The relative effectiveness of regular and ‘para’ teachers in India

by

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Abstract

While the use of contract (para) teachers provides a low-cost way to increase schooling access, relieve multi-grade teaching and reduce class-sizes, it raises the quality concern that these less trained teachers may be less effective in imparting learning. This paper attempts to estimate the causal para teacher effect on student achievement using school fixed effects, value-added, and saturated models of the education production function, using bespoke data from Uttar Pradesh and Bihar. We find a weakly significant positive para teacher effect in UP, where accountability is highest, and an insignificant positive effect in Bihar, where accountability is weaker. These effects are robust to controls for observed teacher effort. Using a saturated model we conclude para-teachers are more effective when pupils’ are of low SES, and that renewable contracts make male teachers more effective.

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1. Introduction

A central plank of India's primary schooling reforms in the past 15 years has been the provision of low-cost 'para' teachers. Use of para teachers increased rapidly in India since the mid-1990s. There were 514,000 para teachers in India in 2006-07 (Mehta, 2007, p212).

The officially stated rationale for provision of para teachers is to achieve three major equity and efficiency aims in an affordable way: expanding access to schooling in unserved communities; eliminating single-teacher schools and relieving multi-grade teaching; and reducing high pupil teacher ratios. Regular teacher pay scales are high. For instance, in the state of Uttar Pradesh, the ratio of regular teacher pay to state per capita GDP was 7:1 in 2005 and since then regular teacher salaries have nearly doubled, following implementation of the Sixth Pay Commission's recommendations (Kingdon, 2009). Nationally, para teacher salary in 2005 was on average about 35% of regular teachers' pay rate and this is likely to have fallen below 25% following Sixth Pay Commission related increases in regular teacher salaries (Kingdon and Sipahimalani-Rao, 2009). Para teacher schemes are favoured because they expand schooling access, relieve multi-grade teaching and reduce class sizes in a fiscally manageable way.

Although the schemes vary somewhat across states, generally para teachers have (often annually) renewable contracts rather than regular teachers' lifetime employment guarantees. They are not required to have pre-service teacher training and the educational qualification requirements for para teachers are also lower than those for regular teachers. Finally, para teachers are typically recruited and paid by the village local government, rather than being employed directly by the state government as regular teachers are.

The relative effectiveness of para and regular teachers is one of the most troublesome policy issues in Indian basic education today. On the one hand, their use provides a low-cost way for the state to increase the number of teachers in the face of rising student populations, budgetary troubles and rapid real increases in salaries of regular teachers, who are unionised and frequently absent from school[1]. On the other, it raises educational quality and educational equity concerns[2]. The quality concern is the fear that these less trained teachers may be less effective in imparting learning. The equity concern arises because many para-teachers are appointed in the remoter schools or in the 'Education Guarantee' schools that serve poorer children (e.g. child labourers, small-habitations or tribal children), raising the fear that poorer children are being condemned to lower quality teachers, exacerbating social inequality[3].

Referring to the dearth of research on para teacher schemes, Drèze and Sen (2002, chapter 5) say: "the overall achievements and potential of this approach remain somewhat uncertain at this time, in the absence of detailed independent evaluations of its diverse applications". This theme is also picked up by the Chairman of the National Council for Teacher Education (Maheshwari, 2002) and by a World Bank report on policies to reduce poverty in India which notes: "Alternatives like using para-teachers instead of regular teachers… need careful evaluation (World Bank, 2000, chapter 2).

The relative effectiveness of regular and para teachers is not obvious, since international research fails to show a consistent positive association between certification (teacher education, training), tenure and salary on the one hand and student achievement on the other. Moreover, even if lower education, training and salary reduce para teachers' effectiveness, there may be compensating positive effects: being appointed by village local government, para teachers are likely to be more locally accountable than regular teachers. Further, para teachers may have greater incentive to apply effort to ensure contract renewal, unlike regular teachers whose tenures are secure, especially given a high graduate unemployment rate of 11%[4] and paucity of well-remunerated employment. Finally, there is some evidence that class size matters to student achievement[5]. Since the employment of para teachers leads to a reduction of pupil teacher ratios, this may be conducive to greater learning. In sum, it cannot be presumed that para teachers are

[1] Kingdon and Banerji (2009)
[2] Govinda and Josephine (2004), Kumar, *et al* (2001)
[3] Drèze and Sen (2002), Leclercq (2002)
[4] Based on our analysis of National Sample Survey (2004-05).
[5] See Krueger; Case and Deaton; and Angrist and Lavy in *Quarterly Journal of Economics*. May 1999.

necessarily less effective in imparting learning than regular government school teachers. Their relative effectiveness are empirical issues worthy of examination.

Since the early 2000s, the effectiveness of para and regular teachers has attracted research interest (Pratichi Trust, 2002; Leclercq, 2002; Govinda and Josephine, 2004; EdCil, 2007). Using descriptive statistics these studies find that achievement and/or attendance levels of children taught by para and regular teachers were similar. A World Bank study by Sankar (2008) is a larger and more systematic study for three Indian states (Andhra, Madhya Pradesh and Uttar Pradesh). It finds that controlling for children's home background in a regression context, there is no significant difference between the learning achievement levels of students taught by para and regular teachers. However, if para teachers are generally more likely to be posted to the remoter villages where communities are more deprived, the para teacher dummy variable will be endogenous and the OLS approach will yield a biased estimate of the para teacher 'effect' due to omitted variable bias.

While the existing literature builds a valuable picture, it does not provide evidence on the causal effects of para teachers on children's schooling outcomes. This paper attempts to get closer to the causal link. Section 2 sets out the methodology and data used. Section 3 presents the results and the last section concludes.

2. Data and methodology

Data

The data used in this paper come from the SchoolTells survey of primary schools in two north Indian states: Uttar Pradesh and Bihar. These are two of the most educationally challenged states of India. The SchoolTells survey was carried out in the 2007-08 school year in 160 rural primary schools across 10 districts of the sample states. It yielded achievement data on over 4000 students of grades 2 and 4 and on their teachers and schools. Each school was visited four times in the school year. Students were tested in language and maths at the start and end of the school year, approximately nine months apart. Although the survey included 35 private schools, we have used only government schools in the analysis in this paper. The survey provides an unusually rich source of data with detailed questions on the children's personal traits (age, gender, height, illness); family background (parental education, household asset ownership); teacher characteristics (qualifications, training, gender, age, regular/para status, absence rate, distance to school, and competency scores in a teacher test of knowledge, ability to explain and ability to spot mistakes); and a wide range of school quality factors.

The same achievement test was used for students of grades 2 and 4. It tested competencies that span the kind of material children encounter in grades 2 through 4. It was understood that most children in grade 2 may not be able to do the more difficult questions. The same type of achievement test with the same competencies tested, was used in time period 2 (near the end of the school year) as in time period 1 (at the start of the school year).

