

# Teacher Shocks and Student Learning: Evidence from Zambia\*

Jishnu Das (DECRG, The World Bank)  
Stefan Dercon (Oxford University)  
James Habyarimana (Georgetown University)  
Pramila Krishnan (Cambridge University)

This version: September 2004

## Abstract

We examine the effect of shocks to teacher inputs on child performance in school. We start with a household optimization framework where parents spend optimally in response to teacher and other school inputs. This helps to isolate the impact of teachers from other inputs. As a proxy measure for these shocks, we use teacher absenteeism during a 30 day period. Shocks to teacher inputs have a significant impact on learning gains. In a sample of students who remained with the same teacher over the two years for which we have test score data, shocks associated with a typical episode of absence lead to a decline of 20-30 percent in learning gains during the year. The size and precision of these estimates is identical for both Mathematics and English. We document that health problems account for over 60 percent of time spent in absence—this is not surprising in a country deeply affected by the HIV/AIDS epidemic. Tackling health problems of teachers and/or reducing the impact of absences by increasing the public provision of teachers (allowing for substitute teachers) is likely to have positive impacts on learning.

---

\*Corresponding Author: James Habyarimana (jph35@georgetown.edu). We thank workshop participants at Harvard University and the World Bank for useful comments and suggestions. Funding for the survey was provided by DFID. The findings, interpretations, and conclusions expressed in this paper are those of the authors and do not necessarily represent the views of the World Bank, its Executive Directors, or the governments they represent.

# 1 Introduction

The relationship between schooling inputs and educational outcomes is an important policy concern and has been the subject of a large body of work in applied economics. In this literature, the role of teachers has received wide attention. However, while there is consistent evidence that teachers matter, isolating the exact attributes of teachers that affect learning achievement has proved more difficult. This paper focuses on the impact of teacher shocks associated with teacher absence and illness on learning. These shocks led to large losses in learning achievement—children taught by teachers who received negative shocks during the academic year lost nearly three months of learning as a result.

As in Das and others (2004a), we start from a model where households determine the path of educational attainment optimally given teacher and other school inputs. Teachers in our framework are embodied by three attributes—observable characteristics (such as age, gender and experience), unobservable non-time varying attributes (such as ability or motivation) and unobservable time varying attributes (such as the health status). For households optimizing over future time periods, there may be uncertainty over time-varying and non-time varying attributes. In this framework, the household decision rule predicts that the impact of shocks to teacher inputs on learning achievement depends on whether parents can observe teacher quality or not. Under plausible conditions, the model suggests that the impact of teacher shocks on learning achievement is higher for the children who stayed with the same teacher compared to those who switched.

We test these predictions using teacher-pupil matched data from Zambia. For our empirical results we require information on (a) learning achievement, (b) negative shocks to teachers and (c) the extent to which parents may observe non-time varying teacher attributes. For the first we use test data in English and Mathematics on a sample of students tested at two different points in time. For the second, we use absenteeism during the last month as a measure of negative shocks received during the year. For the last, we exploit a tradition in which some teachers stay with the same cohort of students throughout primary school. It is likely that as parents build up their experience with the teachers, they also learn about her ability/motivation and other non-time varying attributes. This suggests that parents of these children face less uncertainty regarding non-time varying attributes compared to the parents of children who switched teachers.

The predictions of the model are consistent with the data—there is a large and significant effect of negative shocks (to the teacher) for children who remained with the same teacher, and a smaller and insignificant impact for children who switched. The estimated impacts are of the same magnitude and precision for both English and Mathematics. Since a large fraction of these

shocks are related to factors such as ill health or attending funerals, (and not driven by shirking for instance), the appropriate policy response based on these results is either to decrease the frequency of these shocks, say by broad improvements in health of the teaching workforce, or to mitigate their effects, perhaps by providing more substitute teachers to schools.

How robust are these results? Two issues concern us. First, a correlation between teacher shocks and non-time varying attributes (such as teacher quality) could lead to omitted variable bias in the estimation. This would not affect the estimates from the sample of children that stayed with the same teacher, confirming that teacher shocks indeed matter substantially. However, if children who moved to better teachers also moved to more absent teachers, the impact of absenteeism is attenuated for this particular group. We do not find supporting evidence on observables—there is no relationship between absenteeism and positive changes in observable teacher characteristics. To the extent that the positive correlations hold, preferred estimates of time-varying shocks are given by the cohort of children who remained with the same teacher, where non-time varying effects are swept out through the estimation procedure.

Moreover, selection problems arise if the children who changed teachers were very different from those who stayed with the same teacher. In discussing the robustness of our results, we show that to the extent that children who moved were different from those who stayed, our estimates are a lower bound for the impact of negative shocks on learning for the non-movers. This implies that in the absence of selective matching, the differences in the estimated impact between movers and non-movers would be larger than those obtained here.

The remainder of the paper is organized as follows. Section 2 reviews the literature; Section 3 outlines the theory. Section 4 presents the empirical specification and econometric concerns. Section 5 discusses the data used and section 6 presents the results and robustness tests. We conclude in section 7.

## **2 Literature Review**

Interest in teacher attributes on student learning has recently come to the fore of the educational production function literature. A series of papers using analysis of variance techniques have shown that the variation in test scores explained by teachers is substantial. Hanushek and others (1998) use data from Tennessee schools and find evidence of significant teacher effects. Park and Hannum (2002), using pupil-teacher matched data from China, find that variation due to teacher effects explains about 25 percent of variation in test scores. More traditional regression based studies

have also reached the conclusion that teachers matter. Rockoff (2004) using a 12 year panel of teacher-pupil data from two school districts in New Jersey finds significant teacher fixed effects. A one standard deviation change in the teacher fixed effect (unobserved quality) is associated with gains in mathematics and reading of 0.26 and 0.16 standard deviations respectively.

Less is known about the specific attributes of teachers that affect teacher learning. Limited evidence on teacher experience and training is provided by Rockoff (2004) and Angrist and Lavy (2001), who find that both experience and training have a positive impact on learning achievement.

Closer to the results presented here are the studies by Jacobson (1989) and Ehrenberg and others (1991). Jacobson (1989) describes an interesting policy experiment in which a pot of money was set aside and teachers' claims on the pot were proportional to their share of sick leave days not taken. The policy reduced the number of sick days taken by 30 percent and increased the share of teachers with perfect attendance from 8 percent to 34 percent. Owing to data limitations, he was unable to evaluate the impact of the policy on pupil performance. Ehrenberg and others (1991) study the effect of teacher absenteeism on school level pass-rates using variation in school district leave policies as an instrument for absenteeism. They do not find any direct effects of absenteeism on pass-rates, although they do find that higher teacher absenteeism is associated with higher student absenteeism.

Our paper differs from Ehrenberg and others (1991) in a number of ways. To start with, the focus of this paper on identifying the impact of negative shocks on learning achievement, contrasts with Ehrenberg and others' concerns regarding the identification of absenteeism effects per se. While negative shocks result in higher absenteeism, they also lead to less supplementary inputs by the teacher. A teacher who is sick is likely to be more absent, but is also likely to spend less time on lesson preparation. Our estimates thus capture the *joint* effect of absence from the classroom and lower inputs due to the shock and the policy implications (discussed below) vary accordingly.

