year(2015):Girls	0.113	−0.092	0.724*	0.757	0.460	1.500***	0.730	0.371	0.605
	(0.395)	(0.377)	(0.393)	(0.529)	(0.497)	(0.463)	(0.672)	(0.657)	(0.650)
Treatment:Year(2015):Girls	−0.492	−0.579	−0.266	0.025	0.104	−0.632	−0.803	−0.492	−0.268
	(0.574)	(0.490)	(0.520)	(0.662)	(0.640)	(0.562)	(0.893)	(0.873)	(0.825)
Constant	0.656	0.669	0.247	2.350**	0.842	2.660**	2.310	0.658	−0.393
	(0.799)	(0.616)	(0.703)	(1.120)	(1.160)	(1.140)	(1.770)	(2.080)	(1.960)
Observations	75,902	75,902	75,902	35,582	35,582	35,582	18,841	18,841	18,841
R^2	0.241	0.249	0.274	0.259	0.297	0.307	0.228	0.261	0.273
Note:									*p<0.1; **p<0.05; ***p<0.01

Data used for these regressions include only students from respective caste groups. All regressions include district dummies and controls for school characteristics. Standard errors (in brackets) are clustered at taluk level.

Table A8: Impact of Treatment across Gender+Caste group

	Summary of impact of treatment on :								
	Girls between caste			Girls within caste			Gender gap within caste		
Dep. var.	English	Maths	Science	English	Maths	Science	English	Maths	Science
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OBC	−0.456	−0.037	0.328	−0.305	−0.369	−0.033	−0.492	−0.579	−0.266
	(0.634)	(0.574)	(0.576)	(0.336)	(0.307)	(0.307)	(0.456)	(0.416)	(0.418)
SC	−0.032	0.544	0.106	0.097	0.170	−0.236	0.025	0.104	−0.632
	(0.445)	(0.356)	(0.308)	(0.504)	(0.456)	(0.437)	(0.635)	(0.567)	(0.577)
ST	−1.030	−0.540	−0.542	−0.922	−0.956*	−0.956	−0.803	−0.492	−0.268
	(0.867)	(0.785)	(0.788)	(0.638)	(0.570)	(0.593)	(0.874)	(0.778)	(0.814)
Note:									*p<0.1; **p<0.05; ***p<0.01

All regressions include district dummies and controls for school characteristics. Figures in brackets are standard errors and are clustered at taluk level. Regressions also include a full set of interaction terms with a constant. Only the relevant coefficients are shown here.

Table A9: Impact of General Category Teachers with School Controls, District Dummies, Taluk Clustering