To render achievement level comparable across subjects, grades and time periods, we converted absolute achievement scores into z-scores. The distribution of absolute marks in maths and language (grades 2 and 4 and both time-periods taken together) is shown in Figure 1. Appendix Table 1 sets out the descriptive statistics of variables used in the analysis.

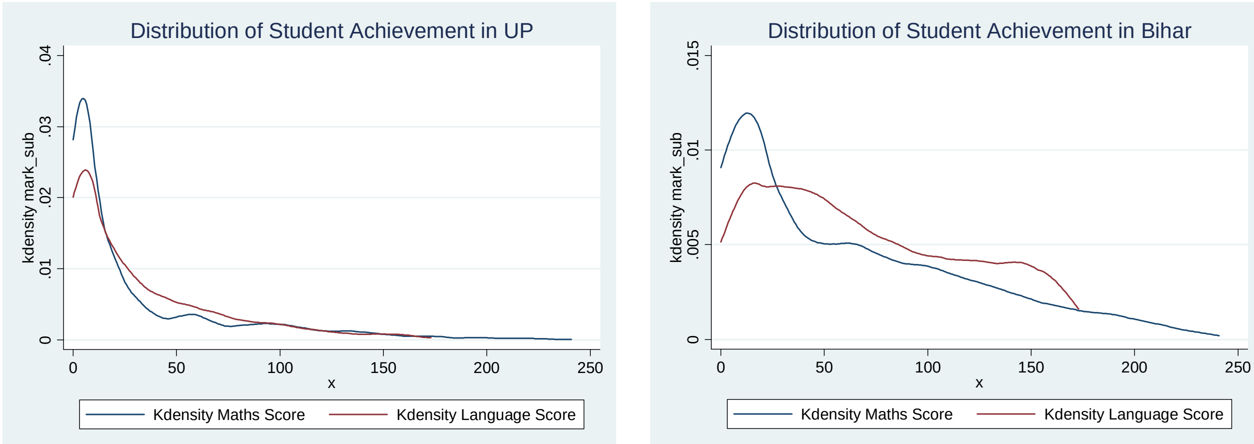

Figure 1: Distribution of student achievement

The distribution of marks in figure one is striking due to the severe left hand skewness of the distribution, especially in UP. Given that the figures show marks for both grades 2 and 4, one would expect a bi-modal distribution, instead, the majority of marks are distributed towards the left of the graph, with a very long tale. The situation is even starker for mathematics achievement. The exception to this is language scores in Bihar, which is more normally distributed. This suggests that learning levels are very low and do not improve much between grades, which is a real cause for concern.

Methodology

The ideal method for impact evaluation of para teachers would be a randomized trial with children randomly assigned to para and regular teachers. However, para teacher schemes are already rolled out in India and, in any case, it is unlikely that education authorities would be amenable to such an approach. While propensity score matching methods may be used, in principle, to create artificial comparator units for each child taught by a para teacher, such an approach controls only for the observed differences between children taught by para and regular teachers. In the absence of an ideal methodology, we use a number of other econometric techniques in the context of an achievement production function. We begin with conventional OLS and fixed effects estimators, before progressing to a saturated model, as suggested by Glewwe and Derecho (2002). We start with an OLS baseline. In this specification of the achievement equation, we will include pupil, home background, teacher and school quality variables. Secondly, we will use school fixed effects estimation. All school level variables will drop out and this specification will control for the non-random matching of children to particular schools that may be more or less likely to have para teachers. In this approach, identification of the para teacher effect comes from within school differences in teacher type. As such, the approach controls for all observed and unobserved school factors that affect student achievement and thus reduces this source of endogeneity bias. Thirdly, we will use a school fixed effects value-added specification of the achievement production function. This regresses change in achievement over the school year on teacher type.

For the saturated model, we take a production function of the form,

$$T_{ijs} = h_s(\mathbf{SC}_j, TC_{k,} \mathbf{FC}_i) + \varepsilon_{ijs} \qquad (1)$$

Where T_{ijks} denotes the test score of child i, in school j, with teacher k in subject s;
And $\mathbf{SC}_j$ denotes the vector of school characteristics;
And TC_k denotes the vector of teacher characteristics;
And $\mathbf{FC}_i$ denotes the vector of child and household characteristics.
ε_{ijks} is defined to incorporate random noise that is uncorrelated with SC, TC and FC.

and estimate a linear approximation of (1) using a Taylor Approximation;

$$T_{ijk} = \beta_0 + \beta_1'\mathbf{SC}_j + \beta_2'\mathbf{TC}_k + \beta_3'\mathbf{FC}_i + \beta_4'\mathbf{SC}_j\otimes\mathbf{TC}_k + \beta_5'\mathbf{SC}_j\otimes\mathbf{FC}_{i+}\beta_6'\mathbf{TC}_k\otimes\mathbf{FC}_i + \beta_7'SC_j\otimes\mathbf{TC}_k\otimes\mathbf{FC}_i + \varepsilon_{ijk} \qquad (2)$$

Where $\mathbf{SC}_j\otimes\mathbf{TC}_k$ denotes the interaction between school and teacher characteristics and so on and so forth.

We wish to know the effect on test scores of being taught by a para-teacher as opposed to a regular teacher. Defining a typical para-teacher as a weighted average of all the characteristics of para-teachers, where the weights are the proportion of children taught by that teacher:

$$\overline{TC}_p = \sum_{j \in P} w_{jp}\mathbf{TC}_k \qquad (3)$$

here P is the set of all para-teachers and w_{jp} is the fraction of total children taught by para-teachers. Similarly the vector of characteristics for the typical regular teacher can be defined as:

$$\overline{TC}_g = \sum_{j \in G} w_{jg}\mathbf{TC}_k \qquad (4)$$

Inserting (3) into (2) we can derive the expected test score of child i if he/she is taught by a para-teacher

$$E[T_i|\ \mathbf{TC}_k, \text{para-teacher}] = \beta_0 + \boldsymbol{\beta}_1'\mathbf{SC}_j + \boldsymbol{\beta}_2'\overline{TC}_p + \boldsymbol{\beta}_3'\mathbf{FC}_i + \boldsymbol{\beta}_4'\mathbf{SC}_j \otimes \overline{TC}_p + \boldsymbol{\beta}_5'\mathbf{SC}_j \otimes \mathbf{FC}_i + \boldsymbol{\beta}_6'\overline{TC}_p \otimes \mathbf{FC}_i + \boldsymbol{\beta}_7'SC_j \otimes \overline{TC}_p \otimes \mathbf{FC}_i \qquad (5)$$