The institutional context presents another source of difference. It is likely that the nature and severity of shocks that teachers are subject to varies dramatically across the U.S. and low income countries. In countries such as Zambia with very high HIV/AIDS rates, shocks due to illnesses and funerals can lead to long absences and substantial declines in teaching performance. In terms of absenteeism, the variation is striking. For instance, absence rates in these US-based studies at 5 percent are low compared to those in low income countries—an ongoing study finds averages of 20 percent and above in Sub-Saharan Africa, 25 percent in India and 11 percent and above in Latin America (Chaudhury and others 2004; World Bank 2003; Glewwe and others 2001).<sup>1</sup> In

---

<sup>1</sup>In fact, even private sector absence in India, at 10 percent is double that reported for public schools in the US.

addition, in the US absent teachers are usually replaced by temporary substitutes so that disruption is minimized. Although evidence on teacher absenteeism in low income countries is sparse, absent teachers are typically not replaced by temporary teachers. Thus, we would expect both the extent of shocks as well as the ability of schools to cope to be accentuated in our data.

Finally, the household optimization approach to learning achievement presents a methodological break. The approach predicts heterogeneity in the estimated impact depending on underlying uncertainty in the model. For the sample of children who changed teachers in the previous year, our results are very similar to Ehrenberg and others (1991). Yet, there are strong effects for children who remained with the same teacher. This difference between the two student cohorts is an important source of variation and could partially explain the results of the previous study.

### 3 Theory

The basic model is based on Das and others (2004a). It is extended here to explicitly focus on the implications of uncertainty in teacher inputs on household decisions about educational inputs and cognitive achievement, proxied by test scores. The model assumes a household (with a single child attending school) that derives (instantaneous) utility from the cognitive achievement of the child  $TS$  and the consumption of other goods  $X$ . The household maximizes an inter-temporal utility function  $U(\cdot)$ , additive over time and states of the world with discount rate  $\beta (< 1)$  subject to an inter-temporal budget constraint (IBC) relating assets in the current period to assets in the previous period, current expenditure and current income. Finally, cognitive achievement is determined by a production function relating current achievement ( $TS_t$ ) to past achievement ( $TS_{t-1}$ ), household educational inputs ( $z_t$ ), teacher inputs ( $m_t$ ), non time-varying child characteristics ( $\mu$ ) and non time-varying teacher and school characteristics ( $\eta$ ). We impose the following structure on preferences and the production function for cognitive achievement:

[A1] Household utility is additively separable, increasing and concave in cognitive achievement and other goods.

[A2] The production function for cognitive achievement is given by  $TS_t = F(TS_{t-1}, m_t, z_t, \mu, \eta)$  where  $F(\cdot)$  is concave in its arguments.

Under [A1] and [A2] the household problem is

$$Max_{(X_t, z_t)} U_\tau = E_\tau \sum_{t=\tau}^T \beta^{t-\tau} [u(TS_t) + v(X_t)] \text{ s.t.} \quad (1)$$

$$A_{t+1} = (1+r) \cdot (A_t + y_t - P_t X_t - z_t) \quad (2)$$

$$TS_t = F(TS_{t-1}, m_t, z_t, \mu_t, \eta) \quad (3)$$

$$A_{T+1} = 0 \quad (4)$$

Here  $u$  and  $v$  are concave in each of its arguments. The inter-temporal budget constraint (2) links asset levels  $A_{t+1}$  at  $t+1$  with initial assets  $A_t$ , private spending on educational inputs  $z_t$ , income  $y_t$  and the consumption of other goods,  $X_t$ . The price of educational inputs is the numeraire, the price of other consumption goods is  $P_t$  and  $r$  is the interest rate. The production function constraint (3) dictates how inputs are converted to educational outcomes and the boundary condition (4) requires that at  $t=T$ , the household must have zero assets so that all loans are paid back and there is no bequest motive.<sup>2</sup>

We assume that teacher inputs consist of two parts, and both are outside the control of the household—inputs conditional on quality,  $m_t^q$  and shocks to these inputs,  $\mu_t$ . The shocks are zero in expectation ( $E(\mu_t) = 0$ ) so that  $m_t = m_t^q + \mu_t$ . Teacher inputs conditional on quality  $m_t^q$  are assumed to be unknown, but at the time the household makes its decision knows the underlying distribution of quality. Finally, the household only knows the stochastic process related to  $\mu_t$  and not the actual level. There are thus two sources of uncertainty in this model—uncertainty about the quality of teachers as well as shocks to teacher inputs.

Maximization of (1) subject to (2) and (3) provides a decision rule related to  $TS_t$ , characterizing the demand for cognitive achievement. To arrive at this decision rule, we define a price for cognitive achievement as the “user-cost” of increasing the stock in one period by one unit, i.e., the relevant (shadow) price in each period for the household. This user cost, evaluated at period  $t$ , is (see Das and others (2004a)):

$$\pi_t = \frac{1}{F_{z_t}(\cdot)} - \frac{F_{TS_t}(\cdot)}{(1+r)F_{z_{t+1}}(\cdot)} \quad (5)$$

The first term measures the cost of taking resources at  $t$  and transforming it into one extra mark in

---

<sup>2</sup>As discussed in Das et al. (2004a), an alternative assumption, that the benefits from the child’s cognitive achievement are only felt in the future, would not change the model fundamentally. Moreover, the results are unaffected if one assumes that households care about the (instantaneous) flow from educational outcomes (rather than the stock of cognitive achievement) provided that this flow is linear in the stock.

the test. When implemented through a production function, the price is no longer constant—if the production function is concave, the higher the initial levels of cognitive achievement, the greater the cost of buying an extra unit as reflected in the marginal value,  $F_{z_t}(\cdot)$ . Of the additional unit bought in period  $t$ , the amount left to sell in period  $t + 1$  is  $F_{TS_t}(\cdot)$  and the second term thus measures the present value of how much of this one unit will be left in the next period expressed in monetary terms. The standard first-order Euler condition related to the optimal path education of educational outcomes between period  $t$  and  $t + 1$  it then:

$$\frac{\frac{\partial U}{\partial TS_t}}{\pi_t} = \beta E_t \left( \frac{\frac{\partial U}{\partial TS_{t+1}}}{\pi_{t+1}} \right) \quad (6)$$

Intuitively this expression (ignoring uncertainty for the moment) suggests that if the user-cost of test scores increases in one period  $t + 1$  relative to  $t$ , along the optimal path this would increase the marginal utility at  $t + 1$ , so that  $TS_{t+1}$  will be lower. This is a standard Euler equation stating that along the optimal path, cognitive achievement will be smooth, so that the marginal utilities of educational outcomes will be equal in expectations, appropriately discounted and priced. Finally, the concavity of the production function will limit the willingness of households to boost education ‘too rapidly’ since the cost is increasing in household inputs. Thus, under reasonable restrictions, the optimal path will be characterized by a gradual increase in educational achievement over time (for an explicit derivation see Deaton and Muellbauer 1980 and Foster 1995).

