# The Permanent Textbook Hypothesis: School Inputs and Student Outcomes in Sierra Leone

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Abstract
The randomized evaluation of a textbook provision program in Sierra Leone demonstrates how volatility in the flow of school inputs exacerbates smoothing in consumption (of those inputs) by school administrators, which can result in low current utilization for student learning. Public textbook provision to schools had modest impacts on teacher behavior but no impacts on student performance. In many treatment schools, student access to textbooks did not increase because a large majority of the books were stored rather than distributed to students. At the same time, the propensity to save books was positively correlated with uncertainty on the part of head-teachers regarding government transfers. We hypothesize that schools that have high uncertainty with respect to future transfers are more likely to store a proportion of current transfers with a view towards smoothing consumption. The results suggest that reducing uncertainty in school input flows could result in more effective current use of inputs, and that public policy programs must take forward-looking behavior among intermediate actors into account.

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# 1. Introduction

In the macroeconomic literature, volatility in aid flows has been linked to reductions in economic growth (Kodama 2012) and significant decreases in overall welfare (Arellano, et al. 2009). This paper explores a similar pattern within one sector, education, at a micro level. We provide evidence that unpredictable variability in flows of school inputs interacts with the desire for actors (in this case, school administrators) to smooth over time, resulting in extremely low utilization of those inputs in student learning.

In education, in the developing world, a growing body of empirical evidence shows that public provision of school inputs does not always lead to improved learning outcomes. In fact, there is very wide variation in estimated coefficients of school inputs on test scores (Glewwe, et al. 2011, McEwan 2013, Krishnaratne, White and Carpenter 2013). Naturally, we want to know why this should be so, especially with regard to inputs like textbooks which are both demonstrably scarce in developing country public schools and at the same time believed to be vital inputs in the education production function. This line of investigation is consistent with the growing emphasis on opening the black box in randomized impact evaluations (Deaton 2010, Pawson and Tiley 1997).

Clearly, a failure to detect the impact of input provision on student learning could arise due to several reasons. It could be because the inputs, due to their inherent nature or their quality, are ineffective, as a result of which their impact on student performance is zero. For instance, a randomized evaluation from Kenya shows that providing textbooks did not raise average test scores, possibly because textbooks are written in English which is a third language for most students – making it hard for them to use textbooks effectively (Glewwe, Kremer and Moulin 2008).

Lack of impacts from input provision could also be because households (or other actors, such as schools) re-optimize their allocation of resources when receiving an input. For example, Das et al (2011) show in both Zambia and India that when school grants for student learning inputs were anticipated by households, the households compensated by reducing private education spending. Alternatively, a study from Kenya shows that insecticide-treated bed-nets distributed to children under age 5 for use over their beds were actually being used for fishing and for drying fish in Lake Victoria (Minakawa et al 2008). These and other studies provide strong evidence that behavioral responses of agents to public programs can strongly mitigate program impacts on ultimate beneficiaries.

In this paper we present evidence of another scenario where the behavioral response of intermediate agents to a public program strongly influenced program outcomes on beneficiaries. In this case the agents in question are school administrators, an often neglected set of actors in empirical work. As in other studies, the behavioral response observed was not anticipated in program design; leading to the observed divergence between policy effects and hypothesized production function parameters.

Analyzing the results from a randomized evaluation of a textbook provision program to schools, we show that the program failed to have any impacts on student outcomes (attendance or performance) because few textbooks reached the students. Instead, publically provided textbooks were stored by school administrators.

Why should publicly provided school inputs to schools be stored instead of being distributed to students? We analyze the correlates of book storage and find that head-teachers who exhibit high uncertainty with respect to government transfers of textbooks are significantly more likely to store them. This behavior makes sense from the perspective of consumption theory: Consumption of current government transfers will be dictated in part by expectations regarding future transfers. If current transfers are seen as a one-time shock (or transitory) then their impact on current consumption will be limited. In other words, when there is uncertainty, school administrators have incentives to store current transfers to smooth consumption overtime, particularly for inputs like school books that depreciate quickly when used.

As mentioned earlier, this paper sheds light on the importance of behavioral responses of intermediate agents like school administrators in determining the overall impacts of public input provision programs to schools and how unpredictable volatility in aid flows exacerbates those responses. In particular, it provides empirical basis to question the assumption that publically provided inputs are deployed effectively within a short time period. It also puts at center stage the question about how future uncertainty regarding government transfers and policies impacts the current behavior of service providers.

On the whole, we hope that this analysis adds to our understanding of why such input provision programs might have been less effective than expected. Broadly speaking, our results are consistent with the premise that mere input provision to schools while ignoring the incentive structure within schools is unlikely to yield much in terms of gains to student learning outcomes.

The remainder of the paper is structured as follows: Section 2 provides a broad outline of the education system in Sierra Leone, and Section 3 lays out the experimental design. Statistics from baseline, actual implementation of the program, and empirical strategy are summarized in Sections 4, 5, and 6. Section 7 presents the overall impacts of the program. These results are discussed in sections 8, 9, and 10. Finally, conclusions and policy implications from this empirical work are laid out in Section 11.

## 2. Context

Sierra Leone has recently emerged from a brutal civil war that lasted a decade (1991–2002). The civil war severely impacted the country's education system leading to large-scale devastation of school infrastructure, severe shortages of teaching materials, overcrowding in many classrooms in safer areas, displacement of teachers, frequent disruptions of schooling, psychological trauma among children, poor learning outcomes, weakened institutional capacity to manage the system, and a serious lack of information and data to plan service provision (World Bank 2007).The education sector is now in the process of being rehabilitated.

The Education Act of 2004 stipulates universal basic education - 6 years of primary school and 3 years of junior secondary school. According to the 2008 EMIS there are around 5000+ primary schools in Sierra Leone, of which private schools make up a very small portion (less than 5 percent). Enrollments doubled in primary school between 2001/02 and 2004/05 (World Bank 2007). The gross completion ratio (GCR) in primary education was 65 percent in 2004/05 (World Bank 2007).

Several challenges on provision of basic education, many of them supply-related, persist. Currently, standard six pupils from 5,000+ primary schools compete for places in fewer than 300 junior secondary schools. Children (particularly girls) from the poorest households and those from rural areas and the Northern Region are lagging behind.

Although the government abolished school fees, primary education is still not completely free because many schools impose a variety of charges on their students. Our baseline data (see Section 3.2 for more details) shows that around 28 percent of the schools charge some kind of fees from parents. As many as 70 percent of the schools received subsidy payment for school fee from the government while 28 percent of the schools also receive support from the community, but there is no systematic correlation between the two sources of support – one is not a substitute for the other.

Most schools in Sierra Leone have very poor classroom conditions and still lack sufficient learning materials and adequately qualified teachers (World Bank 2007). In terms of learning materials, the official policy of the Sierra Leone government is to provide without charge primary grade textbooks in the four core subjects (a set) and to reach a student-textbook ratio of 1:1. The government and development partners have made efforts to provide textbooks, but significant challenges remain. The Poverty Reduction Strategy Paper (PRSP; Government of Sierra Leone 2005) estimated that, in 2004, a ratio of 1 set of textbooks to 3 pupils in urban areas and 1 set to 6 pupils in rural areas had been reached (World Bank 2007).

Also note that with the Local Government Act, 2004, the Government of Sierra Leone commenced a national decentralization process and primary education stands among the first functions scheduled to devolve to the Local Councils. Under the policy of decentralization, local councils will have full control and supervision of all primary schools including such functions as the recruitment and payment of teachers, the provision of textbooks and teaching materials, and the rehabilitation and construction of schools. The decentralization process for education began with the 2005/06 school year and was expected to be complete by 2008.

Our baseline data (see Section 3.2 for more details) show that the process of decentralization is still ongoing in the education sector of Sierra Leone. District Education Officers (DEO; centralized system) and local council officers (LC; decentralized system) are both active, leading to some confusion on the exact chain of command and roles and responsibilities of different agents.

## 3. Experimental Design

### 3.1 The Intervention

This paper seeks to evaluate a basic textbook distribution program of the Government of Sierra Leone in the year 2008. Under the program, textbooks are provided by the Ministry of Education, Youth, and Sports (MEYS) to primary schools based on student enrollment numbers as captured by the EMIS data. The actual transportation of books from central warehouses to schools is undertaken by local service providers who are competitively selected by the Government.

The main objective of the textbook distribution program was to provide a set of core textbooks for every child[1] in the treatment schools.

There are just over 5,000 primary schools in Sierra Leone, but the impact evaluation (IE) only focuses on schools that were registered with MEYS as having up to grade 6 (when the National Primary School Examination is taken). The program included government, government assisted, and community schools, but not private schools. The IE focused on standards 4 and 5, as these are the standards by which education is principally in English (the language of the textbooks).

### 3.2 Sampling

The IE relies on a randomized experimental design using a two-step process. First, 4 out of 19 local councils, stratified at the region level, were randomly selected. All 19 local councils were interested in participating, thus one council from each of Sierra Leone's four regions was chosen: Kailahun (Eastern region), Kambia (Northern region), Pujehun (Southern region), and Western Urban and Western Rural (both districts from the Western region agreed to function as one).

Within the randomly selected councils, 360 program schools were randomly selected using the Education Management Information System (EMIS) data. From the universe of schools in these councils, schools that were already being targeted for textbook interventions by NGOs were eliminated. Also, to avoid providing textbooks to schools that already have many, this project included only schools which had a 3:1 student-textbook ratio or higher. From the reduced sample, 90 schools were selected in each district (except for Western Rural and Western Urban which together amounted to 90 schools).

Within the district, sample schools were assigned equal probability to one of three categories (30 schools in each category in each district): receiving textbooks, receiving textbooks and teacher training, and control. However, due to multiple implementation challenges the teacher training component was not undertaken. Therefore, for the IE, we are left with schools that received textbooks (treatment schools) and schools that did not receive anything (control schools).

Baseline data was captured on 340 schools (out of a total of 360). The 20 schools that were not included in the sample were mainly due to either the inability of enumerators

[1] A set of core textbooks is made up of English, Mathematics, Integrated Science and Social Studies textbooks.

to access the school due to poor road conditions or flooded rivers. For a small portion of these schools, the enumerators were able to access the location, but there was no school at the premises. This could be partly due to the large share of 'ghost schools' in Sierra Leone.[2] The total number of schools for which data is available at baseline and endline, by district, is summarized in Table 1.

On contrasting baseline characteristics for treatment and control schools, we find the sample balanced for the most part (Table 2).

### 3.3 Data

Baseline data collection took place in May 2008 and endline in December 2009. Data collection included head-teacher survey, teacher survey, student survey, and student exams.

The data on the school as a whole were obtained through a comprehensive interview with the head teacher. This includes information observed (like the condition of the buildings, the number of classrooms, and other facilities) and other information obtained from the head teacher about the school finances, record keeping, community participation, management practices, etc. Data was also collected from teachers for grades 4 and 5, through teacher interviews.

One hundred students were selected randomly at each school and were given a written numeracy and literacy test. At baseline (May 2008) the student tests were administered to students in Grades 3 and 4 and at endline the same tests were administered again to the same cohort, which was now in Grades 5 and 6 (Dec 2009). Although a large number of students were tested - around 17,000 at baseline and 15,000 at endline, we were able to definitively match only about 5,300 students from baseline to endline. Therefore, to measure impacts on student performance, only endline scores are used. We do report results for change in score of those students who were matched for baseline and endline, but since there is a possibility of selective attrition, these results are not very reliable.

[2] In 2008 the Government of Sierra Leone did a verification exercise and discovered a large proportion of 'ghost' teachers and schools – teachers and schools that do not exist but are used to collect payroll on behalf of corrupt principals and officials. Over 1,000 'ghost' teachers were discovered alone. http://hello.news352.lu/edito-38098-sierra-leone-axes-1000-ghost-teachers.html?p=movies.

At endline, we also interview students from Grades 4 and 5, to derive a picture of textbook use (note that the books distributed by the program were for Grades 4 and 5).

## 4. Education Service Delivery in Sierra Leone (notes from baseline)

One issue that emerges from our baseline survey in the selected regions (Kailahun, Kambia, Pujehun, Western Urban and Western Rural) is the stark supply-side disadvantage that remote areas face with respect to education service delivery. Pujehun, which is one of the more remote districts in Sierra Leone, is significantly worse off compared to the other regions in terms of the supply of schooling inputs. In this region, less than 50 percent of all schools were considered in good condition, with almost 20 percent falling under the category 'no roof, walls are heavily damaged, needs complete rehabilitation.' Further, almost one-third of the schools do not have a working toilet.

During the baseline survey (May 2008), unannounced classroom visits were carried out in Grade 4 and 5 classrooms. Out of 828 such classrooms, teachers were found to be actively teaching in 54 percent of cases. If we define teaching activities more broadly (including organizing of class, setting of agenda, or disciplining of students) then the corresponding number was 77 percent. Once again, the remote district performed worse than others in terms of service delivery. Only half of all teachers were teaching or engaged in teaching related activity in Pujehun, while the corresponding numbers for some other districts were 90 percent.

As a part of baseline data collection, students in Grades 3 (8740 students) and 4 (8815 students) were given multiple-choice Mathematics and English tests. For mathematics, we find that 49 percent of Grade 3 students and 32 percent of Grade 4 students could not answer a single digit subtraction question (such as "Calculate 9-4"). Results from the test are summarized in Figure 1. On the whole, boys performed better than girls in both subjects.

A student in grade 4 or 5 requires four textbooks: math, English, social studies, and science. On average, at baseline, most students only have 2 textbooks implying that textbook availability is not at the government stipulated level of 4 textbooks per student. Further, only about 40 percent of the teachers claimed that they allowed students to take textbooks home, which implies that student access to textbooks at home is very low. In fact around 36 percent of the sampled schools reported parents complaining about lack of textbooks in the last six months. Likelihood of parents about lack of learning materials is not systematically related to the existence of a school management committee or to schools charging fees.

## 5. Intervention Implementation

To determine implementation of the intervention two sources of data are used: (i) information from the headmaster at endline and (ii) data on textbook distribution collected by IE team from district education officers and service providers.[3] Using these data we determine how many schools actually received books from the project.

As a second step, headmaster data is used to determine if the school received textbooks from other sources (such as from MEYS but outside the project, local government, or NGOs). This then allows us to create a variable for overall treatment i.e. schools in the program that received textbooks in 2008-09.

On contrasting actual treatment variable with the original randomized allocation, we find some non-compliance. Non-compliance to randomized assignment is found in both directions i.e. 15 percent of schools assigned as treatment did not receive any textbooks and 45 percent of schools assigned as control received textbooks from one source or another. This information is summarized in Table 3.

## 6. Empirical Strategy

Given the non-compliance to randomized assignment, the IE relies on Intent-to-Treat (ITT) analysis for identification of program impacts. In ITT analysis, participants are analyzed as if they received the treatment to which they were assigned (Begg 2000). This analysis yields an unbiased estimate only of being assigned to a treatment and not of actually receiving the treatment. Hence, using this methodology we will estimate the impact of being assigned as a treatment schools for receiving textbooks and not of actually having received textbooks. The ITT analysis identifies the mean differences between the population in the treatment and control areas.

Outcomes are tested using OLS regression models that use assignment to treatment group as the explanatory variable and thereby helps calculate how much an outcome of

[3] Headmaster data is given precedence; administrative data is used when headmaster data is missing. In case headmaster and administrative data contradict each other, headmaster data is used, except in 26 cases where in the headmaster claims school received books from the project but is unable to provide information on the number of books received or date books were received.

interest, e.g. change in test scores, differs between schools that are assigned as treatment schools and those that are assigned as control schools.

$$Outcome_i = \beta_0 + \beta_1 Treatment_i + \epsilon_i \quad (1)$$

where $Outcome_i$ is the outcome in school i, Treatment = 1 if school was assigned as a treatment school in randomization and 0 otherwise.

Outcomes are also tested at the classroom and student levels. At the classroom level and school level the specification is as follows:

$$Outcome_{is} = \beta_0 + \beta_1 Treatment_{is} + \epsilon_{is} \quad (2)$$

where $Outcome_{is}$ is the outcome in classroom i and school s for the classroom level regression and , it is the outcome for student i and school s for the student level regression. The variable Treatment = 1 if school was assigned as a treatment school in randomization and 0 otherwise. The errors term $\epsilon_{is}$ is clustered at the school level in these specifications to account for intra-school correlation of outcomes.

The parameter of interest is $\beta_1$ ; which is the average effect of being assigned as a treatment school in the textbook provision program.

To supplement this analysis, treatment on treated (ToT) estimates are also presented. Because actual provision of textbooks to schools outside the randomized assignment could be endogenous, that is, it could be a function of observed and unobserved school characteristics which may also be correlated with the outcomes of interest, we cannot simply compute the difference between outcomes of schools that received textbooks with those that did not.

To correct the potential endogeneity we propose instrumental variables estimation, using the treatment or control status of a school as an instrument for preschool participation. The treatment or control status of a school is a valid instrument given its high correlation with actual provision of textbooks to schools, and because treatment status was assigned randomly, it is orthogonal to school characteristics and as such uncorrelated with the unobserved heterogeneity (the error term in a standard regression model).

For ToT estimation we rely on a two stage least squares model:

$$P_i = \beta_0 + \beta_1 Treatment_i + \epsilon_i \quad (3)$$

Where $P_i$ is an indicator of whether school i received textbooks during the intervention period. In the second stage, the predicted values of $P_i$; $\widehat{P_i}$ acts as an independent variable.

$$Outcome_i = \beta_0 + \beta_1 \widehat{P_i} + \epsilon_i \tag{4}$$

The key parameter of interest is again $\beta_1$which represents the average impact of the program for those schools who received the books.

For most outcomes, both ITT and ToT estimates have been calculated. However, in the discussion and conclusion sections we rely more heavily on the ITT analysis, as being the cleanest estimation of the impact of being assigned as a treatment school for receiving textbooks. The TOT estimates are presented in Annex 1.

## 7. Overall Impacts

At the school level, we find that the program has no impacts on student enrollment. We do find however that the likelihood of parents complaining to head-teachers about lack of textbooks is substantially lower in treatment schools (Table 4).

Information on teaching practices was collected through interviews with teachers for Grades 4 and 5 at endline. These impacts are summarized in Table 5 wherein each teacher interview is a distinct observation and standard errors are clustered at the school level. We find that the program had no impact on likelihood of teacher assigning homework from textbooks. This is most likely because propensity to assign homework from textbooks is fairly high in control schools (93 percent). Likewise, the program did not influence the likelihood of physical punishment for students found mistreating textbooks.

We also find that the program did not impact the likelihood of teacher producing and/or distributing pamphlets (informal notes or study guides) to students. However, we do find significant positive impacts of the program on the likelihood of teacher having a lesson plan (Table 5).

Student attendance data was collected through unannounced visits to classrooms (Grades 4 and 5) at endline. We find no discernible program impacts on student attendance in either grade or by student gender (Table 6).

These unannounced classroom visits also yielded reliable data on teacher activity (Grades 4 and 5) in class. The program did not impact likelihood of finding teacher in class but did lead to increased likelihood of finding teacher in class teaching (Table 7). Note that in the control group about 18 percent of the teachers were not in class at the time of the visit; however of the teachers in class, only 57 percent were found to be actually teaching.

We also don't find any program impacts on learning outcomes as measured by a comprehensive test in English and Mathematics (Table 8a). As noted above, impacts on student performance are measured by comparing student test scores in English and Math at endline between control and treatment schools. Standard errors are clustered at the school level.