	Dependent variable:				
	English	Maths	Science	S.Science	Language-1
	(1)	(2)	(3)	(4)	(5)
Prop.Gen.Teachers	0.840**	0.860***	0.386	0.058	0.596
	(0.389)	(0.332)	(0.301)	(0.444)	(0.536)
OBC:Prop.Gen.Teachers	−0.884	−0.817	−0.553	−0.433	−1.140
	(0.553)	(0.572)	(0.468)	(0.733)	(0.904)
SC:Prop.Gen.Teachers	−0.834	−1.160	−0.198	0.341	−0.787
	(0.780)	(0.834)	(0.599)	(0.878)	(0.915)
ST:Prop.Gen.Teachers	−2.790**	−2.930***	−1.610*	−1.700	−2.680*
	(1.310)	(1.120)	(0.973)	(1.480)	(1.610)
Prop.Gen.Teachers:Treatment	0.036	−0.077	0.106	0.446	0.756
	(1.020)	(0.907)	(0.803)	(1.100)	(1.470)
Prop.Gen.Teachers:Year(2015)	0.136	−0.342	0.051	0.788	−0.293
	(0.518)	(0.562)	(0.546)	(0.695)	(0.962)
OBC:Prop.Gen.Teachers:Treatment	−0.766	−0.074	−0.313	−0.685	−1.130
	(1.420)	(1.290)	(1.160)	(1.590)	(2.110)
SC:Prop.Gen.Teachers:Treatment	−0.017	−0.766	−0.534	−0.870	−0.368
	(1.570)	(1.410)	(1.170)	(1.610)	(2.260)
ST:Prop.Gen.Teachers:Treatment	1.400	1.940	1.400	1.420	−0.023
	(1.940)	(1.790)	(1.580)	(2.230)	(3.010)
OBC:Prop.Gen.Teachers:Year(2015)	0.312	0.712	0.566	0.126	2.090
	(0.671)	(0.888)	(0.816)	(1.060)	(1.370)
SC:Prop.Gen.Teachers:Year(2015)	−0.612	0.473	−0.932	−2.420**	−1.940
	(1.060)	(0.880)	(0.759)	(1.200)	(1.480)
ST:Prop.Gen.Teachers:Year(2015)	1.310	2.160**	0.621	1.010	0.531
	(1.410)	(1.090)	(1.260)	(2.160)	(2.080)
Prop.Gen.Teachers:Treatment:Year(2015)	0.004	0.377	−0.380	−0.328	−0.254
	(0.765)	(0.788)	(0.813)	(1.060)	(1.540)
OBC:Prop.Gen.Teachers:Treatment:Year(2015)	0.465	−0.690	0.343	0.135	−0.378
	(1.000)	(1.110)	(1.070)	(1.480)	(2.000)
SC:Prop.Gen.Teachers:Treatment:Year(2015)	−0.191	−0.107	0.979	0.627	0.341
	(1.500)	(1.390)	(1.160)	(1.750)	(2.640)
ST:Prop.Gen.Teachers:Treatment:Year(2015)	−1.790	−2.450	−1.580	−1.990	1.840
	(1.780)	(1.690)	(1.700)	(2.550)	(3.120)
Note:					*p<0.1; **p<0.05; ***p<0.01

All regressions include district dummies and controls school characteristics. Figures in brackets are standard errors and are clustered at taluk level. Regressions also include a full set of interaction terms with a constant. Only the relevant coefficients are shown here.

Table A10: Impact of Female Teachers with School Controls, District Dummies, Taluk Clustering

	Dependent variable:				
	English	Maths	Science	S.Science	Language-1
	(1)	(2)	(3)	(4)	(5)
Prop.Female Teachers	0.318	−0.371	0.009	−0.539	−1.300
	(0.605)	(0.496)	(0.500)	(0.731)	(1.220)
Girls:Prop.Female Teachers	−1.130	0.468	−0.540	0.604	1.250
	(1.180)	(1.000)	(1.040)	(1.460)	(2.340)
Prop.Female Teachers:Treatment	−0.823	−0.183	−0.539	−0.117	0.201
	(0.835)	(0.700)	(0.650)	(0.957)	(1.580)
Prop.Female Teachers :Year(2015)	−0.450	−0.692	−1.190*	0.116	−1.070
	(0.750)	(0.557)	(0.632)	(0.785)	(1.090)
Girls:Prop.Female Teachers:Treatment	2.310	0.763	1.790	0.907	2.270
	(1.650)	(1.400)	(1.380)	(1.940)	(2.990)
Girls:Prop.Female Teachers:Year(2015)	1.460	1.940*	2.940**	0.051	2.810
	(1.410)	(1.170)	(1.420)	(1.770)	(2.330)
Prop.Female Teachers:Treatment:Year(2015)	0.619	1.190	1.000	0.149	0.903
	(1.010)	(0.810)	(0.853)	(1.070)	(1.530)
Girls:Prop.Female Teachers:Treatment:Year(2015)	−1.880	−3.030*	−2.660	−0.934	−4.200
	(1.990)	(1.670)	(1.910)	(2.350)	(3.290)
Note:					*p<0.1; **p<0.05; ***p<0.01

All regressions include district dummies and controls school characteristics. Figures in brackets are standard errors and are clustered at taluk level. Regressions also include a full set of interaction terms with a constant. Only the relevant coefficients are shown here.