This general framework allows us to make predictions about the impact of information about teacher quality and of shocks to teacher inputs. First, any shock in teacher inputs will affect the path of test scores over time. Secondly, uncertainty *ex-ante* about teacher quality may result in fluctuations *ex-post* in outcomes. For example, if at  $t + 1$  teacher quality is better than expected, then households will have relatively overspent on educational inputs, boosting outcomes in  $t + 1$  beyond the anticipated smooth path. It also implies that the (*ex-post* observable) change in teacher quality between  $t$  and  $t + 1$  matters for describing the change in outcomes and these *changes* should be included in an empirical specification.

The uncertainty faced by households may also result in *ex-ante* responses, affecting outcomes as well as the impact of shocks on outcomes. To see this, consider the first order condition, affecting choices between spending on educational inputs and on other goods, before teacher quality is known. The optimal decision rule equates the marginal utility of spending on other goods to the expected value of spending on educational inputs (taking into account the intertemporal decision rule in (6)), or:

$$\frac{\frac{\partial U}{\partial X_t}}{P_t} = E_{t-1} \left( \frac{\frac{\partial U}{\partial TS_t}}{\pi_t} \right) \quad (7)$$

In general, whether increased risk in teacher quality will increase or reduce household spending on educational inputs will depend on risk preferences and the nature and shape of the cognitive production function. In particular, given  $P_t$ , if increasing risk increases the right hand side of equation (7), households will spend less on other goods  $X_t$  and more on teaching inputs  $z_t$  than before. There would be two implications. First, the expected path of educational outcomes would be higher—although this will not necessarily have an impact on the *changes* in outcomes between two periods. Secondly, the *ex-post impact* of shocks to teacher inputs in a particular period may be different depending on the extent of risk faced by households *ex-ante*.<sup>3</sup>

To develop the circumstances in which this may be the case, let us introduce risk in a specific way. In particular, let  $m_t = \bar{m}_t^q + \tilde{a} + \mu_t$ , whereby  $\tilde{a} = a > 0$  if the teacher is of high quality, and  $\tilde{a} = -a$  if the teacher is of low quality. Increases in  $a$  would then imply an increase in risk in the sense of a standard increase in mean-preserving spread. A sufficient condition for household spending on education to increase in risk is that  $\frac{\frac{\partial U}{\partial TS_t}}{\pi_t}$  is decreasing and convex in  $m_t$ .

As in Das and others (2004a), the following assumptions will be required to derive an empirical specification; they will also help to determine conditions for the convexity of  $\frac{\frac{\partial U}{\partial TS_t}}{\pi_t}$ .

[A1] Household utility is additively separable and of the CRRA form.

[A2]  $TS_t = (1 - \delta)TS_{t-1} + F(w_t, z_t, \mu, \eta)$  where the Hessian of  $F(\cdot)$  is negative semi-definite.

Under [A1] marginal utility is defined as  $TS_t^{-\rho}$ , with  $\rho$  the coefficient of relative risk aversion. Using [A2] and the implicit function theorem with (5), we have

$$\frac{d\pi_t}{dm_t} = -\frac{F_{z_t m_t}}{F_{z_t}^2} \leq 0 \text{ if } F_{z_t m_t} \geq 0 \quad (8)$$

The sign of the cross partial will depend on whether the household can respond to changes to teacher inputs. If  $F_{z_t w_t} = 0$ , households are unable to respond to changes in teacher inputs. This might be a consequence of credit constraints, inability of parents to substitute either via a lack of ability/time and the absence of markets for private tuition. If, however, households are able to respond to changes in teacher inputs and household and teacher inputs are technical substitutes ( $F_{z_t w_t} < 0$ ), increases in teacher inputs at  $t$  will increase the relative user-cost of boosting cognitive

---

<sup>3</sup>Note that the latter possibility only arises due to the fact that households may influence educational outcomes via their own inputs; if outcomes were only produced by teacher inputs, then there would be no difference in observed outcomes conditional on the uncertainty faced by parents about teacher quality, since *ex-ante* no actions could have been taken to avoid this.



achievement at  $t$ . The reverse is true if teacher and household inputs are technical complements ( $F_{z_t w_t} > 0$ ). It follows directly that  $\frac{\frac{\partial U}{\partial TS_t}}{\pi_t}$  will be decreasing in  $m_t$  if teacher and household inputs are technical substitutes and if households are risk averse:

$$\frac{d \frac{\frac{\partial U}{\partial TS_t}}{\pi_t}}{dm_t} = \frac{-\frac{\partial \pi_t}{\partial m_t} \cdot \frac{\partial U}{\partial TS_t} + \frac{\partial^2 U}{\partial TS_t^2} \cdot F_{m_t} \cdot \pi_t}{\pi_t^2} < 0 \quad (9)$$

In (9), the first term in the numerator is negative if inputs are technical substitutes and the second term is negative if households are risk-averse. Furthermore, it can be shown that a sufficient condition for  $\frac{\frac{\partial U}{\partial TS_t}}{\pi_t}$  to be convex in teacher inputs is that inputs are technical substitutes, households are risk averse, the marginal utility of additional cognitive achievement is convex, and the user cost is concave in  $m$  (it increases at a decreasing rate). Convex marginal utility is satisfied under CRRA. The user cost is concave in  $m$  if  $F_z F_{mmz} \geq 2(F_{zm})^2$ <sup>4</sup>.

This result may *at first* seem counter-intuitive: producing cognitive achievement using household inputs is a risky activity. So, responding to increased risk by spending more on the risky activity may go against the basic Sandmo (1969) results. However, since the produced commodity also enters the utility function, these results do not hold, and under reasonable conditions, households may choose to invest more in the activity in response to more uncertainty, as a means of guaranteeing a reasonable amount of the produced commodity for consumption<sup>5</sup>. If the price of boosting cognitive achievement were constant, then convexity of marginal utility is sufficient. If not, then as long as user costs increase only at a decreasing rate in teacher inputs, households will still spend more on household level educational inputs when risk increases.<sup>6</sup>

This provides yet another testable implication in addition to the prediction that negative shocks will affect the path of outcomes. If households can be identified as facing less uncertainty in teacher inputs, we can expect that they spend differentially, and plausibly less, on household inputs than otherwise similar households facing more uncertainty. It follows then, from  $F_{m_t m_t} < 0$ , that the *ex-post* impact of shocks to teacher inputs would be higher, the lower the uncertainty faced *ex-ante*. This prediction will be tested using our data.

---

<sup>4</sup>Concavity of the user cost is not a necessary condition: even with convexity of user cost, sufficiently high risk aversion or substantial convexity of marginal utility could result in the convexity of  $\frac{\frac{\partial U}{\partial TS_t}}{\pi_t}$ .