In Table 8b we also present program impacts on change in student scores between baseline and endline, for the sub-sample of students that were matched with baseline (diff in diff estimation). In these regressions also we do not detect any program impacts. However, since we cannot rule out selective attrition in the matched sample, these results are not very reliable.

Therefore, on the whole we find that the textbook provision program from government to schools has some modest positive impacts on teacher behavior (increased presence of lesson plan and increased likelihood of being in class and teaching) but no discernible impacts at the student level (either on attendance or performance).

## 8. What explains the lack of program impacts on students?

In order to fully understand the reasons for absence of program impacts at the student level, we exploit student survey data to examine how the program impacted textbook use by students. These data come from interviews conducted with students from Grades 4 and 5 at endline.

We find that the program of textbook provision from government to the schools did not significantly impact student use of textbooks. In Table 9 program impacts on broad indicators of student textbook use and related behaviors are summarized. We see that the program did not increase the likelihood that students in treatment schools were using a textbook in class, have a new textbook, or have a textbook given to them by teacher. Likewise, the program did not impact the number of students textbooks are shared with or the likelihood of receiving pamphlets (informal notes or exam guide) from teachers.

Information was also collected on materials used by students for exam preparation, including books, pamphlets, and notes. On these indicators as well, the program had no discernible impacts.

Student use of textbooks is often heavily contingent on teacher behavior. We examine program impacts on teacher behaviors with relation to textbook use in Table 10. This information also comes from student interviews described above. We see that while the program had modest impacts on the likelihood of teacher encouraging the use of textbooks by students and publicly rewarding students for good performance, it did not impact any of the more direct predictors of textbook use such as students reading from textbook in class, students being allowed to take textbooks home, and homework assignment.

Given the lack of program impacts on student textbook use, it is not surprising that we observe no impacts of the textbook provision program on student performance. We are, however, faced with a puzzle – when schools, by their own admission, received textbooks from the government, why then did the students' actual use of these textbooks did not improve? What happened to the government provided textbooks?

To answer this question, we again rely on direct observation data collected during the endline. During unannounced classroom visits, data was collected on number of textbooks per student in class. From this information we find that, at endline, textbooks per capita in classrooms were not significantly higher in treatment schools than control schools (Table 11).

During data collection, enumerators were instructed to request access from the headmaster to the place where textbooks were stored and count the textbooks (of 4 core subjects for grades 4 and 5) in storage. We find that in treatment schools the number of core textbooks stored per capita students present in school, is significantly higher (Table 11). Comparing books stored per capita at endline and baseline, we find that the program led to a strong increase in the number of books stored in treatment schools (Table 11). Box plots depicting book storage at baseline are presented in Figure 2.

Recall that lack of student access to books has already been highlighted given that the program did not increase the likelihood that students have access to books at home (Table 11). It is clear, therefore, that a big reason for lack of student access to textbooks either in classroom or at home could be that a lot of these books are being stored by schools and not distributed to students.

Presumably, the lack of access did not extend to teachers given that the program positively impacted teacher behavior on a number of dimensions[4].

## 9. Why are textbooks stored and not used?

If school administrators exhibit high propensity to store inputs instead of providing them to students, input provision programs to schools are likely to have only limited effectiveness. Therefore, it becomes imperative to understand what prompts school administrators to save government provided inputs instead of using them – clearly an inefficient utilization of resources.

To investigate underlying factors that predict propensity to store, we estimate a cross-sectional model in which book storage (per capita students present) is regressed on a set of school level controls.

$$z_i = \alpha + \beta_1 A_i + \beta_2 X_i + \epsilon_i \tag{5}$$

Where $z_i$ is the number of books stored per capita student in school i, $A_i$ is a dummy for whether school i expected to receive books in the academic year 2008-09 , and $X_i$ includes other school level controls that could influence propensity to store. These include the presence of head teacher at the time of interview, remoteness of school (distance from nearest paved road and from DEO's office), parental pressure (whether school charges fees, whether parents complain to head teacher about lack of textbooks), and whether the school received books from the Government in the last academic year[5].

As noted above, among independent variables we include a proxy for whether the school administrators 'expected' to receive books or not ($A_i$). The proxy for

[4] These results suggest that it would be of interest to derive impacts of textbooks on student performance after controlling for storage. However, book storage is likely to be endogenous and the authors were unable to find a credible IV for storage.

[5] In our sample of 341 schools, 71 schools reported receiving textbooks from the Government in 2008 (the last academic year).

expectations of input receipts from Government is created using head-teacher question at endline:

- Expectations proxy 1: If the head-teacher answers yes to the question: 'Do you know how many books the government was to allocate to your school for Grades 4 and 5?'
- Expectations proxy 2: If the head-teacher is able to answer the question: 'How many books was the government to allocate to your school for Grades 4 and 5?'

The underlying assumption in treating these variables as proxies for expectations is that head-teachers who claim to know whether books were allocated to their schools or, more stringently, who claim to know the exact number of books that were allocated – must have had some expectations of receiving textbooks from the Government in the current academic year.

This proxy is not perfect due to possibility of rationalization: Schools that actually received books will be more likely to claim that they expected to receive books. The r squared of proxy 1 and actually receiving books is 0.038 (with assignment is 0.0015) and proxy 2 and actually receiving books is 0.029 (with assignment is 0.0004).

Results are shown in Table 12. Panels 1 and 3 show results with expectations proxy 1 and Panels 2 and 4, with proxy 2; also in Panels 1 and 2, we examine the predictors of the number of books stored at the school level while in Panels 3 and 4 we examine the change in the number of books stored by including books stored at baseline as one of the independent variables.

We find that, controlling for a number of variables, book storage is significantly higher in treatment schools that did not expect to receive books. In contrast, it is lower in treatment schools that expected to receive books. This seems to suggest that school administrators who do not have expectations about receiving input transfers from Government are likely to hoard them instead of using them by distributing them to students.

This behavior makes sense if we assume that current expectations are positively correlated with future expectations. Head-teachers or teachers who have low current expectations and hence low future expectations of government transfers, hoard or save at least part of the transfers in order to smooth consumption in future periods. In this context, consumption is loosely defined as "intensive use of textbooks by students – at school and at home."

This interpretation calls for the following assumptions: (a) head teacher (teacher) performance is measured by average performance of students in their school (class); (b) head teachers' (teachers') objective function is to maximize their performance over their tenure period; (c) the tenure period extends over more than one year; and (d) head teachers (teachers) believe increased student access to textbooks leads to better student performance.

In this scenario, low expectations/high uncertainty mean that current transfers are seen as a one-time positive shock by head teachers or teachers with a multi-year planning horizon or objective function.[6] To maximize their performance over a multi-year period it would therefore be optimal for school administrators to hoard part of the current transfers of textbooks to smooth future consumption.

Why should expectations of school administrators regarding current and future transfers of textbooks from Government be low? This is discussed in Section 10.

There are other interpretations of this result. For instance, $\beta_1$ could simply be capturing unobserved components of head-teacher quality that are correlated with propensity to save books. It is possible that head teachers who hoard books are the lower quality head teachers who are both (a) less likely to be able to access information on future transfers from government; and (b) more likely to engage in rationing behavior with regard to distribution of books. It is also possible that book storage by school administrators indicates program capture and these stored books would be sold in the future for private gain.

Information from Panels 1 and 2 also highlights the role of parents in influencing propensity of input storage in schools. We find that schools where parents actively complain about lack of learning materials or pay fee have significantly lower likelihood of storing books. Not surprisingly, more remote schools are also more likely to store books. Remoteness is significantly related to overall book storage and change in book storage.

[6] This further assumes that current transfers are not sufficient to lead to an updating of head-teacher/teacher expectations from 'no transfers' to 'guaranteed transfers every year'.

There are obvious caveats to the discussion above, most importantly, the possibility of omitted variable bias. In fact, in the absence of reliable time-series data on past transfers of textbooks from government to schools it is difficult to make strong claims regarding expectations and hoarding behavior on the part of school administrators. More fundamentally, data limitations and empirical challenges make it difficult to assign clear labels to the hoarding behavior – it can be interpreted as 'consumption smoothing' as above, but it can also be seen as program capture or rationing on the part of school administrators.

## 10. Expectations of schools with regard to government transfers

One of the challenges that societies face as they move from conflict and fragility towards development is that trust in the State has to be re-built. Lant Pritchett (2009) argues:

"In seeking to build legitimacy the state will be under pressure to create confidence in the state, in part by delivering on identifiable "quick wins" but also at the same time to build and transform institutions that are capable of delivering on development."

While a government transfer program for textbooks can be seen as a 'quick win'; the system that is expected to deliver these transfers to schools is still far from perfect. There are inefficiencies and uncertainties in the functioning of government systems in Sierra Leone as evidenced by the fact that in 2009, 17 percent of the headmasters and 36 percent of teachers reported not receiving their full pay in the last year.

In addition, relating specifically to the textbook provision program, process data from the impact evaluation reveals that none of the DEOs or LCs had a clear picture of who was responsible for book pick up and distribution, official signatories, or monitoring for textbook delivery. With regard to actual disbursement of books knowledge was also spotty and written records were rarely found.

Further, only in 20 percent of the cases (out of 325) were textbooks ever delivered directly to the school (in other cases, presumably, textbooks are delivered to a central location in the district, like the DEO office) and in as many as 25 percent of the cases headmaster claimed that they had to pay for textbook retrieval from their personal resources with no expectation of reimbursement by the government.

These factors indicate that school administrators might view transfers from government as a one-time positive shock, with little expectation of further replenishment in the short-run. This would explain some of the hoarding behavior we find among school administrators.

## 11. Conclusions and Policy Implications

There is considerable preoccupation in the development community with the disappointing impacts of pure input provision programs on beneficiary outcomes. This paper provides one possible explanation for this phenomenon. We show that public provision of textbooks to schools failed to have any impacts on student outcomes because a large share of the publically provided textbooks was stored by school administrators instead of being distributed to students.

We find that school administrators who did not expect to receive books were more likely to store them. Based on this result, we hypothesize that administrators are forward looking and therefore in times of high uncertainty they store part of current transfers to smooth future consumption. Here consumption is defined as intensive use of textbooks by students, both at school and at home. Therefore, in line with the 'Permanent Income Hypothesis' when current transfers are seen as transitory they will have only limited impact on current consumption of textbooks in schools.

Clearly, behavior of intermediate agents, like school administrators, is likely to exercise a strong mediating influence on the impacts of public provision programs on ultimate beneficiaries. However, the types of intermediate agent behavior that are usually linked to program failure include issues like organizational constraints, problems of human error, and program capture for private gain etc. In this paper we provide empirical evidence of intermediate agent behavior that is rational, calculated, and not entirely driven by private gain but that ends up subverting intending program objectives.

We show that in situations where scarcity of inputs coexists with uncertainty regarding future government transfers, intermediate agents might have strong incentives to store part of current transfers to smooth future consumption of these transfers by ultimate beneficiaries. More fundamentally, in the absence of efficient systems and good information flows, expectations of intermediate agents are likely to become important in determining program impacts.

These results have clear policy implications. First, public (or NGO) provision of those inputs that depreciate quickly when used, like textbooks, will be fully consumed only if agents have expectations of replenishment. In case there is uncertainty regarding recurrence of the transfer, intermediate agents or ultimate beneficiaries will have incentives to store part of the current transfer to smooth future consumption. Therefore, for public programs that are envisaged as recurring transfers, there is need to reliably communicate the timing of the next transfer to intermediate agents with the aim of optimizing use of current transfers.

Secondly, in line with current discourse, empowering ultimate beneficiaries with information about government transfers can promote more effective use of these transfers. On the whole, the way program information is communicated to agents at different levels, is likely to have a strong impact on how effective the program ends up being.

Finally, as in many other empirical studies, we see here that mere input provision does not guarantee much unless adequate attention is paid to actual input use. For the latter it is the incentives and expectations of intermediate agents and ultimate beneficiaries that can make all the difference.

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**Table 1: School Sample**

| District | Total | Western Urban | Western Rural | Pujehun | Kambia | Kailahun |
|---|---|---|---|---|---|---|
| Original Designation | 360 | 72 | 18 | 90 | 90 | 90 |
| Baseline | 341 | 67 | 18 | 82 | 88 | 86 |
| Endline | 341 | 67 | 18 | 82 | 88 | 86 |

**Table 2: Comparing baseline charactieristics of treatment and control groups**

| | Assignment | | |
|---|---|---|---|
| Variable | Control | Treatment | Diff - sig |
| Student teacher ratio | 47.22 | 46.69 | no |
| Student classroom ratio | 66.22 | 75.08 | 5% |
| No. of toilets | 3.13 | 3.15 | no |
| No. of toilets for girls | 1.11 | 1.05 | no |
| Electricity | 0.06 | 0.08 | no |
| Distance from motorable road | 0.36 | 0.45 | no |
| Distance to DEO office* | 19.75 | 17.64 | no |
| School charges fees | 0.29 | 0.28 | no |
| Observations | Assignment | | |
| Variable | Control | Treatment | Diff - sig |
| Avg grade 3 math score | 11.84 | 11.33 | no |
| Avg grade 4 math score | 15.89 | 14.82 | 10% |
| Avg grade 3 eng score | 11.07 | 10.47 | no |
| Avg grade 3 eng score | 12.41 | 12.54 | no |

**Table 3: Compliance to Randomized Design**

| | Overall Takeup | | |
|---|---|---|---|
| Assignment | Control | Treatment | Total |
| Control | 62 | 53 | 113 |
| Treatment | 34 | 192 | 224 |
| Total | 96 | 245 | 341 |

Going by the strict definition of compliance, the non-compliance rate is 25%
15% of the assigned treatment schools did not get books from any source
45% of assigned control schools got books from one source or another

**Table 4: Impacts on Student Enrollment**

| | No. of Students Enrolled[1] | | Parents complain about lack of textbooks (logit) | |
|---|---|---|---|---|
| Treatment School | -6.13 | -8.32 | -0.425* | -0.454* |
| | (15.752) | (16.739) | (0.240) | (0.243) |
| Observations | 325 | 325 | 333 | 333 |
| R-squared | 0.39 | 0.4 | 0.07 | 0.15 |
| District fixed effects | No | Yes | No | Yes |
| Mean in control group | 334.67 | | 0.42 | |

1: Controlling for baseline enrollment

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 5: Impact on teaching practices**

| | Teacher assigns homework from textbook | | Student found mistreating book | | Teacher showed lesson plan | | Teacher has created a pamphlet for | |
|---|---|---|---|---|---|---|---|---|
| Treatment School | 0.027 | 0.025 | 0.01 | 0.009 | 0.109** | 0.101** | 0.064 | 0.072 |
| | (0.025) | (0.024) | (0.057) | (0.046) | (0.050) | (0.048) | (0.052) | (0.048) |
| Observations | 782 | 782 | 788 | 788 | 785 | 785 | 787 | 787 |
| R-squared | 0 | 0.03 | 0 | 0.18 | 0.01 | 0.05 | 0 | 0.08 |
| District fixed effects | No | Yes | No | Yes | No | Yes | No | Yes |
| Mean in control group | 0.93 | | 0.38 | | 0.53 | | 0.27 | |

Standard errors in parentheses, clustered at school level

* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 6: Impacts on Student Attendance**

| | Grade 4 | | | Grade 5 | | |
|---|---|---|---|---|---|---|
| | Girls | Boys | Total | Girls | Boys | Total |
| Treatment School | 0.011 | -0.019 | 0.001 | 0.052 | 0.002 | 0.026 |
| | (0.030) | (0.027) | (0.027) | (0.032) | (0.032) | (0.030) |
| Observations | 318 | 320 | 315 | 300 | 298 | 294 |
| R-squared | 0.18 | 0.14 | 0.18 | 0.14 | 0.11 | 0.13 |
| Mean in control group | 0.671 | 0.715 | 0.690 | 0.660 | 0.672 | 0.663 |

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 7: Teacher Activity in Class**

| | Teacher found in class | Teacher found teaching in class |
|---|---|---|
| Treatment School | 0.030 | 0.111** |
| | (0.034) | (0.046) |
| Observations | 744 | 744 |
| R-squared | 0.07 | 0.07 |
| Mean in control group | 0.815 | 0.571 |

Standard errors in parentheses, clustered at school level
* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 8a: Impacts on Student Performance (only endline) - normalized scores**

| | Grade 5 Math | Grade 5 English | Grade 6 Math | Grade 6 English | Grade 5 Math | Grade 5 English | Grade 6 Math | Grade 6 English |
|---|---|---|---|---|---|---|---|---|
| Treatment School | -0.061 | -0.122 | 0.005 | 0.000 | -0.088 | -0.132 | -0.002 | -0.001 |
| | (0.087) | (0.091) | (0.084) | (0.084) | (0.082) | (0.090) | (0.080) | (0.081) |
| District FE | no | no | no | no | yes | yes | yes | yes |
| Observations | 8011 | 8011 | 7094 | 7094 | 8011 | 8011 | 7094 | 7094 |
| R Sq | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0400 | 0.0100 | 0.0300 | 0.0200 |

**Table 8b: Impacts on Student Performance (endline-baseline; normalized)**

| | Grade 5 Math | Grade 5 English | Grade 6 Math | Grade 6 English | Grade 5 Math | Grade 5 English | Grade 6 Math | Grade 6 English |
|---|---|---|---|---|---|---|---|---|
| Treatment School | 0.055 | -0.24 | 0.097 | -0.042 | 0.029 | -0.235 | 0.084 | -0.024 |
| | (0.174) | (0.187) | (0.119) | (0.130) | (0.170) | (0.187) | (0.120) | (0.124) |
| District FE | no | no | no | no | yes | yes | yes | yes |
| Observations | 2362 | 2306 | 3092 | 3022 | 2362 | 2306 | 3092 | 3022 |
| R Sq | 0.000 | 0.000 | 0.000 | 0.000 | 0.010 | 0.010 | 0.010 | 0.010 |

Robust standard errors in parentheses; clustered at school level

* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 9: Textbook use by students**

| | Use textbook for one core subject | Have a new book | Using book given by teacher | No. of students book is shared with | Received Pamphlet from teacher | Use book for exam | Use Pamphlet for exam | Use notes for exam |
|---|---|---|---|---|---|---|---|---|
| Treatment School | 0.098 | 0.276 | 0.088 | -0.332 | -0.396 | 0.102 | -0.145 | 0.01 |
| | (0.196) | (0.236) | (0.209) | (0.307) | (0.284) | (0.180) | (0.271) | (0.217) |
| Observations | 3150 | 3193 | 3193 | 1685 | 3193 | 3131 | 3130 | 3142 |
| R-squared | | | | 0.04 | | | | |
| Mean in control group | 0.508 | 0.163 | 0.412 | 2.214 | 0.164 | 0.430 | 0.265 | 0.590 |

Robust standard errors in parentheses; clustered at school level

* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 10: Teacher behavior with respect to student textbook use**

| | Teacher encouraged book use during class[1] | Teacher made student read out from book[1] | Student allowed to take any core textbook home[1] | Teacher encouraged use of exercise book[1] | Teacher made students work in groups[1] | Teacher used the blackboard[1] | publicly rewards student for good performanc | Homework assigned at least 3 times a week | Homework includes questions from textbooks |
|---|---|---|---|---|---|---|---|---|---|
| Treatment School | 0.362* | 0.223 | -0.077 | -0.122 | 0.068 | 0.185 | 0.432** | 0.214 | -0.098 |
| | (0.209) | (0.195) | (0.216) | (0.456) | (0.248) | (0.482) | (0.188) | (0.258) | (0.182) |
| Observations | 3150 | 3151 | 2732 | 2990 | 3153 | 2991 | 3148 | 3155 | 3106 |
| Mean in control group | 0.767 | 0.668 | 0.240 | 0.985 | 0.810 | 0.992 | 0.394 | 0.852 | 0.196 |

