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

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Abstract: India has the largest primary education system in the world, catering to over 200 million children. But the public education system is characterized by weak governance, with a nationally-representative survey in 2003 finding that 26.2% of teachers in rural public primary schools were absent on a typical day. Over the past decade, the Government of India has devoted substantial additional resources to primary education. We study the extent to which these investments have translated into improved education system performance by creating a 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% of teachers in public schools across rural India being absent during unannounced visits to schools. We find two robust correlations in the panel data analysis of teacher absence. 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 are not significantly correlated with lower teacher absence. We calculate that the fiscal cost of teacher absence in India is over $1.5 billion per year, and estimate that investing in improved governance by increasing the frequency of monitoring would yield a nine-fold return on investment in terms of reducing the fiscal cost of teacher absence.

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1. Introduction

India has the largest primary education system in the world, catering to over 200 million children. At the same time, the public education system is characterized by substantial challenges of governance. A 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 conducted in 2003 found that over 25% of teachers were absent from work on a typical working day (Kremer et al. 2005). Correlations in this study suggested several possible narratives for high teacher absence including poor infrastructure and working conditions, irregularity of teacher pay, lack of recognition for teaching performance, low levels of community oversight, and inadequate monitoring by senior officials. However, while these were plausible narratives, they were based on correlations in observational data and hence confounded by omitted variables and not reliable as a basis for policy recommendations.

Notwithstanding the challenges in governance, the past decade has seen substantial investments in primary education by the Government of India under the Sarva Shiksha Abhiyan (SSA) or "Universal Education Campaign". Historical inattention to primary education (relative to tertiary education) was sought to be corrected with a substantial increase in annual spending on primary education across all major categories of spending including school infrastructure, teacher quality and quantity, and student inputs such as school feeding programs. Administrative data suggests that SSA has led to an improvement in various observed measures of school quality, but 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 outcome such as test scores. While this is an important question for research and policy, it is not easy to credibly identify the impact of scaled-up nationwide campaigns such as SSA in the absence of exogenous variation in school improvement.

In this paper, we study the impact of this nationwide campaign to improve school quality in India by constructing a nationally-representative panel dataset of education inputs and outcomes. The dataset was created by revisiting (in 2010) a randomly-sampled subset of the villages that were originally surveyed in 2003 and collecting detailed data on school facilities and infrastructure, teacher characteristics, measures of teacher policy, receipts and usage of funds, measures of community participation, and measures of governance such as the frequency of

monitoring visits by officials. We also collected data on teacher absence (measured by direct physical verification of teacher presence during three unannounced visits spread out over a nine-month period), and student learning outcomes (by testing a representative sample of fourth grade students). In addition to reporting updated summary statistics on 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 mitigates unobserved heterogeneity at the village-level, and this paper thereby provides the most credibly identified estimates of the impact of the ambitious nationwide push to improve school quality.

We find that there have been significant improvements in almost all input-based measures of school quality during the period from 2003 to 2010. The fraction of schools with toilets and electricity more than doubled, and the fraction serving mid-day meals nearly quadrupled. There were also 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 went up by 40% and pupil-teacher ratios fell by 16%. The incidence of teachers not being paid promptly fell from 51% to 22%, and the probability of the existence of a teacher recognition program increased from 49% to 81%. Finally, the probability of the school having been inspected recently as well as the likelihood of a PTA meeting in the past three months also went up significantly.

However, we find only modest reductions in teacher absence with the all-India weighted average teacher absence in rural areas falling from 26.3% to 23.7%.[1] The variation across states continues to be high. At one end, the top performing states of Tamilnadu, Punjab, Maharashtra, Chhatisgarh, and Orissa all have teacher absence rates below 15% (with Punjab and Chhatisgarh being the states with the biggest improvement), while at the other end, the poorest performing state continues to be Jharkhand with a teacher absence rate of 46%. Since legitimate absence rates are in the range of 8-10%, the variation between states in unauthorized absence rates is even higher.

While the cross-sectional correlations in 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

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

however find two robust correlations in the panel data.[2] 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 dissipated by an increase in teacher absence rates. Second, we find strong evidence to support the idea that better monitoring can reduce absence. Villages where the fraction of visits in which schools had been inspected in the prior three months went up from zero to one, had teacher absence rates that were 6.5 percentage points lower (which is over 25% of the measured absence rate, and over 40% of our estimated rate of illegitimate absence). We verify that increasing inspections is not correlated with reductions in either authorized leave or official duty, but is mainly correlated with reductions in unauthorized absence rates, and also show that the changes in inspections are not correlated with most of the changes in other inputs.

We calculate that the fiscal cost of teacher absence is over $1.5 billion per year. Using the most conservative estimates of the correlations between increased inspections and reduced absence, and treating these as causal (we discuss further caveats in the text), we estimate that increasing the frequency of school monitoring and supervision (on the margin) would yield a nine-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 eleven times more cost effective. The additional channel considered in these calculations is 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 governance.

This paper makes several contributions to the literature on public economics in developing countries. First, teacher absence is now widely used as a measure of the quality of education system governance.[3] We update the estimates of teacher absence in rural India from 2003 and

[2] 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.

[3] 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

show that in spite of substantial increases in spending on education inputs in the past decade, there has not been much improvement on this key measure of governance. Our estimates of the annual fiscal cost of teacher absence highlight that while a lot of media attention is paid to corruption scandals where there are concentrated benefits to officials and politicians there are also substantial costs due to 'passive' waste and inefficiency (Bandiera, Prat, and Valletti 2009).

Second, while there have been well-identified studies of the impact of improved school access in developing countries (including Duflo 2001 in Indonesia; Burde and Linden 2012 in Afghanistan; Kazianga et al. 2012 in Burkina Faso; and Muralidharan and Prakash 2013 in India), there have been very few studies on the impact of improving school quality on standard measures such as infrastructure and teacher quality/quantity in developing countries (Kazianga et. al. 2012 is a recent exception).[4] In the absence of exogenous variation in school improvement, our correlations based on panel data in a nationally-representative sample provide plausible estimates of the impact of nationwide school improvement programs such as SSA on key outcome measures such as teacher absence. In particular, it is worth highlighting that while identification based on panel data may not be as clean as say with an experiment, it allows us to study the impact of an "as implemented" nationally-scaled up school improvement program.[5]

Third, our results showing that hiring more teachers to reduce class-sizes is correlated with *increased* teacher absence highlights the importance of distinguishing between the 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 the marginal rates of leakage (measured as the extent of non-pass-through of a wage increase to workers) are much higher than the 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 is a result that has also been validated experimentally in multiple settings with both Muralidharan and Sundararaman (2013) and Duflo, Dupas, and Kremer (2012) finding that

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discourses in the past decade and reduction in provider absence rates is often included as a target in aid documents between donors and developing country governments

[4] Even the developed-country literature on the impacts of school quality is typically not very well identified, though it is a much older literature. Two noteworthy studies in the US are Card and Krueger (1992) and Cellini, Ferreira, and Rothstein (2010)

[5] Bold et al. (2012) provide illustrative evidence of the potential for divergence between results from carefully overseen experiments and those likely to be obtained when the same programs are implemented by the government.

programs that provided a randomly-selected set of schools with an extra teacher led to an *increase* in the absence rate of the pre-existing teachers in India and Kenya respectively. Together, this body of evidence suggests that the marginal impacts of increased spending in areas with high pre-existing levels of waste may be even lower than otherwise expected.