<sup>5</sup>The argument is similar to the analysis of precautionary savings, where the choice is between consuming more today compared to tomorrow, as in Deaton (1992). In the basic model, convexity of marginal utility is then sufficient for increased savings in response to increased uncertainty in income, even though the risk related to future utility has increased, affecting the marginal benefit to savings.

<sup>6</sup>In this formulation credit markets are perfect so that there are no bounds on  $A_{t+1}$  apart from (4); the perfect credit market assumption is relaxed in our discussion of the empirical results. To see how the theory is affected, see Das et al. (2004a).

## 4 Empirical model

Under assumption  $[\widehat{A1}]$  (6) can be written as:

$$\frac{TS_t}{TS_{t-1}} \beta^{-\rho} \frac{\pi_{t-1}}{\pi_t} = 1 + e_t \quad (10)$$

where  $e_t$  is an expectation error, uncorrelated with information at  $t - 1$ . Taking logs and expressed for child  $i$ , we obtain:

$$\ln \left( \frac{TS_{it}}{TS_{it-1}} \right) = \frac{1}{\rho} \ln \beta - \frac{1}{\rho} \ln \left( \frac{\pi_{it}}{\pi_{it-1}} \right) + \frac{1}{\rho} \ln(1 + e_{it}) \quad (11)$$

or, the growth path is determined by the path of user-costs, and a term capturing expectational surprises.

The key issue is how changes in the two types of teacher inputs  $m_t^q$  and  $\mu_t$  impact on the optimal path of cognitive achievement. Teacher inputs are subject to various shocks such as teacher illness, attendance of funerals or official obligations outside the classroom.<sup>7</sup> As such the level of teacher inputs are generally not known with certainty until after households make decisions regarding their own inputs. Thus the impact of uncertainty to teacher inputs will depend both on whether households are able to substitute for shortfalls in anticipated teacher inputs as well as the extent of uncertainty faced by households.

To provide a direct measure of the impact of shocks in teacher inputs on the growth path of cognitive achievement, we add a direct measure of the shock into (11). If there is an (unanticipated) shock  $\varepsilon_t$  to teacher inputs *ex-post*, then the change in the growth path is given by  $\ln \left( \frac{TS_{t-1} + \varepsilon_t F_m}{TS_{t-1}} \right)$ , which depends on the relative size of the terms in brackets. It is also possible to use (11) to assess further hypotheses based on the theory. First, if we have information on changes in  $m_t^q$ , in the form of changes in teacher characteristics, then they should help to inform changes in outcomes. Secondly, if we can identify differences in the uncertainty over  $m_t^q$  faced by households, we may expect to find differential responses of test scores to the shocks  $\mu_t$ .<sup>8</sup> In particular, and as discussed in the previous section, under certain reasonable assumptions, greater uncertainty implies a smaller impact of shocks *ex-post*. If we can identify this effect, this would also be evidence for the role of

---

<sup>7</sup>Official obligations include meetings and teacher training.

<sup>8</sup>Our attempts to parse teacher absence into anticipated/unanticipated components using observable characteristics of the teacher suggests that a large fraction of teacher absenteeism can not be explained by observables that would be available to the households. For a detailed discussion of the impact of anticipated versus unanticipated changes in inputs on outcomes in these data, see Das et al. (2004a).

household inputs to compensate for teaching inputs, since without such effects, there would be no a priori reason for differential effects of shocks.

In light of the above, our empirical specification is given by:

$$\ln \left( \frac{TS_{ijkt}}{TS_{ijkt-1}} \right) = \alpha_o + \alpha_1 w_{jkt} + \alpha_2 \Delta t_{jkt} + \alpha_3 \Delta X_{jkt} + \epsilon_{ijkt} \quad (12)$$

where  $TS_{ijkt}$  is the test score of child  $i$  with teacher  $j$  in school  $k$  at time  $t$ ,  $w_{jkt}$  is a measure of a shock to teacher inputs of teacher  $j$  in school  $k$ ,  $\Delta t_{jkt}$  represents a vector of changes in observable teacher characteristics and  $\Delta X_{jkt}$  represents a vector of changes in other variables thought to affect the relative user-cost of boosting cognitive achievement. The more negative is  $\alpha_1$ , the larger the impact of shocks on test scores. We expect  $\alpha_1$  to be more negative for households that face less uncertainty over teacher inputs.

Testing our predictions requires data on shocks to teacher inputs as well as a means of distinguishing the uncertainty faced by households in terms of teacher inputs. The primary source of shocks to teacher inputs used in this paper is teacher absenteeism. As will be shown below, absenteeism is related to a number of factors, largely unpredictable for the households, such as illness and attendance at funerals. To ascertain household information about  $m_t^q$ , the specification will then be tested on two sub-samples of the data. A particular feature of education in Zambia is that in some schools, pupils stay with the same teacher throughout their education (we call these the "non-movers"), while others change their teacher each year (we call these the "movers"). It is plausible to assume that parents of non-movers will have better information on teacher quality,  $m_t^q$ , than parents of movers. It is then possible to test the impact of changes in uncertainty across the two samples; the theory suggests that the impact of negative shocks on learning achievement may well be higher in the sample of non-movers.

The identification assumption implicit in Equation(12) is that  $corr(w_{jkt}, \epsilon_{ijkt}) = 0$ , i.e, the error term in the equation is not correlated with absenteeism. There are two reasons why this assumption might break down. From our model, if  $corr(\Delta m_t^q, w_{jkt}) \neq 0$ , so that the change in unobserved teacher quality is correlated with absenteeism then  $\alpha_1$  captures both the effect of shocks and teacher quality for the movers. Fortunately, we can sign this bias. If  $\alpha_1$  is more negative for the non-movers compared to the movers, it must be the case that the correlation is positive, so that teachers who are high quality also tend to be more absent. While the reverse may be intuitively more appealing, this is effectively an empirical issue to be explored further below.<sup>9</sup>

---

<sup>9</sup>If teacher absences are largely related to ill health or attending funerals, then it is not intuitively obvious to

Our identification is also potentially flawed if there is systematic matching between children and teachers. We address these problems in our discussion on the robustness of the results.

## 5 Data

The data are from Zambia, a landlocked country with a population of 10 million in sub-Saharan Africa. The educational environment is discussed in some detail in Das and others (2004a) and Das and others (2004b). For our purposes, an important factor is the overall decline in GDP per capita in the country from the early eighties due to a decline in worldwide copper prices, the country's main export. This has also impacted on educational attainment. For instance, net primary school enrolment currently at 72 percent is at a historically low level, following a moderate decline over the previous decade. Although the government responded to this deterioration of the education profile by initiating an investment program at the primary and "basic" level in 2000, a continuing problem has been the inability of the government to hire and retain teachers in schools.

Thus, teacher attrition has received a lot of attention, both in the popular press and in institutional reports. Our data as well as data from the census of schools in 2002 corroborates the high rates of attrition (Das and others 2004b). Consequently there is a shortage of teachers, with class sizes regularly above the 40 children per teacher norm (particularly in rural areas), teachers teaching double shifts, and almost no possibility of substitutions when teachers are absent. Combined with this, absenteeism rates are high, primarily due to illness and funerals. The environment is thus characterized by a high level of negative teacher shocks and limited scope for replacement teaching.