1: In the last 7 days

Robust standard errors in parentheses; clustered at school level

* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 11: Books in Class and Books Stored**

| | Books in class per capita[1] | | Books stored per capita [1] | | | | Δ in Books Stored | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Missing values as missing[2] | | Missing values as zeros | | Missing values as missing | | Missing values as zeros | |
| | Grade 4 | Grade 5 | Grade 4 | Grade 5 | Grade 4 | Grade 5 | Grade 4 | Grade 5 | Grade 4 | Grade 5 |
| Treatment School | 0.205 | 0.126 | 1.057** | 1.477*** | 0.984** | 1.360*** | 0.768* | 2.449*** | 0.740* | 2.303*** |
| | (0.180) | (0.183) | (0.484) | (0.445) | (0.439) | (0.395) | (0.463) | (0.910) | (0.420) | (0.819) |
| Observations | 296 | 281 | 299 | 286 | 337 | 337 | 235 | 185 | 263 | 208 |
| R-squared | 0.19 | 0.18 | 0.1 | 0.12 | 0.09 | 0.09 | 0.08 | 0.07 | 0.08 | 0.07 |
| | 0.995 | 0.995 | 2.704 | 2.137 | 2.369 | 1.759 | 1.196 | 0.739 | 0.928 | 0.469 |

1: Per capita students present in school

2: Results remain the same when we correct for schools that have had a robbery in their storage room

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

**Table 12: Predicting propensity to store books**

| | Books Stored per capita (students present) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Expected books (proxy 1) | 2.721*** | | 2.425*** | |
| | (1.025) | | (0.850) | |
| Expected books (proxy 2) | | 2.721*** | | 2.615*** |
| | | (1.025) | | (0.831) |
| Treatment School | 1.776*** | 1.776*** | 1.150** | 1.159** |
| | (0.531) | (0.531) | (0.465) | (0.464) |
| Exp books(1)*Treatment | -2.864** | | -1.930* | |
| | (1.214) | | (1.009) | |
| Exp books(2)*Treatment | | -2.864** | | -2.010** |
| | | (1.214) | | (1.013) |
| Headteacher in school | 0.016 | 0.016 | -0.548 | -0.665 |
| | (0.496) | (0.496) | (0.451) | (0.448) |
| Distance to morotable road | 0.368*** | 0.368*** | 0.462*** | 0.463*** |
| | (0.087) | -0.087 | (0.083) | (0.083) |
| Distance to DEO office | -0.028* | -0.028* | -0.018 | -0.014 |
| | -0.016 | (0.016) | (0.015) | (0.015) |
| Parents complain abt books | -0.862* | -0.862* | -0.428 | -0.425 |
| | -0.477 | (0.477) | (0.413) | (0.411) |
| Parents pay fees | -1.215** | -1.215** | -0.618 | -0.683 |
| | (0.505) | -0.505 | (0.436) | (0.435) |
| Books received from govt last year | -0.052 | -0.052 | -0.561 | -0.508 |
| | (0.638) | -0.638 | (0.578) | (0.567) |
| Books stored at baseline | | | 0.297*** | 0.308*** |
| | | | (0.070) | (0.069) |
| Observations | 265 | 265 | 214 | 220 |
| R-squared | 0.23 | 0.23 | 0.33 | 0.33 |

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Includes District FE

**Figure 1: Student Performance in Mathematics by Grade & Gender**

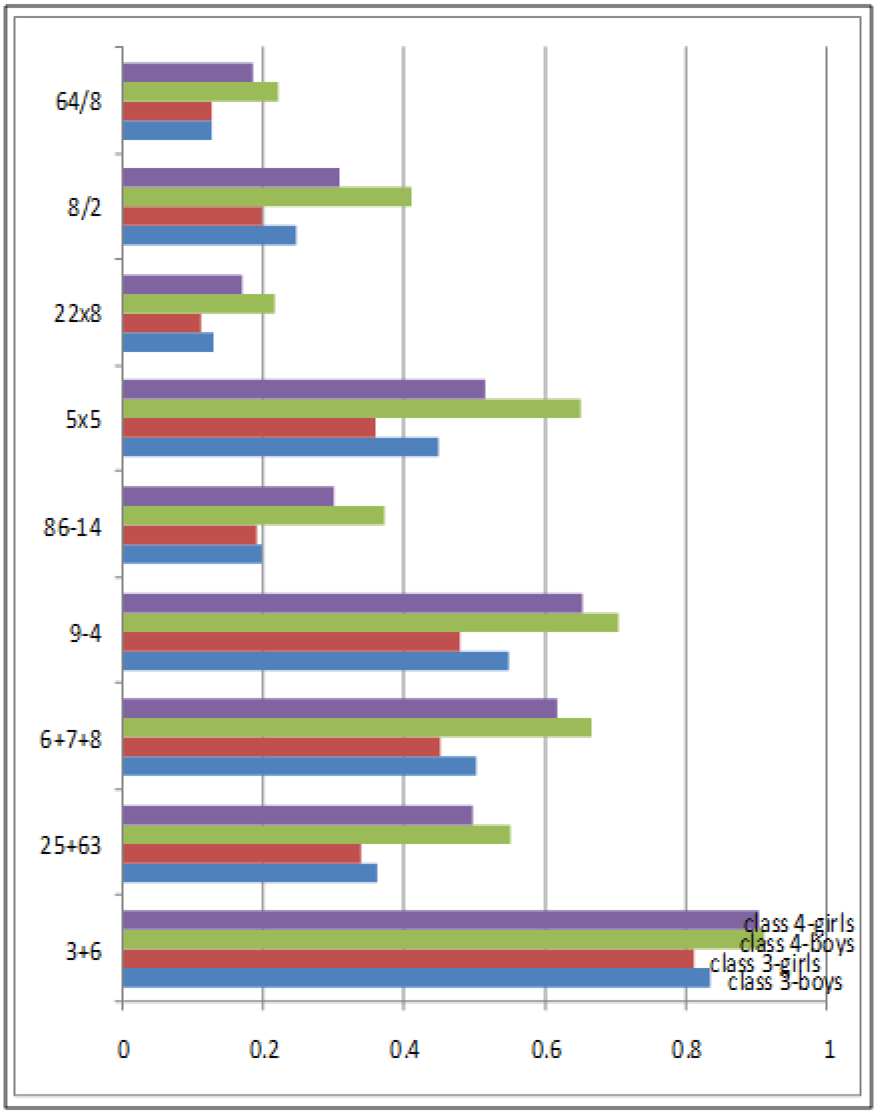
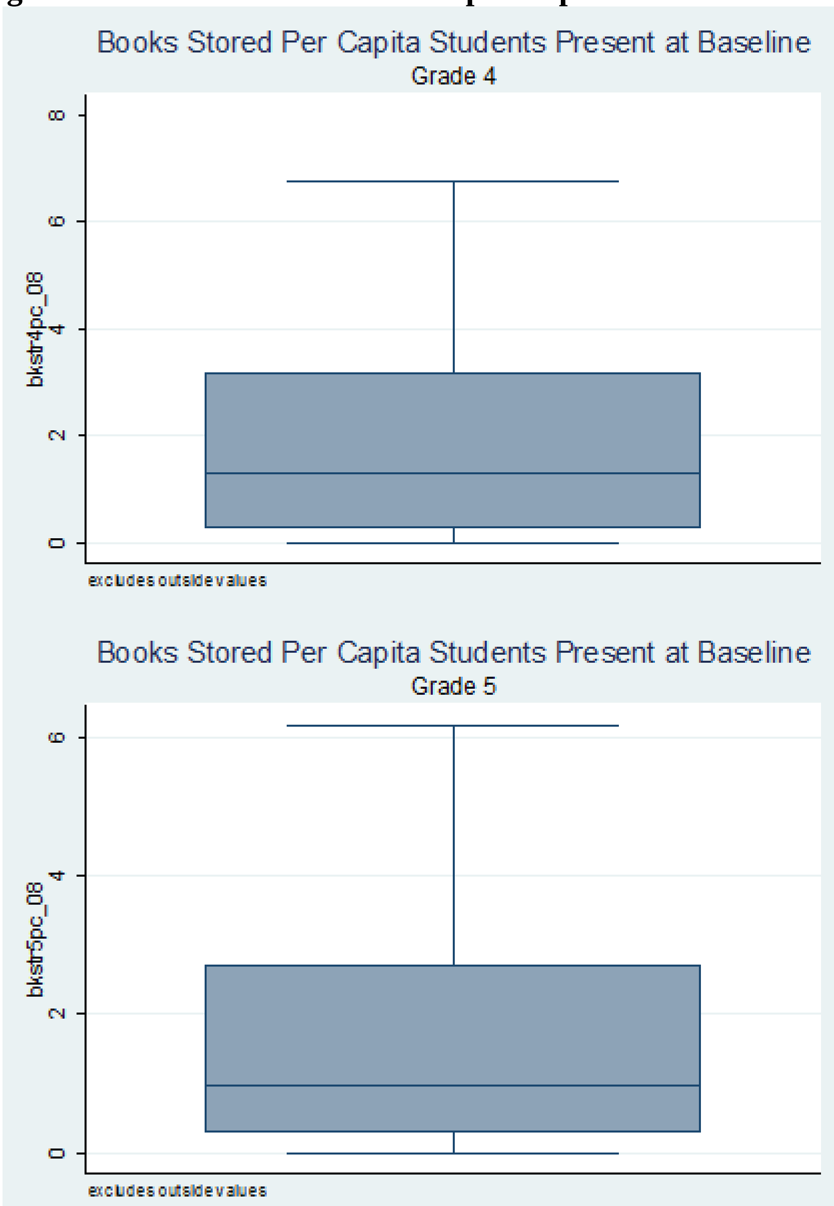


**Figure 2: Estimate of Books Stored per Capita at Baseline**




Note: The line in the middle is the median value. The bottom of the box is the first quartile, and the top of box is the third quartile.

# Using DVD Lectures to Improve Academic Performance of Rural High Schoolers

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**Abstract**

While many developing countries are achieving an increasing completion rate of primary school, the access to higher education is still limited especially in rural areas. Given the recent empirical evidence showing the higher returns from higher-level education than from primary-level education, improving the access to higher education is a crucial issue for economic development and poverty reduction.

Though there are accumulating studies investigating the impact of the interventions aiming at improving the academic performance of students, most of the interventions implemented in developing countries are targeted to primary or secondary school students, and these interventions are not always applicable to higher level education. For example, Banerjee eat al (2007) found the positive impact of remedial education and computer-based learning on student academic performance in India. However, finding remedial education tutors appropriate for high school students will be quite difficult given the lack of human resources in developing countries. It is often argued that in many poor countries, especially in rural areas, the quantity and quality of teachers is far from sufficient (World Bank, 2006). Programming softwares effective enough for high school students is not an easy task for most of the developing countries, probably excluding India. In addition, if one creates new programs from scratch, there are no guarantee for the software to be of good quality. There would be some software or contents outside of the country such as Khan Academy, but the curriculum is different and at least translation is required.

One potential intervention which has been little implemented is DVD lecture series, which could be feasibly implemented in most countries. Every country would have some very talented teachers who are really good at teaching. Once we can identify them, we can record his lecture series and distribute the lecture series DVD to schools or centers across the country. With this DVD lecture intervention, no additional human resources are required, and the quality of the lecture is guaranteed because they are supposed to be among the best teachers. Because they have been teaching ni the existing curriculum, there are no need for adjustment of curriculum and translation. The students can watch the lectures as many as they want at their own pace, which may help lower performing students. Some studies have pointed out the incentive problems of teachers such as absentism (Banerjee et al. 2005) and low incentives, but in the DVD lecture intervention, we can monitor the teachers to lecture which we record, making us less concerned about teacher's incentive problems.

In this paper, we report the results of the impact of the DVD lecture series on the university admission of the rural high school students in Bangladesh using a randomized control trial. We found that the DVD lecture series increased the admission to the top level universities by 5%, and the admission to any universities by 22%. We also found some of the noncognitive abilities such as conscientiousness contributed to increasing the impact of the DVD lectures, which is consistent with the idea that improving academic achievement requires both of the good materials and student's effort, and these two are complements. Present-bias indicator, on the other hand, did not significantly affect the effectiveness of the DVD lectures, probably because in our DVD lecture programs, some commitment mechanisms were embedded such as the exclusion of the students who were absent from the class in three consecutive days and daily and monthly small exams.

In another experiment, we investigate the price sensitiveness of the uptake behavior. We did not find any evidence that the uptake was influenced by the price at least in our price range even among the poor students. Given the increasing returns to education, this might suggest that households are willing to invest in higher education if the quality is ensured. This also suggests that households are not so severely credit constrained that they cannot find any financial resources to send their kids to this additional DVD lectures. This results might imply the possibility of running the DVD lecture series as a social business because people are willing to pay for higher education with good quality, and there are little worry that talented but poor students would be excluded from the service.

**JEL Classification:** I21; I23

# The Fiscal Cost of Weak Governance: Evidence from Primary Education in India

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**15 July 2013**

**Abstract:** India has the largest primary education system in the world, catering to over 200 million children. The public education system, though, is characterized by weak governance. A nationally-representative survey in 2003 found that 26.2 percent of teachers in rural public primary schools were absent on a typical day. We study the extent to which the substantial investments in primary education made by the Government of India over the past decade have translated into improved education system performance using a new nationally-representative panel data set of over 1200 villages that were initially surveyed in 2003. We find that there has been a substantial improvement in several measures of school quality, including infrastructure, pupil-teacher ratios, and monitoring. However, teacher absence rates continue to be high, with 23.7 percent of teachers in public schools across rural India being absent during unannounced visits to schools. We find two robust correlations in the nationally-representative panel data that corroborate findings from smaller-scale experiments. First, reductions in pupil-teacher ratios are strongly correlated with *increased* teacher absence. Second, increases in the frequency of inspections are strongly correlated with lower teacher absence. Improvements in infrastructure and working conditions on the other hand, are not correlated with lower teacher absence. We calculate that the fiscal cost of teacher absence in India is over $1.5 billion per year, accounting for 60 percent of the funds raised from India's special education tax in the year of the survey (2010). Assuming that the correlations using panel data are causal, we estimate that investing in improved governance by increasing the frequency of monitoring could yield a ten-fold return on investment by reducing the fiscal cost of teacher absence.

*JEL Classification*: I21, M54, O15

*Keywords*: teacher absence, teacher absenteeism, India, governance, state capacity, monitoring

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## 1. Introduction

India has the largest primary education system in the world, catering to over 200 million children. During the past decade, the Government of India has made substantial investments in primary education under the Sarva Shiksha Abhiyan (SSA) or "Universal Education Campaign". This national program sought to correct historical inattention to primary education and led to a substantial increase in annual spending on primary education across several major categories of inputs including school infrastructure, teacher quality, pupil-teacher ratio, and school feeding programs.

However, the public education system in India also faces substantial governance challenges. One striking indicator of weak governance is the high rate of teacher absence. A nationally-representative study of over 3,000 government-run primary schools across 19 major Indian states found that over 25 percent of teachers were absent from work on a typical working day in 2003 (Kremer et al. 2005). Thus, while administrative data from the government's official records[1] suggests that SSA has led to an improvement in various observed measures of school quality, there is very little evidence on whether these investments have translated into improvements in education system performance, both with respect to intermediate metrics such as teacher absence and final outcomes such as test scores.

In this paper, we study the impact of this nationwide campaign to improve school quality in India using a new nationally-representative panel dataset of education inputs and outcomes. We collect this data by revisiting (in 2010) a randomly-sampled subset of the villages that were originally surveyed in 2003 and collecting detailed data on school facilities, teachers, community participation, and monitoring visits by officials. We also collected data on teacher absence and student learning outcomes. Thus, in addition to reporting updated estimates of teacher absence, we are able to correlate changes in various input-based measures of school quality with changes in outcomes such as teacher absence and test scores. The panel data help mitigate concerns arising from unobserved heterogeneity at the village-level, and our results provide the best available estimates of how this ambitious nationwide program has improved school quality.

[1] These come from the "District Information System for Education" and are commonly referred to as the DISE data.

We find significant improvements in almost all input-based measures of school quality between 2003 and 2010. The fraction of schools with toilets and electricity more than doubled, and the fraction serving mid-day meals nearly quadrupled. There were significant increases in the fraction of schools with drinking water, with libraries, and with a paved road nearby. The fraction of teachers with college degrees increased by 40 percent, and pupil-teacher ratios fell by 16 percent. The fraction of teachers not paid on time fell from 51 percent to 22 percent, and the prevalence of teacher recognition programs increased from 49 percent to 81 percent. Finally, the frequency of school inspections and parent-teacher association (PTA) meetings increased significantly.

Reductions in teacher absence rates were more modest. The all-India weighted average teacher absence in rural areas fell from 26.3 to 23.7 percent.[2] The variation across states remains high. At one end, top performing states like Tamil Nadu, Punjab, Maharashtra, Chhatisgarh, and Orissa all have teacher absence rates below 15 percent, while at the other, the poorest performing state, Jharkhand (which also had the worst absence rates in 2003), has a teacher absence rate of 46 percent. We estimate legitimate absence rates to be in the range of 8-10 percent; thus, the variation among states in unauthorized teacher absence rates is even higher.

While the cross-sectional correlations in the original teacher absence study (Kremer et al. 2005) suggested a negative relationship between school infrastructure and teacher absence, we find no significant correlation between changes in infrastructure and changes in teacher absence in the panel data. We do however find two robust correlations in the panel data.[3] First, reductions in school-level pupil-teacher ratio (PTR) are correlated with an *increase* in teacher absence, suggesting that the potential benefits from investing in more teachers and smaller class sizes may be partly offset by an increase in teacher absence. Second, we find evidence consistent with the hypothesis that better monitoring can reduce absence. Villages where the fraction of visits in which schools had been inspected in the prior three months increased from zero to one, had teacher absence rates that were 6.5 percentage points lower (which is over 25

[2] While the all-India weighted average teacher absence estimated in 2003 was 25.2 percent, the corresponding figure for the rural sample was 26.3 percent. The panel survey only covered the rural sample.

[3] As we discuss further in the results section, we consider 'robust' correlations to be those where the point estimates are significant and similar in both binary and multiple regressions, and in specifications with no fixed effects, with state fixed effects, and with district fixed effects. These results are therefore least likely to be confounded with omitted variables at the state or district level.

percent of the measured absence rate, and over 40 percent of our estimated rate of illegitimate absence). We verify that these changes in inspections are not correlated with reductions in either authorized leave or official duty, but are mainly correlated with reductions in unauthorized absence rates. We also show that the changes in inspections are not correlated with changes in other teacher or school characteristics.