Finally, we are able to compare the relative effectiveness of improved top-down administrative monitoring (inspections) and improved bottom-up community monitoring (PTA meetings) on reducing teacher absence and find that the former are significantly more effective. This is consistent with the results reported in Olken (2007) comparing the relative effectiveness of administrative and community audits on reducing corruption in Indonesia. More broadly, a growing body of 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). Again, while our panel-data estimates are not as well identified as the smaller scale experiments studied in the papers above, they provide complementary evidence from "as is" nationally-scaled up increases in monitoring of schools. It is encouraging to find these positive results of monitoring in a steady state "as is" expansion, given evidence that improvements in monitoring and incentives can often be subverted (Banerjee, Duflo, and Glennerster 2008). More broadly, these results suggest that investing in better governance and monitoring of service providers may be an important component of improving state capacity in developing countries (Besley and Persson 2009, 2010).

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

2. Sampling, Data Collection, Variable Definitions, and Estimating Equations

2.1 Sampling of districts and villages

The original nationally-representative sample used for the surveys in 2003 covered both urban and rural areas across the 19 most populous states of India (except Delhi) representing

over 95 percent of the population. In each of the 19 states, 10 districts were sampled using Probability Proportional to Size (PPS) and within each district, 10 PSUs (villages and towns) were sampled by PPS, thereby yielding a nationally representative sample of 1,900 PSUs across 190 districts (including towns and villages).[6] To account for the considerable geographic diversity within Indian states, the sample was stratified by geographic socio-cultural region (SCR's), and the 10 districts in each state were allocated to SCR's proportional to the population of the SCR's. Similarly, the 10 PSU's 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.[7]

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. Maintaining representativeness of the survey required that the sampling frame include all the new schools that had been constructed in the 7-year interval between the survey waves. These twin objectives (representativeness and panel) were met 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.[8] Since the 2010 survey only covered rural areas, the sample size was reduced to 8 villages per district (as opposed to 10 villages/towns in 2003). All districts in the 2003 sample were retained in the 2010 sample, with 2 exceptions where fully-urban districts sampled in 2003 were replaced with a new randomly sampled district from the same SCR.

[6] 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).

[7] The rural 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 these additional villages are covered, but all analysis is weighted by SCR populations and so the final estimates continue to be nationally-representative on a population weighted basis.

[8] 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 also 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% of the cases) and had a mean coverage rate of 82.7% of public schools in the sampled villages.

Villages in the 2003 sample were included by default in the 2010 sample (since the original sample was representative). If the 2003 sample had fewer than 8 villages in a district, then new villages were sampled PPS from the universe of all rural habitations listed in the Census of India 1991. Villages with populations less than 250 or greater than 10,000 were removed from the sampling frame.[9] Columns 1 and 2 of Table 1 list the number of villages by state in the 2003 and 2010 studies respectively, and column 3 lists the number of villages in the 'panel' sample. The panel sample of 1281 villages will be the main focus of the analysis in this paper. Not every village in the 2003 sample is in the panel sample. Reasons for this include fewer villages sampled in the district in 2003 than 2010, growth of population between the 1991 and 2001 census so that the 'village' in 2003 was no longer classified as one in 2010, a sampled village not having any schools within village boundaries, refusal of permission to survey any of the schools at the village level (this only affect seven villages). A detailed description of the village sample construction by state are provided in Appendix A and Appendix Tables 1 and 2.

2.2. Sampling of schools

To ensure a representative sample of schools prior to detailed surveys and measurement of teacher absence, enumerators made a "visit zero" to each sampled village to generate a list of all schools in the village.[10] Both public and private schools were listed. Once a school listing was completed, surveyors visited all schools on the list and administered a short 'School Census' to the headmaster of the school which included questions on school hours, management type, a teacher roster, and student enrollment. The school listing in each sampled village provided the frame for school sampling. Field considerations allowed us to sample (for the main study) up to three schools in each village. If the village had three or fewer schools, all schools were selected. If the village had more than three schools, we stratified the sampling by management type and randomly sampled two government schools and one private school. In the event where there were only one government school and two or more private schools, one government and two private schools were sampled. Columns 4-7 of Table 1 report the number of schools and teachers in the final sample by state.

[9] The exception to this is Kerala, a high population density state, where the cut-off was 20,000. The sample was again augmented to include the villages from the REDS sample as described earlier.

[10] Survey enumerators conducted 'Participatory Resource Assessments (PRAs) with households at multiple locations (at least three) within villages to obtain a list of all primary schools within the boundary of the village.

2.3 Data Collection and Variable Definitions

Enumerators made three separate visits to each sampled school over a period of 10 months from January – October 2010.[11] 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 variable metrics such as teacher and student attendance, date of most recent inspections and PTA meetings were collected in each of the three visits. Assessments of student learning were conducted by testing a representative sample of fourth grade students in sampled schools.

Teacher absence was measured by enumerators conducting direct physical verification of teacher presence and activity within the first ten minutes of reaching the school. Data collected from the school and teacher census conducted in "visit zero" were used to pre-populate teacher rosters and school opening hours for the sampled schools, so that enumerators could record teacher activity immediately after their arrival at the school.[12] Teacher activity was recorded in one of the three categories: "present and in class", "present in school but not in class", and "could not be found anywhere". Once teacher activity was recorded, enumerators proceeded to inquire reasons for absence with the headmaster. All other data was collected using interviews and surveys – with school details obtained through a head teacher interview, and teacher details obtained through teacher interviews.[13]

We record teachers as absent on a given visit if they were not found anywhere in the school during the scan of the school conducted by enumerators in the first ten to fifteen minutes after reaching the school. We also consider all the teachers in the school to be absent if the school is closed during regular working hours on a school day, and respondents near the school mention the reason for the school being closed is either because no teacher has arrived yet, or because

[11] 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.
[12] 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.
[13] Of course, not all interviews could be successfully completed. Appendix B describes the interview completion rates across various categories. 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 will not affect the majority of 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.

they have all left early, or that they don't know why the school is closed.[14] To be conservative in our measure of absence, we exclude all school closures due to bad weather, school construction/repairs, school functions and school premises being used for other purposes (for instance, elections). We also exclude all part-time teachers, teacher who were transferred or deputed elsewhere or 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.

We measure the extent of monitoring and supervision as the mean probability of being inspected in the past three months across all three visits. A similar procedure is used for constructing the probability of a parent-teacher association (PTA) meeting. Mean 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.