We surveyed 182 schools in four provinces of the country in 2002.<sup>10</sup> The choice of schools was based on a probability-proportional-to-size sampling scheme, where each of 35 districts in the four provinces was surveyed and schools were randomly chosen within districts with probability weights determined by grade 5 enrollment in the school in 2001. Thus, every *enrolled* child in grade 5 in the district had an equal probability of being in a school that participated in the survey. As part of the survey, questionnaires were administered to teachers and head-teachers with information on a host of topics including their demographics, personal characteristics, absenteeism, outside options and

---

expect a particular correlation. Even if absences also involve some element of shirking, then it is unlikely that high quality teachers are more absent, although it could be argued that they have higher outside options and therefore can afford shirking.

<sup>10</sup>Lusaka, Northern, Copperbelt and Eastern provinces were surveyed. These four provinces account for 58% of the total population in Zambia.

classroom conditions. In addition, we also collected information at the level of the school including financing and the receipts of educational inputs during the academic year.

The pupil-teacher matching involved collecting information on the identity of each pupil's teacher in the current (2002) and the previous year (2001). Where possible (that is, when the teacher was present on the day of the survey), we administered a questionnaire to all these teachers, resulting in information on 541 teachers in our 182 schools. Every teacher interviewed is hence matched to a student, either by virtue of currently teaching the student or having taught the student in the previous year. We collected information on the current teacher for 85 percent of the students and on the past teacher for a smaller 62 percent of these students (some teachers had left the school, although using the sample of teachers teaching the tested cohort in 2001 these accounted for 6.3% of all teachers).

The pupil-teacher matching allows us to identify the non-movers in 2001 and 2002. This subsample represents 26 percent of the students tested both in 2001 and 2002. Tables 1a and 1b show that non-movers are different from the movers: Teachers who teach non-movers are more urban (insignificant), female (significant at 5% level), more experienced (significant, 1%) and better trained (significant, 1%). Similarly, the non-movers themselves are also different. They are more likely to be living with both parents (insignificant), have a higher proportion of mothers and fathers with primary or higher education (significant, 1%), are 0.3 standard deviations richer than different teacher pupils (significant, 1%) and have higher test scores in 2001 (significant, 1%). In essence, the sample of non-movers is primarily urban and we discuss the implications of this below.

To assess learning achievement, a maximum of 20 students in Grade V were randomly chosen from every school in 2001 and an achievement test was administered in Mathematics, English and a Zambian language.<sup>11</sup> The same tests were administered again in 2002 to the same students leading to the construction of a two year panel of test scores. Sampled children were also asked to complete a pupil questionnaire in every year with information on basic assets, demographic information and educational flows within the household.

We used item response theory methods to arrive at a scaled score for every student; essentially the method constructs optimal weights for every question and estimates a latent variable, interpreted as the "knowledge" of the child, using a maximum likelihood estimation procedure. Differencing across the base and final year, the estimated change in "knowledge" is used as the dependent variable in our regressions (see Das and others 2004a for details). The distribution of

---

<sup>11</sup>In schools with less than 20 students in grade 5, the entire grade was sampled.

knowledge in the base year is standardized to have mean zero and variance 1, so that the coefficients of the regression can be interpreted as the impact of the independent variable on standard deviations of estimated (change in) knowledge.

Children learnt very little over the academic year. On average, they were able to answer only 3.2 questions more in Mathematics from a starting point of 17.2 correct answers (from 45 questions) and 2.4 more in English starting from 11.1 correct answers (from 33 questions). In terms of the standardized score, children gained 0.42 standard deviations in Mathematics and 0.40 in English. Thus, after one year of teaching the gains in learning were small.

Finally, our source of variation for shocks to teacher inputs is variation in teacher attendance, where absence is defined as a teacher being away from school during regular school hours.<sup>12</sup> We collected three different measures of absenteeism; a measure of spot absence, self-reported absenteeism and a head teacher’s report of absenteeism. The most satisfactory measure is the head teacher’s report, where the head teachers were asked to provide independent reports of teacher absence over the previous 30 days for the entire matched teacher sample. This is the indicator for teacher shocks used in our analysis below.

Head teachers reported that 304 out of 725 teachers were absent at least once during the last month. Teacher illness accounted for 35 percent of all absence episodes, and illnesses in the family and funerals for another 27 percent (Table 2). This suggests that health related issues are a major source of shocks to teacher inputs.<sup>13</sup>

## 6 Results: Do shocks to teacher inputs affect learning?

We estimate equation (12) using ordinary least squares, with the head teacher report of the number of days absent as our measure of shocks to teacher inputs. We also include additional controls for current and past teacher characteristics. The model predicts that controlling for changes in teacher characteristics, negative shocks to teacher inputs will affect the gains in learning. Further, for pupils that stayed with the same teacher and thus faced less uncertainty about teacher quality, the losses linked to negative shocks will be larger since less ex-ante spending on education for precautionary reasons may have taken place, *ceteris paribus*.

---

<sup>12</sup>Ideally we would like to measure the time that teachers spend away from the classroom when they should be teaching. This would include absence episodes while teachers are in school. Glewwe et al.(2001) find that teachers are in school but absent from class 12% of the time. We focus only on time away from school.

<sup>13</sup>Absences and their reasons are broadly similar for different methods used to collect absenteeism data. Appendix 1 provides a discussion of these alternative measures.

The table reports coefficients based on four different specifications for English and Mathematics. For all specifications, the dependent variable is the change in the knowledge of the child. The first specification uses only a dummy variable for whether the child was a non-mover and an interaction of this dummy variable with the head-teacher’s report of absence. We then introduce present teacher characteristics and a set of controls that proxy for changes in the user cost.<sup>14</sup> The third specification then controls for past teacher characteristics.

Introducing current and past teacher characteristics leads to a decrease in the sample size. Since information on current teacher characteristics is available only for teachers who were present on the day of the survey we lose 240 children (out of 2187) when we introduce these controls. We lose a further 693 on introducing past teacher characteristics since a number of these had left the school by the time of the survey, leaving us with a total of 1,254 students. To check how these changes in the sample affect our results, we include a fourth specification that restricts the sample to children for whom we have observations on current and past teacher characteristics, but uses only current teacher attributes as regressors.

We find strong and significant impacts of teacher shocks on learning achievement in both English and Mathematics for non-movers. The impact for movers is small and insignificant. The first specification (Table 3, Columns 1 and 5) shows that for non-movers, every additional day absent led to a decline of 0.020 standard deviations (English) and 0.022 standard deviations in Mathematics. Including three additional controls for the teacher characteristics—experience, gender and whether the teacher has a certificate—doubles this estimate for both English and mathematics to 0.040 and 0.037 standard deviations respectively (Table 3, Columns 2 and 6). For the full specification with past teacher characteristics, an additional day of absence reported by the head-teacher results in a 0.044 decline in learning for English and a 0.039 decrease for Mathematics (Table 3, Columns 3 and 7).