We combine our estimates of illegitimate teacher absence with data on number of teachers employed and their salaries and calculate that the fiscal cost of teacher absence is over $1.5 billion per year. This represents 60 percent of the entire revenue collected from the special education tax used to fund SSA (in 2010).[4] How can this fiscal cost of teacher absence be reduced? Using the most conservative panel-data estimate of the correlations between increased inspections and reduced teacher absence, and assuming that these effects were causal, we estimate that a marginal increase in the frequency of school monitoring and supervision would yield a ten-fold return on investment of the cost of increased inspections in terms of the salary cost saved through reduced teacher absence. Finally, we consider two policy options for increasing effective teacher-student contact time – hiring more inspectors, and hiring more teachers – and find that the former would be over twelve times more cost effective. Hiring more teachers entails an additional cost because of the increase in absence rates of existing teachers when additional teachers are hired. These results highlight the fiscal costs of weak governance in Indian primary education and the potential returns to investing in better monitoring.

This paper makes several contributions to the literature on public economics in developing countries. First, teacher absence is now widely used as a governance indicator in education in middle- and low-income countries.[5] We update the estimates of teacher absence in rural India from 2003 and show that in spite of substantial increases in spending on education inputs over the last decade, improvements on this key measure of governance have been more modest. Our estimates of the large annual fiscal cost of teacher absence highlight the discrepancy between high-levels of media coverage of corruption scandals where there are concentrated benefits to

[4] http://indiabudget.nic.in/budget2012-2013/ub2012-13/rec/tr.pdf

[5] The World Bank's *World Development Report 2004* focused on service delivery for the poor and provided consistently measured estimates of provider absence in both health and education for a sample of developing countries (see Chaudhury et al. 2006 for the details of this study). These numbers have been widely cited in policy discussions, and reduction in provider absence rates is often included as an objective in aid agreements between donors and aid recipients.

officials and politicians and the relatively low coverage of governance dysfunction that leads to large amounts of 'passive' waste and inefficiency – in our case, accounting for 60 percent of the collections from the special tax for financing education (Bandiera, Prat, and Valletti 2009).

Second, our results showing that decreases in PTRs are correlated with *increased* teacher absence underscores the importance of distinguishing between average and marginal rates of corruption and waste in public spending. Niehaus and Sukhtankar (2013) propose this terminology in the context of wages paid to beneficiaries in a public-works program in India and find that marginal rates of leakage are much higher than average rates. We find the same result in the context of teachers and show that the effective absence rate of the marginal teacher hired is considerably higher than the average absence (because of the increased absence among existing teachers). This result, from a large all-India sample mirrors experimental findings from multiple settings in smaller studies. See Duflo, Dupas, and Kremer (2012) and Muralidharan and Sundararaman (2013) for experimental evidence from Kenya and India that provision of an extra teacher to schools led to an *increase* in the absence rate of the pre-existing teachers.

Finally, if the relationships estimated in the panel are causal, we can compare the relative impacts of top-down (inspections) versus bottom-up monitoring (PTA meetings) for reducing absence. We find that the former are significantly more correlated with reduced absence, which is consistent with results reported in Olken (2007) that compare the relative effectiveness of administrative and community audits on reducing corruption in road construction in Indonesia. More broadly, a growing body of experimental evidence points to the effectiveness of audits and monitoring (accompanied by rewards or sanctions) in improving the performance of public-sector workers and service providers (including Olken 2007 in Indonesia; Duflo, Hanna, and Ryan 2012 in India; and Zamboni and Litschig 2013 in Brazil). Our panel-data estimates provide complementary evidence to these experiments from an "as is" nationwide increase in monitoring of schools, and suggest that investing in better governance and monitoring of service providers may be an important component of improving state capacity in low-income countries (Besley and Persson 2009).

At a minimum, our results make a strong case for an increase in the frequency of school inspections accompanied by a large-scale randomized trial evaluating its impact. We show in section 5 that if our estimates of the correlation between increased inspections and reduced teacher absence are causal, the net present value (in terms of salary costs saved through lower teacher absence rates) of a policy to ensure that all schools are inspected at least once in three months would be $3 billion. We also show that a substantial expansion of school inspections in the context of an experimental evaluation would make sense even if there was only a 1 percent chance of the true effects being the same as our panel-data estimates (and a 99 percent chance that an experimental evaluation finds no significant impact of increased inspections on reducing teacher absence).

From a policy perspective, it is worth highlighting that several of the innovative approaches to improving teacher performance in developing countries that have been experimentally evaluated in recent years (including performance-linked pay, monitoring teacher attendance with cameras, and informing citizens about their rights over schools)[6] often face political and administrative hurdles to scaling up. In contrast, inspection systems are already in place in most countries and are easy to scale up. Further, as we discuss in section 5, schools often do not get inspected on schedule because of staffing shortages. It should therefore be administratively straightforward to expand the frequency of school inspections simply by hiring staff to fill these shortages (and to conduct an experimental evaluation of such an expansion).

The rest of this paper is organized as follows: Section 2 discusses our empirical methods and analytical framework. Section 3 reports summary statistics on school inputs and teacher absence. Section 4 presents the cross-sectional and panel regression results. Section 5 discusses the fiscal costs of weak governance and the returns to investing in better monitoring. Section 6 concludes.

## 2. Data and Analytic Framework

### *2.1 Sampling and Data collection*

The nationally-representative sample used for the 2003 surveys, which our current study uses as the base, covered both urban and rural areas across the 19 most populous states of India, except Delhi. This represented over 95 percent of the country's population. The 2010 sample covered only *rural* India. The sampling strategy in 2010 aimed to maintain representativeness of the current landscape of schools in rural India and also to maximize the size of the panel. We

[6] See Muralidharan and Sundararaman (2011); Duflo, Hanna, and Ryan (2012); and Banerjee et al (2010) for illustrations of each of these type of interventions.

met these twin objectives (representativeness and panel) by retaining the villages in the original sample to the extent possible, while re-sampling schools from the full universe of schools in these villages in 2010, and conducting the panel analysis at the village level.[7]

We conducted school censuses in each village and sampled up to 3 schools per village for the absence surveys. During fieldwork, enumerators made three separate visits to each sampled school over a period of 10 months from January – October 2010.[8] Data on school infrastructure and accessibility, finances (income and expenditure), and teacher demographics were collected once for each school (typically during the first visit, but completed in later visits if necessary), while data on time-varying metrics such as teacher and student attendance and dates of the most recent inspections and PTA meetings were collected in each of the three visits. We also assessed student learning with a test administered to a representative sample of fourth grade students in sampled schools. See Appendix A and Appendix Tables 1-3 for further details on sampling and construction of the village-level panel data set.

Teacher absence was measured by direct physical verification of teacher presence and activity within the first ten minutes of a survey visit. Data collected during the census round were used to pre-populate teacher rosters for the sampled schools, so that enumerators could record teacher activity immediately after their arrival at the school.[9] Teachers could be "present and in class", "present in school but not in class", and "could not be found anywhere". Once teacher activity was recorded, enumerators asked the headmaster for reasons for absence. All

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[7] This also explains why the 2010 wave did not include urban areas. Since the fraction of schools covered in the sampled towns in 2003 (relative to the total number of schools in the sampled town) was very small, it was not possible to construct a credible panel-data estimate of school quality in towns. We did not have school-level identifiers from the 2003 survey (these were not preserved for confidentiality reasons), and so the panel needed to be constructed at the town/village level (and this would be too imprecise at the town level). In rural areas, this was not a concern because we typically covered *all* the public schools in a village (in 84.2 percent of the cases) and had a mean coverage rate of 82.7 percent of public schools in the sampled villages.

[8] While the exact timing of the school year is not identical across states, the typical school year runs from mid-June to mid-April. The three visits therefore spanned two academic years, with the first visit being made during January-March 2010, the second visit being made during June – August, and the third visit during August – October 2010.

[9] Doing this was especially important given the widespread possession of cell phones among teachers, which would allow them to call up absent colleagues as soon as they became aware of an external visit to the school that was measuring absence.

other data were collected using interviews and surveys of head teachers (for school details) and teachers (for teacher details).[10]

We record teachers as absent on a given visit if they were not found anywhere in the school in the first ten to fifteen minutes after enumerators reached a school. We consider all the teachers in the school to be absent if the school was closed during regular working hours on a school day, and respondents near the school did not know why the school was closed or mentioned that the school was closed because no teacher had arrived or they had all left early.[11] To be conservative in our measure of absence, we exclude all school closures due to bad weather, school construction/repairs, school functions and alternative uses of school premises (for instance, elections). We also exclude all part-time teachers, teachers who were transferred or deputed elsewhere, or teachers reportedly on a different shift.

We construct a school infrastructure index by adding binary indicators for the presence of four indicators of school facilities – drinking water, toilets, electricity and library. We construct a remoteness index by taking the average of nine normalized indicators of distance to various amenities including a paved road, bus station, train station, public health facility, private health clinic, university, bank, post-office and ministry of education office. A lower score on the remoteness index represents a better connected school.

During each survey visit, we record the date of the most recent school inspection. We measure the extent of monitoring and supervision as the mean probability of being inspected in the past three months across all three visits. We used a similar procedure for constructing the mean probability of a parent-teacher association (PTA) meeting. Average parental education of children in a school is computed from the basic demographic data collected for the sample of fourth-grade students chosen for assessments of learning outcomes.

[10] Of course, not all interviews could be successfully completed. Most non-responses were at the teacher as opposed to the school level (since absent teachers could not be interviewed, whereas school data could be obtained from either the head teacher or any other senior teacher). These non-responses do not affect the analysis in this paper because the panel-data analysis will focus on aggregated data at the village level as opposed to the individual data at the teacher level.

[11] Field teams obtained lists of state and national school holidays in advance of creating the field plans and ensured that no visits were conducted on these days.

*2.2 Analytical Framework*

For most of the analysis in this paper, we use the village as our unit of analysis and examine mean village-level indicators of both inputs and outcomes because a large number of new schools had been constructed between 2003 and 2010, including in villages that already had schools. This school construction resulted from a policy designed to improve school access by ensuring that every habitation with over 30 school-age children had a school within a distance of one kilometer. Thus, ensuring that our sample was both representative in 2010 as well as amenable to panel data analysis relative to the 2003 data requires us to construct the panel at the village level, with a new representative sample of schools drawn in the sampled villages.[12] All the results reported in this paper are population weighted and are thus representative of the relevant geographic unit (state or all-India).

## 3. Summary Statistics

*3.1 Changes in inputs*

The data show considerable improvements in school inputs between 2003 and 2010 along three broad categories – teacher qualifications and working conditions, school facilities, and monitoring (Table 1). The fraction of teachers with a college degree increased by over 40 percent (from 41 percent to 58 percent), the fraction reporting getting paid regularly rose by around 60 percent (from 49 percent to 78 percent), and the fraction reporting being eligible for a recognition scheme rose by over 60 percent (50 percent to 81 percent). While the fraction of teachers who report a formal teaching credential fell by 12 percent (77 percent to 68 percent), the main contributor to this decline was the large increase in the hiring of contract teachers in several large states leading to an increase in the fraction of contract teachers from 6 percent to 30 percent. The pupil-teacher ratio also fell by around 16 percent (from 47.2 to 39.8)

School facilities and infrastructure have improved on almost every measure. The fraction of schools with toilets and electricity more than doubled (from 40 percent to 84 percent for toilets and 20 percent to 45 percent for electricity); the fraction of schools with functioning midday meal programs nearly quadrupled (from 21 percent to 79 percent); the fraction of schools with a library increased by over 35 percent (from 51 percent to 69 percent), and almost all schools now

[12] Even in the absence of school construction, the survey firm did not retain school and teacher level identifiers from the 2003 survey (complying with data protection norms), which would have made it difficult to construct a school-level panel (especially for villages with more than three schools).

have access to drinking water (96 percent). Initiatives outside the education ministry to increase road construction have also led to increased proximity of schools to paved roads increasing the accessibility of schools for teachers who choose to live farther away. Relative to the distribution observed in 2003, a summary index of school infrastructure improved by 0.9 standard deviations.

Table 1 also documents improvements in both ‘top-down’ administrative and ‘bottom-up’ community monitoring of schools over this period. The fraction of schools inspected in the three months prior to a survey visit increased by over 40 percent (from 39 percent to 56 percent). This increase in inspection probability is even more pronounced over shorter time windows, increasing by over 60 percent for the previous two months and over 70 percent for the previous month. Finally, the extent of community oversight of schools, measured by the frequency of PTA meetings also increased: The probability that a PTA meeting took place during the three months prior to a survey visit increased by 50 percent (from 30 percent to 45 percent).

*3.2 Changes in teacher absence*

Table 1 confirms the substantial improvements in both school inputs and governance over this period. The main objective of this paper is to study the extent to which these investments have translated into improved outcomes, such as teacher absence. Table 2 (Column 2) shows teacher absence rates by state as well as the weighted average national absence rate for rural India. It also shows the corresponding figures for 2003 to facilitate comparison (Column 1). The population-weighted national average teacher absence rate for rural India fell from 26.3 percent to 23.6 percent, a reduction of 10 percent or 2.65 percentage points.

Considerable variation remains in teacher absence rates across states with estimates ranging from 12.9 percent in Tamil Nadu to a high of 45.8 percent in Jharkhand. Encouragingly, teacher absence rates declined in 14 out of 19 states with significant reductions in 12 states. Five states (Tamilnadu, Punjab, Maharashtra, Orissa, and Chhatisgarh) now report teacher absence rates below 15 percent.

Since Chaudhury et al. (2006) find a strong negative correlation between GDP/capita and teacher absence rates (both across countries and within Indian states), one way to interpret the magnitude of these changes is to compare them with the expected reduction in teacher absence that may be attributed simply to the economic growth that has taken place in this period. Using a growth accounting (as opposed to causal) framework, we can decompose the change in teacher absence into a component explained by changes in GDP/capita and one explained by a change in "governance" (equivalent to TFP). Cross-sectional estimates from the 2003 data suggest that a 10 percent increase in GDP/capita is associated with a 0.6 percentage point reduction in teacher absence.[13] In the period between 2002 and 2010, real GDP/capita in India has grown 38 percent. Thus, growth in GDP/capita over this period should have by itself contributed to a reduction in teacher absence of 2.4 percent. Our estimate of the change in teacher absence rate is exactly in this range, and suggests that there may have been limited improvements in teacher governance in this period over and above those induced by income growth. We discuss the policy implication of this decomposition in the conclusion.

Finally, to interpret the cost of teacher absence to students, we note that the effective attention a student receives from a teacher can be increased both by reducing teacher absence as well as by hiring more teachers. To account for the reduced attention that students receive when teachers are absent, we define the "effective pupil teacher ratio (EPTR)" as:

$$EPTR = \frac{PTR}{(1 - Teacher\ Absence\ Rate)}.$$

We use official DISE data on total enrollment and total number of teachers, combined with the absence rates from our survey to calculate both the PTR and EPTR by state (Table 2 – columns 4-9). Even though all-India PTR norms were below 40, the effective PTR after accounting for teacher absence was over 52. These figures illustrate that teacher absence can sharply increase the effective PTR experienced by students relative to the PTR calculated using state-level figures on enrollment and number of teachers.

### *3.3 Official records, teaching activity, and stated reasons for absence*

Enumerators recorded whether a teacher had been marked as present in the log-books on the day of the visit and also on the previous day, and we see in Table 3 - Panel A that going by these records would suggest a much lower teacher absence rate of 16 percent (based on the same day's

[13] The cross-sectional relationship is estimated by regressing village-level teacher absence on the log of district-level per-capita consumption (from the National Sample Survey) in the 2003 survey. Estimates without state fixed effects are larger (and equal -1.17) whereas estimates with state fixed effects are smaller but still significant (and equal to -0.63). Our default estimate is based on using state-fixed effects since cross-state variation in per-capita income is much more likely to be correlated with unmeasured governance quality. Tables are available on request.

records) or as low as 10.2 percent (based on the previous day's records). These data suggest that official records can be easily manipulated, and highlight the importance of measuring teacher absence by direct physical verification as opposed to official records on log books (and the figures suggest that the discrepancy between the two has increased over time).

Enumerators also record the activity that teachers were engaged in at the point of observation, and we see that 53 percent teachers on the payroll were found to be actively teaching at the point of observation, and another 4 percent were coded as passively teaching (defined as minding the class while students do their own work). 19 percent of teachers were in school but were either not in the classroom or not engaged in teaching activity while in the classroom. Thus a total of 42 percent of teachers on the payroll were either absent or not teaching at the time of direct observations (Table 3 - Panel B).[14]

In cases where a teacher was not found in the school, enumerators asked the head teacher (or senior-most teacher who was present) for the reason for absence. These stated reasons are summarized in Table 3 (Panel C). Two categories of clearly unauthorized absence (school closure during working hours and no valid reason for absence) account for just under half the cases of teacher absence (48 percent), which provides a lower bound on the extent of unauthorized absences of 11.3 percentage points. The two other categories of stated absence (authorized leave and other official duties) that account for 52 percent of the observed absence are plausibly legitimate but cannot be verified.

There is some reason, however, to believe that responses by head teachers may overstate the extent of official duties to shield absent colleagues, which is an important caveat to the interpretation of these stated reasons.[15] We can, however, reasonably treat the stated reasons for absence as an upper bound for duty-induced absence. This yields the important finding that one commonly cited reason for teacher absence - namely, that teachers are often asked to perform non-teaching related duties such as conducting censuses and monitoring elections - is a very small contributor to the high rates of observed teacher absence. Table 3 - Panel C shows that

[14] This is almost surely an underestimate (and hence a lower bound) because in many cases it is easy for a teacher who may not have been teaching to pick up a book and look like he or she is actively teaching when it is known that someone is visiting the school (see Muralidharan and Sundararaman 2010 for evidence documenting this).
[15] We see this most clearly in Table 3 - Panel A, where over 7.5 percent of teachers who were not found in the school during the direct observation were marked present in the official log books, suggesting collusion among teachers in the reporting of absence in official records.

official non-teaching duties account for less than 1 percent of the observations and under 4 percent of the cases of teacher absence.

## 4. Cross-section and Panel Regression Results

### *4.1. Correlates of teacher absence in 2010*

Table 4 presents cross-sectional correlations between indicators of school quality and teacher absence in 2010. As discussed in section 2.4, this analysis is done at the village-level since our panel analysis will be done at the village-level. Column 1 shows the mean level of each covariate in the sample, columns 2-4 present the coefficients on each indicator in binary regressions with the dependent variable being teacher absence, while columns 5-7 do so in multiple regressions that include all the variables shown in Table 5.

We first show the correlations with no fixed effects, and then with state fixed effects, and finally with district fixed effects. The comparison of results with and without state fixed effects is important for interpretation. Many indicators of school quality vary considerably across states in a manner that is likely to be correlated with other measures of governance and development as well as the history of education investments in these states. On a similar note, while primary education policy is typically made at the state level, there is often important variation across districts within a state based on historical as well as geographical factors (Banerjee and Iyer 2005; Iyer 2010). Thus, specifications with district fixed effects that are identified using only within-district variation are least likely to be confounded by omitted variables correlated with historical or geographical factors. However, there may still be important omitted variables across villages (such as the level of interest in education in the community) that are correlated with both measured quality of schools and teachers as well as teacher absence. We therefore present the correlations in Table 4 for completeness and focus our discussion on the panel regressions presented in Table 5.