2.4 Analytical Framework

Most of the analysis in this paper is based on mean village-level indicators of both inputs and outcomes. The main reason for this is that a large number of new schools have been constructed in the interval between 2003 and 2010 including in villages that already had schools. The reason for this is the policy priority placed on improving 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 (which in turn were sampled from the universe of representatively-sampled villages drawn for the 2003 survey). A further reason for this is that 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

[14] 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.

construct a school-level panel in any case (especially for villages with more than three schools). 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 quality and working conditions, school facilities and infrastructure, and community and administrative monitoring (Table 2). The fraction of teachers with a college degree went by over 40% (from 41% to 58%), the fraction reporting getting paid regularly rose by around 60% (from 51% to 22%), and the fraction reporting being eligible for a recognition scheme rose by over 60% (49% to 81%). One measure of teacher quality that fell a little bit is the fraction of teacher reporting having a formal teaching credential, which fell by 12% (77% to 68%). The main contributor to this decline was the large increase in the hiring of contract teachers in several large states (see Appendix Table 3 for a state-level breakdown of changes in key teacher characteristics). Another key metric of teacher working conditions and school quality is the pupil-teacher ratio, which fell by around 16% (from 47.4 to 39.8)

School facilities and infrastructure have improved on almost every measure. The fraction of schools with toilets and electricity has more than doubled (from 40% to 84% for toilets and 20% to 45% for electricity); the fraction of schools with functioning midday meal programs has nearly quadrupled (from 21% to 79%); almost all schools have access to drinking water (96%) and the fraction of schools with a library has increased by over 35% (from 51% to 69%). 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 further away. A summary index of school infrastructure has improved by 0.9 standard deviations (relative to the distribution of the school infrastructure index in 2003).

Finally, Table 2 also documents improvements in both 'top-down' administrative and 'bottom-up' community monitoring of schools over this period. We see that the probability of a school having been inspected in the three months prior to a survey increased by over 40% (from 39% to 56%). The increase in inspection probability is even more pronounced over shorter time windows increasing by over 60% for the previous two months, and over 70% for the previous

month. We define the extent of community oversight of schools by the frequency of PTA meetings, and find that the probability of a PTA meeting having taken place during the three months prior to the survey increased by 50% (from 30% to 45%).

3.2 Changes in teacher absence

Table 2 confirms that there have been substantial improvements in both school inputs as well as governance in this period. The main objective of this paper is to study the extent to which these investments have translated into improved outcomes, with a key metric of education system performance being the rate of teacher absence. Table 3 (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). We find that the population-weighted national average teacher absence rate for rural India fell from 26.3% to 23.6%, which is a reduction of around 10% or 2.7 percentage points.

There continues to be considerable variation in teacher absence rates across states with estimates ranging from 12.7% in Tamil Nadu to 45.8% in Jharkhand.[15] However, the majority of states (14 out of 19) show a reduction in teacher absence rates, with 12 of the states showing a significant reduction in teacher absence rates. On the contrary only 5 states show increases in teacher absence rates, with only 3 of these increases being significant. States with noticeable reductions in teacher absence rates (of 10 percentage points or more) are Assam, Bihar, Chhatisgarh, Punjab, and Uttaranchal). The broad-based reduction has led to five states (Tamilnadu, Punjab, Maharashtra, Orissa, and Chhatisgarh) having teacher absence rates below 15% (see Figure 1 for a map that illustrates these changes at the state level). Column 3 of Table 3 shows the changes in teacher absence rates in each state, and column 5 shows the contribution of each state to changes in the national absence rate on a population weighted basis. The state that has had the highest impact on the reduction of all-India teacher absence is Bihar.[16] Unfortunately, this is counteracted by a significant increase in teacher absence in the most populous Indian state of Uttar Pradesh.

[15] While most of the analysis in this paper will focus on all-India estimates, it is worth highlighting that Indian states are large and diverse administrative entities. For instance, the 10 most populous Indian states have populations that are larger than all but the 25 most populous countries in the world.

[16] These findings are consistent with several media and policy reports citing significant improvements in governance in Bihar during the period since 2004 under a new state government.

3.3 Stated reasons for absence

In cases where a teacher is not found in the school, enumerators ask the head teacher (or senior-most teacher who is present) for the reason for absence. These stated reasons are summarized in Table 4 (Panel A). Two categories of clearly unauthorized absence (the school being closed during working hours, and no valid reason being given for absence) account for just under half the cases of teacher absence (48%) providing a lower bound on the extent of unauthorized absences of 11.25 percentage points. The two other categories of stated absence (authorized leave and other official duties) accounting for 52% of the observed absence are plausibly legitimate but cannot be verified.

There is some reason 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.[17] However, we can reasonably treat the stated reasons for absence as an upper bound on that reason. 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 4 - Panel B shows that official non-teaching duties account for less than 1% of the observations and under 4% of the cases of teacher absence. Appendix Table 4 shows the state-level breakdown of the stated reasons for absence, and we return to the issue of estimating the 'legitimate' rate of absence in section 5.

4. Cross-section and Panel Regression Results

4.1. Correlates of teacher absence in 2010

Table 5 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.[18] Column 1 shows the mean level of each covariate in the sample, columns 2-4 present the coefficients on each indicator in binary

[17] For instance we found that in 2.7 percent of all observations, teachers who were not found in the school during the direct observation were marked present in the official log books, suggesting some collusion among teachers in the reporting of absence in official records.

[18] Correlations at the teacher-visit level are presented in Appendix Table 5. These are the parallel specifications to the ones presented in Kremer (2005) but are not the focus in this paper since we consider the panel data estimates to be more credible than the cross-sectional correlations.

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 are important for interpreting the correlations because many of the indicators of school quality studied vary considerably across states (as summarized in Appendix Table 3), and variation in these indicators across states is likely to be correlated with other measures of governance and development more broadly, as well as the history of investment in education 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 5 for completeness and focus our discussion on the panel regressions presented in Table 6.

Without any fixed effects, we find that 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 5 – 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, we see 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 was 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

As mentioned earlier, the main identification challenge in the cross-sectional correlations presented in Table 5 (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 mitigates these concerns to a large extent since our correlations are now identified using changes in village-level measures of school quality. Table 6 (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 ΔAbs_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 quality, $\Delta \boldsymbol{S_i}$ is the change in village-level means of measures of school quality, 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 in the specifications with fixed effects (state or district) and ε_i is the residual. Since changes in the measures of school quality included above may be correlated, we report both binary regressions with only measure at a time (columns 1-3) as well as multiple regressions with all the measures of school quality reported in Table 2 (columns 4-6).

The results in Table 6 suggest that several narratives for the reasons for teacher absence that are supported anecdotally 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 self-identification (measured by the fraction of teachers with college degrees and with formal training) or professional conditions (such as regularity of pay) and changes in teacher absence. There is some evidence to suggest that villages that saw an increase in the probability of having a teacher recognition scheme saw a reduction in teacher absence in the binary regressions, but the relationship is only significant in the binary and not in the multiple regressions.[19]

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

[19] See Muralidharan and Sundararaman (2011) and Muralidharan (2012) for further discussions on the low extent to which teachers in India are rewarded for performance and the large impacts on student test scores (though not on absence) of performance-linked pay.

consistent across all these specifications (i.e. we cannot reject that the estimates are the same across all these specifications). We discuss these in detail below.

First, we find that villages that saw a reduction in pupil-teacher ratio (PTR)[20] have significantly *higher* rates of teacher absence. This is a potentially counter-intuitive result because a common narrative for teacher absence is that their working conditions are poor, with high PTR's being a prominent example of poor 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 teacher is present.[21] 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 getting partially offset through increased teacher absence. The estimates suggest that a 10% reduction in PTR is correlated with a 0.5% increase in mean teacher absence.

The stability of the estimates to the introduction of state and district fixed effects as well as across both binary and multiple regressions with a full set of controls (also measured in *changes*) makes us confident that these estimates are not significantly confounded by omitted variables and can plausibly be interpreted as causal. While the identification challenges in a cross-section are obvious, they are less so 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.[22] Finally, it is worth highlighting that a causal relationship between increased teacher hiring and increased absence of existing teachers has been established experimentally in multiple developing country settings including in India (Muralidharan and Sundararaman 2013) and Kenya (Duflo, Dupas, and Kremer 2012). Our estimates provide complementary evidence and greater external validity to

[20] 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.

