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Smarter Teachers, Smarter Pupils?
Some New Evidence from Sub-Saharan Africa[*]

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Abstract

We study the effect of teacher subject knowledge on student achievement in mathematics and reading by using a dataset from six Sub-Saharan African countries. By using a difference-in-difference between pupils' and teachers' scores in two skills, we are able to avoid potential endogeneity bias. In most estimations, we do not find a significant teacher knowledge effect in most countries. The main reason is teacher absenteeism and the need to focus on core knowledge. Indeed, more knowledgeable teachers improve student learning only if certain conditions are met. For instance, a high level of teacher absenteeism and low teacher performance in a subset of items that are also administered to students can dampen the teacher subject knowledge effect on student learning. When these conditions are met, teacher subject knowledge has a significant and positive effect on student achievement in most countries.

Key words: Teacher knowledge; Africa; Learning; SACMEQ; cognitive skills

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1. Introduction

The role of teachers in promoting student learning is beyond doubt. Among different aspects of teacher quality, teacher skills, as measured by their scores in subjects and by pedagogical knowledge tests or observations of teaching practices, are one of the observable if not commonly available factors significantly correlated with learning achievement (Hanushek & Rivkin, 2010; Wayne & Youngs, 2003). Several studies have focused on developing countries but most of them suffer from biases due to omitted student and teacher characteristics.[1] One exception is Metzler and Woessmann (2012) who used a unique dataset from Peru and tested both students and their teachers. Based on the methodology provided in Dee (2005), they found that one standard deviation (SD) in subject-specific teacher scores increased student achievement by about 0.09 SD in mathematics.

Relatively few papers have focused on Sub-Saharan Africa. They have mostly relied on the data from the Southern and Eastern Africa Consortium for the Monitoring of Education Quality (SACMEQ), a survey on reading and mathematics learning achievement which was administered to grade 6 students in 15 countries in three waves: 1995, 2000, and 2007.[2] The survey also administers a teacher knowledge test on these two subjects. Bonnet (2008) combined both teachers' knowledge and their behaviour using SACMEQ II data.[3] However, Bonnet (2008) explores the relationship by controlling only two variables, which may lead to biased estimates. Wechtler, Michaelowa and Fehrler (2007) provide results on the cost-

[1] For example, Harbison and Hanushek (1992) on Brazil; Tan et al. (1997) on the Philippines; Bedi and Marshall (2002) on Honduras; Santibañez (2006) on Mexico; Behrman et al. (2008) on Pakistan; Marshall (2009) on Guatemala; and Metzler and Woessmann (2012) on Peru. For recent review of literature on the education production function in developing countries, see Behrman (2010), Gleewe et al. (2011), and Murname & Ganimian (2014).

[2] Countries included in SACMEQ are Botswana, Kenya, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Swaziland, Tanzania, Zanzibar, Uganda, Zambia and Zimbabwe.

[3] SACMEQ is an assessment which includes 15 Sub-Saharan African countries. Mostly of them are anglophone countries.

effectiveness of inputs in primary education by using data from PASEC[4] and SACMEQ. These authors combine several factors at three different levels (pupil, school and country) and provide results for all the SACMEQ countries. Although they allow specific constants for each country, the estimation model used assumed that the effects of each variable are the same across countries and they do not include the teacher score variable in their estimation, replacing this variable by teacher academic qualification. Hungi and Thuku (2010a) used a hierarchical regression model on the data of the 2000 round to assess the impact of a large number of factors on student achievement, including teacher subject knowledge. They found that the teacher reading score had an effect on pupil reading achievement in only 2 of the 12 countries analysed. However, they did not correct their specification for selection bias or measurement error (Hungi & Thuku, 2010b). Shepherd (2013) examined teacher subject knowledge in South Africa using the 2007 wave and found that teacher knowledge improves student achievement in the wealthiest quintile of schools. Hein and Allen (2013) use a pupil-fixed effects estimation technique and find that most observable characteristics are weak predictors. Teacher subject competency test scores are only significant in the Seychelles. Bold et al. (2017) estimated the teacher subject knowledge effect in sub-Saharan Africa, using the World Bank-funded Service Delivery Indicators surveys. These surveys were administered to grade 4 students in seven countries. The authors found a significant effect for mathematics but not for reading. However, their analysis supposed that the teacher subject knowledge effect was the same across countries. Indeed, no specific estimation was done for each country, on the assumption that the teacher knowledge effect would be identical across Sub-Saharan African countries.

This paper investigates the effect of teacher subject knowledge on student achievement using the 2007 wave of SACMEQ data in order to make two contributions. Firstly, we allow

[4] PASEC is a pupil assessment conducted by the CONFEMEN. It is mainly conducted for francophone countries.

the teacher subject knowledge effect to differ across countries given the large differences in education systems and the distribution of teacher knowledge. Figure 1 shows, for example, that teacher mathematics and reading knowledge scores vary much more in Malawi and Swaziland than in South Africa or Zambia. In particular, the skewness and kurtosis[5] of teacher maths scores in Malawi are close to a normal distribution (skewness = 0.086; kurtosis = 2.823). On the contrary, the statistics for South Africa indicate a different distribution to, suggesting that teacher performance is positively skewed, and results which are more concentrated in the right part of the distribution. For these reasons, we prefer to estimate the effect of teacher knowledge by distinguishing between countries, instead of focusing on the pool of countries.

Secondly, we focus attention on additional initial conditions which may temper the effect of teacher knowledge on pupil performance. Everyone may agree with the fact that teacher quality matters. However, in specific conditions, the knowledge of teachers may not be sufficiently mediated towards pupils. We suppose that two main initial conditions may be verified to obtain the true effect of teacher knowledge. For instance, teachers may not have the basic skills taught to their pupils. On this way, a subset of common items that were administered to both students and teachers, which could be more closely related to the ability of teachers to transfer their knowledge. When the analysis is restricted to students who are taught by teachers with a high score in these items, the effect on student achievement is strongly positive in five out of six countries included in the final sample for reading. Another factor is related to teacher absenteeism which may be very high in some countries. When we distinguish between schools with low and high absenteeism, a positive and significant relationship reappears in three countries for reading, while we find contradictory results for

[5] Skewness shows to what extent a distribution is positively or negatively skewed. Kurtosis indicates if there is a big clump of cases concentrated in one part of the distribution. The values of skewness and kurtosis for a normal distribution are respectively 0 and 3.

the sample of teachers with high absenteeism. These two initials conditions may explain why previous papers find only weak effects of teacher knowledge in the case of low-income countries.

The results of this analysis respond to key questions for policy makers, especially in poorer countries, which are related to teacher recruitment criteria, teacher allocation decisions, and the content of teacher education. To the extent that teacher subject knowledge is a significant predictor of learning outcomes, then this is a factor that needs to be taken into account in all these policy decisions. The effect of teacher subject knowledge on student learning outcomes differs greatly between countries. But what does this effect mean in countries where it is positive and statistically significant? Compared to previous research, these are sizeable effects. For instance, Metzler and Woessmann (2012) found that the effect on reading scores was 0.085 standard deviations in Peru. These estimated effects of teacher subject knowledge are also higher relative to estimates from school systems in high-income countries. According to Rockoff (2004), a one standard deviation increase in teacher knowledge raised student reading and mathematics scores by approximately 0.10 standard deviations in the United States. We find a significantly higher effect for teacher knowledge in SACMEQ countries when we control for the two initial conditions highlighted above. For instance, we find that an increase in teacher reading scores by one standard deviation raises student reading test scores by 0.19 of a standard deviation in South Africa for the subsample of teachers who perform well in basic skills items.