And inserting (4) into (2) we can derive the expected test score of child i if he/she is taught by a regular teacher.

$$E[T_i|\ \mathbf{TC}_k, \text{regular-teacher}] = \beta_0 + \boldsymbol{\beta}_1'\mathbf{SC}_j + \boldsymbol{\beta}_2'\overline{TC}_r + \boldsymbol{\beta}_3'\mathbf{FC}_i + \boldsymbol{\beta}_4'\mathbf{SC}_j \otimes \overline{TC}_r + \boldsymbol{\beta}_5'\mathbf{SC}_j \otimes \mathbf{FC}_i + \boldsymbol{\beta}_6'\overline{TC}_r \otimes \mathbf{FC}_i + \boldsymbol{\beta}_7'SC_j \otimes \overline{TC}_r \otimes \mathbf{FC}_i \qquad (6)$$

If we then normalize all SC, TC and FC variables to have means equal to zero, then we are left with

$\beta_0 + \boldsymbol{\beta}_2'\overline{TC}_p$ = expected test score of *average* child with average para-teacher in average school

$\beta_0 + \boldsymbol{\beta}_2'\overline{TC}_r$ = expected test score of *average* child with average regular teacher in average school

We are interested in the expected change in test scores by switching from having a regular teacher to a para-teacher. That is

$$\beta_2' \, (\mathbf{TC}_{p} - \mathbf{TC}_r) \qquad (7)$$

Which we can estimate through regression analysis using a conventional dummy variable, $D_c = 1$ if a child is taught by a para-teacher, and $D_c = 0$ if the child is taught by a regular teacher. If children are assigned to para-teachers randomly, then we can simply estimate an OLS regression with this dummy variable and we would have an estimate of the para-teacher effect. Unfortunately we know that this isn't the case, and that para-teachers are non-randomly assigned to schools. We can overcome this problem by estimating the model using school-fixed effects, whereby identification of D_c comes from within-school variation in teacher types – that is variations in test scores within a school dependent on teacher type. This reduces our model to

$$T_{ik} = \beta_0 + \beta_1 TC_k + \beta_2 FC_i + \beta_3 TC_k FC_i + \varepsilon_{ij} \qquad (8)$$

Which we can estimate using the dummy variable D_c in the following equation

$$T_{ij} = (\beta_0 + \beta_1 \overline{TC}_r) + \beta_1(\overline{TC}_p - \overline{TC}_r)D_c + (\beta_2 + \beta_3 \overline{TC}_r)FC_i + \beta_3(\overline{TC}_p - \overline{TC}_r)D_c FC_i + \varepsilon_{ij} \quad (9)$$

We are estimating the achievement equations on a sample of enrolled children only and, in principle, this could be a selected sample. Ideally one should use a sample selectivity correction approach. In practice, it is difficult to find variables that affect enrolment choice but not achievement, i.e. there are no convincing exclusion restrictions with which one could identify the selectivity term lambda using a Heckman selectivity correction model. However, primary school enrolment rates are high with more than 90% of primary age children in school in the two sample states. Thus, we do not expect selectivity to be too much of a problem. All models include controls for clustering and heteroskedasticity. Given the nature of our data, clustering is likely to be a major issue. Estimating the model with and without controls for clustering leads to noticeably different conclusions with regards our teacher level variables. As our data is clustered at the child, class and school level, our standard errors increase as we correct for this. By clustering at the school level we allow for non-independence of observations within the cluster, and only assume independence across clusters. Therefore any remaining clustering at the pupil-level is unlikely to severely change our conclusions. As such all regressions will include controls for clustering at the school-level.

Given the dominance of low scores in our data-set, and the subsequent skewness of the test-score distribution, we are likely to suffer from heteroskedasticity in our estimations. Indeed, even after controlling for this our model still fails Greene's (2000) test for group-wise heteroskedasticity. A consequence of this is that our inference is likely to be inefficient as our standard errors are too high, so we will understate significance. Given our high number of observations (8,185 falling to 3942 in the value-added specification) this is unlikely to be much of a problem. An alternative would be to estimate a non-linear model, such as a count model; however we then lose the ability to estimate using within-schools as a true fixed effects estimator for the negative binomial[6] model does not exist (Allison and Waterman 2002). As such, we prefer the linear estimator and accept the resulting inefficiency.

3. Findings

Due to some potentially important differences between the contracts of para-teachers in Uttar Pradesh and Bihar, we estimate the achievement model for each state separately. The analysis is restricted to government schools only.

[6] A simple Poisson model is excluded as this assumes the mean and variance of the dependent variable are equal – this is not the case in our data, where the mean is approximately 1/10 of the variance. Thus the negative binomial model is the obvious choice.

We initially estimate the model using OLS, school-fixed effects and as a value added model of achievement. We first pool the two surveys (and introducing a fixed effect for time of testing) and then re-estimate focusing on test scores at the end of the year, using the initial test score as an additional control.

The main results for UP are presented in table 1. The first model pools subjects, grades and both surveys and we therefore include controls for subject, grade and survey number. The dependent variable is the z-score of achievement. The model includes child and teacher characteristics, as well as our variable of main interest: the contractual status of the teacher. Column 1 estimates the model using OLS. This specification includes school quality variables such as class size, school resources, availability of cooked school meals and textbook availability. Column 2 moves to school fixed effects estimation, which will correct for bias due to the potentially non-random assignment of para-teachers to particular schools. These columns represent within-school estimation so that all school level factors that influence student achievement, including unobserved school characteristics, are controlled for.

Column 3 estimates a school fixed effects model this where the dependent variable is the z-score at the end of the school year (visit 4) and uses the z-score in visit one as an additional control. This gives us the relative impact of being taught by a para-teacher rather than a regular teacher within the same school after taking into account initial performance. Column 4 estimates a school fixed effects value-added model, where the dependent variable is the change in pupil achievement over the school year. This will tell us how para-teachers affect the growth of cognitive skills over the school year. By controlling for prior achievement the methodology used in column (4) controls for child ability. As we move from column 1 (OLS) to column 4 (school fixed effects with value-added), our identification strategy becomes more stringent.