Encouragingly, there is no difference in the estimated impact once we include past teacher characteristics. This suggests little correlation between changes in teacher quality and teacher shocks; we return to this in the discussion below. Finally, these results are not driven by the choice of the sample—once we condition on current teacher characteristics, the estimated coefficients are stable across samples (Table 3, Columns 4 and 8).

---

<sup>14</sup>These include the funding received by the school during the current year (a flow), whether the head-teacher changed (a change in stock), whether the head of the parent-teacher association changed, the change in parent-teacher association fees and dummies for whether the school is private (there are 4 such schools in our sample) and whether the school is in a rural region (proxying for different input prices).

These results are consistent with predictions from theory: a significant impact of teacher shocks on learning gains for non-movers, which are larger relative to the movers. These estimates are also large. Given that average learning during the year in both English and Mathematics was 0.40 standard deviations, the estimated impact is a 10 percent decrease in learning for every additional day that the teacher was absent among the non-movers. As discussed previously, the estimated impact captures both the direct effect of absenteeism (that is, not teaching in class) and the effect of lower classroom inputs for teachers who were more absent.

In the case of the non-movers, the choice of sample "differences-out" the non-time varying unobservable inputs of the teacher, and hence the estimate accurately captures the effect of time-varying shocks to teaching inputs on learning: teacher absence has a large effect on pupils. Among the movers however, we can control only for observable past teacher characteristics and, to the extent that absenteeism is correlated with non-time varying unobservables our estimates for those changing teachers are not consistent. The next sections presents some evidence that such correlations are in the opposite direction to what we would expect if there is a bias towards zero in the movers.

## 6.1 Robustness: Sampling Differences

The theory focused on differential household behavior for movers compared to non-movers. Due to the higher risks associated with unknown teacher quality among the movers, these households would incur higher educational spending, primarily driven by a precautionary motive. Furthermore, we assumed that teacher shocks are unanticipated and that households cannot respond to negative shocks to teacher inputs *ex post*; only precautionary *ex-ante* responses are possible. For technical substitutes, the impact of anticipated shocks will be lower than for unanticipated shocks, since households can smooth shocks to school and teacher inputs by spending decisions on household inputs (see Das and others 2004a). Similarly, if households can respond to negative shocks *ex-post*, then the impact of these shocks on outcomes can be reduced by household spending, compared to the case in which there were no ex-post substitution possibilities.

Can these arguments be responsible for the pattern of results between movers and non-movers? It is likely that the parents of non-movers have more information on their teachers and thus are better able to anticipate shocks during the coming year. If this is indeed the case then negative shocks should have a *smaller* impact on learning gains for this group compared to those that moved. This suggests that informational advantages in terms of anticipation of shocks are unlikely to be relevant.

Furthermore, as discussed previously, the sample appears to be biased in the opposite direction



in terms of opportunities for substitution —movers tend to come from rural and less wealthy households compared to non-movers. To the extent that wealth and urbanization capture substitution possibilities (less wealthy and more rural households are less likely to hire private tutors) this would suggest that negative shocks should impact on movers more than non-movers, rather than the other way around. In short, this is suggestive evidence that precautionary behavior rather than sampling differences is driving our differential findings between movers and non-movers.

A more systematic approach is to ensure that we exclude children with very different backgrounds in our estimation. We implement this by the analog of a propensity score matching technique. We first estimate the probability that a child is a mover on household, teacher and school characteristics and use this regression to predict the probability of moving. We then look only at the area of "common support", that is, we only keep in the sample those children whose predicted scores are found in both the sample of movers and the sample of children with same-teachers. Table 4 reports the results for two specifications using this "matched" sample. The first specification is the analog of Table 3, columns (2) and (6) for the full sample with the full control set and current teacher characteristics; the second specification then adds in past teacher characteristics as well (the equivalent of Columns 3 and 7 in Table 3). We find no difference in the estimated coefficients for English and a decline in Mathematics among the same teacher sample; the estimated coefficients for the movers remains insignificant and zero.

## 6.2 Robustness: Selective Matching

The relative pattern of our results between movers and non-movers could also arise from selective matching among teachers and students rather than precautionary behavior linked to differential uncertainty. In particular, there could be a correlation between changes in teacher quality and absenteeism. If  $cov(\Delta m_t^q, w_t) > 0$ , i.e. time-varying shocks are positively correlated with non-time varying teacher attributes (better teachers tend to be more absent), our results are biased towards zero for the movers. Importantly, this problem does not affect the estimated coefficients for the sample of non-movers since teacher characteristics that do not vary are differenced out.

It is hard to assess how plausible this is, and narratives for both positive and negative correlation between teacher quality and are possible. Although we cannot directly test the relevance and importance of this selection effect, there are two important observations. First, our estimate for  $\alpha_1$  remains consistent and unbiased for students who remained with the same teacher. Second, we can use observable past teacher characteristics to check whether changes in observed teacher characteristics satisfy the covariance requirement. That is, we can check whether among the movers, positive movements were correlated with higher absenteeism. For two important variables—whether

the teacher holds a certificate and teacher experience—we do not find any correlation between absenteeism and movements.

Finally, note that the differential impact between movers and non-movers implicitly also suggests that ex-ante responses are relevant, and that models allowing for household responses are helpful to understand the impact of schooling inputs on learning outcomes. Standard education production models do not allow for household responses and substitution in inputs (see also Hanushek, 1986; Todd and Wolpin, 2003). They would also not predict this differential response between movers and non-movers, unless one also appealed to a positive correlation between teacher quality and absenteeism. To see this, note that in the standard value-added production function approach, we can write  $\Delta_{t-1}^t TS_{it} = \alpha + \beta_1 w_t + [\beta_1(m_t^q - m_{t-1}^q) + \varepsilon_{it}]$ . where  $w_t$  is absenteeism in the current period and child level heterogeneity is differenced out. If we could observe  $m_t^q$ , our estimate of  $\beta_1$  would be consistent. However, in the absence of data on  $m_t^q$ , the additional term  $(m_t^q - m_{t-1}^q)$  is subsumed in the bracketed error term. Thus, a *positive* correlation between the change in  $m_t^q$  and  $w_t$  leads to an inconsistent estimate  $\beta_1$ , less negative than the true value.

## 7 Conclusion and Caveats

This paper constructs a framework to identify the impact of shocks to teacher inputs on learning gains. The theory model allowed for intertemporal optimization, household substitution possibilities in educational inputs, and differential uncertainty faced by parents. The theory predicts a negative impact of teacher shocks on educational achievement. Moreover, the impact of these shocks depends on the uncertainty that students and parents face—greater uncertainty leads to a precautionary response, attenuating the effects of such shocks on learning.

Our data from Zambia are consistent with the theory. Shocks to teacher inputs have a substantial effect on student learning. Shocks associated with an increase in absence of one day a month led to a 10 percent decrease in student gains. This impact is larger for students that stayed with the same teacher, compared to those that changed teachers.