The remainder of the paper is structured as follows. Section 2 presents the estimation strategy. Section 3 describes the data. Section 4 presents the main results and provides evidence on heterogeneous effects. Section 5 reports results from robustness checks and section 6 concludes.

2. Methodology

We consider an education production function with an explicit focus on teacher skills. As in Metzler and Woessmann (2012), we specify the following correlated random effects model:

(1a) $$y_{i1} = \beta_1 T_{t1} + \gamma U_{t1} + \alpha Z_i + \delta X_{i1} + \mu_i + \tau_{t1} + \varepsilon_{i1}$$

(1b) $$y_{i2} = \beta_2 T_{t2} + \gamma U_{t2} + \alpha Z_i + \delta X_{i2} + \mu_i + \tau_{t2} + \varepsilon_{i2}$$

where y_{ij} are test scores of student i in subjects j ($j = 1$ for mathematics, 2 for reading). Teachers t are characterized by subject-specific knowledge T_{tj} and non-subject-specific characteristics U_{tj} such as pedagogical skills and general motivation. The latter can differ across the two equations when students are taught by different teachers in each subject. Additional factors are non-subject-specific (Z_i) and subject-specific (X_{ij}) characteristics of students and schools.

Three issues are important for modelling the relationship. First, there is potential endogeneity bias when unobserved teacher characteristics may be correlated with teacher subject knowledge. Second, the available measure of teacher skills can potentially be stripped down further to a subject-specific and a core-skills component. Third, even after this refinement, an error in the measurement of subject-specific teacher knowledge can also bias the estimate of its effect. The coefficient vectors β_1, β_2 and γ characterize the impact of all subject-specific and non-subject-specific teacher characteristics that represent the overall teacher quality as estimated by value-added studies (Hanushek & Rivkin, 2010). However, endogeneity bias is likely to hamper identification of the effect of teacher quality in equations (1a) and (1b). Indeed, the error term consists of a student-specific component μ_i, a teacher-specific component τ_t, and a subject-specific component ε_{ij}. The unobserved student effect μ_i is correlated with the observed inputs such as $\mu_i = \eta_1 \mathrm{T}_{t1} + \eta_2 \mathrm{T}_{t2} + \theta_1 \mathrm{U}_{t1} + \theta_2 \mathrm{U}_{t2} + \chi \mathrm{Z}_i + \Phi \mathrm{X}_{i1} + \Phi \mathrm{X}_{i2} + \omega_i$ where ω_i is the white noise (Chamberlain, 1982). After grouping terms, the model becomes

(2a) $$y_{i1} = (\beta_1 + \eta_1)\mathrm{T}_{\mathrm{t1}} + \eta_2\mathrm{T}_{\mathrm{t2}} + (\gamma + \theta_1)\mathrm{U}_{\mathrm{t1}} + \theta_2\mathrm{U}_{\mathrm{t2}} + (\alpha + \chi)\mathrm{Z}_{\mathrm{i}} + (\delta + \Phi)\mathrm{X}_{\mathrm{i1}} + \Phi\mathrm{X}_{\mathrm{i2}} + \tau_{t1} + \varepsilon'_{i1}$$

(2b) $$y_{i2} = \eta_1\mathrm{T}_{\mathrm{t1}} + (\beta_2 + \eta_2)\mathrm{T}_{\mathrm{t2}} + \theta_1\mathrm{U}_{\mathrm{t1}} + (\gamma + \theta_2)\mathrm{U}_{\mathrm{t2}} + +(\alpha + \chi)\mathrm{Z}_{\mathrm{i}} + \Phi\mathrm{X}_{\mathrm{i1}} + (\delta + \Phi)\mathrm{X}_{\mathrm{i2}} + \tau_{t2} + \varepsilon'_{i2}$$

where $\varepsilon'_{ij} = \varepsilon_{ij} + \omega_{\mathrm{i}}$ is the new error term. Estimations can be performed by seemingly unrelated regressions (SUR), adjusted for clustering at school level. The effect of teacher subject knowledge on student achievement in mathematics (β_1) is given by the difference between the coefficient associated with the teacher's mathematics test score in equation (2a) and that in equation (2b). The effect of teacher subject knowledge in reading (β_2) is computed similarly.

In this model, teacher scores in each subject enter the reduced-form equation of both subjects. The β parameters represent the effect of teacher subject knowledge, while the η coefficients capture the extent to which standard models would be biased due to the omission of unobserved teacher factors.

Available fixed-effects estimators implicitly require that teacher effects are the same across subjects. Instead of imposing this kind of restriction a priori, it is possible to test for the overidentification restrictions $\beta_1 = \beta_2 = \beta$ and to test whether $\eta_1 = \eta_2 = \eta$. If these overidentification restrictions cannot be rejected, it is possible to specify correlated random effects models that constrain the β coefficients, or both of them (i.e. β and η) to be the same across subjects in equations (2a) and (2b).

If in a correlated random effects model, both of these restrictions are valid, the estimation becomes similar to a conventional fixed-effects models, and hence it eliminates bias from unobserved non-subject-specific student characteristics (Clotfelter, Ladd, & Vigdor, 2010; Dee, 2005, 2007; Metzler & Woessmann, 2012). It should be noted however that, for the identification strategy of β and γ in equations (2a) and (2b), it has to be assumed that either there is no specific assignment of students to teachers, or there is no correlation between the assignment and students' subject-specific propensity for achievement. Such assignments are generally considered to be unlikely in the case of the countries analysed in this paper.

In order to avoid the bias that can arise when there is a specific assignment of teachers to students on the basis of student subject-specific propensity for achievement, we restrict the analysis to the sample of students who are taught by the same teacher in the two subjects (called 'same teacher' sample). In such a setting, $\mathrm{U}_{t1} = \mathrm{U}_{t2} = \mathrm{U}_{\mathrm{t}}$ and $\tau_{t1} = \tau_{t2} = \tau_t$.

3. Data

The SACMEQ survey is suitable for this identification strategy, as it evaluates both student and teacher skills in two subjects, reading and mathematics. The SACMEQ 2007 round was collected using a stratified two-stage cluster sample design. At the first stage, schools were selected within provinces with probability proportional to the number of students in the defined target population. At the second stage, a sample of 25 grade 6 students was randomly selected in each school. In addition, the mathematics and reading grade 6 teachers of the three largest classes in each school were tested.

The student and teacher tests used different sets of items but had some common items (20 and 13 items for reading and mathematics respectively) in order to anchor the results. Student and teacher tests in both subjects were scaled using Rasch modelling. All student test scores were placed on a common scale with mean 500 and standard deviation 100 across students.[6]

From the full sample, three groups of students were excluded: those who could not be linked to a teacher (4,772 students), those who had at least one teacher with missing test scores (4,055 students), and those with missing test scores (83 students). As mentioned above,

[6] Teacher scores are not scaled with a specific mean. However, we found that the overall mean score in reading is equal to approximately 750 with a standard deviation of 70, while for maths, we find higher values (mean 790 and standard deviation 105).

the identification strategy requires that the same teacher teaches both subjects. The proportion of students who are taught both subjects by the same teacher in grade 6 varies greatly between SACMEQ countries (Table A.1). For this reason, the analysis only focuses on six countries with a sufficient number of observations: Botswana, Malawi, South Africa, Swaziland, Zambia, and Zimbabwe. The percentage of students with the same teacher in the two subjects ranges from 17% in Swaziland to 92% in Zimbabwe. The total sample of pupils taught by the same teacher includes 11,999 pupils (46% of the full sample).