[21] Doing so does not deviate from the norm in the context of rural Indian government-run primary schools because close to 80% 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.

[22] 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.

these experimental results and suggest that they generalize broadly to nationally scaled up programs of reducing class sizes by hiring more teachers in developing countries.

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 therefore suggest that villages where the probability of inspection in the past three months increased from zero to one had a reduction in mean teacher absence of between 8.2% (with no fixed effects and no controls) and 6.4% (district fixed effects and a full set of controls). These are very large effects, and even the most conservative estimate suggest that the absence rates in schools that are regularly inspected are over 25% lower than in schools that are not.

To better interpret this result, Table 7 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 5) while Panel B shows the panel ones (corresponding to Table 6). We see clearly that increased inspections are mostly correlated with reductions in unauthorized teacher absences and that there is no significant relationship between inspections and reductions in teacher absence due to either official duty or authorized leave.[23] These results are consistent with the interpretation that improved 'top down' administrative monitoring can have a significant and substantial impact on reducing teacher absence.

On the contrary, we find weaker evidence to support the idea 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 teacher absence (Table 6). While some of the estimated

[23] 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.

coefficients on "PTA met in last 3 months" in Tables 5 and 6 are negative and significant, none of the estimates are significant in our most preferred specifications (Table 6 - columns 4-6), and the point estimate of the impact of increased frequency of PTA meetings on teacher absence is always less than those of "Inspected in last 3 months" (which 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). PTA's 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,[24] but the administrative rules provide inspectors with the powers to take these actions, whereas PTA's do not have any such powers (Center for Policy Research 2012).

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 across both binary and multiple regressions with a full set of controls makes us confident that these estimates are not significantly confounded by omitted variables and can plausibly be interpreted as causal. To further address identification concerns, we examine the extent to which changes in inspection frequency can be explained by other observables and show in Table 8 that there are no correlations between changes in inspections and changes in other measures of school quality that are significant across our six standard specifications. Finally, it is worth highlighting that our results are consistent with experimental evidence from India that find significant reduction in teacher absence in response

[24] The low frequency of formal action being taken against teachers (in spite of high observed absence rates) may suggest that the inspection system is not very effective (especially, given that it can be quite costly for an inspector to take action given pressure from unions and the administrative procedures that need to be followed). However, qualitative evidence from field interviews suggest that an important channel of the deterrence effect of increased inspections on teacher absence may be the fact 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.

to improved monitoring and professional consequences 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.

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 8). Qualitative interviews on school governance in India conducted at the district level suggest two important sources of variation (Center for Policy Research 2012).[25]

The first is staffing. Districts are broken down further into administrative blocks,[26] 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% of the cases even the position of the "District Education Officer (DEO)" (who is 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 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

[25] 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%) 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).

[26] The size of blocks varies by state, but a typical number is 10-15 blocks per district.

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 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 5.3.

4.3. Correlates of changes in student outcomes

While the focus of our analysis has been on teacher absence as the outcome of interest, we also briefly consider the extent to which the improvements in school quality described in Table 2 are correlated with learning outcomes. Table 9 presents panel regressions of the form in equation (1), with the dependent variable being changes in normalized mean math test scores at the village level, and the regressors including the changes in village-level teacher absence. The only variable that is significantly correlated with changes in test scores is 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. These are that teacher absences significantly hurt student learning, and that school infrastructure, teacher qualifications, and training certification are not correlated with improved student learning.[27] Thus, while the majority of the education budget is

[27] 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

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.[28]

5. The Fiscal Cost of Weak Governance

5.1. The fiscal cost of teacher absence

High levels of teacher absence translate into considerable wastage of public spending since teacher salaries are the largest component of education spending in most countries, including India.[29] Calculating these fiscal costs requires us to make an estimate of the extent of legitimate absence and not include these in our calculations. As part of the institutional background work for this project, we obtained teacher policy documents from several states across India.[30] Analysis of these documents indicates that the annual allowance for personal and sick leave is 5% on average across states. This is close to the survey estimate of 5.9% (Table 4), but we use the official data since the stated reasons may be over-reported.

Estimating the extent of legitimate absence due to being on 'official duty' is more difficult 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 4 for the fraction of absences that are claimed to be due to "official duty" are therefore likely to 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% (5% authorized leave, and 3% official duty). We also consider a more conservative case where the legitimate rate of absence is 10%. We are comfortable that the correct range of

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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).

[28] See Waldinger (2012) for an interesting parallel in the context of post-World War II higher education in Germany.

[29] 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.

[30] These were collected as part of the World Bank's initiative on documenting "Teacher Policies around the World (TPAW)". Further details are available at: NEED TO PUT UPDATED LINK HERE.

legitimate absence is 8 to 10% 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 (see Appendix Table 4).

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 10). We provide two estimates of the fiscal cost of teacher absence in columns 3 and 4 of Table 10. The first estimate assumes that the rate of legitimate teacher absence is 8%, while the second one assumes that it is 10%, and these calculations suggest that the annual fiscal cost of teacher absence is around Rs. 73 to 84 billion (1.4 – 1.6 billion US dollars/year). Our mean estimated fiscal cost of teacher absence of $1.5 billion/year is likely to be a lower bound because they do not include the annual value of the pension commitments made to government employees.

5.2. Calculating the returns to better governance in education

The panel data regressions presented in Table 6-8 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 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%); (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 6); (c) the full cost (salary and travel) of an inspector is three times that of a teacher; (d) an inspector works 200 days per year and can cover 2 schools per day. [31]

[31] 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 a

The results of this estimation are presented in Table 11 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 benefits from this investment in terms of reduced teacher absence are estimated at a little over Rs. 4 billion/year (based on the salary cost of teacher absence) suggesting that the returns to investing in better governance are nine times greater than the cost. Thus, improving school governance by hiring enough staff to increase the frequency of monitoring would on the margin be a highly cost-effective investment.

5.3. Hiring more inspectors vs. more teachers

The amount of effective attention that 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 11 – columns 1 and 2). The 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. Column 5 of Table 11 calculates the extent to which the EPTR can be reduced by hiring enough inspectors to increase the probability of a school being 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 these numbers are reported in column 6. Comparing columns 3 and 6, we see that hiring more inspectors would be 11.6 times more cost effective at reducing EPTR than doing so by hiring more teachers. The difference between the estimates in columns 4 and 6 is that we also account for the fact that hiring more teachers will increase the absence rates of the existing

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).

teachers, which is the other robust result in the panel regressions presented in Table 6 (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).

The difference in the relative cost effectiveness of the two policy options is so stark (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%), the marginal return to hiring an additional inspector would still be over eight times more cost effective at reducing EPTR than hiring an additional teacher. To summarize, the calculations in this section suggest that the extent of monitoring of schools and teachers may be sub-optimally low, and that the returns to better monitoring are high enough to warrant an expansion on the margin and that these returns are even higher when compared with the cost effectiveness of hiring more teachers at the current levels of monitoring (Shapiro and Stiglitz 1984).