Table A11: Impact of Male Teachers with School Controls, District Dummies, Taluk Clustering

	Dependent variable:				
	English	Maths	Science	S.Science	Language-1
	(1)	(2)	(3)	(4)	(5)
Prop.Male Teachers	−0.314	0.369	−0.006	0.546	1.320
	(0.603)	(0.494)	(0.499)	(0.730)	(1.220)
Girls:Prop.Male Teachers	1.120	−0.464	0.531	−0.626	−1.280
	(1.180)	(0.999)	(1.040)	(1.460)	(2.340)
Prop.Male Teachers:Treatment	0.830	0.205	0.539	0.124	−0.188
	(0.830)	(0.698)	(0.648)	(0.955)	(1.580)
Prop.Male Teachers:Year(2015)	0.437	0.684	1.180*	−0.129	1.050
	(0.748)	(0.555)	(0.629)	(0.783)	(1.080)
Girls:Prop.Male Teachers:Treatment	−2.330	−0.800	−1.770	−0.908	−2.290
	(1.640)	(1.390)	(1.380)	(1.940)	(3.000)
Girls:Prop.Male Teachers:Year(2015)	−1.440	−1.920*	−2.930**	−0.024	−2.770
	(1.410)	(1.170)	(1.420)	(1.770)	(2.320)
Prop.Male Teachers:Treatment:Year(2015)	−0.610	−1.190	−1.010	−0.107	−0.796
	(1.000)	(0.808)	(0.846)	(1.070)	(1.530)
Girls:Prop.Male Teachers:dummytT:Year(2015)	1.860	3.020*	2.630	0.826	3.950
	(1.970)	(1.660)	(1.890)	(2.340)	(3.280)
Note:					*p<0.1; **p<0.05; ***p<0.01

All regressions include district dummies and controls school characteristics. Figures in brackets are standard errors and are clustered at taluk level. Regressions also include a full set of interaction terms with a constant. Only the relevant coefficients are shown here.

Table A12: School Level Value Add Average Scores - District Dummies - Taluk Cluster

	Dependent variable:					
	English	Maths	Science	English	Maths	Science
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.447	0.078	0.983	0.490	-0.043	1.020
	(0.666)	(0.781)	(0.634)	(0.640)	(0.756)	(0.623)
Avg.English(2014)	-0.459^{***}			-0.461^{***}		
	(0.031)			(0.030)		
Avg.Maths(2014)		-0.420^{***}			-0.414^{***}	
		(0.043)			(0.043)	
Avg.Science(2014)			-0.398^{***}			-0.400^{***}
			(0.032)			(0.031)
Prop.OBC Students				-0.471	0.162	-0.198
				(0.911)	(1.000)	(1.000)
Prop.SC Students				-1.010	-1.590	-2.040
				(1.840)	(1.660)	(1.550)
Prop.ST Students				0.435	4.430^{*}	2.380
				(1.870)	(2.420)	(2.000)
Prop.Girl Students				-1.300	-3.330^{**}	-2.610^{**}
				(1.270)	(1.440)	(1.330)
Pupil-Teacher Ratio				0.019^{*}	-0.013	0.011
				(0.012)	(0.013)	(0.012)
Pupil-Classroom Ratio				0.008	-0.014	0.017^{*}
				(0.012)	(0.011)	(0.009)
Infra.score				-0.236	0.112	-0.006
				(0.258)	(0.264)	(0.239)
Acad.qual.score				-0.147	-0.202^{*}	0.047
				(0.103)	(0.113)	(0.135)
Professional.qual.score				0.571	0.763	0.206
				(0.548)	(0.726)	(0.810)
10th Class Strength(2015)				-0.013^{***}	-0.007	-0.024^{***}
				(0.005)	(0.006)	(0.005)
Constant	16.000^{***}	19.300^{***}	18.200^{***}	19.600^{***}	22.300^{***}	19.300^{***}
	(1.430)	(2.510)	(2.500)	(2.830)	(3.280)	(3.560)

Note: *p<0.1; **p<0.05; ***p<0.01

All regressions include district dummies and controls school characteristics. Figures in brackets are standard errors and are clustered at taluk level.