Descriptive statistics are provided in Tables A.1 and A.2. Among countries included in the study, the highest performing country is Swaziland in both reading and mathematics, followed by Botswana. The lowest performing country in our sample is Malawi with about 100 score points less than Swaziland. Although scores between teachers and pupils are not directly comparable, a sample of similar items have been included in both tests. As expected, teachers perform higher than pupils. The highest performing teachers are in Zimbabwe with approximately 800 score points in reading and 850 in maths. In all countries, approximately half the pupils are girls, and a very low proportion of pupils speak English at home (Table A.2). A socio-economic status index serves to compare the inequalities between and among countries (Dolata, 2005). The poorest country in our sample appears to be Malawi with a SES index lower than 5. Conversely, the SES index for South Africa is almost 10, indicating a better socio-economic level of pupils enrolled in this country. This difference is also highlighted by a higher proportion of pupils with parents with university level in South Africa, compared to other countries like Zambia. While the proportion of pupils with a mother with a university level is equal to 24% in South Africa, less than 5% of pupils in Malawi are in the same position. Some countries are more urban than others. This is especially the case of South Africa where approximately 72% of pupils live in urban areas, compared to 40% of pupils who live in Malawi. Teacher characteristics are very different between countries.

While most teachers are female in Swaziland (70%), the exact opposite is true in Malawi where approximately three quarters of teachers are male. The group of teachers with university education and teacher training constitute the majority of teachers in South Africa and Swaziland, whereas a very low proportion of such teachers are present in Malawi and Zambia.

All results provided above support the idea that we should not group all countries into a single group for the estimation of the teacher knowledge effect on pupil performance. We provide the results of both the full sample and individual country samples in order to see to what extent results differ between countries.

Since our estimation strategy is more focused on pupils who are taught by the same teacher, we must accept the hypothesis that the subsample constituted by the group is representative of the whole population. As can be seen in Table A.1., teacher performances between the full sample and the same teacher sample do not significantly differ. Similarly, pupil performances across countries are quite similar between the two samples. Another important point is the degree of reliability of teacher scores. While the reliability ratio is expected to be equal to 0.80 in order to obtain a good estimation of teacher subject knowledge, we found that Cronbach's alpha (i.e. a proxy for the reliability ratio) is lower than 0.5 in most countries (Cronbach, 1951). In countries like Swaziland, the teacher scores are only explained at 33%, which is a very low level. A good estimation of teacher scores should be at least at 70%, which is never the case for the countries included in our study. This low level of Cronbach's alpha raises the question of the reliability of teacher scores. This may explain why results are sometimes counterintuitive.

4. Results

4.1. Baseline results

The regression results are presented in Tables 1-3. Table 1 presents ordinary least squares regression results with several controls to test for the stability of coefficients and potential omitted variables bias. Table 2 presents the results of the correlated random effects model. Table 3 reports the most interesting results where we address the issues of teacher knowledge transferability and teacher absenteeism. To facilitate the reading of results, only coefficients concerning the teacher knowledge variable are presented. Moreover, both student and teacher test scores are standardized with a mean of 0 and a standard deviation of 1 across countries. Throughout our analysis, standard errors are clustered at the school level to account for possible correlations in the error structure within schools.

Table 1 begins by reporting the result of regressing student learning achievement on teacher knowledge without any control variables (columns 1 and 2). Significant and positive effects are found for only two countries in mathematics and in reading. Indeed, the teacher knowledge effect is positive and significant in both subjects for only two countries (Botswana and South Africa). Meanwhile, the size of the effect is quite high. For instance, an increase of one standard deviation of teacher knowledge induces an increase of about 0.40 standard deviations in South Africa in both subjects. When all countries are pooled, there is a positive and significant effect in both subjects equal to 0.16 standard deviations. Results are quite similar, regardless of the skill tested.

The next set of regressions, which adds controls for student, teacher and school variables, reduces the size of the correlations (columns 3 and 4). There is a significant and positive teacher subject knowledge effect in both skills only in South Africa, while the effect becomes significant only for reading in Swaziland. Compared to the baseline results, the size of the teacher subject knowledge effect is either reduced and/or no longer significant. For instance, in South Africa, the teacher subject knowledge effect for mathematics is equal to 0.10

standard deviations in mathematics and 0.07 standard deviations in reading when all controls are introduced. When all countries are pooled, the size of the effect drops by two thirds to approximately 0.05 standard deviations but remains positive and significant. Controlling for omitted variable bias is hence important for reducing the potential bias regarding the amplitude of the effect of teacher knowledge on pupil achievement.

In the meantime, omitted teacher characteristics such as pedagogical skills and motivation, included in the teacher-specific error component τ_t, could bias estimates of the observed teacher attributes. To avoid such bias, the analysis is then restricted to samples of students who were taught by the same teacher in the two subjects (columns 5-8). When we both use the same-teacher sample and include controls, the effect of teacher subject knowledge is 0.04 standard deviations for both skills. At the individual country level, while the teacher subject knowledge is only significant in one country for mathematics (South Africa), we now find a significant effect in three countries in reading, out of the six included in the study. Taken as a whole, the SACMEQ sample shows that there is still a significant effect of teacher knowledge on pupil performance. The amplitude of the effect is quite close to that found in the literature, i.e. 0.04 SD.

Table 2 presents the results of the correlated random effects models of equations (2a) and (2b). The effect of teacher subject knowledge on student achievement in mathematics (implied β_1) is given by the difference between the regression coefficient on the teachers' mathematics test score in the mathematics equation minus the regression coefficient on the teachers' mathematics test score in the reading subject (see equations (2a) and (2b)), and vice versa for reading (implied β_2). Regressions include controls for student gender, student speaking English at home, urban area, private school, teacher gender and teacher university degree, factors which have been found to be the most powerful predictors in a simple OLS regression.

When both the same teacher sample and the correlated random effects model are used (columns 1 and 2), the teacher subject knowledge effect is no longer significant when all countries are pooled for mathematics, while we find a (positive) and significant effect for reading, but with a very low amplitude (i.e. 0.2 standard deviations). At the individual country level, results are insignificant for all countries in mathematics and only significant for Malawi in reading with a high positive effect (i.e. 0.13 standard deviations). Restrictions on η's and β's are then conducted in columns 3 to 5, but results are almost similar to the unrestricted estimations.

The above results might guide us to think that teacher knowledge does not matter in Sub-Saharan African countries. We believe that these results are biased because we do not control for specific unmeasured teacher characteristics, which may reduce the overall teacher knowledge effect on pupil achievement. Even if we restrict our sample to the same-teacher sample, unobserved teacher characteristics may still not be sufficiently captured in our estimations and thus may distort the size and the significance of our estimated coefficients. For instance, in almost all studies, it is assumed that teachers with a high level of subject knowledge are able to transfer it to students, while those with a low level of subject knowledge cannot do so. However, the ability to transfer knowledge is often neglected because it is difficult to measure. Two approaches can be examined. First, it is possible to focus on teacher absenteeism. Bold et al. (2017) analysed data from five countries of Sub-Saharan Africa (Kenya, Uganda, Nigeria, Mozambique, and Togo) based on an unannounced visit to schools and classroom observations. Only 72% of teachers were found in the classroom they were supposed to be in. Moreover, they found that the actual teaching time was only 3.25 hours per day on average, despite a scheduled duration of 5.2 hours.