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% 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 find two robust correlations in the panel data analysis of teacher absence. 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 dissipated 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 ten 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 governance 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. Nevertheless, the analysis does suggest that improving school governance by increasing the extent of administrative monitoring of teachers and schools can (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.

The main caveat to our results is that they are not based on exogenous variation in the covariates we study. On the other hand, our use of village-level panel data substantially mitigates the possibility of unobserved variables at the community level that are correlated with both changes in inputs and changes in teacher absence. The panel data also provides the most credibly-identified estimates of the impact of the nationwide investment in improved school quality. Finally, the two robust significant correlations in this paper (on monitoring and on class-size reductions) that we base our main policy recommendations on, are consistent with the evidence found in smaller-scale experimental studies in India. Our results, which are based on "as is" implementation of SSA over the past decade, therefore provide external validity to these experimental results and increase our confidence in their generalizability at a systemic level.

References:

BANDIERA, O., A. PRAT, and T. VALLETTI (2009): "Active and Passive Waste in Government Spending: Evidence from a Policy Experiment," *American Economic Review*, 99, 1278-1308.

BANERJEE, A., and E. DUFLO (2006): "Addressing Absence," *Journal of Economic Perspectives*, 20, 117-32.

BANERJEE, A., E. DUFLO, and R. GLENNERSTER (2008): "Putting a Band-Aid on a Corpse: Incentives for Nurses in the Indian Public Health Care System," *Journal of the European Economic Association*, 6, 487-500.

BANERJEE, A., and L. IYER (2005): "History, Institutions, and Economic Performance: The Legacy of Colonial Land Tenure Systems in India," *American Economic Review*, 95, 1190-1213.

BESLEY, T., and T. PERSSON (2009): "The Origins of State Capacity: Property Rights, Taxation, and Politics," *American Economic Review*, 99, 1218-44.

— (2010): "State Capacity, Conflict, and Development," *Econometrica*, 78, 1-34.

BOLD, T., M. KIMENYI, G. MWABU, N. A. A. ALICE, and J. SANDEFUR (2013): "Scaling-up What Works: Experimental Evidence on External Validity in Kenyan Education," Washington DC: Center for Global Development.

BURDE, D., and L. LINDEN (2013): "The Effects of Village-Based Schools: Evidence from a Randomized Control Trial in Afghanistan," *American Economic Journal: Applied Economics*.

CARD, D., and A. KRUEGER (1992): "Does School Quality Matter: Returns to Education and the Characteristics of Public Schools in the United States," *Journal of Political Economy*, 100, 1-40.

CELLINI, S. R., F. FERREIRA, and J. ROTHSTEIN (2010): "The Value of School Facility Investments: Evidence from a Dynamic Regression Discontinuity Design," *Quarterly Journal of Economics*, 125, 215-261.

CHAUDHURY, N., J. HAMMER, M. KREMER, K. MURALIDHARAN, and F. H. ROGERS (2006): "Missing in Action: Teacher and Health Worker Absence in Developing Countries," *Journal of Economic Perspectives*, 20, 91-116.

CPR (2012): "Quality of Education in Rural India (Queri): Governance Report," New Delhi: Center for Policy Research.

DUFLO, E. (2001): "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment," *The American Economic Review*, 91, 795-813.

DUFLO, E., P. DUPAS, and M. KREMER (2012): "School Governance, Teacher Incentives, and Pupil-Teacher Ratios: Experimental Evidence from Kenyan Primary Schools," National Bureau of Economic Research. Working Paper 17939.

DUFLO, E., R. HANNA, and S. RYAN (2012): "Incentives Work: Getting Teachers to Come to School," *American Economic Review*, 102, 1241-78.

IYER, L. (2010): "Direct Versus Indirect Colonial Rule in India: Long-Term Consequences," *Review of Economics and Statistics*, 92, 693-713.

KAZIANGA, H., D. LEVY, L. LINDEN, and M. SLOAN (2013): "The Effects of "Girl-Friendly" Schools: Evidence from the Bright School Construction Program in Burkina Faso," *American Economic Journal: Applied Economics*.

KREMER, M., K. MURALIDHARAN, N. CHAUDHURY, F. H. ROGERS, and J. HAMMER (2005): "Teacher Absence in India: A Snapshot," *Journal of the European Economic Association*, 3, 658-67.

MURALIDHARAN, K. (2012): "Long Term Effects of Teacher Performance Pay: Experimental Evidence from India," UC San Diego.

MURALIDHARAN, K., and N. PRAKASH (2013): "Cycling to School: Increasing Secondary School Enrollment for Girls in India," UC San Diego.

MURALIDHARAN, K., and V. SUNDARARAMAN (2011): "Teacher Performance Pay: Experimental Evidence from India," *Journal of Political Economy*, 119, 39-77.

— (2013): "Contract Teachers: Experimental Evidence from India," UC San Diego.

NIEHAUS, P., and S. SUKHTANKAR (2013): "The Marginal Rate of Corruption in Public Programs: Evidence from India," UC San Diego.

OLKEN, B. (2007): "Monitoring Corruption: Evidence from a Field Experiment in Indonesia," *Journal of Political Economy*, 115, 200-249.

PRATHAM (2012): *Annual Status of Education Report*.

SHAPIRO, C., and J. E. STIGLITZ (1984): "Equilibrium Unemployment as a Worker Discipline Device," *American Economic Review*, 74, 433-444.

WALDINGER, F. (2012): "Bombs, Brains, and Science: The Role of Human and Physical Capital for the Creation of Scientific Knowledge," University of Warwick.

WORLD BANK (2003): *World Development Report 2004: Making Services Work for Poor People*. Washington, DC: Oxford University Press for the World Bank.

ZAMBONI, Y., and S. LITSCHIG (2013): "Audit Risk and Rent Extraction: Evidence from a Randomized Evaluation in Brazil," Universitat Pompeu Fabra.

Table 1. Description of Sample

	Number of villages			Number of Public Schools		Number of Public Teachers	
	2003	2010	Panel	2003	2010	2003	2010
Andhra Pradesh	78	87	71	123	131	428	511
Assam	93	83	71	155	150	580	525
Bihar	90	81	77	131	124	389	757
Chattisgarh	73	75	61	101	100	266	450
Gujarat	81	85	66	118	119	506	944
Haryana	68	80	63	93	105	420	519
Himachal	80	59	43	89	70	317	270
Jharkhand	73	81	57	106	132	363	493
Karnataka	89	88	82	128	120	648	572
Kerala	59	65	31	127	105	807	608
Madhya Pradesh	91	88	76	144	146	457	476
Maharastra	85	86	73	111	101	509	504
Orissa	88	83	73	107	114	355	483
Punjab	76	80	71	81	88	373	469
Rajasthan	90	94	83	142	141	524	671
Tamilnadu	77	80	62	159	97	619	446
Uttar Pradesh	108	111	100	140	135	469	616
Uttaranchal	71	67	52	89	73	243	206
West Bengal	83	87	68	131	151	404	668
India	1,553	1,560	1,280	2,275	2,202	8,677	10,188

Notes:

1) Indudes only those villages that have public schools, the total number of villages is higher