Table 1: Achievement Production Function, Uttar Pradesh

	(1)	(2)	(3)	(4)

	OLS cluster	School FE	School FE controls initial ability model	School FE value added model
class	0.350***	0.435***	0.197***	0.157***
	(3.98)	(5.62)	(5.32)	(4.02)
subject	0.0511*	0.0644**	0.0647***	0.0627***
	(1.99)	(2.65)	(3.39)	(3.21)
surveynumber	0.315***	0.327***		
	(8.53)	(8.99)		
child_age	0.0482***	0.0796***	0.0124	0.00793
	(2.75)	(4.98)	(1.24)	(0.84)
child_male	0.156***	0.145***	0.0456*	0.0365
	(3.77)	(3.47)	(1.96)	(1.59)
childheight	0.0163***	0.0136***	0.00115	-0.00000755
	(7.01)	(5.83)	(0.77)	(-0.00)
ill_last3mon	-0.0942***	-0.0909***	-0.0608**	-0.0530**
	(-3.16)	(-2.95)	(-2.53)	(-2.27)
fa_edyrs	0.0262***	0.0216***	0.00598	0.00448
	(5.11)	(4.49)	(1.35)	(0.97)
mo_edyrs	0.0282***	0.0292***	0.0216***	0.0199***
	(3.44)	(3.49)	(3.44)	(3.25)
logasset	0.0472*	0.0310	0.0115	0.00916
	(1.98)	(1.41)	(0.76)	(0.60)
tuition	0.244***	0.255**	0.0843	0.0672
	(3.04)	(2.58)	(1.56)	(1.39)
age_tea	0.0117***	0.0117*	0.00253	0.00176
	(2.98)	(1.99)	(0.68)	(0.45)
male_t	-0.0195	-0.111*	-0.0894	-0.0827
	(-0.32)	(-1.67)	(-1.63)	(-1.44)
ba	0.0261	0.0971	0.0183	0.0109
	(0.36)	(1.25)	(0.23)	(0.13)
ma	-0.0308	0.0805	0.000542	-0.00780
	(-0.40)	(0.89)	(0.01)	(-0.10)
first_div	0.0652	0.165*	-0.0203	-0.0360
	(0.69)	(1.83)	(-0.36)	(-0.63)
para_t	0.0959	0.167	0.143*	0.133
	(0.79)	(1.17)	(1.80)	(1.55)
ptratio	0.000641			
	(0.34)			
textbook_ratio	0.435***			
	(3.79)			
school_resources1	0.0971***			
	(2.81)			
mdm_always	0.0976			
	(1.38)			
zscore_prior			0.919***	
			(29.46)	
N	8185	8185	3942	3942
N_g		62	62	62
r2	0.286	0.276	0.678	0.0312

Notes: Model also includes dummies for missing observations in parental education, private tuition and child health. All regressions control for clustering within schools and for heteroskedasticity. Constant included but not shown.

There is evidence of improvement in pupils' achievement between grades. The average child in grade four scores 0.435 of a SD higher than the average child in grade 2 (the base category). Pupils in class 4 learn more over the school year than those in class 2, having value-added scores of 0.157 standard-deviations higher. This may be because the difficulty level of the tests is pitched at the type of competencies that are learnt better at the grade 4 stage in Uttar Pradesh. Pupils score 0.06 SD lower in mathematics than in reading in all specifications.

Boys outperform girls by 0.136 standard deviations, a noticeable amount given that any selection bias in school enrolment is likely to benefit girls' scores relative to boys. This declines to 0.045, but is still weakly significant when we control for initial ability, suggesting the composite gender gap found in the previous regressions to be part of a steady divergence in learning throughout the years.

Older children do slightly better, scoring 0.08 standard deviations higher per year of age. Healthier children do better, with long term health (measured by height) having positive significant effects, but this effect disappears when we control for initial ability, showing the effects of long-term health on schooling to be more long-term. Short term health affects achievement: a child who had been ill in the last three months to the extent that they had to take four or more consecutive days or more off school scores 0.09 standard deviations lower than other children, even after controlling for long term health. This holds in all specifications. Parental education has strong significant coefficients, with both paternal and maternal education positively correlated with achievement. The difference in achievement between having a father whose education is one SD below the mean value of fathers' education, to having a father whose education is one SD above the mean value of fathers' education is 0.20 SD of achievement. A similar shift in maternal education increases scores by 0.187 SD. Paternal education has a far lower effect on the *change* in scores when compared to its impact on the *level* of scores, with each additional year of father's schooling increasing the value-added by 0.0048 marks. Interestingly, while the impact of maternal education falls, it does so by far less and has a significant coefficient of nearly 4 times the magnitude of paternal education. This suggests that more educated mothers have children who learn more throughout the school year. These findings are unsurprising if we consider that mothers spend relatively more time with their offspring, while the fathers are at work.

Children from wealthier households score higher, with the effect diminishing as expected as we move from OLS to within-school estimation. Private tuition has strong effects, with children who receive external tuition scoring over a quarter of a SD higher than those who do not. The effect of receiving private tuition is extremely large, and is approximately equal to the effect of spending three quarters of a year in school. Its impact diminishes and becomes insignificant when we control for prior ability.

In OLS regressions (column 1 of Table 1), the school quality controls are all significant with the exception of the pupil-teacher ratio, which is insignificant and positive. Such a finding is not uncommon in the literature (Hanushek, 2003), with Lazear (2001) providing a theoretical model as to why this may occur. An index of school resources has strong positive effects. Moving from a school that has resources one s.d. below the mean to one with a resource level one s.d. above the mean would increase pupils' score by 0.31 standard deviations. The provision of textbooks also has positive benefits, with a school which has 1 SD below the mean provision level to one which has provision levels 1 SD above the mean (which in this case would entail a shift from just over one book per two children to one textbook per pupil) would increase scores by 0.21 standard deviations, again a large effect. Pupils in schools which always provide free mid-day meals score 0.10 s.d. higher than those who provide meals more sporadically, though this effect is not significant.

In the school fixed-effects regression (which allows us to control for unobserved school level effects) male teachers have a significantly negative association with achievement, with a pupil who is taught by a male teacher scoring 0.111 s.d. lower than one in the same school who is taught by a female teacher. Teachers with BA or higher qualifications have better performing pupils than those with only higher secondary qualifications or less, though there is no discernable difference between teachers with Bachelor's and

Master's qualifications. A teacher who graduated in the first division has higher performing pupils.

Turning our focus to the relative effectiveness of para and regular teachers, in the OLS regression para-teachers have a positive yet insignificant association with student achievement. Upon moving to a within-school analysis in column 2, the coefficient increases noticeably with para-teachers having a strongly positive relationship with achievement, raising scores by 0.167 standard deviations. This increase in the size of the positive coefficient on the para teacher dummy variable when we move from OLS to school fixed effects estimation is unsurprising; the coefficient on the para-teacher variable in OLS estimations is likely to be biased downwards since para-teachers are generally more likely to be assigned to the more isolated schools and communities where households are more deprived. In other words, in across school estimation, the para teacher variable is partly 'picking up' the effect of community's deprivation.

The effect of para-teachers remains even after we control for prior ability. Given the high predictive power of this variable (a coefficient of 0.919 implies that it explains nearly 92% of variation in scores in the fourth round) a para-teacher impact of 0.14 SD is quite large, even if it is only weakly significant.

