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CESifo Working Paper No. 5470
Category 5: Economics of Education
August 2015

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ISSN 2364-1428

CESifo
Center for Economic Studies & Ifo Institute

CESifo *Working Paper No. 5470*

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Abstract

Student performance in Sub-Saharan Africa is tragically low. We study the importance of teacher subject knowledge for student performance in this region using unique international assessment data for sixth-grade students and their teachers. To circumvent potential bias due to unobserved student heterogeneity, we exploit variation within students across math and reading. After measurement-error correction, a one-standard-deviation increase in teacher subject knowledge raises student performance by 4% of a standard deviation. Results are robust to adding teacher fixed effects and are not driven by student or teacher sorting. Furthermore, teacher knowledge and school resources appear to be complements in student learning.

JEL-Code: I210, J240, O150.

Keywords: teacher knowledge, student performance, Sub-Saharan Africa.

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July 30, 2015
We thank Martin Abel, Manuel Arellano, Manuel Bagues, David Dorn, Joshua S. Goodman, Eric A. Hanushek, Ricardo Hausmann, Asim Khwaja, Frank Neffke, Randall Reback, Ludger Woessmann, and seminar participants at the Ifo Institute for helpful comments. Bietenbeck acknowledges funding from the Spanish Ministry of Science and Innovation (BES-2011-050947). Wiederhold is thankful for the hospitality provided by the Center for International Development at Harvard University, and is especially grateful to Ricardo Hausmann, Ljubica Nedelkoska, and Frank Neffke. Wiederhold also greatly appreciates the financial support provided by the Fritz Thyssen Foundation for financing the research stay at Harvard University.

1 Introduction

Developing countries have made considerable progress in increasing school enrollment over the past few decades (Glewwe et al., 2013). However, children in these countries are learning remarkably little in school. For instance, in a large-scale assessment across Sub-Saharan African countries, sixth-grade students were asked to choose the correct formula for calculating the number of remaining pages in a 130-page book when the first 78 pages have already been read. Only 30% of the students were able to answer this question correctly. In comparison, two-thirds of *fourth-grade* students from OECD countries answered this question correctly. Even in the worst-performing OECD country, the United Kingdom, fourth-grade students did substantially better than the average sixth-grade student in Sub-Saharan Africa.[1] Moreover, the average performance of students in Sub-Saharan Africa is dismal compared to students in other countries at the same stage of economic development (see, e.g., Hanushek and Woessmann, 2012, for a comparison with students in India). These are alarming findings for Sub-Saharan Africa since previous studies have shown that it is the skills of the population, and not the number of years spent in school, that drive economic growth (Hanushek and Woessmann, 2012).

While average student performance is dramatically low in Sub-Saharan Africa, there are substantial differences between countries. For example, correct-answer rates for the math question described above range from 14% in Malawi to almost 50% in Kenya and Tanzania. This variation is unlikely to be explained by differences in school resources, given that the most convincing evidence from randomized interventions shows at best small effects of resources on student performance (see Murnane and Ganimian, 2014, for a survey). In contrast, a growing literature documents the importance of teachers for student learning (see Jackson et al., 2014, for a recent overview), suggesting a role for teacher quality in explaining the observed cross-country differences in student performance.

In this paper, we use unique data from 13 Sub-Saharan African countries that provide consistent measures of teacher subject knowledge as one main dimension of teacher quality.[2] We estimate the causal effect on student performance of having a teacher with higher subject knowledge, exploiting the fact that both students and their teachers were tested in two subjects, math and reading. This allows us to identify the effect of teacher subject knowledge only from differences within students between math and

[1] These figures are based on data from the Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ) and from the Third International Mathematics and Science Study (TIMSS), respectively. The question reads: "Tanya has read the first 78 pages of a book that is 130 pages long. Which number sentence could Tanya use to find the number of pages she must read to finish the book?" Students had to choose between the correct answer, $130 - 78 = X$, and three incorrect answers: $130+78 = X$, $X-78 = 130$, and $130/78 = X$. Other questions that are comparable across these two assessments reveal similarly large differences in the performance of Sub-Saharan African students and their younger peers in developed countries.

[2] We draw on the 2000 and 2007 assessments of SACMEQ, a collaboration between African Ministries of Education and the UNESCO International Institute for Educational Planning.

reading, thus eliminating any unobserved student heterogeneity that is constant across subjects.[3] Additionally, we control for subject-varying teacher characteristics and school resources.

We find that teacher subject knowledge has a positive and significant impact on student performance. After correcting for measurement error, the student fixed-effects results indicate that increasing teacher subject knowledge by one standard deviation (SD) raises student performance by 0.04 SD.[4] Assuming that the variation in teacher effectiveness in Sub-Saharan Africa is similar to that in the United States, this implies that teacher subject knowledge explains about 25% of the variation in teachers' overall effectiveness.[5] The effect is robust to restricting the sample to students taught by the same teacher in both subjects, thus also holding constant any teacher characteristics that do not differ across subjects. Further robustness checks indicate that results are not driven by across-school or within-school sorting of students or teachers.