Table 2. 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	0.173***
Have teacher training	0.77	0.68	-0.086***
Are paid regularly	0.49	0.78	0.288***
Recognition scheme exists	0.49	0.81	0.313***
SCHOOL VARIABLES			
Pupil-teacher ratio	47.40	39.81	-7.588***
Mid-day meals	0.21	0.79	0.581***
Infrastructure index (0-4)	2.13	3.35	1.215***
Has drinking water	0.80	0.96	0.161***
Has toilets	0.40	0.84	0.441***
Has electricity	0.21	0.45	0.240***
Has library	0.51	0.69	0.184***
Road is within 1km	0.69	0.78	0.092***
MONITORING & COMMUNITY VARIABLES			
Inspected in last 3 months	0.39	0.56	0.175***
Inspected in last 2 months	0.31	0.50	0.189***
Inspected in last 1 month	0.22	0.38	0.154***
PTA met at least once in last 3 months	0.30	0.45	0.156***
Mean parental education (1-7 scale)	2.02	2.43	0.403***

Notes:

1) Summary statistics are weighted by SCR populations

2) Data for number of days since inspection and expected number of days since inspection truncated at 99%

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

Table 3. Absence Rate of Teachers in Rural Public Schools by State by Year

	Absence Rates (%)			Rural Population (in millions)	Contribution to National Change
	Year 2003	Year 2010	Change		
Andhra Pradesh	23.4	21.5	-1.9	55.40	-0.15
Assam	36.1	26.3	-9.9 ***	23.22	-0.32
Bihar	39.4	28.7	-10.7 ***	74.32	-1.10
Chattisgarh	31.6	14.2	-17.4 ***	16.65	-0.40
Gujarat	17.9	16.1	-1.8 *	31.74	-0.08
Haryana	21.1	17.8	-3.3 **	15.03	-0.07
Himachal Pradesh	22.7	30.7	8.1 ***	5.48	0.06
Jharkhand	43.7	45.8	2.1	20.95	0.06
Karnataka	22.6	23.9	1.3	34.89	0.06
Kerala	19.6	15.8	-3.8 ***	23.57	-0.12
Madhya Pradesh	18.9	26.3	7.4 ***	44.38	0.46
Maharastra	15.4	14.1	-1.3	55.78	-0.10
Orissa	21.7	14.2	-7.5 ***	31.29	-0.32
Punjab	36.7	13.5	-23.1 ***	16.10	-0.52
Rajasthan	25.1	22.7	-2.4 *	43.29	-0.14
Tamilnadu	20.4	12.7	-7.7 ***	34.92	-0.37
Uttar Pradesh	26.7	31.2	4.5 ***	131.66	0.82
Uttaranchal	32.3	21.0	-11.3 ***	6.31	-0.10
West Bengal	26.4	21.0	-5.4 ***	57.75	-0.44
India	26.3	23.6	-2.7 ***	722.72	-2.70

Notes:

1) All figures are weighted by SCR 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) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 4. Reasons for Absence, 2010 Data

Panel A: Stated Reasons for Absence (%)

Absence Rate	School Closed	On Official Duty	Authorized	No Reason
23.65	6.60	6.48	5.91	4.65

Panel B: Decomposition of Official Duty (%)

	Official Teaching Related (Trainings, Meetings, etc.)	Official Non-Teaching Related (Elections, Health Campaigns, etc.)	Official Other (Panchayat Meetings, Political Meetings, etc.)	Total
Fraction of Official Duty	80.40	14.36	5.40	100.00
Fraction of Absence	22.03	3.93	1.48	27.40
Fraction of Observations	5.21	0.93	0.35	6.48

Notes:

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

2) Teaching related duties include - trainings, meetings, invigilation, elections, health campaigns etc.

Table 5. Cross-section OLS Regressions Results, Village Level, 2010 Data
(Dependent Variable: Percentage Absence)

	SUMMARY STATISTICS	BINARY REGRESSIONS			MULTIPLE REGRESSIONS		
	(1) Year 2010	(2) w/o fixed effects	(3) w/ state fixed effects	(4) w/ district fixed effects	(5) w/o fixed effects	(6) w/ state fixed effects	(7) w/ district fixed effects
TEACHER VARIABLES							
Have bachelors degree	0.58	-1.03	-6.23**	-6.52***	-1.03	-5.79**	-5.71**
	(0.32)	(1.97)	(2.47)	(2.48)	(1.87)	(2.50)	(2.51)
Have teacher training	0.68	-11.96***	-3.50	-3.05	-5.15*	-2.40	-2.19
	(0.31)	(2.45)	(2.44)	(2.71)	(2.79)	(2.73)	(2.85)
Are paid regularly	0.78	-7.72***	-1.50	-0.62	-4.25**	-1.07	-0.05
	(0.39)	(1.95)	(1.86)	(2.02)	(2.09)	(1.90)	(2.01)
Recognition scheme exists	0.81	-6.55***	-1.46	-1.68	-3.58*	-0.31	-1.07
	(0.37)	(2.20)	(1.90)	(2.05)	(2.09)	(1.83)	(2.00)
Log of Salary	9.25	-3.70***	-0.58	-0.22	0.53	-0.02	0.25
	(0.62)	(1.09)	(0.88)	(0.94)	(0.97)	(0.89)	(0.95)
SCHOOL VARIABLES							
Log pupil-teacher ratio	3.50	1.89	-2.28*	-3.90***	-1.22	-1.64	-3.20***
	(0.59)	(1.27)	(1.19)	(1.38)	(1.14)	(1.02)	(1.23)
Mid-day meals	0.79	0.77	0.57	2.56	0.53	0.55	2.12
	(0.38)	(1.70)	(1.73)	(2.00)	(1.70)	(1.74)	(1.98)
Infrastructure index (0-4)	3.35	-3.44***	-0.23	-0.39	-2.12***	0.05	-0.02
	(1.30)	(0.57)	(0.72)	(0.80)	(0.59)	(0.70)	(0.78)
Remoteness index (normalized)	0.04	0.26	0.58	0.96	-0.50	0.16	0.30
	(0.95)	(0.71)	(0.62)	(0.64)	(0.68)	(0.63)	(0.65)
MONITORING & COMMUNITY VARIABLES							
Inspected in last 3 months	0.56	-10.50***	-7.89***	-7.90***	-6.75***	-6.21***	-6.44***
	(0.29)	(2.07)	(2.14)	(2.35)	(1.98)	(2.09)	(2.35)
PTA met in last 3 months	0.45	-6.72***	-2.80**	-2.98**	-3.45**	-1.77	-1.81
	(0.48)	(1.58)	(1.28)	(1.36)	(1.42)	(1.23)	(1.36)
Mean parental education	2.43	-3.17***	0.36	-0.70	-1.57	0.47	-0.79
(1-7 scale)	(0.74)	(1.02)	(0.98)	(1.07)	(1.01)	(1.02)	(1.07)
REGRESSION STATISTICS							
Constant					48.38***	37.20***	41.84***
					(10.32)	(9.42)	(10.40)
R-squared					0.120	0.235	0.412
Adjusted R-squared					0.108	0.215	0.293
Number of villages					1,554	1,554	1,554

Notes:
1) In summary statistics, standard deviations are in italics; in binary and multiple regressions, robust standard errors clustered at the
2) In binary regressions, each column is a separate regression of the row variables with the dependent variable percentage 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, higher is better; remoteness index uses distances to nine places of
5) Summary statistics and regressions are weighted by SCR populations
6) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 6. Panel OLS Regression Results, Village-Level
(Dependent Variable: Percentage Points Change in Absence)