The first part of Table 3 reports results for the sub-samples of schools with high and low absenteeism (according to the teacher measure). Teachers were asked how many days they were absent during the current school year due to specific reasons. We added answers to all possible reasons in order to obtain the total number of days where teachers were absent.[7] Then we divided the sample into two parts by using the third quintile of the number of days of absenteeism inside each country. The group of teachers with high absenteeism is defined as the teachers who were more absent than this threshold (the threshold can be found in Table A.2). Teacher absenteeism is approximately equal to 10 days in most countries. However, big differences still exist. In particular, South Africa appears to be the country with the highest teacher absenteeism with 19 days, while absenteeism is the lowest in Zambia with about 6 days. As a comparison, Chaudhury et al. (2006) present results which cover several continents including Africa, where the average teacher absence rate is equal to 19 percent. Bruns and Luque (2014), based on data from a large sample of classrooms in Latin American and Caribbean countries, find that teachers only spend between 52 and 85 percent of class time on academic activities. In India, Kremer et al. (2013) find similar results and even fewer teachers who are actually engaged in teaching activities. All these findings support the idea that teacher absenteeism may be an important factor explaining why we fail to find a significant effect for teacher knowledge.

Results from Table 3 show that when teacher absenteeism is high, there is a negative and significant teacher subject knowledge effect in mathematics in Botswana (reading), South Africa (mathematics) and Swaziland (both skills). Conversely, in schools where teacher absenteeism is low or absent, a positive and significant teacher subject knowledge effect is present in mathematics (South Africa) and in reading (Malawi and South Africa). The case of

[7] This question (number 21 of the teacher questionnaire) is formulated as follows: "How many days were you absent during this school year due to the following reasons? (Please write the numbers in the box for each country. Please write 'O' for a particular category if you were not absent for this reason.)". Possible reasons: 21.01. "My own illness". 21.02. "My own injury". 21.03. "Family member's illness". 21.04. "Family member's injury". 21.05. "Funerals (family, colleagues, friends)". 21.06. "Medical appointment(s)". 21.07. "Bad weather / road not accessible". 21.08. "Official business (for example: meeting, examination, course)". 21.09. "Maternity leave". 21.10. "Security reasons (riots, civil disturbance, etc.)". 21.11. "Teachers' strikes". 21.12. "Other reasons".

South Africa is very interesting, since the sign of the effect is opposite when we divide the sample between low and high absenteeism teacher groups: this may explain why when we estimate the teacher knowledge effect over the whole same-teacher sample, the overall effect will be biased downward and thus provide wrong results. At the same time the correction made for teacher absenteeism is not perfect in our estimation since it is based on direct information provided from the teachers themselves.

As a second approach, we used the fact that the teacher subject knowledge test included a subset of questions that were also administered to students. It is therefore possible to consider the proportion of common items answered correctly by both teachers and students as a measure of teacher subject knowledge that is more relevant to students. The hypothesis is that if teachers were able to answer most of these common items correctly, then this particular kind of knowledge would be more likely to have a positive effect on student performance in that subject. Taylor and Taylor (2013) differentiate between three patterns of teacher knowledge. First, there are items in the teacher test in which both teachers and their students achieve good scores. Teachers may well be transferring knowledge in these knowledge areas. Additionally, knowledge impedance and complex impedance rely on cases where teachers think that it is difficult to transmit knowledge. All these factors may be important in understanding why smarter teachers do not always increase pupil test scores. However, due to the difficulty of measuring all these three dimensions, we focus on knowledge transmission difficulties, which we call ‘knowledge transferability’. In almost all studies, it is assumed that teachers with a high level of subject knowledge manage to transfer it to students, while those with a low level of subject knowledge cannot do so. However, despite its importance, the transfer of knowledge is often neglected because it is almost impossible to evaluate in assessments. Only a subset of the teacher knowledge questions are identical to the student knowledge questions. It remains possible to compare the proportion of common items answered correctly by both teachers and students as a measure of teacher subject knowledge that is more relevant to the needs of the student.

Part II of Table 3 reports results for the 20% of teachers who scored either lowest or highest in these common items and compares them with the other teachers. As with previous results, teacher subject knowledge is found to be more significant and positive for reading than for mathematics. For the full sample of students, we find a significant and positive teacher knowledge effect for both skills. The amplitude of the effect is dramatically reduced from 0.17 SD in a standard OLS estimation to 0.03 in our preferred estimation. This suggests that the true teacher knowledge effect can only be found if one includes controls, uses a precise estimation technique and focuses on specific skills which are more suited to transferability of skills from teachers to students. If we now focus on individual countries, results clearly show that focusing on the subsample of teachers performing the best on 'core skills' shows the true effect of teacher knowledge on pupil achievement. While the teacher reading knowledge effect is significant in the top-performing teachers in four countries among the six studied, it is significant in only one country for the sample of low-performing teachers. For mathematics, the effect is significant in two countries for the top-performing teacher group, while there is no country where it has an effect for the lowest performing teacher group. For instance, in South Africa, the effect of teacher subject knowledge in both subjects is significantly positive only among the top-performing group of teachers, while it is insignificant for the low-performing teacher group. In countries like Zambia or Zimbabwe, teacher subject knowledge has a higher effect in the top-performing teacher sample.

4.2. Robustness check

We run a robustness check in order to see to what extent our previous results are stable. First, we suppose that heterogeneity issues may exist within each country, leading to contradictory results for the teacher knowledge effect. Second, we restrict the sample to pupils who are taught by the same teacher and in schools where there is only one classroom for grade 6 pupils, called the 'same teacher one classroom' (STOC) sample. This restriction serves to avoid potential endogeneity issues. We do not find a clear heterogeneity issue in the countries studied. Moreover, results for the STOC population are somewhat similar to the previous results presented in Table 3.

A potential reason for the absence of a positive and significant teacher subject knowledge effect is the existence of heterogeneous effects across the population. Table A.5. reports results for three such subsamples (by student gender, teacher gender and school socio-economic index) to test for heterogeneity. Results of tests for differences between subsamples are shown in the Table A.5. Looking first at results from the pooled sample, in the case of mathematics the teacher subject knowledge effect is significant and positive only in the subpopulation of students taught by female teachers – and is low at 0.02 standard deviations. In the case of reading, the effect is positive and significant – and of a comparable order of magnitude – for the subpopulations of male students, students taught by male teachers, and students in schools with a low average socio-economic index.