A couple of things to note. Our theory relates household inputs into children’s education to uncertainty in the schooling environment. We would have liked to directly test whether this prediction is correct—do parents of movers spend more time or money with their children than those of non-movers? Unfortunately, our data on household inputs does not allow us to investigate this directly. Although we surveyed households matched to these schools (see Das and others 2004a), these were all rural households and our sample of non-movers is too small to draw any meaningful inferences (recall that most non-movers were in urban areas).

In the absence of a direct test relating precautionary spending to school level uncertainty, we analyzed the robustness of these findings to sampling differences and selection processes between movers and non-movers. As far as we can tell, our estimates are robust to these problems. Both the fact that non-movers come from predominantly urban areas and that there is no correlation between changes in observable teacher characteristics and teacher shocks support the idea that precautionary motives drive the differential impacts across movers and non-movers. Further, restricting the sample to ensure comparability across movers and non-movers does not affect our estimates, or their comparison across these two groups.

Nevertheless, the data do not allow us to explicitly rule out the possibility of a positive correlation between changes in teacher quality and shocks in the current year. What can we say in the presence of such correlations? Our results on the sample of movers is biased towards zero; nevertheless our estimates for non-movers remain consistent and unbiased. For those concerned about selective matching between teachers and students, estimates from the sample of non-movers are preferred in assessing the impact of teacher shocks on learning gains.

This raises a second important issue. These estimates are not the impact of absenteeism per se, but rather, the impact of negative shocks that are proxied by teacher absence. Teacher absenteeism in our sample does not simply relate to teacher discipline and shirking, but in most cases is linked to health problems and attendance of funerals. These negative shocks lead not only to absences, but also to decreased teaching performance in class and this might explain the large effects that we find in the data. In a country deeply affected by HIV/AIDS, this suggests that policies to improve health care provision and combating HIV/AIDS, as well as flexible approaches to provide replacement teaching to cover absences could have substantial benefits for children.

Finally, if we believe that households play an important role in determining educational outcomes of their children, this paper suggests direction for future work. Using a model allowing for household responses to teacher and school inputs allows for richer insights than standard production function approaches. The impact of current year shocks on learning achievement depends on other sources of uncertainty (non time-varying attributes of the teacher in this paper) and this has important implications for future evaluation work.<sup>15</sup> Currently there is little research on the

---

<sup>15</sup>Suppose that an experiment were designed to study the effect of absenteeism on learning achievement. The "treatment on the treated" estimator will represent the average effect, averaged across children who changed and remained with the same teacher. This paper suggests that the external validity of the experiment may be compromised due to this important source of heterogeneity—an empirical implication is to try and capture information on this and other changes that have occurred during the year of the experiment.

link between household and school inputs, and none on the precautionary motive discussed in this paper. Evidence either way would be helpful.

## References

- [1] Angrist, J. and Lavy, V., 2001. "Does Teacher Training Affect Learning? Evidence from Matched Comparisons in Jerusalem Public Schools", *Journal of Labor Economics*, 343-369.
- [2] Chaudhury, N., Hammer, J., Kremer, M., Muralidharan, K. and Rogers, F.H., 2004. "Teacher and Health Care Provider Absenteeism: A Multi-Country Study." World Bank: Washington, DC.
- [3] Das, J., Dercon, S., Habyarimana, J., and Krishnan, P., 2004a. "When Can School Inputs Improve Test Scores" Policy Research Working Paper 3217, World Bank, Washington, D.C.
- [4] Das, J., Dercon, S., Habyarimana, J., and Krishnan, P., 2004b. "Public and Private Funding in Zambian Basic Education: Rules Vs. Discretion". Africa Human Development Working Paper Series #62. Washington D.C.: The World Bank.
- [5] Deaton, A., 1992. *Understanding Consumption*. Oxford: Clarendon Press.
- [6] Ehrenberg, R. G, Ehrenberg R. A, Rees, D and Ehrenberg E, 1991. "School District Leave Policies, Teacher Absenteeism, and Student Achievement" *Journal of Human Resources*, Vol. 26:1, 72-105
- [7] Foster, A., 1995. "Prices, Credit Markets and Child Growth in Low-Income Rural Areas" *The Economic Journal* 105 (430) 551-570.
- [8] Glewwe, P, Kremer M, and Moulin, S, 2001. "Textbooks and Test scores: Evidence from a Prospective Evaluation in Kenya", University of Minnesota, mimeo.
- [9] Hanushek, E., 1986. "The Economics of Schooling: Production and Efficiency in Public Schools", *Journal of Economic Literature* XXIV, 1141-1177.
- [10] Hanushek, E., Kain, J. and Rivkin, S., 1998 "Teachers, schools and academic achievement" NBER Working Paper, Number w6691.
- [11] Jacobson, S., 1989. "The Effects of Pay Incentives on Teacher Absenteeism" *Journal of Human Resources* 243:2, 280-286.
- [12] Park, A and Hannum E, 2002. "Do Teachers Affect Learning in Developing Countries?: Evidence from Student-Teacher data from China", Harvard University, mimeo.
- [13] Rockoff, J., 2004. "The Impact of Teachers on Student Achievement: Evidence from Panel Data", *American Economic Review*, 94(2), 247-252.

- [14] Sandmo, A., 1969, "Capital risk, Consumption and Portfolio Choice", *Econometrica*, 37, 586-599.
- [15] Todd, P and Wolpin K, 2003. "On the Specification and Estimation of the Production Function for Cognitive Achievement", *The Economic Journal* 113 (February), F3-33.
- [16] World Bank,.2003, *Making Services Work for the Poor*, World Development Report 2004, Washington, D.C.: The World Bank.

## 1. Appendix 1: Teacher Absence Measures

We also collected a spot measure of teacher absence by checking attendance on the day of the survey for all teachers in small schools and a non-random sample of 20 teachers in larger schools. Given that this measure is based only on one visit, it is only a prevalence rate and is noisy. For instance, a one visit spot absence of 0.2 does not distinguish between all teachers being absent 20% of the time, or half the teachers being absent 40% of the time. If half of the teachers have an absenteeism incidence of 40% and the other half are always present, to distinguish between the two types of teachers with 95% confidence, we would require at least 6 visits (assuming that absence follows a Bernouli process). We also collected a self-reported absence profile over the last 30 days for teachers matched to pupils. This measure is biased because it is missing for teachers absent on the day. Also, it is plausible that low quality teachers may report absenteeism in different ways than high quality teachers.

The differences between the measures appear to be in line with expectations regarding the bias and noisy entailed in self-reported or spot absenteeism measures. The extent of these differences can be partially assessed by using the sampling differences between the different measures of absenteeism. For instance we can check for a selection effect in the self-reported measure (we don't have a report for those who were absent on the day) by comparing the reports of the head-teacher for the sample who were present on the day of the survey and those who were not. Using the head-teacher's report, teachers who were absent on the day of the survey miss an average of 2.39 days compared to 1.5 days for teachers who were present. This difference is significant at the 5 percent level, also suggesting problems with the spot measure based on those absent at the time of the visit.