	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
CHANGES IN TEACHER VARIABLES						
Have bachelors degree	-0.43	-1.89	-3.54	-1.45	-2.73	-4.54
	(2.58)	(2.58)	(2.92)	(2.59)	(2.66)	(3.17)
Have teacher training	1.14	1.20	0.73	1.66	1.44	1.55
	(2.62)	(2.83)	(3.12)	(2.81)	(2.90)	(3.31)
Are paid regularly	-0.25	-0.78	-1.49	-0.63	-0.83	-0.72
	(1.71)	(1.82)	(2.19)	(1.68)	(1.79)	(2.20)
Recognition scheme exists	-4.05**	-3.45*	-3.74*	-2.90	-2.18	-3.24
	(1.80)	(1.79)	(1.93)	(1.78)	(1.74)	(2.33)
CHANGES IN SCHOOL VARIABLES						
Log pupil-teacher ratio	-5.26***	-4.86***	-4.96***	-5.37***	-4.90***	-5.06***
	(1.81)	(1.68)	(1.90)	(1.72)	(1.56)	(1.81)
Mid-day meals	1.20	1.78	4.14	1.53	0.88	1.96
	(1.66)	(1.99)	(2.61)	(1.66)	(2.01)	(2.80)
Infrastructure index (0-4)	-1.08	-0.97	-1.22	-0.85	-0.61	-1.07
	(0.67)	(0.70)	(0.79)	(0.67)	(0.68)	(0.81)
Remoteness index (normalized)	-1.13	-0.85	-0.51	-1.40	-1.06	-0.79
	(1.06)	(1.07)	(1.12)	(0.97)	(0.94)	(1.14)
CHANGES IN MONITORING & COMMUNITY VARIABLES						
Inspected in last 3 months	-8.15***	-7.20***	-6.68***	-7.35***	-6.54***	-6.38***
	(1.99)	(2.02)	(1.93)	(1.89)	(1.87)	(2.03)
PTA met in last 3 months	-1.80	-3.24*	-3.92**	-1.39	-2.09	-3.14
	(1.81)	(1.69)	(1.77)	(1.76)	(1.69)	(2.11)
Mean parental education (1-7 scale)	-1.36	-0.17	0.80	-1.52	-0.42	0.58
	(1.39)	(1.39)	(1.51)	(1.32)	(1.33)	(1.51)
REGRESSION STATISTICS						
Constant				-1.22	-1.42	-1.57
				(1.86)	(2.04)	(2.46)
R-squared				0.079	0.142	0.356
Adjusted R-squared				0.063	0.114	0.195
Number of villages				1,278	1,278	1,278

Notes:
1) Robust standard errors clustered at the district-level are in italics
2) The infrastructure index variable uses availability of four items, higher is better; remoteness index uses distances to nine places of interest,
3) Regressions are weighted by SCR populations
4) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 7. OLS Regressions Results, Village Level, 2010 Data
(Dependent Variable: Percentage of/ Percentage Change in Absence Type)

	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						
(Coefficient on Inspection Reported)						
On Official Duty	-2.18**	-2.52**	-2.34*	-1.67	-2.23**	-1.81
	(1.00)	(1.03)	(1.29)	(1.04)	(1.06)	(1.30)
Authorized Leave	2.36***	1.66*	1.47	2.23***	1.44*	1.35
	(0.78)	(0.85)	(1.04)	(0.83)	(0.85)	(1.07)
Unauthorized Absence	-10.68***	-7.03***	-7.03***	-7.36***	-5.52***	-5.99***
	(1.95)	(1.89)	(2.08)	(1.87)	(1.90)	(2.10)
PANEL B: PANEL ANALYSIS						
(Coefficient on Change in Inspection Reported)						
On Official Duty	-1.73*	-0.99	-1.46	-1.59*	-1.01	-1.48
	(0.92)	(0.87)	(1.00)	(0.93)	(0.86)	(0.99)
Authorized Leave	0.72	0.38	0.60	0.51	0.26	0.52
	(0.84)	(0.86)	(0.93)	(0.84)	(0.85)	(0.93)
Unauthorized Absence	-7.14***	-6.59***	-5.82***	-6.28***	-5.79***	-5.43***
	(1.75)	(1.91)	(1.81)	(1.69)	(1.84)	(1.77)

Notes:
1) Robust standard errors clustered at the district-level are in italics
2) The binary dependent variable (0=Present, 1=Absent) has been multiplied by 100 to allow the coefficients to be read as percentage
3) Regressions are weighted by SCR populations
4) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 8. Panel OLS Regression Results, Village-Level
(Dependent Variable: Change in Inspection)

	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
CHANGES IN TEACHER VARIABLES						
Have bachelors degree	-0.004	0.041	0.041	0.003	0.039	0.031
	(0.048)	(0.055)	(0.051)	(0.047)	(0.052)	(0.056)
Have teacher training	0.034	0.045	0.067	0.015	0.027	0.046
	(0.057)	(0.057)	(0.055)	(0.056)	(0.055)	(0.063)
Are paid regularly	-0.031	-0.006	0.007	-0.035	-0.002	0.010
	(0.032)	(0.036)	(0.036)	(0.033)	(0.037)	(0.043)
Recognition scheme exists	0.070**	0.062*	0.022	0.066**	0.060*	0.022
	(0.028)	(0.031)	(0.033)	(0.029)	(0.032)	(0.038)
CHANGES IN SCHOOL VARIABLES						
Log pupil-teacher ratio	0.055*	0.032	0.035	0.046	0.021	0.018
	(0.031)	(0.033)	(0.034)	(0.030)	(0.031)	(0.038)
Mid-day meals	0.008	-0.005	-0.025	0.004	-0.003	-0.015
	(0.032)	(0.040)	(0.046)	(0.033)	(0.042)	(0.050)
Infrastructure index (0-4)	0.008	0.009	-0.003	0.007	0.008	-0.005
	(0.012)	(0.013)	(0.015)	(0.012)	(0.013)	(0.015)
Remoteness index (normalized)	-0.023	-0.026	-0.030	-0.020	-0.024	-0.027
	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.023)
CHANGES IN MONITORING & COMMUNITY VARIABLES						
PTA met in last 3 months	0.017	0.051**	0.068**	0.017	0.052**	0.070**
	(0.024)	(0.024)	(0.029)	(0.024)	(0.024)	(0.027)
Mean parental education	-0.025	-0.039	-0.038*	-0.028	-0.042	-0.045*
	(0.026)	(0.026)	(0.023)	(0.025)	(0.024)	(0.026)
REGRESSION STATISTICS						
Constant				0.163***	0.150***	0.178***
				(0.037)	(0.048)	(0.045)
R-squared				0.039	0.090	0.321
Adjusted R-squared				0.023	0.062	0.154
Number of villages				1,280	1,280	1,280

Notes:
1) The infrastructure index variable uses availability of four items, higher is better; remoteness index uses distances to nine places of interest,
2) Regressions are weighted by SCR populations
3) *** Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 9. Panel OLS Regression Results, Village-Level
(Dependent Variable: Change in Normalized Math Score)