Table A13: Pooled Regression - Quartiles - School Level Average Scores - District Dummies

	School Average Scores											
	English				Maths				Science			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Treatment	−0.189	−0.214	−0.885	−0.958	0.369	0.161	0.427	−0.178	0.926	−1.417**	−0.686	−1.253
	(0.683)	(0.603)	(0.697)	(0.956)	(0.773)	(0.658)	(0.704)	(0.964)	(0.754)	(0.673)	(0.682)	(0.846)
Year(2015)	−3.951***	−7.653***	−6.973***	−10.338***	1.793**	−2.662***	−1.391*	−4.596***	−2.156***	−5.869***	−6.394***	−8.814***
	(0.652)	(0.591)	(0.710)	(0.991)	(0.737)	(0.645)	(0.718)	(1.000)	(0.720)	(0.659)	(0.695)	(0.877)
Treatment:Year(2015)	1.184	2.109**	−0.605	0.796	0.085	1.493	−1.200	0.335	−0.412	1.830*	1.084	2.575**
	(0.911)	(0.842)	(0.962)	(1.318)	(1.030)	(0.920)	(0.973)	(1.329)	(1.005)	(0.940)	(0.942)	(1.166)
Constant	40.699***	45.928***	49.178***	56.854***	38.022***	46.047***	48.540***	54.448***	40.990***	48.272***	51.342***	58.436***
	(1.492)	(1.029)	(0.996)	(1.694)	(1.688)	(1.124)	(1.007)	(1.708)	(1.648)	(1.149)	(0.975)	(1.499)
Observations	624	622	624	622	624	622	624	622	624	622	624	622
R^2	0.182	0.357	0.344	0.322	0.120	0.109	0.118	0.164	0.175	0.241	0.274	0.280
Adjusted R^2	0.155	0.335	0.323	0.300	0.091	0.080	0.088	0.136	0.148	0.216	0.250	0.256
Residual Std. Error	5.685	5.250	5.985	8.146	6.428	5.734	6.051	8.215	6.275	5.861	5.857	7.208
F Statistic	6.717***	16.654***	15.832***	14.292***	4.102***	3.695***	4.015***	5.899***	6.402***	9.560***	11.394***	11.678***