We also find evidence of reporting bias in the self-reported measure. To investigate the reporting biases of the self-report, we divide teachers into those who had pupils with high and low learning gains, and examine the correlation between the self-report and the head-teacher report for these two groups. If there are self-reporting biases, the correlation between the two reports should be higher for the teachers with high performing children compared to teachers with low learning gains. The correlation between self-reported and head teacher for the 'good' teachers is 0.39 compared to 0.28 for the 'bad' teachers. Gains in English suggest a similar, albeit weaker result. This pattern is broadly consistent with 'bad' teachers under-reporting duration of absence assuming that the head teacher's report is the true measure.

**Table 1a: Pupil-teacher matching: Teacher Characteristics**

	Same Teacher	New Teachers	Difference significant
Rural	0.19	0.31	Yes
Gender (1=Male)	0.31	0.48	Yes
Experience (1= >= 5 years)	0.61	0.34	Yes
Has teaching certificate	0.97	0.74	Yes

Notes to Table 1a: The data used to construct this table comes surveys of matched teachers present during the survey team visit.



**Table 1b: Pupil-Teacher Matching: Pupil Characteristics**

	Non-movers	Movers	Difference significant
Child lives with parents	0.62	0.64	No
Proportion of mothers completed primary school	0.62	0.53	Yes
Proportion of fathers completed primary school	0.76	0.7	Yes
Proportion living within 15 minutes of school.	0.44	0.45	No
Wealth: Asset Index	0.19	-0.13	Yes
English Test score, 2001	0.07	-0.02	Yes
Math Test score, 2001	0.15	-0.08	Yes

Notes to Table 2: The data used to construct this table comes from pupil surveys conducted by the Examinations Council of Zambia during the re-testing of the pupils.

**Table 2: Teacher Absence by stated reason**

	# episodes	Fraction of HT absence episodes	Mean days absent	Median days absent
Own Illness	106.00	0.35	3.77	2.00
Illness in Family	36.00	0.12	3.67	2.00
Away on Training	13.00	0.04	10.23	5.00
Travel to Town	27.00	0.09	1.74	1.00
Funeral	45.00	0.15	4.67	3.00
Other reasons	46.00	0.15	4.70	2.50
Leave	10.00	0.03	19.00	20.00
Official Work/Workshops	21.00	0.07	4.86	5.00
Not Absent in last month	420.00	-	0.00	0.00
Total	724.00	1.00	1.98	0.00

Notes to Table 2: The data used to construct this table comes from head teacher reports of absence for teachers matched to the pupils that took that ECZ tests in 2001 and 2002. Head teachers were asked to report the primary reason for any absence episode in the 30 days prior to the survey team visit.

**Table 3: Estimated Impact of Teacher Shocks on Learning Gains using Full Sample**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	English, OLS	English, OLS: All Controls, Teacher char	English, OLS: All Controls, All Teacher Sample	English, OLS: All Controls, All Teacher Sample	math, OLS	math, OLS: All Controls, Teacher char	math, OLS: All Controls, All Teacher Sample	math, OLS: All Controls, All Teacher Sample
Non-movers	0.061 [0.062]	0.063 [0.076]	0.082 [0.082]	0.079 [0.083]	0.045 [0.057]	0.062 [0.068]	0.074 [0.073]	0.072 [0.070]
Days Absent Last Month	0.002 [0.005]	0.001 [0.005]	0.006 [0.007]	0.005 [0.006]	0.002 [0.003]	0.004 [0.004]	0.004 [0.005]	0.003 [0.004]
Non-movers * Days Absent Last Month	-0.013 [0.008]	-0.041 [0.022]*	-0.045 [0.021]**	-0.044 [0.021]**	-0.019 [0.011]*	-0.037 [0.019]*	-0.039 [0.019]**	-0.038 [0.019]**
Constant	0.383 [0.028]***	0.523 [0.138]***	0.416 [0.284]	0.507 [0.177]***	0.371 [0.025]***	0.163 [0.136]	0.314 [0.181]*	0.333 [0.143]**
Other Controls Current Teacher Controls Past Teacher Controls		X  X	X  X	X  X		X  X	X  X	X  X
Observations	2214	1947	1254	1254	2214	1947	1254	1254
R-squared	0.00	0.03	0.03	0.03	0.00	0.01	0.01	0.01
F-Test Teachers Matter prob>F		2.85	0.91	1.63		0.33	0.56	1.07
		0.04	0.49	0.18		0.81	0.76	0.36

**Notes for Table 3**

Standard errors in parentheses. Significantly different from zero at 90 (\*); 95 (\*\*); 99 (\*\*\*) percent confidence. Dependent variable defined as change in test scores in English or Maths. Reported coefficients estimated from a regression of changes in test scores on days absent and province dummies. Current and Past Teacher controls include teacher gender, a dummy for 5 or more years of teaching experience and the possession of a teaching certificate. Other controls include funding received in the current year, dummies for location, changes in the head teacher, parents teachers association (PTA) chairperson, private schools and changes in PTA fees. F-test performs the joint test that current and past teacher characteristics are significantly different from zero. Standard errors are clustered at the teacher level. The full sample of pupils that took both tests is used in these estimations.

**Table 4: Estimated Impact of Teacher Shocks on Learning Gains using Matched Sample**

	(1) English_ps, OLS: All Controls, Teacher char	(2) English_ps, OLS: All Controls, All Teacher Sample	(3) Math_ps, OLS: All Controls, Teacher char	(4) Math_ps, OLS: All Controls, All Teacher Sample
Non-movers	0.007 [0.078]	0.015 [0.086]	0.023 [0.069]	0.025 [0.074]
Days Absent Last Month	0.002 [0.006]	0.008 [0.008]	0.003 [0.005]	0.005 [0.005]
Non-Movers* Days Absent in Last Month	-0.039 [0.021]*	-0.044 [0.022]**	-0.026 [0.018]	-0.030 [0.019]
Constant	0.531 [0.139]***	0.477 [0.278]*	0.205 [0.149]	0.309 [0.242]
Other Controls	X	X	X	X
Current Teacher Controls		X	X	X
Past Teacher Controls			X	
Observations	1506	980	1506	980
R-squared	0.02	0.02	0.01	0.01
F-Test Teachers Matter	1.85	0.82	0.47	0.60
prob>F	0.14	0.55	0.70	0.73

Notes for Table 4

Standard errors in parentheses. Significantly different from zero at 90 (\*); 95 (\*\*); 99 (\*\*\*) percent confidence. Dependent variable defined as change in test scores in English or Maths. Reported coefficients estimated from a regression of changes in test scores on days absent and province dummies. Current and Past Teacher controls include teacher gender, a dummy for 5 or more years of teaching experience and the possession of a teaching certificate. Other controls include funding received in the current year, dummies for location, changes in the head teacher, parents teachers association (PTA) chairperson, private schools and changes in PTA fees. F-test performs the joint test that current and past teacher characteristics are significantly different from zero. Standard errors are clustered at the teacher level. The sample of non-movers and matched movers that took both tests is used in these estimations. Matching is done using a propensity score estimated using child and school characteristics.