Without any fixed effects, teachers who have formal training, who are paid more regularly, who are eligible for recognition schemes, and who are in schools with better infrastructure are less likely to be absent (Table 4 – Column 2 and 5). However, none of these correlations are significant with state or district fixed effects suggesting that states that have a longer history of investing in education may have better indicators of school and teacher quality, and also lower teacher absence, but that these metrics of teacher quality do not predict teacher absence within states or districts. Overall, there are few robust correlations across all specifications except that schools that have been inspected recently have significantly lower rates of absence. One important result in the correlations is that there appears to be no significant relationship between teacher salary and the probability of teacher absence. Since salary data were not collected in the 2003 survey, this variable is not included in the panel analysis below.

*4.2. Correlates of changes in teacher absence between 2003 and 2010*

The main identification challenge in the cross-sectional correlations presented in Table 4 (and in Kremer et al. 2005) is that we cannot rule out the possibility that the results are confounded with village-level omitted variables. The use of panel data helps mitigate these concerns since our correlations are now identified using changes in village-level measures of school inputs. Table 5 (columns 4-6) presents results from the following regression:

$$\Delta Abs_i = \beta_0 + \boldsymbol{\beta_1} \cdot \Delta \boldsymbol{T_i} + \boldsymbol{\beta_2} \cdot \Delta \boldsymbol{S_i} + \boldsymbol{\beta_3} \cdot \Delta \boldsymbol{M_i} + \boldsymbol{\beta_4} \cdot \boldsymbol{Z_i} + \varepsilon_i \qquad (1)$$

where $\Delta Abs_i$ is the change in the mean teacher absence rate in government schools in village *i* between 2003 and 2010, $\Delta \boldsymbol{T_i}$ is the change in village-level means of measures of teacher attributes, $\Delta \boldsymbol{S_i}$ is the change in village-level means of measures of school facilities, and $\Delta \boldsymbol{M_i}$ is the change in village-level means of measures of school monitoring and supervision. $\boldsymbol{Z_i}$ represents different levels of fixed effects (state or district) and $\varepsilon_i$ is the residual. Since changes in the measures of school quality included above may be correlated, we report both binary regressions with only covariate at a time (columns 1-3) as well as multiple regressions that include all the measures of school quality reported in Table 2 (columns 4-6).

The results in Table 6 suggest that several anecdotal narratives for the reasons for teacher absence are not supported in the panel data regressions. In particular, we find no correlation between changes in school infrastructure or proximity to a paved road and teacher absence. We also find no correlation between changes in teacher professional qualifications or professional conditions (such as regularity of pay) and changes in teacher absence.

We find two robust relationships in the panel regressions, where we define 'robust' as correlations that are significant in both binary and multiple regressions; significant in all our three main specifications (no fixed effects, state fixed effects, and district fixed effects) and consistent across all these specifications (we cannot reject that the estimates are the same across all these specifications).

First, villages that saw a reduction in pupil-teacher ratio (PTR)[16] have significantly *higher* rates of teacher absence. This is a potentially counterintuitive result because a common narrative for teacher absence is that their working conditions are poor, with high PTR's cited as a prominent example of burdensome working conditions. However, the most common outcome for students when their teacher is absent is that they are combined with other classes (typically from other grades) whose teachers are present.[17] Our results therefore suggest that having more teachers may make it easier for teachers to be absent (since other teachers can handle their class), and that the impact of hiring additional teachers may be partially offset through increased teacher absence. The estimates suggest that a 10 percent reduction in PTR is correlated with a 0.5 percent increase in average teacher absence.

The estimates remain stable when we include state and district fixed effects, and are unchanged even when we introduce a full set of controls (also measured in *changes*). These results are consistent with the hypothesis that the relationship is causal. Some identification challenges in a cross-section are less salient in the panel. Decisions on teacher placement are largely based on administrative criteria of whether schools are above or below the PTR norms and are unlikely to be correlated with *contemporaneous changes* in teacher absence.[18] Indeed, a causal relationship between increased teacher hiring and increased absence of existing teachers has been established experimentally in other low-income countries, such as Kenya (Duflo, Dupas, and Kremer 2012) and India (Muralidharan and Sundararaman 2013). Our estimates provide complementary evidence and greater external validity to these experimental results and

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[16] We focus on the school-level pupil-teacher ratio (PTR) because the policy goals for teacher hiring are stated in terms of PTR. But in practical terms, lowering PTR is equivalent to lowering class-sizes.

[17] Doing so does not deviate from the norm in the context of rural Indian government-run primary schools because close to 80 percent of schools practice multi-grade teaching (where one teacher simultaneously teaches students across multiple grades at the same time in the same classroom) in any case. Multi-grade teaching in turn is necessitated by the policy priority placed on primary school access. Thus, while most habitations in India now have a primary school within a radius of one kilometer, many of them are 'sub-scale' with enrollment of less than 100 students across five grades, which in turn necessitates multi-grade teaching since the PTR norms are typically between 30:1 to 40:1 (varies by state). These calculations are based on the same survey data used for this paper.

[18] The most likely omitted variable concern would in fact go the other way. If communities that cared more about education were more likely to be able to get additional teachers, they would also be more likely to ensure better teacher attendance, suggesting that our results may be a lower bound on the magnitude of this effect.

suggest that they generalize to nationally scaled-up programs of reducing class sizes by hiring more teachers in contexts with weak teacher accountability.

The second robust result in the panel data estimates is the strong negative correlation between improved school monitoring and teacher absence. In each of the three visits to a school, enumerators record the date of the most recent inspection and we average across the three visits to construct the "Inspected in last 3 months" variable which ranges from zero (not inspected in the prior three months in any of the three visits) to one (inspected in the prior three months in all of the three visits). The results suggest that villages where the probability of inspection in the past three months increased from zero to one had a reduction in average teacher absence of between 8.2 percent (with no fixed effects and no controls) and 6.4 percent (district fixed effects and a full set of controls). The estimates are remarkably consistent across all 6 specifications, and even the most conservative estimate suggests that teacher absence rates in schools that are regularly inspected are over 25 percent lower than in schools that are not.

To further check for patterns in the data that could support a causal interpretation of this result, Table 6 breaks down the dependent variable (teacher absence) by the various categories of stated reasons for absence ("absence due to being on official duty", "absence due to being on authorized leave" and "unauthorized absence"), and shows the coefficient on the "inspections" variable on each of these dependent variables. Panel A shows the cross-section estimates (corresponding to Table 4) while Panel B shows the panel ones (corresponding to Table 5). Increases in inspections are mostly correlated with reductions in unauthorized teacher absences, whereas there is no significant relationship between inspections and reductions in teacher absence due to either official duty or authorized leave.[19] These results are consistent with the interpretation that improved 'top down' administrative monitoring can have a significant and substantial impact on reducing unauthorized teacher absence.

In contrast, there is little evidence that increases in 'bottom up' monitoring by the community (measured by whether the PTA had met in the past 3 months) are correlated with reductions in

[19] The point estimates on these categories suggest that increasing inspections may reduce the fraction of teacher absence that is recorded as "official duty" and increase the fraction that is recorded as "authorized leave". These results are consistent with head teachers and teachers colluding to some extent to record absences as being due to official duty that do not count against a teacher's quota of authorized leave. Increased inspections may make it difficult to sustain this collusion (since the inspector will be able to verify if the teacher is away on official duty) and require more of the absences to be counted against a teacher's official leave quota.

teacher absence (Table 5). This is consistent with the experimental results reported in Olken (2007) on the impacts of monitoring corruption in Indonesia. These results should not be interpreted as suggesting that bottom-up monitoring *cannot* be effective, since it is also likely that they reflect differences in the effective authority over teachers possessed by administrative superiors (high) and parents (low). PTAs in India typically do not have any authority on appointment or retention of regular civil-service teachers and cannot sanction teachers for absence or non-performance. Inspectors and administrative superiors, on the other hand, do possess considerable authority over teachers, including the ability to demand explanations for absence, to make adverse entries in their performance record, and in extreme cases to initiate disciplinary proceedings. These actions do not take place very often, but the administrative rules provide inspectors with the powers to take these actions, whereas PTAs do not have any such powers. [20]

As in the case of the changes in PTR, the stability of the estimates of the correlations between increases in inspection frequency and reduction in teacher absence to the introduction of state and district fixed effects as well as a full set of controls helps mitigate concerns about omitted variables bias. To further address identification concerns, we examine the extent to which changes in inspection frequency can be explained by other observables (Table 7). There are no correlations between changes in inspections and changes in other measures of school quality that are significant across our three standard specifications. Finally, these results are also consistent with experimental evidence from India that finds significant reduction in teacher absence in response to improved monitoring and professional consequences that are linked to better attendance (Duflo, Hanna, and Ryan 2012). Since the experimental study was carried out in a small sample of informal schools in one state in India, our estimates using a nationally-representative panel dataset of rural public schools provides complementary evidence on the role of improved monitoring on reducing teacher absence.

[20] The low frequency of formal action against teachers (in spite of high observed absence rates) may suggest that the inspection system is not very effective. It can be costly for an inspector to take action given pressure from unions and the administrative procedures that need to be followed. Qualitative evidence from field interviews suggest that an important channel of the deterrence effect of increased inspections on teacher absence may be that inspectors can often extract informal payments from teachers who are found to be absent in return for not making an adverse entry on their record. Social norms would make it difficult to 'extort' such payments from teachers who are actually present, but it would be much easier to demand a payment from an absent teacher. Thus, even if the actual incidence of disciplinary action is low, there may be other channels through which more frequent inspections serve as a disincentive for teacher absence.

In interpreting the result on school inspections, it is useful to consider *why* there might be variation in the frequency of inspections across villages in a district and what this would imply for interpreting the results causally. One obvious explanation is that inspectors are more likely to visit villages that are more accessible, but the data do not support this hypothesis since there is no correlation between changes in proximity/remoteness to facilities and changes in inspection rates (Table 7).

Qualitative interviews on school governance in India conducted at the district level suggest two important sources of variation (Center for Policy Research 2012).[21] The first is staffing. Districts are broken down further into administrative blocks,[22] and schools within blocks are organized into clusters. School supervision is typically conducted by "block education officers" and "cluster resource coordinators". We find that a significant fraction of these posts are often unfilled. For instance, in 19 percent of the cases (where we have data) even the position of the "District Education Officer (DEO)", the senior-most education official in a district, was vacant. Further, there is high turnover in education administration (the average DEO had a tenure in office of just one year) creating periods when the positions are vacant during transitions. Our interviews suggest that similar staffing gaps at the block and cluster level are the most important source of variation in inspection frequency within districts, since blocks and clusters without supervisory staff are much less likely to get inspected.

The second source of variation in inspections is the diligence of the concerned supervisory officer. Even if all the positions of block and cluster-level administrative staff were filled, there would be variation in the zealousness with which these officers visited villages/schools, which might lead to some areas being inspected more often than others based on whether they were in the coverage area of a more diligent officer or not. However, variation in inspection frequency that is driven by inspector-level unobservable characteristics is unlikely to be correlated with other village-level characteristics that are also correlated with absence (and as a result, the

[21] This module was designed to complement the school surveys by allowing us to create quantitative estimates of measures of district-level education governance. Unfortunately, non-completion rates for these interviews was very high (over 40 percent) due to non-availability and non-response of district-level administrators. Since this non-response is clearly not random, we do not use the quantitative measures in regressions. Also, the interviews only cover staffing questions at the district level and not the sub-district level, which would be needed if we wanted to use them as regressors. Nevertheless, important qualitative insights can be obtained from these interview transcripts. These results are summarized in a companion policy report (Center for Policy Research 2012).
[22] The size of blocks varies by state, but a typical number is 10-15 blocks per district.

estimated coefficients on "inspected in the last 3 months" are unlikely to be biased). Of course, this source of variation in inspection frequency has implications for thinking about the effectiveness of hiring new staff. We discuss this issue in section 5.4.

*4.3. Correlates of changes in student outcomes*

While the focus of our analysis has been on teacher absence, we also briefly consider the extent to which the improvements in school quality described in Table 2 are correlated with learning outcomes. Table 8 presents panel regressions of the form in equation (1), where changes in normalized mean math test scores at the village level are regressed on changes at the village-level, including teacher absence, school facilities, and monitoring. The only variables that are significantly correlated with changes in test scores are changes in mean parental education and changes in the fraction of students taking private tuition. School-level variables are not consistently significant though higher PTR's and higher teacher absence are both correlated with lower test scores (and significant in some specifications). However, there is no positive correlation between the improvements in most of the standard measures of school quality and student learning outcomes - including school infrastructure, mid-day meals, and teacher qualifications and training.

We only treat these results as suggestive because the data (with a seven-year gap in mean village-level test scores) is not ideal for testing the impact of school characteristics on test scores. The ideal specifications would use annual panel data on student test scores matched to these characteristics and estimate value-added models of student learning. Nevertheless, the main findings here are consistent with those in studies set in India using data sets that are better suited to study student learning outcomes that find that teacher absences significantly hurt student learning, and that school infrastructure, teacher qualifications, and training certification are not correlated with improved student learning.[23] Thus, while the majority of the education budget is

[23] Duflo et al (2012) show experimentally that lower teacher absence raises test scores, while Muralidharan (2012) shows this in value-added estimates with five years of annual panel data on test scores in the state of Andhra Pradesh matched with the absence rate of the teacher of each student that year. Das et al. (2007) show that high teacher absences in Zambia (mainly due to teachers falling sick) lead to significantly lower student test score gains. While not explicitly focusing on the impact of school infrastructure and teacher qualifications on learning outcomes, Muralidharan (2012) also shows that these are not correlated in the control schools (which represent the 'business as usual' scenario).

allocated to improving traditional input-based measures of school quality, these appear to not matter for learning outcomes as much as teacher attendance and effort.[24]

## 5. The Fiscal Cost of Weak Governance

### *5.1. The fiscal cost of teacher absence*

High levels of teacher absence translate into considerable waste of public money since teacher salaries are the largest component of education spending in most countries, including India.[25] Calculating these fiscal costs requires us to estimate and exclude the extent of legitimate absence from our calculations. As part of the institutional background work for this project, we obtained teacher policy documents from several states across India. Analysis of these documents indicates that the annual allowance for personal and sick leave is 5 percent on average across states. This is close to the survey estimate of 5.9 percent (Table 3), but we use the official data since the stated reasons may be over-reported.

Estimating the extent of legitimate absence due to 'official duty' (outside the school) is harder because there are no standard figures for the 'expected' level of teacher absence for official duties. Policy norms prescribe minimal disruption to teachers during the school day and typically stipulate that meetings and trainings be carried out on non-school days or outside school hours. The figures in Table 3 for the fraction of absences that are claimed to be due to "official duty" are therefore likely an overestimate. Since we are not able to verify the claim that teachers were on official duty, and since there is evidence that head teachers may try to cover up for teacher absences by claiming that these are due to 'official duties', our default estimate treats half of these cases as legitimate. This gives us a base case of legitimate absence of 8 percent (5 percent authorized leave, and 3 percent official duty). We also consider a more conservative case where the legitimate rate of absence is 10 percent. This 8-10 percent range of legitimate absence also makes sense because the fraction of teacher observations that are classified as either 'authorized leave' or 'official duty" is in this range for the five states with the lowest overall absence rates – even treating the stated reasons for absence as being fully true (tables available on request).

[24] See Waldinger (2012) for an interesting parallel in the context of post-World War II higher education in Germany.
[25] This waste is especially costly in developing countries because they typically have low tax/GDP ratios and hence face greater fiscal constraints on mobilizing resources for public investment.

To estimate the fiscal cost of teacher absence, we use teacher salary data from our surveys and use administrative (DISE) data on the total number of primary school teachers by state (these are summarized by state in columns 1 and 2 of Table 9).[26] We provide three estimates of the fiscal cost of teacher absence in columns 3 to 5 of Table 9 (based on assuming the rate of legitimate teacher absence to be 8, 9, and 10 percent respectively), and these calculations suggest that the annual fiscal cost of teacher absence is around Rs. 80 to 92 billion (1.4 – 1.6 billion US dollars/year).

*5.2. Calculating the returns to better governance in education*

The panel data regressions presented in Table 5-7 suggest that of all the investments made in improving school quality in the period from 2003 to 2010, the only one that had a significant impact on reducing absence was increased administrative monitoring and supervision. In this section, we calculate the returns to a marginal increase in the probability of a school being inspected. We make the following assumptions: (a) enough inspectors are hired to increase the probability of a school being inspected in the past 3 months by 10 percentage points (relative to a current probability of 58 percent); (b) increasing inspection probability by 10 percentage points would reduce mean teacher absence across the schools in a village by 0.64 percentage points (this is based on the most conservative estimate of the correlation between increased inspection probability and reduced teacher absence from Table 5); (c) the full cost (salary and travel) of an inspector is 2.8 times that of a teacher; (d) an inspector works 200 days per year and can cover 2 schools per day.[27]

The results of this estimation are presented in Table 10 and we see in column 3 that the cost of hiring enough inspectors to increase the probability of a school being inspected by 10 percentage points is Rs. 448 million/year. However, the reduction in wasted salary from this

[26] The salary figures in our surveys do not include the fiscal cost of the benefits provided to civil service teachers. Imputing the value of these benefits is difficult for the majority of teachers who are on a defined benefits pension program. However, newer cohorts of government employees are covered by a (less generous) defined contribution retirement program where the government contributes 10% of pay to a retirement account. We use this conservative estimate and add 10% to the average salary figures. No adjustment is made for medical benefits.

[27] We use DISE data on the number of schools in each state to calculate the number of inspectors who will be required to increase the probability of inspections in a 3-month interval by 10 percentage points. The cost estimates are conservative and assume that the salary costs are double that of a teacher and that the travel costs are equal to 80 percent of a full months' salary (which is higher than the typical travel and daily allowance provided to education department employees to travel to/from a village to district headquarters).

investment in terms of reduced teacher absence amounts to Rs. 4.5 billion/year, suggesting that the returns to investing in better governance are ten times greater than the cost. Thus, improving school governance by hiring enough staff to increase the frequency of monitoring could be a highly cost-effective investment (on the current margin).

### *5.3. Hiring more inspectors vs. more teachers*

Column 5 of Table 10 calculates the extent to which the EPTR can be reduced by hiring enough inspectors to increase the probability that a school was inspected in the past three months by 10 percentage points (the same amount used in the calculations in the previous section). To compare the relative cost effectiveness of hiring more inspectors versus hiring more teachers, we calculate the salary cost of hiring more teachers to achieve the same reduction in EPTR and report these numbers in column 6. Comparing columns 3 and 6, we see that hiring more inspectors would be 12.8 times more cost effective at reducing EPTR than doing so by hiring more teachers. The difference between the estimates in columns 4 and 6 stems from accounting for the fact that hiring more teachers will increase the absence rates of the existing teachers, which is the other robust result in the panel regressions presented in Table 5 (again, we use the most conservative estimate). Thus, the estimates in column 6 account for the fact that the marginal rate of absence from hiring an extra teacher is higher than the average absence rate (as in Niehaus and Sukhtankar 2013).

### *5.4. Policy Implications*

The difference in the relative cost effectiveness of the two policy options is large enough (greater than a factor of 10), that the policy recommendation of hiring more inspectors would be unchanged even if the inspectors were to work less efficiently than assumed in these calculations. For instance, if inspectors were absent at the same rate as teachers (say 25 percent), allocating marginal funds to hire an additional inspector would still be over nine times more cost effective at reducing EPTR than using those funds to hire an additional teacher. At the same time, our estimates are based on correlations and may not be convincing enough to warrant a universal scale up. However, as we show below, our results are strong enough to at least recommend a substantial expansion of school inspections *in the context of a large experimental evaluation*.