Children who are taught by a para-teacher have value-added scores of 0.133 s.d. higher than those who are not. Given that our a school fixed effects estimate utilizing information regarding test scores at the start and the end of the school year (not shown) suggest a 0.31 s.d. increase in learning over the school year, being taught by a para-teacher yields equivalent benefits to a 1/3 of a year in school.

It appears then that despite their lower levels of training and experience (a full breakdown of teacher characteristics by teacher type can be found in appendix 2), para-teachers are more effective than regular teachers. This result is robust to the inclusion of additional controls for teachers' subject knowledge.

Given that para-teachers have lower levels of experience and far less teacher training; this begs the question as to why they are more effective? Our saturated model suggests that this is due to two factors; male para-teachers are more efficient than male regular teachers; para-teachers mitigate the negative effects of being of low SES.

An additional possible explanation is that para-teachers, due to their short-term insecure contracts, face greater accountability pressures and thus exhibit more effort than regular teachers. One way of measuring teacher effort is through the teachers' absence rate. In table 4 we also control for a number of measures of teacher effort, including whether or not they report spending time supporting weak children, whether they undertake private tuition, the proportion of time they spend teaching in the average school day and the proportion of time spent preparing for teaching.

Table 4 shows that the relative effectiveness of para and regular teachers inclusive of controls for teacher effort. The child and home background variables were included but are not shown in Table 4. The model estimated here replicates column (2) of table 2, but the results are similar using the other specifications.

Table 2: Achievement Production Function with controls for teacher effort, Uttar Pradesh

	(1) School FE	(2) School FE with teacher absence	(3) School FE w/Support weak children	(4) School FE w/teach private tuition	(5) School FE w/time spent preparing
age_tea	0.0117*	0.0116*	0.0119**	0.0111*	0.0119**
	(1.99)	(1.96)	(2.04)	(1.93)	(2.02)
male_t	-0.111*	-0.110*	-0.121*	-0.118*	-0.111
	(-1.67)	(-1.69)	(-1.81)	(-1.82)	(-1.62)
ba	0.0971	0.0969	0.0649	0.0973	0.0937
	(1.25)	(1.26)	(0.74)	(1.25)	(1.17)
ma	0.0805	0.0882	0.0581	0.0781	0.0765
	(0.89)	(0.93)	(0.65)	(0.87)	(0.84)
first_div	0.165*	0.154	0.170*	0.168*	0.182*
	(1.83)	(1.62)	(1.95)	(1.88)	(1.97)
para_t	0.167	0.158	0.167	0.163	0.189
	(1.17)	(1.08)	(1.16)	(1.17)	(1.20)
tabs_rate		-0.0667			
		(-0.33)			
support_weak			0.138		
			(1.14)		
t_gives_tuition				-0.197	

				(-1.21)	
time_allocated to beneficial activities					-0.0325
					(-0.32)
N	8185	8185	8185	8185	8185
N_g	62	62	62	62	62
r2	0.276	0.276	0.277	0.277	0.276

Note: All equations control for child and home background characteristics but these are not shown.

Column (1) replicates the school fixed-effects model of Table 1. Column (2) displays results including the teacher's absence rate. Column (3) show the results with controls for whether or not the teacher spends special time to support weak pupils on a regular basis[7], while column (4) controls for whether or not the teacher reports giving private tuition. Column (5) includes controls for teachers' time allocation. This is done through a composite index measuring the percentage of time devoted to teaching, prayers and games and preparation.

The main thing to draw from table 3 is how robust the para-teacher effect is to inclusion of controls for teacher effort. Statistically there is no difference among the point estimate between all specifications. This result is robust to allowing non-linearity's in the relationship between teacher effort and achievement (not shown).

Column (2) shows that teacher absence rates are negatively related to achievement as expected, but are insignificant. Similarly, having a teacher who gives private tuition reduces grades (but is insignificant). This might suggest that teachers who provide private tuition may do so at the expense of children within their classes, but this cannot be confirmed using the data here. Having a teacher who supports weak children on a regular basis has a positive, but insignificant effect. A higher percentage of time devoted towards beneficial teaching activities has a slight negative, but insignificant) effect on outcomes.

Bihar

The results for Bihar are presented in table 4. Again as we move from column 1 – OLS, to column 4 – value added specification with school fixed effects, our estimation

[7] Regular here is defined as most of the days (8 or more out of the last 10 days).

technique becomes more stringent as we eliminate more bias from unobservable characteristics of schools and pupils.

There are strong achievement differences between grades in Bihar, with pupils in grade 4 scoring 0.9 higher than those in grade 2. This is double the achievement differential found in UP, suggesting a higher relative level of learning occurs between grades in Bihar than in UP. Given that scores increase by approximately the same amount over the school year (0.30 SD), it is unclear why this should be the case. The difference between grade 4 scores and grade 2 scores, after controlling for initial achievement, is far lower in Bihar than UP. Grade 4 students are also learning at a lower rate than grade 2 students. This suggests that learning at the lower levels is stronger in Bihar than UP, but declines as children age. So while in Bihar children are likely to learn in the early grades, their pace of learning slows as they progress.

Another possible explanation is that while much of the cognitive skills tests are pitched at the grade 4 level of difficulty, in UP grade 4 pupils are more akin to grade 2 pupils in terms of their level of competency and that is why they exhibit lower levels of achievement growth – because the test is too difficult for them – while in Bihar grade 4 children are at the grade 4 level of competency and thus exhibit the sort of gain in learning over the school year that one would expect from a grade 4 child.

Table 3: Achievement Production Function, Bihar

	(1) OLS	(2) School FE	(3) School FE controls for initial ability	(4) School FE value added model
class	0.824***	0.925***	0.0934**	-0.0723*
	(10.53)	(11.43)	(2.13)	(-1.90)
subject	0.173***	0.194***	0.0502	0.0208
	(6.68)	(7.62)	(1.55)	(0.63)
surveynumber	0.283***	0.288***		
	(12.11)	(11.47)		
child_age	0.0475***	0.0380**	-0.00672	-0.0123
	(3.07)	(2.45)	(-0.67)	(-1.27)
child_male	0.270***	0.259***	0.0700**	0.0345
	(7.09)	(7.10)	(2.53)	(1.26)
childheight	0.00387*	0.00193	-0.000246	-0.000403
	(1.95)	(0.87)	(-0.16)	(-0.26)
ill_last3mon	-0.0666**	-0.0536**	-0.0160	-0.00895
	(-2.28)	(-2.02)	(-0.83)	(-0.45)