Looking at the results by country, there is no clear pattern of teacher subject knowledge effects across specific subsamples. Interestingly, the effect of teacher knowledge is significant in the female student group in two countries (Malawi and South Africa), while there is no clear difference in other countries, with the exception of Zambia where the effect is significant for the male group only in reading. In the case of teacher gender, there is a strong and positive effect of being taught by a female teacher in South Africa and Zambia. However, the effect is somewhat misleading, suggesting that teacher gender does not have a specific effect on pupil knowledge in the countries studied. Finally, with respect to the socio-economic level of schools, the teacher subject knowledge effect is positive and significant for mathematics in the wealthiest schools in South Africa but not significant in the poorest schools, a finding that echoes those of Shepherd (2013). Similar results can be found for Malawi and Zimbabwe. Meanwhile, no clear pattern emerges from the estimations, suggesting the absence of a general heterogeneity issue in our estimations.

As highlighted in section 2, the estimation of the effect of teacher subject knowledge on student learning can be biased when an ordinary least squares regression estimation is used. For example, it is possible that when there is more than one class per grade in a school, the best students are assigned to the class with the best teacher. Although this is highly unlikely to be the case in low developing countries, we perform some additional robustness checks. One way to control for such a bias is to restrict the sample to schools that have only one classroom per grade, which we can call the 'same teacher one classroom' (STOC) sample with reference to Metzler and Woessmann (2012). This restriction eliminates any bias from sorting between classes within the grade of a school. Moreover, since most schools with one classroom are located in rural regions, the restricted sample additionally eliminates any possible issue of non-random selection of schools by parents. This sample restriction also rules out a bias from prior differences in student achievement, as students cannot be allocated on grounds of within-student performance differences between the subjects to appropriate teachers.

One drawback of using the 'same teacher one classroom' sample is that results cannot be generalized. Indeed, the sample size drops dramatically for some countries, such as South Africa where it covers only 7% of the total population. Moreover, such estimation can be done for only four of the six countries. Results are presented in Table A.6. There are no strong differences between the results of the 'same teacher' sample (Table 2) and the 'same teacher one classroom' sample (Table A.6), although the magnitude of the effect is reduced. Results for reading are more robust and significant for Malawi and Swaziland (restricted model). While the teacher subject knowledge effect was equal to 0.02 standard deviations for the SACMEQ group in the 'same teacher' sample, it is increased to 0.04 standard deviations in the 'same teacher one classroom' sample, indicating a small upward bias due to measurement error.

5. Concluding remarks

The effect of teacher subject knowledge on student learning outcomes differs greatly between countries. The effect is sizeable and higher than in existing studies, even in high-income countries, when accounting for measurement error in teacher test scores and focusing on specific groups of teachers. This paper focused on the effect of teacher subject knowledge on student learning outcomes in six Southern and Eastern African countries which took part in a regional student learning achievement survey in 2007. The estimation focused on students who were taught by the same teacher in two subjects, reading and mathematics, in order to control for bias estimation. Initial estimates controlling for unobserved student characteristics, omitted school and teacher variables, found positive and significant effects for some though not all countries, suggesting that our results may be still biased due to specific factors.

Two main reasons were proposed to help explain these findings. First, a high level of teacher absenteeism can weaken the linkage between teacher knowledge and student learning scores. This is especially the case for countries like South Africa, where teacher absenteeism concerns about one-fifth of pupils. This might explain that, even if teachers have a high skill level, the high prevalence of absenteeism can distort the expected positive effect of teacher knowledge on pupil performance. Taken to the extreme, it may also lead to a negative and significant effect when, all things being equal, the highest performing teachers are more frequently absent than other teachers in a given country. South Africa is probably the country where teacher absenteeism reduces the expected positive effect of teacher knowledge on schooling quality the most.

Moreover, even if teachers score well in subject knowledge tests, they may lack pedagogical skills in order to transfer their knowledge to pupils. We then focused on items that were common in teacher and student questionnaires and divided the sample according to the level of performance of teachers in these common items. We show that in the sample of teachers who perform the best on these common items, the teacher subject knowledge effect is strong and significant for most countries while the effect is either null or not significant in the sample of teachers who do not perform well in common skills.

Compared to previous research, these are sizeable effects. For instance, Metzler and Woessmann (2012) found that the effect on reading scores was 0.085 SD in Peru. Our estimates are also higher than existing results for school systems in high-income countries. According to Rockoff (2004), a one SD increase in teacher knowledge raises student reading and mathematics scores by approximately 0.10 SD in the United States.

The results indicate that teacher knowledge is thus a significant predictor of learning outcomes, suggesting that it should be accounted for in policy decisions related to teacher recruitment criteria, teacher allocation decisions, and the content of teacher education.

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Figure 1. Kernel distributions of teacher performance for SACMEQ countries