Formally, consider a simple binary policy regarding the number of inspectors to be hired that can take the values {0, 1}; where the current policy is {0}; and {1} represents a 'new' policy of hiring enough inspectors to ensure that all schools are inspected once in three months. The costs of the new policy are the additional salary and operational costs of hiring inspectors and the benefits are the reduced fiscal cost of teacher absence. Denote these by C{1} and B{1} respectively, and assume that it is optimal to implement the policy if B{1} > C{1}. However, while C{1} is known, there is uncertainty around B{1} and thus a randomized trial in the context of a policy movement towards {1} would reduce the uncertainty around B{1}.

Suppose that after the conduct of the trial, the likelihood that the optimal policy switches from {0} to {1} is $p$ and that the expected per-period benefit of such a switch is $q$. Denote the cost of data collection and analysis of a trial as C{data} and let the discount rate be $r$. Let the period of the trial be one year; let the fraction of the population participating in the trial be N and assume that half of those in the trial are allocated to a treatment group and the other half to a control group. Since data collection will be based on a representative *sample* of trial sites (whose size will be determined based on power calculations), we assume that C{data} does not vary with the size of the trial. The one period cost of the trial is then C{data} + (N/2)*C{1}. The benefits of the trial are the expected one-period benefit of the new policy (during the trial) and the discounted benefits of switching to a new policy (in perpetuity), weighted by the probability that the trial will lead to a switch in the policy. Thus, the trial should be conducted as long as:

$$C\{data\} + (N/2)*C\{1\} < (N/2)*B\{1\} + [\{1/(1-r)\}pq] * [1/(1+r)].$$

To focus on the benefits of *learning* if the optimal policy should be {1} instead of {0}, we abstract away from the benefit of the policy during the trial period and the one-period delay in implementing the new policy (if found to be optimal), in which case the trial should be conducted as long as:

$$C\{data\} + (N/2)*C\{1\} < [\{1/(1-r)\}pq].$$

Using our results to calibrate these quantities, it is straightforward to see that the expected benefits of a trial are very large even under extremely conservative assumptions. The estimates in table 10 suggest that the marginal cost of {1} would be $33 million and that the marginal benefit would be \$331 million (using our panel data estimates).[28] Thus, if our estimates are true, $q$ would be around \$300 million/year, and using a discount rate of 10%, the net present value of moving to {1} would be \$3 *billion*. Now suppose there is only a 1 in 10 chance that the causal impacts of inspections on teacher absence are as great as the panel data estimates presented here and that there is a 9 in 10 chance that the causal impacts of inspection are not significantly different from zero (i.e. $p = 0.1$). Even then, we see that $[\{1/(1\text{-}r)\}pq]$ is \$300 million.

On the cost side, we conservatively estimate (using data from our own field costs) that a highly-powered trial would have C{data} \$ 0.5 to 1 million (depending on whether we use our existing data as a baseline or collect a new baseline). A trial with an N of 0.06 would be a very large trial and could cover a nationally-representative sample across all major Indian states, but would only cost \$ 1 million/year.[29] Thus, even including all costs of data collection, the upper bound of the costs of such a trial would be \$2 million compared to a likely lower-bound expected benefit of \$300 million.[30] An expansion of school inspections in the context of an experimental evaluation would therefore make sense even if there was only a 1% chance of the true effects being the same as our panel-data estimates.[31]

[28] The estimates in Table 10 are based on hiring enough inspectors to increase the probability of a school being inspected in the previous 3 months by 10 percentage points. Since the current probability of a school being inspected in the previous 3 months is 56 percent (Table 1), we scale up the estimates in Table 10 by a factor of 4.4 since moving to {1} would imply that the other 44 percent of schools should also be inspected. We use an exchange rate of 1 US Dollar equals 60 Indian Rupees.

[29] India has around 600,000 villages, 44% of which would be 264,000 villages. An N of 0.06 with half the sample getting the treatment would imply that an additional 7900 villages would be treated (3% of 264,000), which would be a very large trial by the standards of most experiments. Since covering all the remaining 264,000 villages is estimated to cost \$33 million, the cost of covering 3% of the villages would be \$1 million.

[30] Note that we use extremely conservative estimates for $p$ assigning only a 10 percent probability of true estimates as large as our panel-data based estimates and assigning the rest of the 90 percent probability to finding a zero effect. If we were to assign a uniform distribution of likely point estimates between zero and our panel-data estimates (this is also conservative because we would not assign any probability to the true estimate being larger than the panel-data estimate), the expected benefit would be even larger.

[31] If we use a medical ethics perspective in this setting, we also need to consider the costs of *not* providing a treatment that is known (or highly likely) to be effective. In this case, that would be the foregone one-period benefit of scaling up the treatment immediately. However, since the main benefit in our calculations above is the net present value of learning and adopting the 'better' policy, a prior belief that the treatment is more effective would *still* yield an optimal policy of conducting an experimental evaluation, but with a large N and with a greater fraction than 50% being assigned to the treatment group (while only 'denying' treatment to a smaller control group to enable the evaluation).,

## 6. Conclusion

The central and state governments in India have considerably increased spending on primary education over the past decade. We contribute towards understanding the impact of these substantial nationwide investments in primary education in India by constructing a unique nationally-representative panel data set on education quality in rural India. We find that there has been a substantial improvement in several measures of school quality including infrastructure, pupil-teacher ratios, and monitoring. However, teacher absence rates continue to be high, with 23.7 percent of teachers in public schools across rural India being absent during unannounced visits to schools.

Using village-level panel data, we find no correlation between improved school infrastructure and other measures of working conditions on teacher absence. We do find two robust correlations in the panel data that provide external validity in nationally-representative data to results established in smaller-scale experiments. First, reductions in pupil-teacher ratios are strongly correlated with *increased* teacher absence, suggesting that the impact of hiring additional teachers on education outcomes may be partly offset by increased shirking among existing teachers. Second, increases in the frequency of inspections are strongly correlated with lower teacher absence, suggesting that of all the investments in improving school quality, the one that was most effective in reducing teacher absence was improved administrative monitoring of schools and teachers. We calculate that the fiscal cost of teacher absence is over $1.5 billion per year, and estimate that investing in improved governance by increasing the frequency of monitoring would be over twelve times more cost effective at increasing student-teacher contact time than doing so by hiring additional teachers.

In interpreting our results, it may be useful to think of the performance of the education system as comprising two components – those that are more easily measured and monitored (such as school infrastructure, and class size), and those where this is more difficult (such as teacher performance). Our panel data suggest that the Indian state has made significant progress on the former, but made less progress on the latter. Using a growth accounting perspective, we see that the reduction in teacher absence observed between 2003 and 2010 is exactly in line with what we would expect from the growth in per-capita income that has taken place during this period. This is consistent with the growth in income enabling an expansion of a broad range of inputs into education that was for the most part a proportional increase along existing spending patterns (uninformed by empirical research on the relative effectiveness of different inputs in reducing teacher absence). On the other hand, improving the TFP of public spending (or 'governance') to achieve a greater reduction in teacher absence for a given level of GDP/capita would require a strategic reallocation of spending to programs that are more effective..

Our results suggest that a promising way of improving school governance and achieving such a reallocation of resources, would be to simply expand the existing system of administrative monitoring of teachers and schools by hiring more supervisory staff. Our calculations indicate that such an expansion could (on the current margin) have a significant impact on reducing teacher absence, and that this would be highly cost effective in terms of reducing the fiscal cost of weak governance. More broadly, our results suggest that the returns to investing in state capacity to better monitor the implementation of social programs in developing countries may be quite high, and that at the very least there is a strong case for expanding such programs in the context of large experimental evaluations of "as is" implementation to obtain more precise estimates of their benefits.[32]

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[32] Muralidharan, Niehaus, and Sukhtankar (2013) is an example of just such an experimental evaluation, in the context of an ambitious initiative by the Government of Andhra Pradesh to improve governance in public welfare programs through biometric authentication of beneficiaries.

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## Table 1. Changes in Key Variables Between 2003 and 2010, Village-Level Data

| | Summary Statistics | | Difference |
|---|---|---|---|
| | Year 2003 | Year 2010 | (Ho: No diff) |
| **TEACHER VARIABLES** | | | |
| Have bachelors degree | 0.41 | 0.58 | 0.174*** |
| Have teacher training | 0.77 | 0.68 | -0.085*** |
| Are contract teachers | 0.06 | 0.30 | 0.233*** |
| Are paid regularly | 0.49 | 0.78 | 0.285*** |
| Recognition scheme exists | 0.50 | 0.81 | 0.309*** |
| **SCHOOL VARIABLES** | | | |
| Pupil-teacher ratio (PTR) | 47.19 | 39.80 | -7.388*** |
| Mid-day meals | 0.22 | 0.79 | 0.576*** |
| Infrastructure index (0-4) | 2.14 | 3.35 | 1.205*** |
| Has drinking water | 0.80 | 0.96 | 0.160*** |
| Has toilets | 0.40 | 0.84 | 0.440*** |
| Has electricity | 0.22 | 0.45 | 0.236*** |
| Has library | 0.51 | 0.69 | 0.183*** |
| **MONITORING & COMMUNITY VARIABLES** | | | |
| Road is within 1km | 0.69 | 0.78 | 0.092*** |
| Inspected in last 3 months | 0.38 | 0.56 | 0.176*** |
| Inspected in last 2 months | 0.31 | 0.50 | 0.189*** |
| Inspected in last 1 month | 0.22 | 0.38 | 0.155*** |
| PTA met in last 3 months | 0.30 | 0.45 | 0.153*** |
| Mean parental education (1-7 scale) | 2.03 | 2.43 | 0.394*** |
| State per-capita GDP (thousands of Rs.) | 14.74 | 30.21 | 15.473*** |

Notes:

1) Summary statistics (except PTR) are weighted by rural population of Socio-Cultural Regions (SCRs) in Census 2001

2) Pupil-teacher ratio is weighted by SCR school enrolment

3) Data for number of days since inspection and truncated at 99th percentile

4) State per-capita GDP figures are in 2004-2005 prices; obtained from Central Statistical Organization, India

5) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

## Table 2. Absence Rate of Teachers & Pupil-Teacher Ratios in Rural Public Schools by State by Year

| | Absence Rates (%) | | | Pupil-Teacher Ratio | | | Effective Pupil-Teacher Ratio | | |
|---|---|---|---|---|---|---|---|---|---|
| | Year 2003 | Year 2010 | Change | Year 2003 | Year 2010 | Change | Year 2003 | Year 2010 | Change |
| **Andhra Pradesh** | 23.38 | 21.48 | -1.90 | 27.51 | 25.79 | -1.71 | 35.90 | 32.85 | -3.05 |
| **Assam** | 36.15 | 26.26 | -9.89*** | 28.21 | 36.07 | 7.86*** | 44.18 | 48.92 | 4.74 |
| **Bihar** | 39.42 | 28.69 | -10.73*** | 72.44 | 69.01 | -3.43 | 119.57 | 96.78 | -22.79 |
| **Chattisgarh** | 30.47 | 14.20 | -16.28*** | 42.12 | 33.05 | -9.07*** | 60.59 | 38.52 | -22.07 |
| **Gujarat** | 17.92 | 16.14 | -1.77* | 40.42 | 31.94 | -8.48*** | 49.24 | 38.09 | -11.15 |
| **Haryana** | 21.07 | 17.75 | -3.31** | 34.40 | 36.34 | 1.94 | 43.58 | 44.18 | 0.60 |
| **Himachal Pradesh** | 22.67 | 30.74 | 8.07*** | 18.04 | 21.73 | 3.69** | 23.33 | 31.38 | 8.04 |
| **Jharkhand** | 43.50 | 45.84 | 2.34 | 52.30 | 42.84 | -9.47*** | 92.57 | 79.09 | -13.48 |
| **Karnataka** | 22.60 | 23.93 | 1.33 | 29.07 | 23.62 | -5.45*** | 37.56 | 31.05 | -6.51 |
| **Kerala** | 19.60 | 15.79 | -3.81*** | 24.84 | 24.49 | -0.36 | 30.90 | 29.08 | -1.82 |
| **Madhya Pradesh** | 18.19 | 26.34 | 8.16*** | 37.19 | 46.57 | 9.39*** | 45.45 | 63.23 | 17.78 |
| **Maharastra** | 15.43 | 14.12 | -1.31 | 34.54 | 28.66 | -5.88*** | 40.84 | 33.38 | -7.47 |
| **Orissa** | 21.69 | 14.24 | -7.46*** | 47.01 | 36.63 | -10.38*** | 60.04 | 42.72 | -17.32 |
| **Punjab** | 36.66 | 13.54 | -23.13*** | 30.80 | 31.43 | 0.63 | 48.63 | 36.36 | -12.28 |
| **Rajasthan** | 25.13 | 22.72 | -2.42* | 38.91 | 32.05 | -6.86*** | 51.97 | 41.47 | -10.50 |
| **Tamilnadu** | 20.43 | 12.92 | -7.51*** | 29.56 | 25.85 | -3.71** | 37.15 | 29.69 | -7.47 |
| **Uttar Pradesh** | 26.72 | 31.21 | 4.49*** | 69.37 | 47.40 | -21.97*** | 94.66 | 68.90 | -25.76 |
| **Uttaranchal** | 32.29 | 21.02 | -11.27*** | 24.49 | 31.02 | 6.54** | 36.17 | 39.28 | 3.12 |
| **West Bengal** | 26.41 | 20.97 | -5.44*** | 58.23 | 41.61 | -16.62*** | 79.12 | 52.65 | -26.47 |
| **India** | **26.29** | **23.64** | **-2.64*****| **47.19** | **39.80** | **-7.39***** | **64.02** | **52.13** | **-11.89** |

Notes:

1) All figures are weighted by SCR's rural population

2) The absence figures for 2003 differ slightly from the figures in the Kremer et al (2005) paper. This is because the urban schools are removed from the sample

3) We do not conduct inference on the changes in "Effective Pupil-Teacher Ratio" because the data on total number of teachers are obtained from administrative (DISE) data

4) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

## Table 3. Teacher Activity and Reasons for Absence

PANEL A: PHYSICAL VERIFICATION & LOGBOOK RECORDS OF ABSENCE

| | Physical verification (%) | Log-book records (today) | Logbook records (last working day) |
|---|---|---|---|
| **Year 2003** | 26.29 | 19.07 | - |
| **Year 2010** | 23.64 | 15.94 | 10.24 |

PANEL B: PHYSICAL VERIFICATION & TEACHER ACTIVITY

| | **Teacher Found in Classroom (%)** | | | **Teacher Found outside classroom (%)** | **Absent (%)** |
|---|---|---|---|---|---|
| | Actively teaching | Passively teaching | Not Teaching | | |
| **Year 2003** | 42.93 | 5.56 | 15.88 | 9.35 | 26.29 |
| **Year 2010** | 53.08 | 4.16 | 8.96 | 10.15 | 23.64 |

PANEL C. STATED REASONS FOR ABSENCE

| | **School Closed (%)** | **On Official Duty (%)** | | | | **Authorized Leave (%)** | **No Reason (%)** |
|---|---|---|---|---|---|---|---|
| | | Total | Offical teacher related (trainings, meetings, etc.) | Official non-teaching related (elections, health campaigns, etc.) | Official other (panchayat meetings, political meetings, etc.) | | |
| **Year 2003** | **6.08** | **7.19** | 5.93 | 0.95 | 0.31 | **7.62** | **5.40** |
| **Year 2010** | **6.60** | **6.43** | 5.21 | 0.93 | 0.29 | **5.91** | **4.70** |

Notes:

1) All figures are weighted by SCR's rural population

2) In 2003, log-book records of last working day were not recorded in the survey

3) In 0.37 percent of cases, respondents said that a log-book was not maintained in the school, 0.23 percent refused to show log-book

4) Full list of activities under for not teaching are - doing administrative/paper work, talking to/accompanying the surveyor, chatting/talking (with teachers, others), reading magazines/newspapers, sleeping, watching TV/listening to radio, doing other personal work, idle

5) Reasons for school closed are - opening hours but no one has arrived yet, opening hours but everyone left, and no reason

**Table 4. Cross-section OLS Regressions Results, Village Level, 2010 Data**
**(Dependent Variable: Village-Level Teacher Absence Rate)**

| | SUMMARY STATISTICS | BINARY REGRESSIONS | | | MULTIPLE REGRESSIONS | | |
|---|---|---|---|---|---|---|---|
| | (1) Year 2010 | (2) no fixed effects | (3) w/ state fixed effects | (4) w/ district fixed effects | (5) no fixed effects | (6) w/ state fixed effects | (7) w/ district fixed effects |
| **TEACHER VARIABLES** | | | | | | | |
| Have bachelors degree | 0.58 | -1.03 | -6.20*** | -7.51*** | -1.96 | -5.78** | -6.84*** |
| | (0.32) | (1.94) | (2.39) | (2.57) | (1.76) | (2.45) | (2.59) |
| Have teacher training | 0.68 | -11.95*** | -3.48 | -2.92 | -2.39 | -2.43 | -2.09 |
| | (0.31) | (2.38) | (2.39) | (2.73) | (2.81) | (2.69) | (2.87) |
| Are contract teachers | 0.30 | 10.97*** | 0.46 | -1.12 | -2.25 | -0.27 | -2.32 |
| | (0.30) | (2.37) | (2.48) | (2.97) | (2.83) | (2.71) | (3.21) |
| Are paid regularly | 0.78 | -7.72*** | -1.51 | -1.24 | -2.53 | -1.10 | -0.60 |
| | (0.39) | (1.95) | (1.92) | (2.20) | (2.00) | (1.95) | (2.17) |
| Recognition scheme exists | 0.81 | -6.53*** | -1.43 | -1.72 | -2.25 | -0.19 | -0.94 |
| | (0.37) | (2.12) | (1.86) | (2.07) | (2.08) | (1.81) | (2.01) |
| Log of salary | 9.25 | -3.70*** | -0.58 | -0.30 | 0.43 | -0.18 | -0.15 |
| | (0.62) | (1.08) | (0.88) | (0.96) | (1.01) | (0.94) | (0.99) |
| **SCHOOL VARIABLES** | | | | | | | |
| Log pupil-teacher ratio | 3.50 | 1.88 | -2.31** | -4.07*** | -2.42** | -1.65* | -3.29*** |
| | (0.59) | (1.26) | (1.15) | (1.40) | (1.10) | (0.99) | (1.24) |
| Mid-day meals | 0.79 | 0.77 | 0.57 | 2.62 | 0.49 | 0.47 | 2.01 |
| | (0.38) | (1.74) | (1.80) | (2.07) | (1.70) | (1.77) | (2.03) |
| Infrastructure index (0-4) | 3.35 | -3.44*** | -0.23 | -0.31 | -0.89 | 0.07 | 0.07 |
| | (1.30) | (0.56) | (0.70) | (0.80) | (0.68) | (0.69) | (0.77) |
| Remoteness index (normalized) | 0.04 | 0.26 | 0.58 | 0.76 | 0.19 | 0.17 | 0.14 |
| | (0.95) | (0.68) | (0.59) | (0.64) | (0.64) | (0.61) | (0.65) |
| **MONITORING & COMMUNITY VARIABLES** | | | | | | | |
| Inspected in the last 3 months | 0.56 | -10.47*** | -7.87*** | -7.63*** | -6.64*** | -6.32*** | -6.20*** |
| | (0.29) | (2.07) | (2.08) | (2.39) | (1.90) | (2.04) | (2.37) |
| PTA met in last 3 months | 0.45 | -6.72*** | -2.80** | -3.22** | -2.59* | -1.77 | -2.13 |
| | (0.48) | (1.51) | (1.17) | (1.32) | (1.33) | (1.13) | (1.32) |
| Mean parental education (1-7 scale) | 2.43 | -3.16*** | 0.37 | -0.46 | -0.90 | 0.64 | -0.82 |
| | (0.74) | (1.00) | (0.97) | (1.08) | (1.00) | (0.95) | (1.07) |
| Log state per-capita GDP | 3.29 | -11.01*** | | | -9.27*** | | |
| | (0.49) | (1.51) | | | (2.50) | | |
| **REGRESSION STATISTICS** | | | | | | | |
| Constant | | | | | 74.58*** | 38.50*** | 47.55*** |
| | | | | | (11.76) | (10.04) | (11.17) |
| R-squared | | | | | 0.139 | 0.231 | 0.394 |
| Adjusted R-squared | | | | | 0.126 | 0.211 | 0.273 |
| F-statistic (Inspected = PTA met) | | | | | 3.186* | 3.450* | 2.024 |
| Number of villages | | | | | 1,555 | 1,555 | 1,555 |