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 1: Intervention Design

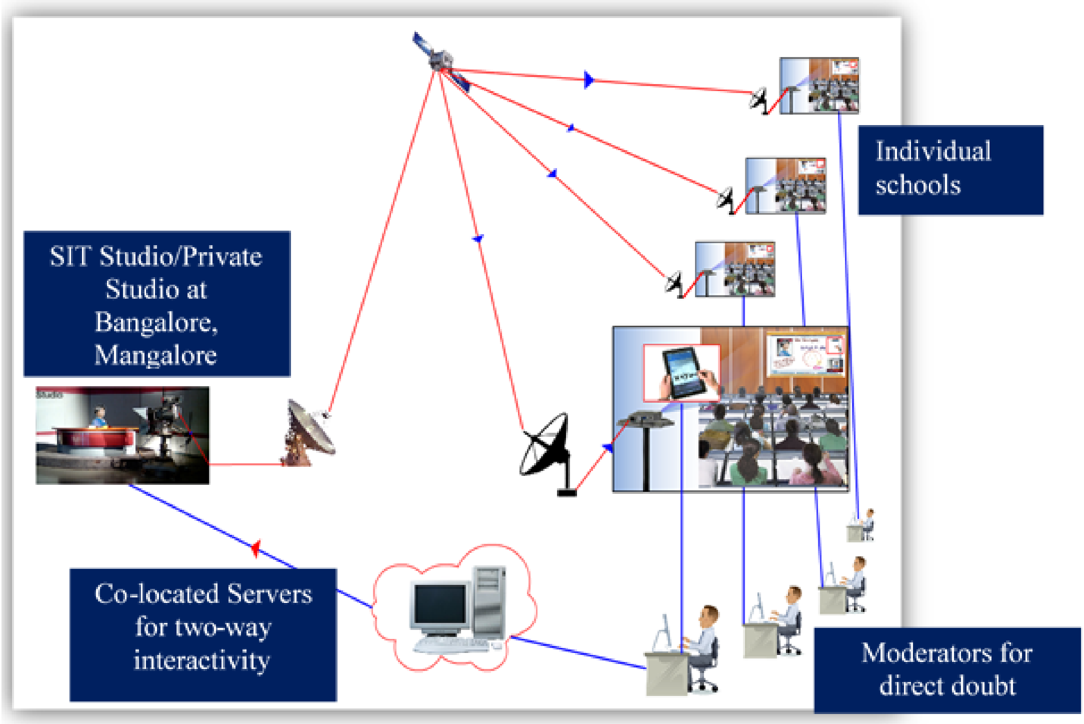

Figure 2: SAMIE Class

Figure 3: Districts selected for intervention

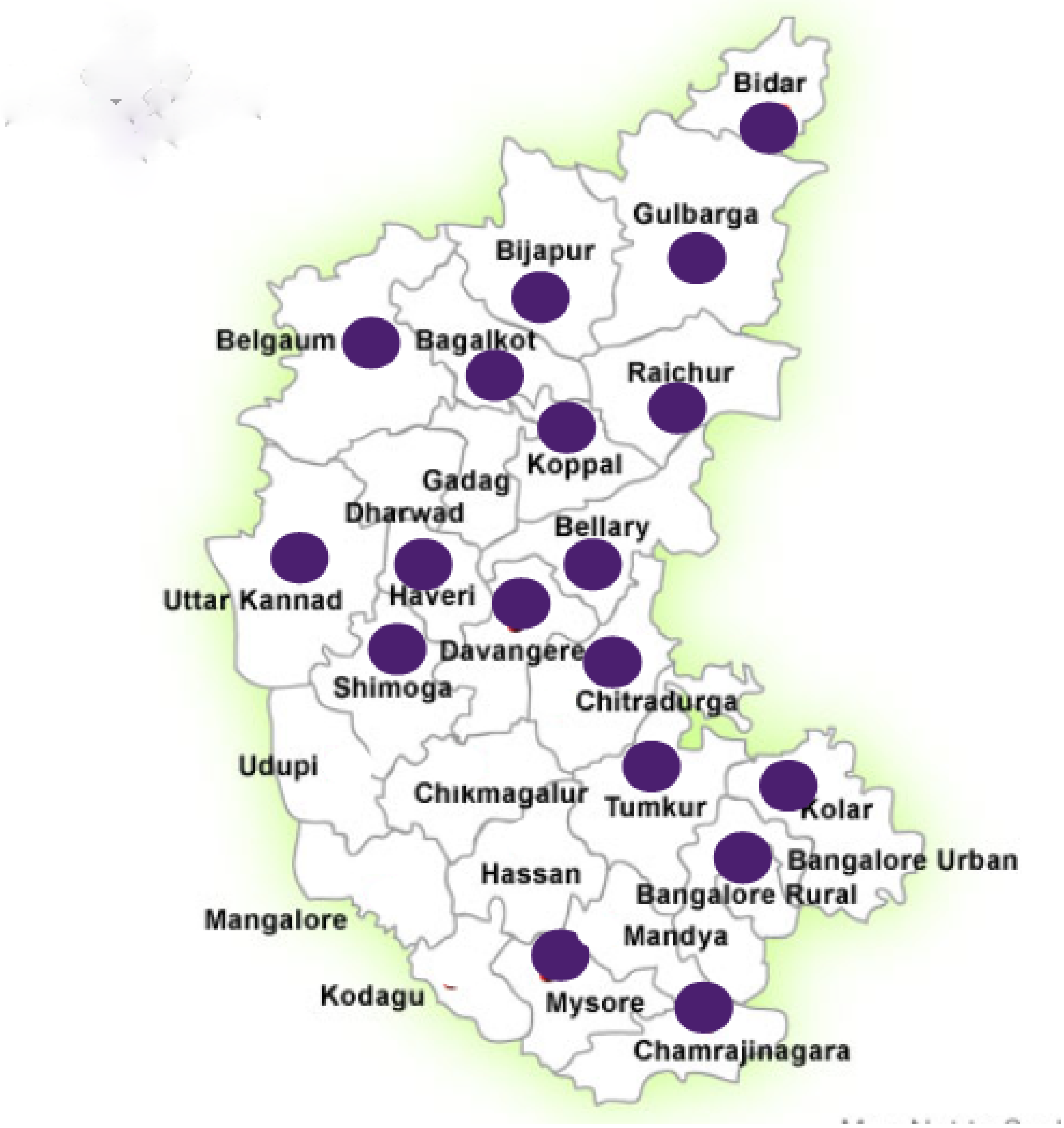

Figure 4: Difference between school average scores in control and treatment groups