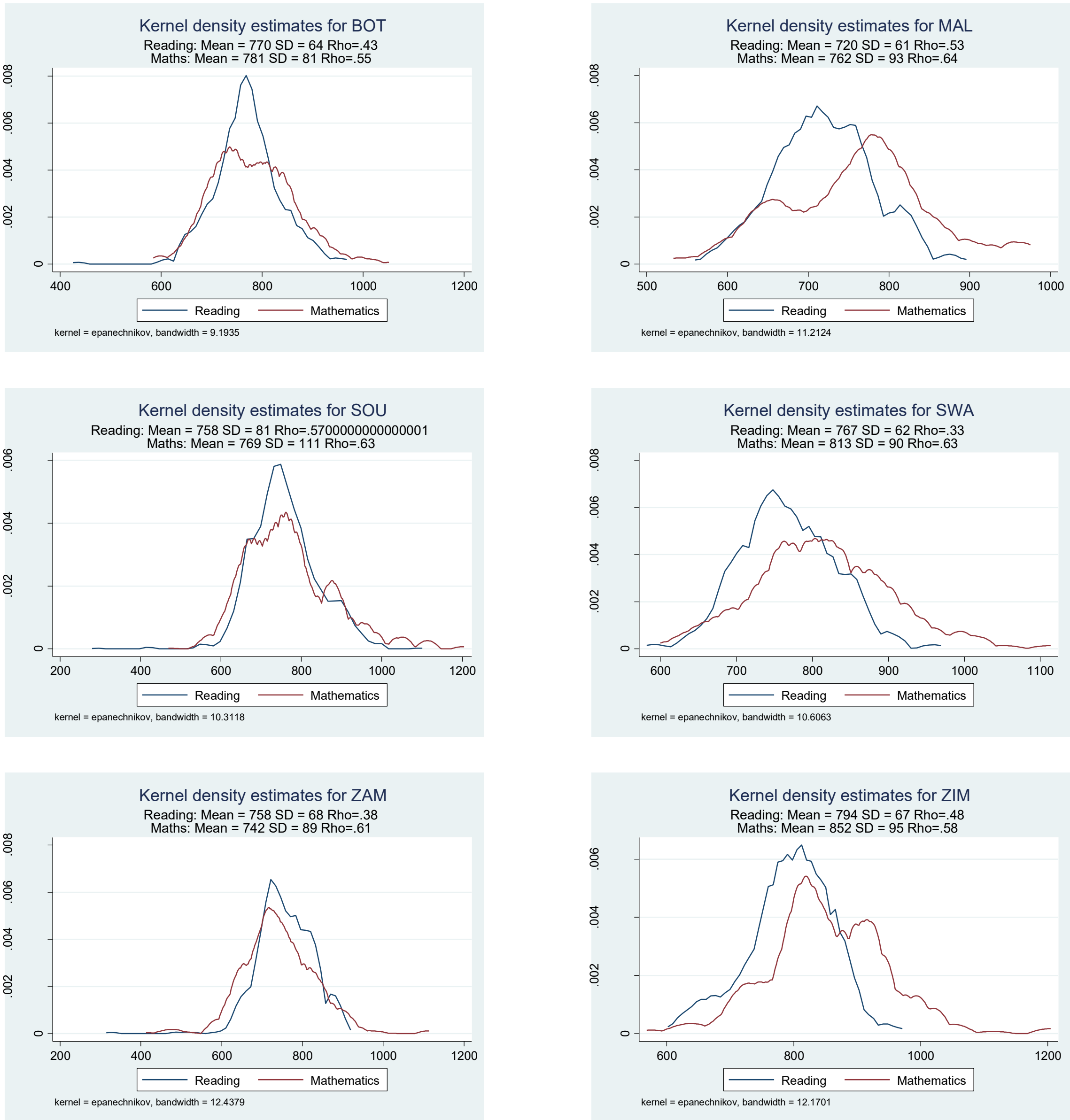

Figure 2. Relationship between teacher and pupil knowledge

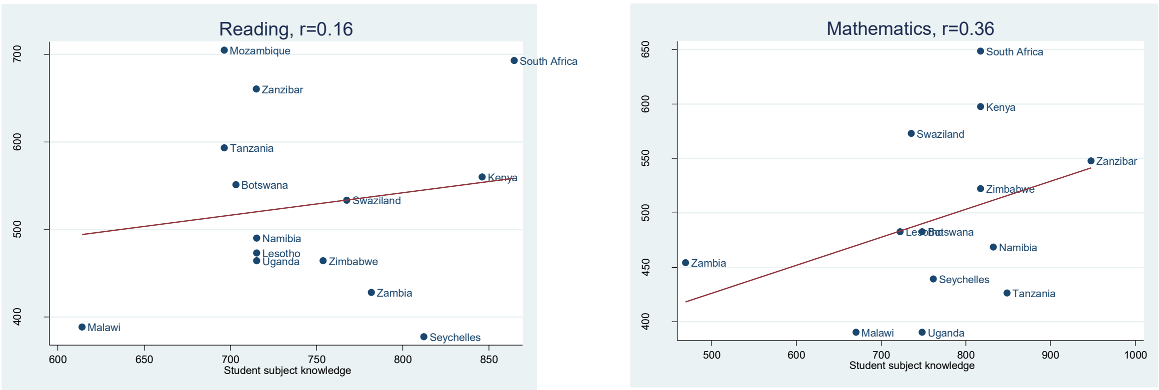

Table 1. Baseline results – cross-sectional regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				Same teacher sample			
	OLS		SUR		OLS		SUR	
	Mathematics	Reading	Mathematics	Reading	Mathematics	Reading	Mathematics	Reading
SACMEQ	0.165	0.168	0.065	0.054	0.082	0.011	0.042	0.045
	(0.020)***	(0.021)***	(0.010)***	(0.010)***	(0.024)***	(0.029)***	(0.013)***	(0.014)***
Botswana	0.113	0.131	0.030	0.021	0.132	0.102	0.026	0.017
	(0.045)**	(0.053)**	(0.016)*	(0.015)	(0.050)***	(0.055)*	(0.019)	(0.016)
Malawi	0.044	0.056	0.055	0.079	0.111	0.148	0.102	0.199
	(0.051)	(0.073)	(0.042)	(0.053)	(0.075)	(0.121)	(0.075)	(0.088)**
South Africa	0.411	0.405	0.097	0.072	0.459	0.553	0.126	0.128
	(0.035)***	(0.039)***	(0.016)***	(0.018)***	(0.078)***	(0.077)***	(0.051)**	(0.043)***
Swaziland	0.052	0.040	0.022	0.044	-0.140	0.177	-0.088	0.064
	(0.033)	(0.048)	(0.020)	(0.025)*	(0.059)**	(0.074)**	(0.057)	(0.065)
Zambia	0.028	0.038	0.007	0.036	0.028	0.047	0.013	0.036
	(0.040)	(0.043)	(0.023)	(0.023)	(0.042)	(0.044)	(0.022)	(0.022)*
Zimbabwe	-0.014	-0.039	0.024	-0.006	-0.013	-0.026	0.026	-0.010
	(0.043)	(0.049)	(0.019)	(0.018)	(0.042)	(0.049)	(0.018)	(0.019)

Note: Dependent variable: student test score in mathematics and reading, respectively. Clustered standard errors in the SUR models are estimated by maximum likelihood. Robust standard errors (adjusted for clustering at classroom level) in parentheses: significance at ***1, **5, and *10%.

Table 2. Effect of teacher test scores: correlated random effects models (same teacher sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Unrestricted model		Restricted model		Fixed-effect model	Unrestricted model		Restricted model	
	Mathematics	Reading	Mathematics	Reading	Mathematics+Reading	Chi² ($\eta_1 = \eta_2$)	Chi² ($\beta_1 = \beta_2$)	Chi² ($\beta_1 = \beta_2$)	Observations
SACMEQ	0.014	0.020	0.013	0.021	0.017	0.38	0.16	0.40	11,585
	(0.249)	(0.106)*	(0.296)	(0.087)*	(0.098)*	(0.54)	(0.69)	(0.53)	
Botswana	0.000	-0.010	0.001	-0.010	-0.005	0.03	0.25	0.37	3,142
	(0.990)	(0.618)	(0.968)	(0.589)	(0.760)	(0.87)	(0.62)	(0.54)	
Malawi	0.064	0.137	0.065	0.135	0.103	0.01	2.55	1.49	1,394
	(0.369)	(0.024)**	(0.376)	(0.031)**	(0.096)*	(0.93)	(0.12)	(0.22)	
South Africa	0.064	0.074	0.064	0.072	0.070	0.02	0.05	0.04	892
	(0.272)	(0.117)	(0.269)	(0.111)	(0.125)	(0.88)	(0.82)	(0.84)	
Swaziland	0.002	0.036	n.a.	n.a.	n.a.	8.14	0.24	8.74	709
	(0.974)	(0.572)	n.a.	n.a.	n.a.	(0.00)***	(0.63)	(0.00)***	
Zambia	0.018	0.034	0.015	0.036	0.027	0.15	0.37	0.52	2,656
	(0.496)	(0.117)	(0.560)	(0.103)*	(0.172)	(0.70)	(0.54)	(0.47)	
Zimbabwe	0.004	-0.029	0.005	-0.031	n.a.	0.09	2.55	3.05	2,792
	(0.786)	(0.113)	(0.737)	(0.011)	n.a.	(0.77)	(0.11)	(0.08)*	

Note: Dependent variable: student test score in mathematics and reading, respectively. Regressions in the two subjects estimated by seemingly unrelated regressions (SUR). Sample: pupils who are taught by the same-teacher. Coefficients are "implied beta". Implied beta represents the effects of the teacher test score, given by the difference between the estimate on the teacher test score in the respective subject and the equation of the student test score in the other subject (see Eqs. (2a) and (2b)). Regressions include controls for student gender, student 1st language, urban area, private school, complete school, teacher gender, and teacher university degree. Clustered standard errors in the SUR models are estimated by maximum likelihood. Robust standard errors (adjusted for clustering at classroom level) in parentheses: significance at ***1, **5, and *10%.