Notes:

1) In summary statistics, standard deviations are in parentheses; in binary and multiple regressions, robust standard errors clustered at the district-level are in parentheses

2) In binary regressions, each cell is a separate regression of the row variables with the dependent variable being the percentage of teacher absence

3) The binary dependent variable (0=Present, 1=Absent) has been multiplied by 100 to allow the coefficients to be read as percentage changes

4) The infrastructure index variable uses availability of four items (as in Table 1) with higher values being better; the remoteness index uses distances to nine sets of facilities, with higher values being more remote

5) Summary statistics and regressions are weighted by SCR's population

6) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

**Table 5. Panel OLS Regression Results**
**(Dependent Variable: Percentage Points Change in Village-Level Teacher Absence)**

| | BINARY REGRESSIONS | | | MULTIPLE REGRESSIONS | | |
|---|---|---|---|---|---|---|
| | (1) no fixed effects | (2) w/ State fixed effects | (3) w/ district fixed effects | (4) no fixed effects | (5) w/ State fixed effects | (6) w/ district fixed effects |
| **CHANGES IN TEACHER VARIABLES** | | | | | | |
| Have bachelors degree | -0.42 | -1.69 | -3.69 | -1.68 | -2.31 | -4.71 |
| | (2.55) | (2.52) | (2.91) | (2.51) | (2.57) | (3.04) |
| Have teacher training | 1.10 | 1.12 | 0.52 | 1.08 | 0.79 | 1.53 |
| | (2.51) | (2.76) | (3.12) | (2.81) | (2.85) | (3.19) |
| Are contract teachers | -4.89 | -3.39 | -0.86 | -5.26 | -3.84 | -0.83 |
| | (3.20) | (3.41) | (3.52) | (3.37) | (3.60) | (4.03) |
| Are paid regularly | -0.18 | -0.83 | -1.47 | -0.28 | -0.97 | -0.56 |
| | (1.70) | (1.81) | (2.11) | (1.67) | (1.77) | (2.24) |
| Recognition scheme exists | -3.87** | -3.34* | -3.69** | -3.06* | -2.03 | -3.34 |
| | (1.76) | (1.75) | (1.87) | (1.71) | (1.69) | (2.23) |
| **CHANGES IN SCHOOL VARIABLES** | | | | | | |
| Log pupil-teacher ratio | -5.33*** | -4.89*** | -4.48** | -5.56*** | -4.95*** | -4.69*** |
| | (1.83) | (1.68) | (1.91) | (1.81) | (1.57) | (1.78) |
| Mid-day meals | 1.31 | 1.81 | 4.19 | 1.62 | 0.95 | 2.14 |
| | (1.73) | (2.09) | (2.59) | (1.73) | (2.08) | (2.85) |
| Infrastructure index (0-4) | -1.10* | -0.97 | -1.01 | -0.97 | -0.68 | -0.96 |
| | (0.66) | (0.69) | (0.76) | (0.66) | (0.66) | (0.78) |
| Remoteness index (normalized) | -1.16 | -0.93 | -0.55 | -1.25 | -1.04 | -0.81 |
| | (1.05) | (1.06) | (1.08) | (1.00) | (0.95) | (1.13) |
| **CHANGES IN MONITORING & COMMUNITY VARIABLES** | | | | | | |
| Inspected in the last 3 months | -8.23*** | -7.31*** | -6.60*** | -7.35*** | -6.56*** | -6.41*** |
| | (1.94) | (1.98) | (1.91) | (1.83) | (1.83) | (2.01) |
| PTA met in last 3 months | -1.65 | -3.18* | -3.80** | -1.71 | -2.08 | -2.96 |
| | (1.74) | (1.63) | (1.72) | (1.67) | (1.64) | (2.02) |
| Mean parental education (1-7 scale) | -1.29 | -0.09 | 0.48 | -1.13 | -0.46 | 0.51 |
| | (1.40) | (1.38) | (1.44) | (1.29) | (1.32) | (1.46) |
| Log state per-capita GDP | -4.69 | | | -6.18 | | |
| | (7.39) | | | (7.18) | | |
| **REGRESSION STATISTICS** | | | | | | |
| Constant | | | | 3.43 | -0.62 | -1.95 |
| | | | | (5.50) | (2.26) | (2.72) |
| R-squared | | | | 0.071 | 0.143 | 0.346 |
| Adjusted R-squared | | | | 0.054 | 0.115 | 0.188 |
| F-statistic (Inspected = PTA met) | | | | 4.419** | 2.921* | 1.268 |
| Number of villages | | | | 1,297 | 1,297 | 1,297 |

Notes:
1) Robust standard errors clustered at the district-level are in parentheses
2) The infrastructure and remoteness index are as defined in Table 4
3) Regressions are weighted by SCR's population
4) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

## Table 6. Correlation between Inspection Frequency and Teacher Absence by Reason

| | BINARY REGRESSIONS | | | MULTIPLE REGRESSIONS | | |
|---|---|---|---|---|---|---|
| | (1) w/o fixed effects | (2) w/ State fixed effects | (3) w/ district fixed effects | (4) w/o fixed effects | (5) w/ State fixed effects | (6) w/ district fixed effects |
| PANEL A. CROSS-SECTION ANALYSIS | Dependent Variable: Village-Level Teacher Absence by Reason (2010) | | | | | |
| (Coefficient on Inspection Reported) | | | | | | |
| On Official Duty | -2.16** | -2.51** | -2.48* | -1.55 | -2.16** | -2.06 |
| | (1.01) | (1.02) | (1.29) | (1.03) | (1.04) | (1.30) |
| Authorized Leave | 2.35*** | 1.65** | 1.26 | 2.28*** | 1.44* | 1.17 |
| | (0.78) | (0.84) | (1.05) | (0.82) | (0.85) | (1.08) |
| Unauthorized Absence | -10.67*** | -7.02*** | -6.41*** | -7.39*** | -5.59*** | -5.30** |
| | (1.96) | (1.84) | (2.10) | (1.77) | (1.81) | (2.12) |
| PANEL B: PANEL ANALYSIS | Dependent Variable: Change in Village-Level Teacher Absence by Reason between 2003 and 2010 | | | | | |
| (Coefficient on Change in Inspection Reported) | | | | | | |
| On Official Duty | -1.77* | -1.05 | -1.45 | -1.43 | -1.00 | -1.49 |
| | (0.92) | (0.85) | (0.97) | (0.91) | (0.83) | (0.96) |
| Authorized Leave | 0.77 | 0.42 | 0.59 | 0.59 | 0.33 | 0.50 |
| | (0.83) | (0.84) | (0.91) | (0.85) | (0.84) | (0.91) |
| Unauthorized Absence | -7.22*** | -6.68*** | -5.74*** | -6.51*** | -6.07*** | -5.41*** |
| | (1.69) | (1.86) | (1.78) | (1.66) | (1.79) | (1.75) |

Notes:

1) Robust standard errors clustered at the district-level are in parenthesis

2) The binary dependent variable (0=Present, 1=Absent) has been multiplied by 100 to allow the coefficients to be read as percentage changes

3) Regressions are weighted by SCR's population

4) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

**Table 7. Panel OLS Regression Results, Village-Level**
**(Dependent Variable: Change in Village-Level Inspection Frequency)**

| | BINARY REGRESSIONS | | | MULTIPLE REGRESSIONS | | |
|---|---|---|---|---|---|---|
| | (1) no fixed effects | (2) w/ State fixed effects | (3) w/ district fixed effects | (4) no fixed effects | (5) w/ State fixed effects | (6) w/ district fixed effects |
| **CHANGES IN TEACHER VARIABLES** | | | | | | |
| Have bachelors degree | -0.003 | 0.042 | 0.039 | 0.006 | 0.037 | 0.030 |
| | (0.046) | (0.053) | (0.050) | (0.046) | (0.051) | (0.055) |
| Have teacher training | 0.041 | 0.054 | 0.085 | 0.029 | 0.046 | 0.064 |
| | (0.056) | (0.057) | (0.054) | (0.053) | (0.055) | (0.061) |
| Are contract teachers | 0.055 | 0.063 | -0.040 | 0.108* | 0.088 | -0.009 |
| | (0.053) | (0.073) | (0.069) | (0.059) | (0.070) | (0.082) |
| Are paid regularly | -0.036 | -0.010 | -0.010 | -0.037 | -0.005 | -0.004 |
| | (0.030) | (0.035) | (0.035) | (0.031) | (0.035) | (0.041) |
| Recognition scheme exists | 0.069** | 0.062** | 0.020 | 0.067** | 0.060* | 0.023 |
| | (0.028) | (0.031) | (0.032) | (0.028) | (0.031) | (0.037) |
| **CHANGES IN SCHOOL VARIABLES** | | | | | | |
| Log pupil-teacher ratio | 0.055* | 0.032 | 0.029 | 0.049 | 0.024 | 0.012 |
| | (0.031) | (0.032) | (0.034) | (0.030) | (0.031) | (0.037) |
| Mid-day meals | 0.007 | -0.008 | -0.024 | 0.018 | -0.008 | -0.017 |
| | (0.032) | (0.041) | (0.046) | (0.034) | (0.042) | (0.050) |
| Infrastructure index (0-4) | 0.010 | 0.011 | 0.005 | 0.006 | 0.011 | 0.004 |
| | (0.012) | (0.013) | (0.015) | (0.013) | (0.013) | (0.015) |
| Remoteness index (normalized) | -0.023 | -0.026 | -0.032 | -0.024 | -0.024 | -0.028 |
| | (0.022) | (0.022) | (0.020) | (0.021) | (0.021) | (0.024) |
| **CHANGES IN MONITORING & COMMUNITY VARIABLES** | | | | | | |
| PTA met at least once in last 3 months | 0.018 | 0.052** | 0.068** | 0.033 | 0.053** | 0.070** |
| | (0.023) | (0.024) | (0.029) | (0.023) | (0.024) | (0.027) |
| Mean parental education (1-7 scale) | -0.03 | -0.04 | -0.04** | -0.04 | -0.04* | -0.05** |
| | (0.026) | (0.026) | (0.022) | (0.023) | (0.024) | (0.025) |
| Log state per-capita GDP | -4.69 | | | 0.40** | | |
| | (7.392) | | | (0.167) | | |
| **REGRESSION STATISTICS** | | | | | | |
| Constant | | | | -0.13 | 0.13*** | 0.18*** |
| | | | | (0.138) | (0.051) | (0.048) |
| R-squared | | | | 0.051 | 0.093 | 0.315 |
| Adjusted R-squared | | | | 0.034 | 0.065 | 0.152 |
| Number of villages | | | | 1,300 | 1,300 | 1,300 |

Notes:
1) Robust standard errors clustered at the district-level are in parentheses
2) The infrastructure and remoteness index are as defined in Table 4
3) Regressions are weighted by SCR's population
4) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

**Table 8. Panel OLS Regression Results, Village-Level**
**(Dependent Variable: Change in Normalized Math Score)**

| | BINARY REGRESSIONS | | | MULTIPLE REGRESSIONS | | |
|---|---|---|---|---|---|---|
| | (1) no fixed effects | (2) w/ State fixed effects | (3) w/ district fixed effects | (4) no fixed effects | (5) w/ State fixed effects | (6) w/ district fixed effects |
| **CHANGES IN STUDENT VARIABLES** | | | | | | |
| Average age | 0.09** | 0.05 | 0.07 | 0.10** | 0.07 | 0.09 |
| | (0.05) | (0.04) | (0.05) | (0.05) | (0.04) | (0.05) |
| Proportion male | 0.14 | 0.13 | 0.14 | 0.07 | 0.10 | 0.10 |
| | (0.15) | (0.15) | (0.17) | (0.15) | (0.15) | (0.17) |
| Private tuition | 0.29** | 0.27** | 0.19 | 0.26** | 0.30** | 0.21 |
| | (0.13) | (0.13) | (0.18) | (0.12) | (0.13) | (0.18) |
| **CHANGES IN TEACHER VARIABLES** | | | | | | |
| Have bachelors degree | -0.22** | -0.13 | 0.03 | -0.28** | -0.17 | -0.02 |
| | (0.12) | (0.12) | (0.12) | (0.11) | (0.12) | (0.12) |
| Have teacher training | -0.05 | -0.02 | 0.03 | -0.06 | 0.06 | 0.07 |
| | (0.12) | (0.11) | (0.13) | (0.12) | (0.11) | (0.13) |
| Are contract teachers | -0.13 | 0.10 | -0.07 | 0.07 | 0.12 | -0.05 |
| | (0.15) | (0.15) | (0.18) | (0.16) | (0.15) | (0.19) |
| Are paid regularly | -0.04 | 0.11 | 0.12 | -0.02 | 0.10 | 0.11 |
| | (0.08) | (0.07) | (0.08) | (0.08) | (0.07) | (0.08) |
| Recognition scheme exists | -0.05 | 0.04 | 0.03 | -0.03 | 0.02 | 0.01 |
| | (0.08) | (0.08) | (0.09) | (0.08) | (0.08) | (0.09) |
| **CHANGES IN SCHOOL VARIABLES** | | | | | | |
| Absence rate of teachers | -0.005*** | -0.004*** | -0.002 | -0.006*** | -0.005*** | -0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Log pupil-teacher ratio | -0.07 | -0.11* | -0.13* | -0.09 | -0.13* | -0.15* |
| | (0.08) | (0.07) | (0.08) | (0.08) | (0.07) | (0.08) |
| Mid-day meals | -0.23* | -0.06 | -0.05 | -0.16* | -0.05 | -0.04 |
| | (0.08) | (0.09) | (0.12) | (0.08) | (0.09) | (0.11) |
| Infrastructure index (0-4) | 0.00 | -0.03 | 0.01 | -0.01 | -0.02 | 0.00 |
| | (0.03) | (0.03) | (0.04) | (0.03) | (0.03) | (0.04) |
| Remoteness index (normalized) | 0.05 | 0.04 | 0.03 | 0.03 | 0.04 | 0.03 |
| | (0.05) | (0.04) | (0.05) | (0.05) | (0.04) | (0.05) |
| Inspected in the last 3 months | -0.01 | -0.06 | -0.10 | -0.02 | -0.07 | -0.12 |
| | (0.08) | (0.08) | (0.09) | (0.09) | (0.08) | (0.09) |
| **CHANGES IN MONITORING & COMMUNITY VARIABLES** | | | | | | |
| PTA met at least once in last 3 months | -0.06 | 0.01 | 0.07 | -0.03 | 0.01 | 0.06 |
| | (0.07) | (0.07) | (0.08) | (0.08) | (0.07) | (0.08) |
| Mean parental education (1-7 scale) | 0.17*** | 0.15*** | 0.16*** | 0.17*** | 0.15*** | 0.17*** |
| | (0.05) | (0.04) | (0.06) | (0.05) | (0.05) | (0.06) |
| Log state per-capita GDP | -5.91 | | | 0.71 | | |
| | (7.59) | | | (0.44) | | |
| **REGRESSION STATISTICS** | | | | | | |
| Constant | | | | -0.86** | -0.52** | -0.40 |
| | | | | (0.41) | (0.25) | (0.32) |
| R-squared | | | | 0.066 | 0.180 | 0.434 |
| Adjusted R-squared | | | | 0.042 | 0.146 | 0.277 |
| Number of villages | | | | 1,155 | 1,155 | 1,155 |

Notes:
1) Robust standard errors clustered at the district-level are in italics
2) The infrastructure and remoteness index are as defined in Table 4
3) Regressions are weighted by SCR's population
4) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

## Table 9. The Fisal Cost of Absence (in 2010 Prices and Salaries)

| | Average Monthly Teacher Salary (Rs.) | Number of Teachers | Total Loss Due to Absence (millions of Rs.) | | |
|---|---|---|---|---|---|
| | | | Allowed Absence: 8% | Allowed Absence: 9% | Allowed Absence: 10% |
| **Andhra Pradesh** | 10,299 | 347,875 | 6,374 | 5,901 | 5,428 |
| **Assam** | 9,567 | 167,161 | 3,855 | 3,644 | 3,433 |
| **Bihar** | 8,645 | 336,359 | 7,942 | 7,559 | 7,175 |
| **Chattisgarh** | 8,290 | 155,573 | 1,055 | 885 | 715 |
| **Gujarat** | 15,804 | 198,584 | 3,374 | 2,960 | 2,546 |
| **Haryana** | 16,236 | 77,980 | 1,630 | 1,463 | 1,296 |
| **Himachal Pradesh** | 12,199 | 48,507 | 1,776 | 1,698 | 1,620 |
| **Jharkhand** | 9,734 | 135,690 | 6,598 | 6,423 | 6,249 |
| **Karnataka** | 10,897 | 195,929 | 4,489 | 4,207 | 3,925 |
| **Kerala** | 10,751 | 54,976 | 608 | 529 | 451 |
| **Madhya Pradesh** | 9,294 | 267,846 | 6,027 | 5,698 | 5,370 |
| **Maharastra** | 17,246 | 288,914 | 4,025 | 3,367 | 2,710 |
| **Orissa** | 9,382 | 192,119 | 1,484 | 1,246 | 1,008 |
| **Punjab** | 12,654 | 105,930 | 980 | 803 | 626 |
| **Rajasthan** | 14,165 | 271,205 | 7,463 | 6,956 | 6,448 |
| **Tamilnadu** | 18,489 | 150,820 | 1,811 | 1,443 | 1,075 |
| **Uttar Pradesh** | 10,370 | 491,455 | 15,615 | 14,942 | 14,269 |
| **Uttaranchal** | 17,155 | 45,782 | 1,350 | 1,246 | 1,143 |
| **West Bengal** | 10,555 | 416,633 | 7,527 | 6,946 | 6,366 |
| **India** | 11,368 | 3,949,338 | 92,699 | 86,773 | 80,847 |

Notes:

1) 2010 Teacher Salaries are from Teacher Long and School Census Data

2) Data on total number of teachers is obtained from DISE State Report Cards

3) All figures are in 2010 prices

## Table 10. Marginal Returns to Investing in Governance (in 2010 Prices and Salaries)

| | Pupil-Teacher Ratio (2009-2010) | | Effect of Increasing Probability of Inspection in Past 3 months by 10 percentage points | | | Cost to Produce Equal Effect Through Teacher Hiring |
|---|---|---|---|---|---|---|
| | Pupil-teacher Ratio | Effective Pupil Teacher Ratio | Annual Cost (Rs. millions) | Annual Savings From Reduced Teacher Absence (Rs. millions) | Expected Effective Pupil-teacher Ratio | Annual Cost (Rs. millions) |
| **Andhra Pradesh** | 17.8 | 22.7 | 31.0 | 350.8 | 22.5 | 433.5 |
| **Assam** | 24.5 | 33.2 | 15.9 | 154.5 | 33.0 | 204.2 |
| **Bihar** | 58.2 | 81.6 | 21.2 | 273.6 | 80.8 | 374.9 |
| **Chattisgarh** | 24.5 | 28.5 | 13.9 | 120.1 | 28.3 | 135.0 |
| **Gujarat** | 29.8 | 35.5 | 19.1 | 291.8 | 35.3 | 336.2 |
| **Haryana** | 26.8 | 32.5 | 8.8 | 118.9 | 32.3 | 139.8 |
| **Himachal Pradesh** | 15.4 | 22.2 | 6.8 | 56.0 | 22.0 | 79.2 |
| **Jharkhand** | 41.3 | 76.2 | 14.8 | 127.9 | 75.3 | 236.3 |
| **Karnataka** | 23.6 | 31.0 | 18.5 | 201.6 | 30.8 | 257.7 |
| **Kerala** | 19.6 | 23.2 | 2.0 | 56.3 | 23.1 | 64.5 |
| **Madhya Pradesh** | 39.8 | 54.0 | 40.6 | 250.9 | 53.5 | 332.1 |
| **Maharastra** | 25.7 | 29.9 | 45.0 | 486.8 | 29.7 | 546.8 |
| **Orissa** | 29.4 | 34.3 | 20.5 | 177.5 | 34.1 | 199.7 |
| **Punjab** | 20.5 | 23.7 | 10.2 | 137.4 | 23.5 | 153.2 |
| **Rajasthan** | 26.2 | 33.9 | 40.0 | 361.6 | 33.6 | 454.5 |
| **Tamilnadu** | 28.3 | 32.5 | 24.6 | 264.9 | 32.3 | 293.2 |
| **Uttar Pradesh** | 40.1 | 58.2 | 58.4 | 489.4 | 57.7 | 697.1 |
| **Uttaranchal** | 20.6 | 26.0 | 10.7 | 73.3 | 25.8 | 90.0 |
| **West Bengal** | 32.3 | 40.8 | 30.1 | 409.4 | 40.5 | 502.5 |
| **India** | 31.7 | 41.5 | 448.0 | 4,509.6 | 41.1 | 5,742.0 |

Notes:

1) Number of schools, number of teachers, and enrollment figures are from administrative (DISE) data

2) Simulation assumes that one inspection every 3 months reduces absence linearly by 6.4 percentage points

3) Inspector costs are assumed to be two times teacher salaries, travel costs are assumed to be 80 percent of monthly salary

4) An inspector is assumed to work 200 days a year and inspect two schools every day

## Appendix A: Sampling and Construction of Village-Level Panel Dataset

The original survey in 2003 covered the 19 largest states of India by population (except Delhi). Within each state, 10 districts were sampled using Probability Proportional to Size (PPS) and within each district, 10 primary sampling units PSUs (which could be villages or towns) were sampled by PPS, thereby yielding a nationally representative sample of 1,900 PSUs across 190 districts (including towns and villages). The exception is Uttar Pradesh where 11 districts were sampled and Uttaranchal where 9 districts were sampled (since Uttaranchal had only 9 districts, and Uttar Pradesh is the largest state in India). Additionally, to account for the considerable geographic diversity within Indian states, the sample was stratified by geographic socio-cultural region (SCRs), and the 10 districts in each state were allocated to SCRs proportional to the population of the SCRs. Similarly, the 10 PSUs within each district were allocated to villages/towns proportional to the rural/urban population split in the district. All sampling was done on the basis of the 1991 census, since that was the latest Census data available at the time of the study.

The 2003 sample was augmented to include 241 villages from the REDS survey (Foster and Rosenzweig 1996). Since the REDS villages are drawn as a representative sample within districts, including these villages does not change the representativeness of the sample. If a REDS district was in our main sample, the REDS villages were included (typically 2 to 4 per REDS district) and additional villages were sampled randomly to make up the total desired sample size. If a REDS district was not in our sample, those villages were covered in addition to our core sample. Including these villages provides more precise estimates of outcomes in the SCRs where they are located, but all analysis is weighted by SCR populations and so the final estimates continue to be nationally-representative on a population weighted basis.

The final sample in 2003 comprised of 2,141 rural and urban PSUs across 19 states of India. In 2010, since the survey only covered rural areas, the sample size was reduced from 10 to 8 villages per district. All districts in the 2003 sample were retained in the 2010 study, with three exceptions where full-urban districts sampled in 2003 were replaced with a new PPS sampled district from the same SCR. The three replaced districts are Hyderabad in Andhra Pradesh, Ahmedabad in Gujarat, and Greater Bombay in Maharashtra, which are highly urban districts containing their respective state capitals.

As we highlight in the paper, to meet our objective to maintain both representativeness of the current landscape of schools in rural India and to maximize the size of the panel, we retain villages from the 2003 study to the extent possible. In Column 1 of Table A1, we provide state-wise counts of rural PSUs that were sampled in the 2003 study. After removing PSUs in the three replaced districts altogether and all other urban PSUs from the 2003 study, the maximum panel size we could draw, including the REDS villages was 1,668. We sampled a 2003 village by default as long as the village had a population between 250 and 10,000 as per the 1991 Census, and we could locate the village in the 2001 Census[1]. In districts where we had more than 8 rural PSUs in 2003, we sampled 8 PSUs randomly. The lower cutoff on population was based on the Government of India's mandate that all rural habitations exceeding 250 people should have a school with 1 km. Since villages and hamlets can be absorbed into expanding cities over time, we match the originally sampled 1991 village to the villages in the 2001 Census to make sure that the sampled village still exists

From the 2003 list of 1,668 villages, we had to remove 249 from the 2010 sampling frame for reasons we discuss below (see Columns 5 through 9 of Table A1 for the distribution of these villages across states). 69 villages were dropped because they fall in districts that had more than 8 villages in the 2003 round. A further 129 villages were removed either because their population was below 250, or had far exceeded 10,000 in the 2001 Census (20,000 for Kerala). A total of 36 villages could not be located in the 2001 Census (suggesting that they had either been depopulated or absorbed into nearby towns). Finally, 15 villages were replaced due to safety, logistical and accessibility reasons. Thus, our sample consists of 1,419 villages from 2003 (Table A1 - column 3).

In districts where we had fewer than 8 villages in the 2003 sample (recall that the rural/urban sampling within districts was done on the basis of population ratios, and thus districts where over 25% of the population in 1991 was urban would have fewer than 8 villages), we sample more villages as required to reach a minimum sample size of 8 villages per district for the 2010 survey. The new villages were sampled PPS from the universe of eligible villages in the 2001 Census that were not already sampled. The cross-section sample (including REDS villages) thus consists of 1,650 villages (Table A1 - column 2).

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[1] The exception to this is Kerala, which has a much higher population density, where the upper cut-off was 20,000

Of the 1,650 villages that comprise our 2010 sample, data from 1,555 villages were included in the analysis presented in this paper (Table A2 - column 2). First, we found that 29 of the 1,650 villages have no schools in the village. A large proportion of these villages (12 out of 29) are in Himachal Pradesh, which is a sparsely populated mountainous state, with many small habitations. Another 39 villages did not have a public school within the village, but did have a private school. Since this paper focuses on changes in public schools, these villages are not included in the analysis. In Kerala, we lose another 12 villages, because all schools in the village refused to be allowed to be surveyed.[2] Finally, we drop 15 more villages from our analysis because in these villages, schools were either not functional or closed in all three visits, which means we were unable to complete surveys. A state-level breakdown of these 95 villages is provided in Columns 4-7 of Table A2. The decline in the cross-section sample size for reasons we discussed above, also reduces the number of villages for which we have panel data. After accounting for the above 95 villages and 53 villages in 2003 for which we have no data (for similar reasons as outlined for the 2010 survey round), our final panel size is 1,297 villages. These 1,297 villages form the core of our analysis.

To ensure a representative sample of schools, enumerators first conducted a full mapping of all public and private schools in each sampled village. Enumerators conducted "Participatory Resource Assessments" with households at multiple locations (at least three) within each village to obtain a list of all primary schools within the boundary of the village. All enumerated schools were administered a short survey that included questions on school administration such as management (public or private), enrollment, infrastructure etc. Enumerators also collected a list of all teachers in the school and their demographic characteristics. This school listing in each sampled village provided the frame for school sampling. We sampled up to three schools per village. If the village had three or fewer schools, all schools were sampled. If the village had more than three schools, we stratified the schools by management type and randomly sampled two public schools and one private school to the extent possible. In the event that there were only one public school and two or more private schools, one government and two private schools were sampled. Table A3 provides the state-level breakdown of the number of schools and teachers in the final (public school) sample used in this paper (both cross section and panel).

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[2] Permission to survey was refused in spite of the survey team possessing the required permission documents. Kerala has a history of strong unions and it was not possible for the field teams to overcome this opposition.

## Table A1. Description of Sample: Panel Construction

| | Number of Villages | | | Reduction in Panel Size | Reasons for Reduction in Panel Size | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Year 2003 Sample | Year 2010 Sample | Panel Sample | | More than 8 panel villages in district | Village population less than 250 | Village population more than 10,000 | Village not found in Census 2001 | Other Reasons |
| **Andhra Pradesh** | 81 | 87 | 73 | 8 | 3 | 0 | 4 | 1 | 0 |
| **Assam** | 98 | 87 | 77 | 21 | 5 | 3 | 0 | 10 | 3 |
| **Bihar** | 94 | 84 | 84 | 10 | 10 | 0 | 0 | 0 | 0 |
| **Chattisgarh** | 85 | 80 | 76 | 9 | 1 | 0 | 1 | 2 | 5 |
| **Gujarat** | 82 | 88 | 74 | 8 | 2 | 2 | 2 | 0 | 2 |
| **Haryana** | 81 | 81 | 75 | 6 | 3 | 1 | 1 | 1 | 0 |
| **Himachal Pradesh** | 89 | 80 | 60 | 29 | 2 | 22 | 0 | 4 | 1 |
| **Jharkhand** | 87 | 84 | 73 | 14 | 7 | 4 | 0 | 1 | 2 |
| **Karnataka** | 91 | 89 | 84 | 7 | 2 | 3 | 2 | 0 | 0 |
| **Kerala** | 83 | 83 | 43 | 40 | 0 | 0 | 40 | 0 | 0 |
| **Madhya Pradesh** | 88 | 90 | 81 | 7 | 3 | 1 | 2 | 1 | 0 |
| **Maharastra** | 85 | 91 | 80 | 5 | 2 | 0 | 3 | 0 | 0 |
| **Orissa** | 92 | 87 | 79 | 13 | 4 | 5 | 1 | 3 | 0 |
| **Punjab** | 78 | 82 | 75 | 3 | 0 | 0 | 1 | 2 | 0 |
| **Rajasthan** | 91 | 98 | 85 | 6 | 1 | 1 | 0 | 4 | 0 |
| **Tamilnadu** | 84 | 87 | 69 | 15 | 5 | 0 | 6 | 4 | 0 |
| **Uttar Pradesh** | 114 | 113 | 104 | 10 | 9 | 1 | 0 | 0 | 0 |
| **Uttaranchal** | 80 | 72 | 57 | 23 | 6 | 14 | 1 | 2 | 0 |
| **West Bengal** | 85 | 87 | 70 | 15 | 4 | 3 | 5 | 1 | 2 |
| **India** | 1,668 | 1,650 | 1,419 | 249 | 69 | 60 | 69 | 36 | 15 |

Notes:

1) The upper population cutoff for all states was 10,000 as per the 1991 census, except Kerala where the cutoff was 20,000

2) The category others include: replaced because high Naxalite activity (6 villages), replaced because duplicate in 2003 sample (2 villages), replaced because district was replaced (2 villages) replaced because village too remote (1 village), replaced because name missing in 2003 list (1 village), replaced because of floods in village (2 village), replaced because village could not be located (1 village)

## Table A2. Description of Sample: Data and Attrition

| | Year 2010 Sample | | | Reasons for Attrition (Year 2010) | | | | Panel Sample | | | Reasons for Attrition (Panel) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Sampled | Included in Analysis | Attrition | No school in village | No public school in village | School(s) refused to survey | Other reasons | Sampled | Included in Analysis | Attrition | No data for year 2010 | No data for year 2003 |
| **Andhra Pradesh** | 87 | 86 | 1 | 0 | 0 | 0 | 1 | 73 | 70 | 3 | 1 | 2 |
| **Assam** | 87 | 83 | 4 | 1 | 3 | 0 | 0 | 77 | 72 | 5 | 3 | 2 |
| **Bihar** | 84 | 81 | 3 | 1 | 1 | 0 | 1 | 84 | 77 | 7 | 3 | 4 |
| **Chattisgarh** | 80 | 75 | 5 | 2 | 1 | 0 | 2 | 76 | 69 | 7 | 4 | 3 |
| **Gujarat** | 88 | 85 | 3 | 0 | 3 | 0 | 0 | 74 | 71 | 3 | 3 | 0 |
| **Haryana** | 81 | 80 | 1 | 0 | 1 | 0 | 0 | 75 | 63 | 12 | 0 | 12 |
| **Himachal Pradesh** | 80 | 59 | 21 | 16 | 5 | 0 | 0 | 60 | 43 | 17 | 16 | 1 |
| **Jharkhand** | 84 | 81 | 3 | 2 | 1 | 0 | 0 | 73 | 58 | 15 | 3 | 12 |
| **Karnataka** | 89 | 88 | 1 | 0 | 1 | 0 | 0 | 84 | 82 | 2 | 1 | 1 |
| **Kerala** | 83 | 65 | 18 | 0 | 5 | 12 | 1 | 43 | 31 | 12 | 8 | 4 |
| **Madhya Pradesh** | 90 | 88 | 2 | 0 | 1 | 0 | 1 | 81 | 78 | 3 | 2 | 1 |
| **Maharastra** | 91 | 83 | 8 | 1 | 3 | 0 | 4 | 80 | 73 | 7 | 7 | 0 |
| **Orissa** | 87 | 83 | 4 | 2 | 1 | 0 | 1 | 79 | 73 | 6 | 3 | 3 |
| **Punjab** | 82 | 80 | 2 | 1 | 1 | 0 | 0 | 75 | 71 | 4 | 2 | 2 |
| **Rajasthan** | 98 | 94 | 4 | 1 | 2 | 0 | 1 | 85 | 83 | 2 | 2 | 0 |
| **Tamilnadu** | 87 | 79 | 8 | 1 | 5 | 0 | 2 | 69 | 62 | 7 | 5 | 2 |
| **Uttar Pradesh** | 113 | 111 | 2 | 0 | 2 | 0 | 0 | 104 | 100 | 4 | 2 | 2 |
| **Uttaranchal** | 72 | 67 | 5 | 1 | 3 | 0 | 1 | 57 | 52 | 5 | 4 | 1 |
| **West Bengal** | 87 | 87 | 0 | 0 | 0 | 0 | 0 | 70 | 69 | 1 | 0 | 1 |
| **India** | 1,650 | 1,555 | 95 | 29 | 39 | 12 | 15 | 1,419 | 1,297 | 122 | 69 | 53 |

Notes:

1) The category others include: high Naxalite activity, village not reachable, schools not functional, schools closed in all three visits

2) In 2003, if a village did not have any schools, surveyors went to the neighboring village. In 2010, the village was simply recorded as having no school

## Table A3. Description of Sample: Final Sample

| | Year 2010 Sample | | | Panel | | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of villages | Number of schools | Number of teachers | Number of villages | Number of schools in 2003 | Number of schools 2010 | Number of Teachers in 2003 | Number of Teachers in 2010 |
| **Andhra Pradesh** | 86 | 130 | 509 | 70 | 107 | 107 | 372 | 405 |
| **Assam** | 83 | 150 | 525 | 72 | 122 | 134 | 437 | 473 |
| **Bihar** | 81 | 124 | 757 | 77 | 112 | 119 | 341 | 731 |
| **Chattisgarh** | 75 | 100 | 450 | 69 | 94 | 92 | 259 | 412 |
| **Gujarat** | 85 | 119 | 944 | 71 | 101 | 98 | 419 | 798 |
| **Haryana** | 80 | 105 | 520 | 63 | 85 | 83 | 386 | 395 |
| **Himachal Pradesh** | 59 | 70 | 270 | 43 | 44 | 51 | 172 | 205 |
| **Jharkhand** | 81 | 132 | 493 | 58 | 76 | 94 | 244 | 374 |
| **Karnataka** | 88 | 120 | 572 | 82 | 117 | 112 | 598 | 530 |
| **Kerala** | 65 | 105 | 608 | 31 | 57 | 50 | 353 | 307 |
| **Madhya Pradesh** | 88 | 146 | 476 | 78 | 116 | 133 | 367 | 427 |
| **Maharastra** | 83 | 98 | 495 | 73 | 96 | 88 | 441 | 451 |
| **Orissa** | 83 | 114 | 483 | 73 | 88 | 101 | 295 | 439 |
| **Punjab** | 80 | 88 | 469 | 71 | 75 | 76 | 355 | 417 |
| **Rajasthan** | 94 | 141 | 671 | 83 | 132 | 121 | 497 | 565 |
| **Tamilnadu** | 79 | 96 | 445 | 62 | 124 | 75 | 455 | 363 |
| **Uttar Pradesh** | 111 | 135 | 616 | 100 | 131 | 119 | 442 | 542 |
| **Uttaranchal** | 67 | 73 | 207 | 52 | 61 | 57 | 177 | 151 |
| **West Bengal** | 87 | 151 | 668 | 69 | 108 | 121 | 331 | 531 |
| **India** | 1,555 | 2,197 | 10,178 | 1,297 | 1,846 | 1,831 | 6,941 | 8,516 |

Notes:

# The Effect of a Change in Language of Instruction: The Case of Malaysia's National Education Policy

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(EXTENDED ABSTRACT ONLY)

**Abstract**

We estimate the impacts of the 1970 schooling reform in Malaysia on several forms of literacy, schooling, and wages. Previous analyses have examined the changes to the supply of secondary and tertiary education, but our study focuses on a particular feature of the policy change: in 1970, the language of instruction in English-language primary schools was abruptly changed to Bahasa Malaysia. The policy change switched the language of instruction experienced by the new cohort: in 1970, the change affected Standard 1; in 1971, Standards 1 and 2; and so on. As a consequence, two adjacent cohorts - those starting school in 1969 and those starting in 1970 - experienced different instructional environments in primary school. Exploiting this discrete policy change, we are able to estimate the impacts of the language change on outcomes. Our analysis takes place in an unprecedented collection of large survey datasets, allowing us to test for program impacts with unusual rigor. While we find no evidence of change in literacy rates, we see that for some sections of the population, schooling and wages clearly increased. The relationship between the policy change, education, and wage is not the same for all sections of the population, however.

JEL Codes: I25,I28,J15,J24
Keywords: Malaysia, language of instruction, regression discontinuity

*The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors, and do not necessarily represent the views of the World Bank, its Executive Directors, or the governments of the countries they represent.