	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
CHANGES IN STUDENT VARIABLES						
Average age	0.09*	0.05	0.08	0.11**	0.07	0.09*
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Proportion male	0.14	0.13	0.06	0.09	0.09	0.02
	(0.15)	(0.15)	(0.16)	(0.14)	(0.15)	(0.16)
Private tuition	0.29**	0.27**	0.19	0.26**	0.30**	0.21
	(0.13)	(0.13)	(0.18)	(0.13)	(0.13)	(0.18)
CHANGES IN TEACHER VARIABLES						
Have bachelors degree	-0.22*	-0.13	0.02	-0.27**	-0.16	-0.03
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)
Have teacher training	-0.05	-0.02	0.00	-0.06	0.04	0.04
	(0.12)	(0.11)	(0.13)	(0.12)	(0.11)	(0.14)
Are paid regularly	-0.04	0.11	0.11	-0.01	0.10	0.10
	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)
Recognition scheme exists	-0.05	0.04	0.01	-0.04	0.03	-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***	-0.004***	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log pupil-teacher ratio	-0.07	-0.11	-0.11	-0.10	-0.13*	-0.14
	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)
Mid-day meals	-0.23***	-0.06	-0.00	-0.18**	-0.05	0.00
	(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)	(0.03)	(0.03)	(0.03)	(0.04)
Remoteness index (normalized)	0.05	0.04	0.02	0.04	0.04	0.03
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
CHANGES IN MONITORING & COMMUNITY VARIABLES						
Inspected in last 3 months	-0.01	-0.06	-0.11	-0.02	-0.07	-0.13
	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)
PTA met in last 3 months	-0.06	0.01	0.06	-0.04	0.02	0.06
	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)
Mean parental education	-0.03	-0.04	-0.04*	0.19***	0.15***	0.16***
(1-7 scale)	(0.03)	(0.03)	(0.02)	(0.05)	(0.05)	(0.06)
REGRESSION STATISTICS						
Constant				-0.36	-0.51**	-0.41
				(0.24)	(0.24)	(0.32)
R-squared				0.063	0.181	0.452
Adjusted R-squared				0.039	0.146	0.296
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 index variable uses availability of four items, higher is better; remoteness index uses distances to nine places of interest, higher is more remote

3) Regressions are weighted by SCR populations

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

Table 10. The Fisal Cost of Absence (in 2010 prices)

	Average Monthly Teacher Salary (Rs.)	Number of Teachers (in thousands)	Total Loss Due to Absence (millions of Rs.)	
			Allowed Absence: 8%	Allowed Absence: 10%
Andhra Pradesh	10,299	348	5,794	4,934
Assam	9,567	167	3,505	3,121
Bihar	8,645	336	7,220	6,523
Chattisgarh	8,287	156	959	650
Gujarat	15,804	199	3,067	2,314
Haryana	16,236	78	1,482	1,178
Himachal Pradesh	12,199	49	1,615	1,473
Jharkhand	9,735	136	5,998	5,681
Karnataka	10,897	196	4,081	3,568
Kerala	10,751	55	552	410
Madhya Pradesh	9,281	268	5,472	4,875
Maharastra	17,246	289	3,659	2,463
Orissa	9,382	192	1,349	916
Punjab	12,654	106	890	569
Rajasthan	14,165	271	6,784	5,862
Tamilnadu	18,487	151	1,575	906
Uttar Pradesh	10,370	491	14,195	12,972
Uttaranchal	17,155	46	1,227	1,039
West Bengal	10,555	417	6,843	5,787
India	11,368	3,949	84,254	73,480

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

Table 11. Marginal Returns to Investing in Governance

	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 (Rs. millions)
	Pupil-teacher Ratio	Effective Pupil Teacher Ratio	Annual Cost (Rs. millions)	Annual Savings From Reduced Teacher Absence (Rs. millions)	Expected Effective Pupil-teacher Ratio	
Andhra Pradesh	17.8	22.7	31.0	313.9	22.5	392.8
Assam	24.5	33.2	15.9	138.3	33.0	185.0
Bihar	58.2	81.6	21.2	244.9	80.8	339.7
Chattisgarh	24.5	28.5	13.9	107.5	28.3	122.4
Gujarat	29.8	35.5	19.1	261.2	35.3	304.7
Haryana	26.8	32.5	8.8	106.4	32.3	126.7
Himachal Pradesh	15.4	22.2	6.8	50.1	22.0	71.8
Jharkhand	41.3	76.2	14.8	114.4	75.3	214.2
Karnataka	23.6	31.0	18.5	180.4	30.8	233.5
Kerala	19.6	23.2	2.0	50.4	23.1	58.5
Madhya Pradesh	39.8	54.0	40.6	224.6	53.5	300.9
Maharastra	25.7	29.9	45.0	435.7	29.7	495.6
Orissa	29.4	34.3	20.5	158.9	34.1	181.0
Punjab	20.5	23.7	10.2	123.0	23.5	138.9
Rajasthan	26.2	33.9	40.0	323.6	33.6	411.9
Tamilnadu	28.3	32.5	24.6	237.1	32.2	265.0
Uttar Pradesh	40.1	58.2	58.4	438.0	57.7	631.8
Uttaranchal	20.6	26.0	10.7	65.6	25.8	81.6
West Bengal	32.3	40.8	30.1	366.4	40.5	455.4
India	31.7	41.5	448.0	4,036.1	41.1	5,203.5

Notes:

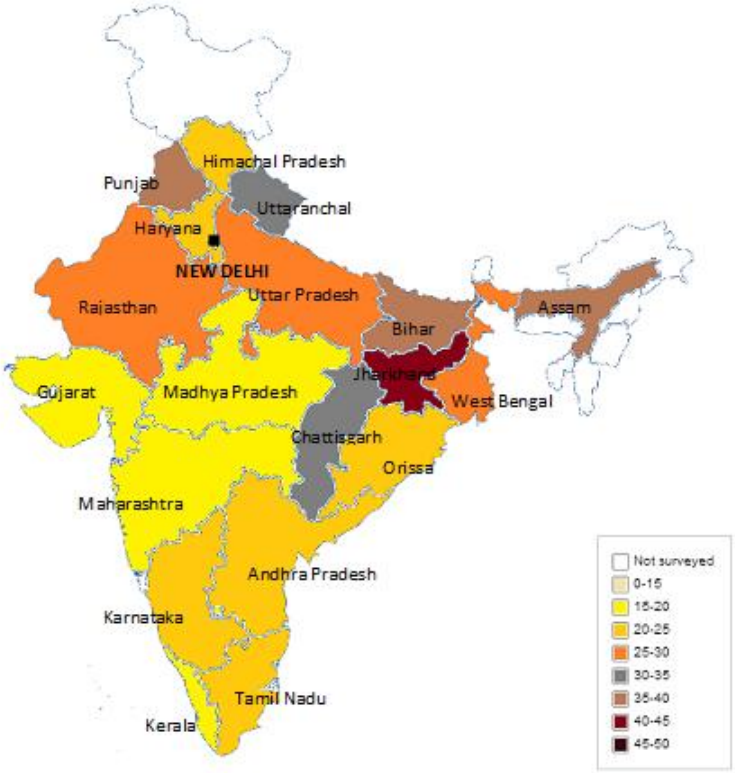
1) Number of schools, number of teachers, and enrollment figures are from DISE data

2) Simulation assumes that one inspection every 3 months reduces absence linearly by 6 percentage points

3) Inspector costs are assumed to be three times teacher salaries; an inspector works 200 days a year and inspects two schools every day

Figure 1. Absence Rate of Teachers (Percentage Absence)

2003-2004



2009-2010