fa_edyrs	0.0101*	0.0147***	0.00441	0.00230
	(1.89)	(2.85)	(1.36)	(0.73)
mo_edyrs	0.0272***	0.0242***	0.00964*	0.00679
	(3.63)	(3.18)	(1.93)	(1.42)
logasset	0.0810***	0.0684***	0.0369**	0.0293*
	(3.46)	(3.05)	(2.29)	(1.91)
tuition	0.268***	0.187***	0.116***	0.0951***
	(6.33)	(4.70)	(4.05)	(3.27)
age_tea	-0.00234	0.00346	0.00398**	0.00359*
	(-0.86)	(1.36)	(2.10)	(1.81)
male_t	0.0443	-0.0343	0.0246	0.0368
	(0.82)	(-0.63)	(0.63)	(0.92)
ba	-0.0376	-0.0196	0.00360	0.00666
	(-0.77)	(-0.37)	(0.09)	(0.16)
ma	-0.000256	0.0584	-0.0798	-0.0965
	(-0.00)	(0.85)	(-1.16)	(-1.37)
first_div	0.00946	0.0108	0.0240	0.0220
	(0.26)	(0.33)	(0.71)	(0.64)
para_t	-0.0324	0.0605	0.0423	0.0364
	(-0.59)	(1.29)	(0.89)	(0.74)
ptratio	0.000575			
	(0.28)			
textbook_ratio	0.145			
	(1.03)			
school_resources1	0.0284			
	(1.51)			
mdm_always	-0.114			
	(-0.96)			
zscore_prior			0.840***	
			(44.50)	
_cons	-2.129***	-1.800***	-0.0725	0.171
	(-6.96)	(-5.78)	(-0.34)	(0.83)
N	6772	6772	3315	3315
N_g		71	71	71
r2	0.353	0.347	0.673	0.0258

Notes: Model also includes dummies for missing observations in parental education, private tuition and child health. All regressions control for clustering within schools and for heteroskedasticity. Constant included but not shown.

The differential between maths and language scores is greater in Bihar than UP, at nearly 0.20 SD (compared to 0.06 in UP). The gender gap is also nearly double, with boys outperforming girls within the same school by 0.26 SD. Measures of child health – illness and height – are significantly related to cognitive outcomes. Both maternal and paternal education is related to performance, though less so than in UP, and again maternal education has a slightly stronger effect than paternal. Household wealth has strong effects, with pupils from families' who lie one SD above the mean level of the asset index having marks 14% higher than those with assets one SD below the mean level. Private tuition again has strong effects on achievement, with pupils taking tuition scoring 0.19 SD higher than those who do not. To put this into perspective, private tutoring has the equivalent benefits of 2/3 of a years schooling in this scenario. This may explain why private tutoring is so much in demand in Bihar.

In Bihar, the majority of teacher characteristics are insignificantly correlated with student achievement. The exception to this is the age of the teacher, which has a positively significant coefficient in school-fixed effects estimation. The effect is small; a teacher aged 40 would outperform the mean-aged teacher (32 years old) by just 0.024 SD. Other characteristics, such as gender and qualifications are insignificant.

With regards our variable of most interest, teacher type, para-teachers have an insignificant negative correlation with pupil achievement in the OLS regressions. Upon moving to a school-fixed effects regression, where estimation is based on differences in test scores across pupils with different teacher types within a school, we eliminate bias due to non-random matching of teachers to schools. Here the para-teacher variable has a positive and weakly significant coefficient, with para-teachers having pupils who score 0.063 SD higher than their regular counterparts in the same school. It is noted that this effect is substantially smaller than that found in UP, a point we return to below.

Table 5 (columns 1 to 5) show achievement production functions inclusive of controls for effort. Again they replicate column (3) of table 4, but are robust to other specifications. Again all controls for observed/reported measures teacher effort used have no statistically significant impact on the para-teacher variable.

While teacher absence has a robust negative effect on achievement, its inclusion in the model does not change the coefficient on the para-teacher variable. This is unsurprising, as in Bihar para teachers do not have lower levels of absenteeism than regular teachers that we observed in UP. Having a teacher who supports weak children has an insignificantly negative impact on achievement, as does having a teacher who spends more time on beneficial activities. Conversely to Bihar, having a teacher who gives private tuition has a positive, but insignificant effect.

Table 4: Achievement Production Function with controls for teacher effort, Bihar

	(1) School FE	(2) School FE with teacher absence	(3) School FE w/Support weak children	(4) School FE w/teach private tuition	(5) School FE w/time spent preparing
age_tea	0.00346	0.00289	0.00345	0.00336	0.00341

	(1.36)	(1.07)	(1.48)	(1.21)	(1.41)
male_t	-0.0343	-0.0333	-0.0201	-0.0309	-0.0244
	(-0.63)	(-0.62)	(-0.37)	(-0.55)	(-0.45)
ba	-0.0196	-0.0110	-0.0231	-0.0184	-0.0196
	(-0.37)	(-0.20)	(-0.45)	(-0.32)	(-0.38)
ma	0.0584	0.0566	0.0466	0.0634	0.0439
	(0.85)	(0.82)	(0.65)	(0.84)	(0.61)
first_div	0.0108	0.00970	0.00350	0.00639	0.00250
	(0.33)	(0.30)	(0.10)	(0.20)	(0.08)
para_t	0.0605	0.0625	0.0623	0.0605	0.0595
	(1.29)	(1.31)	(1.35)	(1.28)	(1.32)
tabs_rate		-0.154			
		(-1.53)			
support_weak			-0.0483		
			(-1.04)		
t_gives_tuition				0.0417	
				(0.44)	
time_allocated to beneficial activities					-0.0221 (-0.47)
N	6772	6772	6772	6772	6772
N_g	71	71	71	71	71
r2	0.347	0.348	0.349	0.348	0.348

Note: All equations control for child and home background characteristics but these are not shown.

In Bihar, it appears that differences in teacher effort cannot explain why para-teachers outperform regular teachers. These results hold even when controlling for whether the teacher lives in the village/panchayat, whether or not the teacher knows the children well, teachers' subject knowledge and host of other co-variates (results of background regressions not shown) and non-linearity's.

As an additional issue, in Bihar there was a court ruling in 2006 which stipulated that applicants with teacher training certificates should be given preference in para teacher appointments even if they did not live locally (to the school). Many of the para teachers appointed in 2006 were thus individuals who possessed teacher training (typically unemployed persons who had done teacher training some time ago). As a result, we can classify Bihar para-teacher into multiple types. If we consider those who were appointed in 2006 and have received training as a separate group to those who were appointed either pre-2006 or in 2006 without training, then we can further strengthen the idea that it is the para-teacher contract itself that is key to the relative efficiency.

Re-estimating the model with separate groups for each type of para-teacher, we can test hypothesis that the difference between coefficients is equal to zero. This is the case when comparing both para-teachers without training to para-teachers with training (F=0.01, P=0.921) and further splitting the groups to account for appointments made pre-and-post 2006 (F=0.01, P=0.995).