Table 3. Effect of teacher test scores in sub-samples relative to teacher absenteeism

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High teacher absenteeism (according to teachers)						Best performing teachers in 'core items'					
	Yes		No		Difference		Yes		No		Difference	
Mathematics:	Implied β	Probability	Implied β	Probability	Implied β	Probability	Implied β	Probability	Implied β	Probability	Diff	Probability
SACMEQ	-0.007	(0.662)	0.022	(0.034)**	-0.030	(0.249)	0.032	(0.101)*	0.015	(0.196)	0.018	(0.564)
Botswana	-0.038	(0.137)	0.021	(0.249)	-0.059	(0.089)*	0.007	(0.839)	-0.005	(0.791)	0.013	(0.786)
Malawi	0.079	(0.280)	0.061	(0.175)	0.018	(0.887)	0.067	(0.348)	0.013	(0.812)	0.054	(0.696)
South Africa	-0.140	(0.050)**	0.172	(0.000)***	-0.312	(0.002)***	0.160	(0.016)**	0.058	(0.289)	0.102	(0.413)
Swaziland	-0.414	(0.002)***	0.051	(0.260)	-0.464	(0.002)***	0.061	(0.762)	0.061	(0.219)	-0.000	(0.999)
Zambia	0.075	(0.039)**	0.004	(0.886)	0.071	(0.106)	-0.036	(0.425)	0.019	(0.500)	-0.055	(0.279)
Zimbabwe	-0.012	(0.669)	0.016	(0.350)	-0.028	(0.536)	0.082	(0.051)**	-0.011	(0.489)	0.094	(0.031)**
Reading												
SACMEQ	-0.008	(0.634)	0.029	(0.006)***	-0.037	(0.139)**	0.036	(0.059)*	0.011	(0.300)	0.026	(0.405)
Botswana	-0.084	(0.008)***	0.014	(0.415)	-0.098	(0.010)***	0.092	(0.019)**	-0.021	(0.193)	-0.113	(0.029)**
Malawi	0.177	(0.018)**	0.156	(0.001)***	0.021	(0.834)	0.268	(0.000)***	0.081	(0.081)*	0.187	(0.301)
South Africa	0.018	(0.790)	0.139	(0.003)***	-0.121	(0.168)	0.191	(0.005)***	0.044	(0.290)	0.148	(0.170)
Swaziland	-0.195	(0.047)**	0.069	(0.216)	-0.264	(0.052)*	0.160	(0.241)	-0.051	(0.366)	0.211	(0.117)
Zambia	0.024	(0.546)	0.037	(0.148)	-0.012	(0.773)	0.100	(0.044)**	0.034	(0.155)	0.067	(0.213)
Zimbabwe	-0.027	(0.300)	-0.036	(0.043)**	0.008	(0.829)	-0.033	(0.378)	-0.028	(0.090)*	-0.005	(0.924)

Note: Dependent variable: student test score in mathematics and reading, respectively. Regressions in the two subjects estimated by seemingly unrelated regressions (SUR). Sample: pupils who are taught with same-teacher. Coefficients are "implied beta". Implied beta represents the effects of the teacher test score, given by the difference between the estimate on the teacher test score in the respective subject and the equation of the student test score in the other subject (see Eqs. (2a) and (2b)). Regressions include controls for student gender, student 1st language, urban area, private school, complete school, teacher gender, and teacher university degree. Clustered standard errors in the SUR models are estimated by maximum likelihood. Robust standard errors (adjusted for clustering at classroom level) in parentheses: significance at ***1, **5, and *10%.

Appendix Tables (Not for Publication)

Table A.1. Baseline information about samples, scores and Cronbach alphas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
	Full sample							Same teacher					Same teacher, one classroom				
	Pupils	Teacher Score		Pupil Score		Cronbach alpha for teachers		Pupils	Teacher Score		Pupil Score		Pupils	Teacher Score		Pupil Score	
		Reading	Mathematics	Reading	Mathematics	Reading	Mathematics		Reading	Mathematics	Reading	Mathematics		Reading	Mathematics	Reading	Mathematics
SACMEQ	25,666	762	784	499	498	0.48	0.61	11,999	765	785	491	491	4,477	750	779	457	465
Botswana	3,868	770	780	537	522	0.43	0.55	3,142	767	777	553	520	271	757	755	541	526
Malawi	2,781	720	762	433	447	0.53	0.64	1,394	717	764	427	444	1,331	715	761	425	442
South Africa	9,071	758	769	498	497	0.57	0.63	892	769	756	510	507	635	725	713	457	469
Swaziland	4,030	767	813	550	542	0.33	0.63	709	761	798	542	536	709	749	816	535	532
Zambia	2,895	758	742	435	435	0.38	0.61	2,656	758	743	436	436	920	765	747	427	428
Zimbabwe	3,021	794	852	506	517	0.48	0.58	2,792	794	853	506	515	800	807	875	471	484

Note: The sample of SACMEQ countries only includes the countries listed above. The following countries are not included: Kenya, Lesotho, Mauritius, Mozambique, Namibia, Seychelles, Tanzania, Uganda and Zanzibar.

Table A.2. Descriptive statistics

	Botswana	Malawi	South Africa	Swaziland	Zambia	Zimbabwe
Student level						
Reading score	535	433	495	549	434	508
Mathematics score	521	447	495	541	435	520
% Girl	50	49	51	50	49	56
Abs. SES level	9.00	4.99	9.61	8.39	6.08	7.24
% speak English	10	7	15	6	8	13
% mother univ. level	17	5	24	21	8	23
% father univ. level	20	12	28	24	17	28
% not repeated	69	40	72	44	66	69
% read. homework	56	20	56	76	31	54
% math. homework	56	20	56	76	31	54
School level						
% rural areas	48	76	50	70	65	71
School size	583	1,251	703	544	932	749
School SES level	9.00	4.99	9.61	8.39	6.08	7.24
School resources index	2.07	2.34	1.93	2.10	2.33	2.13
Teacher level						
Reading						
Score	769	720	758	768	758	795
% Female	66	26	68	70	53	29
% university level	41	1	61	93	25	52
% training	63	8	87	78	8	92
Experience	13.07	11.40	16.54	10.69	6.14	11.47
Teacher absenteeism (days)	10.76	9.78	18.86	8.17	15.00	11.97
Threshold for high absenteeism	11	13	25	16	9	14
Resources	2.90	2.72	2.96	3.05	2.59	2.58
Mathematics						
Score	780	762	764	811	740	852
% Female	67	25	58	51	53	29
% university level	42	1	66	93	25	52
% training	64	11	91	76	8	92
Experience	13.42	12.23	15.31	10.51	6.14	11.47
Teacher absenteeism (days)	11.03	9.24	19.17	7.63	15.00	11.97
Threshold for high absenteeism	10	12	26	16	9	14
Resources	2.60	2.76	2.82	2.75	2.59	2.58

Table A.3. Descriptive statistics on teacher absenteeism and teacher performance (same-teacher sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Source: teachers							Source: school directors						
	Low absenteeism			High absenteeism			Δ btw high & low	Low absenteeism			High absenteeism			Δ btw high & low
	%	Score in reading	Score in maths	%	Score in reading	Score in maths		%	Score in reading	Score in maths	%	Score in reading	Score in maths	
SACMEQ	31	753	779	29	755	769	-4	83	755	777	17	744	771	-9
Botswana	75	767	774	25	768	786	7	91	767	775	9	764	799	11
Malawi	72	715	768	28	722	753	-4	76	716	764	24	719	764	2
South Africa	59	796	785	41	726	718	-69	91	771	761	9	733	717	-41
Swaziland	76	753	808	24	783	767	-6	83	760	807	17	763	757	-24
Zambia	71	754	747	29	770	728	-2	86	761	746	14	748	729	-15
Zimbabwe	74	796	856	26	787	846	-10	32	797	856	68	778	839	-18