Table 5 : Differentiating by type of para-teacher, Bihar

	(1) No differentiation	(2) Para-teachers with and without training	(3) Full differentiation of type of para-teacher
para_t	0.0605 (1.29)		
para_notrain		0.0631 (1.25)	
para2006_train		0.0550 (0.71)	0.0551 (0.72)
para2005			0.0626 (1.32)
para2006_notrain			0.0641 (0.86)
F-test equal coefficients		0.01	0.01
P-value		0.921	0.995
N	6772	6772	6772
N_g	71	71	71
r2	0.347	0.347	0.347

Note: The equations include all child, home background and teacher variables included in the previous achievement tables but we do not show the results.

Table 5 shows achievement equations with different teacher types. The base category for teacher type in all equations is ‘regular teacher’. The results suggest that despite the on-paper differences in characteristics between different types of para-teachers (appointed pre-and-post 2006, and most those with training), there is statistically no difference in their relative effectiveness. Thus, Bihar para teachers with pre-service training are no more effective than para teachers without such training (when comparing teachers of the same age, qualifications and gender). This calls into question the usefulness of training.

Looking inside the box – average treatment effects and interactions

The previous models have shown that the para-teacher effect is both positive and robust to the inclusion of controls for effort. While it is possible that these effects are driven by unobserved characteristics of para-teachers, notably higher effort due to the differential contractual structure, it is also possible that it partly may be due to differential effects of observable characteristics by teacher type. In the saturated model, our estimations are based on controls on observed characteristics, and their interaction with the para-teacher variable. By introducing interaction terms between our variable of interest (para-teacher dummy variable), and all other observable characteristics, and mean-centering all child, school and teacher characteristics, we can estimate the Average Treatment Effect of being taught by a para teacher. A child with characteristics that are exactly average, in the average school with a teacher with average characteristics, will not deviate from the mean value for any variable – therefore all variables will equal zero with the exception of the para-teacher variable.

In addition to this, the coefficients on the interaction terms tell us *how* para teachers affect child learning. A significant coefficient on these terms shows that the interaction between para teachers and these inputs leads to significantly different outcomes for pupils taught by para teachers when compared to those taught by regular teachers. This should allow us to open the black box of why a para-teacher is equally, less, or more effective than a regular teacher.

Table 6: Saturated School Fixed Effects Model with Para-teacher interactions

	(1) UP		(2) Bihar	
	Regular Teachers	Additional effect of Para-Teacher	Regular Teachers	Additional effect of Para-Teacher

Class	0.360***	0.118	0.839***	0.214**
	(5.49)	(1.46)	(10.93)	(2.51)
subject	-0.0264	0.110**	0.252***	-0.0821
	(-0.60)	(2.31)	(5.48)	(-1.59)
surveynumber	0.399***	-0.121**	0.278***	0.0198
	(8.59)	(-2.41)	(7.01)	(0.44)
child_age	0.0398*	0.0231	0.0921***	-0.0847***
	(1.94)	(1.06)	(4.92)	(-4.02)
child_male	0.0944**	0.0669	0.235***	0.0268
	(2.17)	(1.41)	(5.82)	(0.58)
childheight	0.0107***	-0.00706*	0.0106**	-0.00530
	(2.91)	(-1.78)	(2.23)	(-1.02)
Ill	-0.214***	0.169***	-0.0394	-0.0196
	(-4.91)	(3.55)	(-0.99)	(-0.43)
fatheredu	0.0324***	-0.0148**	0.0168***	-0.00374
	(5.99)	(-2.44)	(2.99)	(-0.58)
motheredu	0.0373***	-0.0134	0.0269***	-0.00307
	(3.90)	(-1.23)	(3.60)	(-0.36)
logasset	0.0504*	-0.0260	0.0362	0.0346
	(1.74)	(-0.83)	(1.35)	(1.14)
Tuition	0.321**	-0.0351	0.269***	-0.112**
	(2.48)	(-0.25)	(6.01)	(-2.21)
ageteacher	0.00948***	-0.0125**	0.000728	0.00524
	(3.21)	(-2.30)	(0.27)	(1.44)
maleteacher	-0.338***	0.373***	-0.192**	0.170**
	(-6.20)	(6.03)	(-2.44)	(2.03)
Ba	0.0323	0.0676	0.105	-0.130
	(0.48)	(0.89)	(1.45)	(-1.60)
Ma	0.0875	0.0302	0.155**	-0.161
	(0.96)	(0.28)	(2.23)	(-1.63)
firstdiv	0.0304	0.0875	-0.0482	0.0877
	(0.33)	(0.92)	(-0.77)	(1.25)
para_t	0.0165		-0.0108	
	(0.25)		(-0.21)	
_cons	-0.0455		0.0167	
	(-0.76)		(0.36)	
N	8185		6772	
N_g	62		71	
r2	0.297		0.370	
F_diff	5.412		2.513	
P_diff	8.95e-16		0.0000831	

In UP the ATE of the para-teacher variable is positive but insignificant, taking a value of 0.0165. In Bihar the ATE is negative but again insignificant. This shows that the average treatment effect of having a para-teacher is zero – that is, para-teachers are no less effective than regular teachers having controlled for all possible interaction effects.

An F-test of insignificance of the interaction terms is decisively rejected in both states, showing that interactions between para-teachers and our observable characteristics have a significant effect on learning outcomes.

In both states we find male para-teachers to be more effective than male regular teachers, raising achievement by 0.340 SD. Female para-teachers have no such efficiency gains over female regular teachers, though among regular teachers female score 0.343 SD more than men. Overall, in schools with more than the average male/female teacher ratio, we find a positive para-teacher effect.

Para-teachers appear to mitigate the negative effects of below average health, both in terms of long term measures such as child height and short term effects of absence through illness. Any child that has below average height or a father with below average levels of education will gain from having a para-teacher in UP. Given that fathers' education is likely to have more indirect effects than maternal education (which has equal effects for both teacher types) – fathers are less likely to be active in the day to day education of the child, more in determining attitudes to schooling and school choice - this may suggest that para-teacher reduce the negative impact of coming from families with lower SES. Also, a child who has a para-teacher and is ill for more than 4 days in the last 3 months would lose 0.09 SD relative to his healthier peers, while a child in the same situation with a regular teacher would have a mark 0.24 SD lower than his healthier peers.

In Bihar, aside from teacher gender, the only other significant differential effect is through lowering the benefits of receiving private tuition. Given that time-on-task is substantially lower in Bihar than UP (with teachers spending approximately 111 minutes teaching compared to 187), private tuition is far more pervasive, being undertaken by 40% of our sample. It appears that having a para-teacher narrows the achievement gap between those who take private tuition and those who do not.