Table A.4. Descriptive statistics on knowledge transferability and teacher performance (same-teacher sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Teachers performance for all items							Teachers performance for 'core items'						
	Low performance			High performance			Δ btw high & low	Low performance			High performance			Δ btw high & low
	%	Score in reading	Score in math	%	Score in reading	Score in math		%	Score in reading	Score in math	%	Score in reading	Score in math	
SACMEQ	80	734	750	20	832	881	115	68	730	737	32	806	862	101
Botswana	80	749	750	20	840	884	113	77	756	751	23	804	863	80
Malawi	79	696	732	21	795	879	123	69	693	726	31	770	845	98
South Africa	78	733	716	22	890	906	174	71	734	714	29	849	865	133
Swaziland	80	743	764	20	829	933	128	75	742	769	25	817	887	97
Uganda	78	688	779	22	792	887	106	69	685	775	31	767	966	137
Zambia	80	737	714	20	841	850	120	77	742	715	23	811	826	90
Zimbabwe	80	777	829	20	862	949	103	76	781	834	24	834	912	66

Table A.5. Robustness check: Effect of teacher test scores in sub-samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Student is female				Teacher is female				School with a high socio-economic index			
	Yes		No		Yes		No		Yes		No	
Mathematics:	Implied β	Probability	Implied β	Probability	Implied β	Probability	Implied β	Probability	Implied β	Probability	Implied β	Probability
SACMEQ	0.017	(0.15)	0.011	(0.37)	0.035	(0.01)***	-0.003	(0.82)	0.014	(0.52)	0.013	(0.19)
Botswana	0.002	(0.90)	-0.001	(0.96)	0.010	(0.61)	0.002	(0.94)	0.031	(0.47)	-0.005	(0.76)
Malawi	0.084	(0.10)*	0.046	(0.41)	0.017	(0.52)	0.060	(0.12)	0.181	(0.08)*	0.047	(0.25)
South Africa	0.142	(0.02)**	0.021	(0.72)	0.164	(0.00)***	-0.103	(0.19)	0.214	(0.01)***	0.011	(0.84)
Swaziland	0.005	(0.93)	0.011	(0.84)	-0.004	(0.94)	0.057	(0.49)	-0.137	(0.14)	0.041	(0.33)
Zambia	0.003	(0.92)	0.036	(0.21)	0.056	(0.07)*	-0.017	(0.57)	-0.040	(0.48)	0.036	(0.12)
Zimbabwe	0.030	(0.11)	-0.030	(0.15)	-0.010	(0.67)	0.014	(0.44)	0.091	(0.02)**	0.004	(0.78)
Reading:												
SACMEQ	0.011	(0.34)	0.028	(0.03)**	0.010	(0.43)	0.022	(0.06)*	-0.016	(0.43)	0.026	(0.01)***
Botswana	-0.002	(0.92)	-0.017	(0.43)	-0.036	(0.07)*	0.014	(0.51)	-0.009	(0.81)	-0.010	(0.53)
Malawi	0.116	(0.00)***	0.112	(0.01)**	0.091	(0.64)	0.118	(0.00)***	0.133	(0.12)	0.110	(0.00)***
South Africa	0.103	(0.05)**	0.027	(0.61)	0.120	(0.01)***	-0.070	(0.34)	0.126	(0.16)	0.041	(0.33)
Swaziland	0.003	(0.95)	0.082	(0.16)	0.034	(0.49)	0.073	(0.30)	-0.018	(0.04)**	0.111	(0.02)**
Zambia	0.027	(0.37)	0.050	(0.10)*	0.041	(0.19)	0.030	(0.30)	0.025	(0.59)	0.037	(0.11)
Zimbabwe	-0.042	(0.02)**	-0.009	(0.67)	-0.019	(0.45)	-0.032	(0.06)*	-0.031	(0.42)	-0.030	(0.05)**

Note: Dependent variable: student test score in mathematics and reading, respectively. For each sub-sample, regressions in the two subjects estimated by seemingly unrelated regressions (SUR). Sample: Same-teacher sample, stratified in two sub-samples based on whether combined teacher-student characteristic in head column is true or not. Coefficients are "implied beta". Implied beta represents the effects of the teacher test score, given by the difference between the estimate on the teacher test score in the respective subject and the equation of the student test score in the other subject (see Eqs. (2a) and (2b)). Regressions include controls for student gender, student 1st language, urban area, private school, complete school, teacher gender, and teacher university degree. Clustered standard errors in the SUR models are estimated by maximum likelihood. Robust standard errors (adjusted for clustering at classroom level) in parentheses: significance at ***1, **5, and *10%.

Table A.6. Robustness check: Effect of teacher test scores: correlated random effects models (same teacher one classroom sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Unrestricted model		Restricted model		Fixed-effect model	Unrestricted model		Restricted model	
	Mathematics	Reading	Mathematics	Reading	Math + Reading	Chi² ($\eta_1 = \eta_2$)	Chi² ($\beta_1 = \beta_2$)	Chi² ($\beta_1 = \beta_2$)	Observations
SACMEQ	0.037	0.047	0.0312	0.005	0.042	0.64	0.14	0.52	4,278
	(0.145)	(0.091)*	(0.222)	(0.065)*	(0.063)*	(0.42)	(0.71)	(0.47)	
Malawi	0.061	0.119	0.064	0.134	0.100	0.14	1.71	1.28	1331
	(0.413)	(0.035)**	(0.403)	(0.055)**	(0.130)	(0.71)	(0.19)	(0.25)	
Swaziland	0.052	0.062	0.013	0.113	n.a.	4.00	0.06	3.86	471
	(0.327)	(0.310)	(0.771)	(0.085)*	n.a.	(0.05)**	(0.81)	(0.06)*	
Zambia	0.044	-0.005	0.043	-0.001	0.021	0.01	0.42	0.33	920
	(0.34)	(0.91)	(0.370)	(0.969)	(0.559)	(0.90)	(0.52)	(0.56)	
Zimbabwe	0.037	-0.045	0.041	-0.051	-0.004	0.18	1.58	2.37	800
	(0.386)	(0.447)	(0.368)	(0.317)	(0.926)	(0.68)	(0.21)	(0.12)	

Note: Dependent variable: student test score in math and reading, respectively. Regressions in the two subjects estimated by seemingly unrelated regressions (SUR). Sample: Same-teacher or same-teacher-one classroom (STOC). Coefficients are "implied beta". Implied beta represents the effects of the teacher test score, given by the difference between the estimate on the teacher test score in the respective subject and the equation of the student test score in the other subject (see Eqs. (2a) and (2b)). Regressions include controls for student gender, student 1st language, urban area, private school, complete school, teacher gender, and teacher university degree. Clustered standard errors in the SUR models are estimated by maximum likelihood. Robust standard errors (adjusted for clustering at classroom level) in parentheses: significance at ***1, **5, and *10%.