In both states para-teachers appear to mitigate the impact of being from a disadvantaged background, be it having below averagely educated father (in UP), health problems (in UP) or not being able to take private tuition (Bihar). This is consistent with fact that para-teachers are closer in terms of social standing to their pupils. Regular teachers, who enjoy salaries far above the average in the areas they teach in, may consider under-privileged pupils less capable, and may neglect struggling students.

The saturated model suggests that while the ATE effect of a para-teacher effect is positive but insignificant, para teachers have significant interaction effects with the impact of observables. Most notably they are good for increasing the efficiency of male teachers', and also appear to lessen the disadvantages which stem from being of lower socio-economic status.

Conclusions

This paper sought to measure the relative effectiveness of regular and para-teachers in two Indian states. We used a number of models of the education production function to try and identify the causal impact of having a para-teacher relative to having a regular teacher. In all models we find that para-teachers do no worse than regular teachers, and indeed may be more effective than regular teachers.

Para-teachers are generally more likely to teach in more deprived schools and this may lead to an incorrect conclusion regarding their effectiveness. After controlling for all school factors (in a school fixed effects regression) as well as for pupil and teacher characteristics, para-teachers in UP are relatively more effective than regular teachers. The fact that much of the para teacher effect remains even after we take their lower absence rates and other measures of teacher effort into account suggests that they apply greater effort in dimensions other than being present in school. Another reason why para teachers apply greater effort than regular teachers is plausible due to the insecure annually renewable nature of their contracts. Given this uncertainty they are liable to exhibit more effort, which could lead to higher child outcomes.

In Bihar, para-teachers do not face such strong accountability, yet are still no less effective than regular teachers. This holds irrespective of the type of para-teacher. This shows that it is something intrinsic in the contracting of para-teachers that leads them to be equally as effective as regular teachers, despite the lack of training and experience, their lower competency scores, and their far lower pay. In Bihar, there is a clause in para teacher contracts saying that appointments can be reviewed every three years, creating some weak accountability pressures. While these pressures are clearly not strong enough to elicit a difference in para teachers' school attendance habits, it may lead to a weak increase in effort-levels that we have not been able to capture here.

A saturated model suggests that part of the para-teacher effect is due to para-teachers mitigating the negative impact of being socially disadvantaged, possibly due to the closer social-standing of para-teachers to their pupils relative to regular teachers. In conjunction with the fact that para-teachers live closer to school this may induce more effort by making teachers more accountable to parents. Para-teachers also substantially mitigate the negative effects of male teachers, with a strong para-teacher effect occurring in schools where the male/female teacher ratio is above average. This is consistent with previous literature which finds that males are more efficient when monitored.

In conclusion, it appears that by making teachers more accountable their performance improves. This is partly due to para-teachers mitigating the negative effect of being of low SES (a product of being more accountable to the local community) and partly due the para-teacher contract making male teachers noticeably more effective (a product of renewable contracts). The effects are strongest when the accountability is strongest, suggesting that yearly assessment of teachers may lead to improved performance. Even when accountability is weak, as in the case of Bihar, such weak accountability is sufficient to ensure that para-teachers are weakly more effective or, at worst, no less effective than regular teachers.

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Appendix

Appendix 1: Descriptive statistics of key variables

	UP		Bihar	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Child characteristics				
Math Score	31.05	43.20	62.40	58.16
Reading Score	32.71	37.39	69.36	49.39
Male child	0.50	0.50	0.54	0.50
Age of child	8.79	1.70	9.09	1.63
Weight of child (log)	9.26	2.51	9.50	2.26
Height of child (cm)	121.94	10.66	127.08	10.60
Illness - Was ill enough to to take 4 days or more off school in past 3 months	0.41	0.49	0.48	0.50
Father's education (years)	3.48	4.38	4.41	4.80
Mother's education (years)	0.91	2.41	1.68	3.30
Asset index (log) [1]	1.20	0.97	1.11	0.99
Takes private tuition	0.04	0.20	0.40	0.49
Teacher characteristics				
Age of the teacher	32.50	11.18	32.30	9.38
Male teacher	0.51	0.50	0.59	0.49

Teacher has BA qualification	0.38	0.49	0.31	0.46
Teacher has MA qualification	0.22	0.41	0.12	0.33
Teacher graduated in first division	0.17	0.38	0.47	0.50
Para-teacher	0.71	0.46	0.73	0.44
Teachers absence rate	0.12	0.18	0.20	0.20
School characteristics				
School resources index[2]	6.85	1.31	4.82	1.24
Pupil Teacher ratio[3]	35.38	16.35	34.30	13.13
Textbook ratio[4]	0.79	0.23	0.63	0.23
Always get a mid-day meal	0.81	0.39	0.04	0.19

[1]The asset index is a composite index of the following items with following weightings: Charpai, bed, wallclock, chair and table – enter directly; fan, bicycle, cd player and radio – multiply by 2; B&W TV, gas stove, cooker, mobile and telephone- multiply by 3; colour tv, fridge or motorbike- multiply by 5.

[2] The school resource index was incorporates information on not only the availability of resources, but whether or not they are in working order. It includes the following items; table for the teacher, existence of a fan, ability to open windows, blackboard that can be written on with chalk, mat or jute for children to sit on, desk for the majority of children, a library, a working tape-recorder, working electricity, a boundary wall, drinkable water and a working toilet.

[3] The pupil-teacher ratio was calculated taking into account the fluidity of class-room arrangements in the schools. It explicitly accounts for multi-grade teaching, and is measured by the total-number of pupils within the class, irrespective of grade.

[4] The textbook ratio is the number of children with a textbook for each subject, divided by the number of pupils in the class.

Appendix 2: Descriptive statistics of Teachers, by state and teacher type

UP

	Regular	Para-teacher	t-value of test of differences
Male	0.53	0.50	-0.53
Age of teacher	45.71	26.91	-20.64
BA	0.30	0.50	3.64
MA	0.23	0.19	-0.89
Graduated in first division	0.14	0.19	1.09
Teacher has received training	0.96	0.35	-13.65
Teacher absence rates	0.23	0.11	-5.73
Minutes spent teaching each day	171	174	0.27
Tenure	6.48	3.27	-6.87
Salary per month (Rupees)	11843	2985	-46.98

Bihar

	Regular	Para-teacher	t-value of test of differences
Male	0.86	0.54	-6.93
Age of teacher	44.22	30.23	-16.71
BA	0.27	0.31	0.85
MA	0.31	0.10	-5.79
Graduated in first division	0.24	0.56	6.85
Teacher has received training	0.81	0.43	-8.29
Teacher absence rates	0.22	0.21	-0.41
Minutes spent teaching each day	106	111	0.47
Tenure	7.76	2.75	-6.91
Salary per month	11194	4232	-26.13