By far the most popular policy in developing countries for increasing student performance is to provide additional resources to schools. We find that such resource-based policies may be more effective in the presence of highly knowledgeable teachers. Specifically, there is a positive interaction between teacher subject knowledge and a composite index of school resources. Similarly, students' access to textbooks is more strongly related to their performance when they are taught by teachers with high subject knowledge. This might explain previous findings from Kenya which show that providing free textbooks does not improve the performance of the average student (Glewwe et al., 2009). While the authors argue that this was because most students could not read the English-language textbooks, our results suggest that teachers might simply have lacked the subject knowledge necessary to make productive use of them. Additionally, we find that the effect of teacher subject knowledge depends on the extent of teacher absenteeism, which is a widespread problem in developing countries.[6] In particular, high subject knowledge is less beneficial for student learning when teachers are frequently absent from the classroom.

[3]Within-student across-subject variation has been exploited in previous studies (e.g., Dee, 2007; Clotfelter et al., 2010; Lavy, Forthcoming).

[4]Like all test scores, teacher subject knowledge in our data is likely measured with error. Measurement error in the explanatory variable might lead to an attenuation bias, which is aggravated in the student fixed-effects model (Angrist and Krueger, 1999, Section 4). We address measurement error by correcting the estimated coefficients using a reliability ratio estimated on the basis of answers to all items on the teacher tests (see Section 5.3).

[5]This estimate is based on the midpoint (= 0.15 SD) of the range of estimates on how much student performance increases when teacher value-added increases by one SD in the United States (Jackson et al., 2014). This figure is in line with recent evidence on teacher value-added from India (Azam and Kingdon, Forthcoming).

[6]See Banerjee and Duflo (2006) and Chaudhury et al. (2006) for overviews on absenteeism in the education and health sector. In Kenya, for example, teacher absenteeism rates are as high as 20% (Glewwe et al., 2010). Duflo et al. (2012) provide evidence that paying teachers bonuses for attending school significantly reduces teacher absenteeism, which in turn increases student performance.

Finally, we gauge the extent to which differences in teacher subject knowledge are responsible for the large cross-country differences in student performance in Sub-Saharan Africa. To this end, we simulate how much student performance in a given country would increase if the country's average teacher subject knowledge was raised to the level in the country with the most knowledgeable teachers. Our back-of-the-envelope calculation suggests that these effects would be modest in all countries (less than 0.1 SD). However, given that teacher knowledge appears to be complementary to school resources in the education production function, simultaneously enhancing teacher subject knowledge and resources (such as availability of textbooks) can be expected to lead to larger improvements in student performance than raising teacher subject knowledge alone.

Our work is related to the literature on the determinants of student achievement, which mostly deals with developed countries, particularly with the United States. This literature shows that teachers differ greatly in their ability to enhance student learning (see Jackson et al., 2014, for a review). However, easily-observed teacher characteristics, such as education, gender, and teaching experience (except for the first few years), are not consistently related to teacher effectiveness (Hanushek and Rivkin, 2006). The only teacher trait consistently associated with gains in student performance is teacher cognitive skills as measured by achievement tests (e.g., Eide et al., 2004; Hanushek, 1986; Hanushek and Rivkin, 2006; Rockoff et al., 2011).[7] Hanushek et al. (2014), to date the only international study on this topic, also find positive effects of teacher cognitive skills on student achievement across OECD economies. However, in contrast to this paper, the authors do not observe the skills of individual teachers, but instead rely on country-level measures of teacher skills.

In the context of developing countries, several studies have found positive correlations between teacher test scores and student achievement; see, for example, Santibañez (2006) for Mexico, Marshall (2009) for Guatemala, and Behrman et al. (2008) for Pakistan.[8] However, these studies likely suffer from bias due to omitted student and teacher characteristics and non-random sorting of students and teachers. Metzler and Woessmann (2012) circumvent these problems by exploiting within-teacher within-student variation across two subjects for sixth-grade students and their teachers in Peru, finding a significant impact of teacher skills on student achievement. However, they do not investigate complementarities between teacher quality and school resources.[9]

[7] The evidence for teachers' scores on licensure tests affecting student performance is mixed (Clotfelter et al., 2006; Harris and Sass, 2006; Goldhaber, 2007).

[8] See Behrman (2010), Glewwe et al. (2013), and Murnane and Ganimian (2014) for recent overviews of the literature on the education production function in developing countries.

[9] Two other studies aim at identifying the impact of teacher subject knowledge on student performance using the SACMEQ data, but they substantially differ from our paper: Shepherd (2015) restricts her attention to a single country (South Africa) and Altinok (2013) uses a simple OLS model without student fixed effects. Moreover, Hein and Allen (2013) focus primarily on other teacher characteristics such as teacher experience.

Our paper contributes to the literature by providing the first rigorous evidence on the importance of teacher subject knowledge for student learning in a large group of developing countries with the lowest-performing students worldwide. In particular, our focus is on teacher knowledge that is essential for teaching the material included in the curriculum; this curriculum-based measure of teacher knowledge differs considerably from more general teacher ability measures such as licensure test scores in the United States. We are also the first who show that teacher subject knowledge and school resources are complements in student learning. This is an important finding as it suggests that a lack of teacher quality might explain why resources, in and of themselves, have proven to be so little effective in improving student performance.

The remainder of the paper is structured as follows. Section 2 describes the data and reports descriptive statistics. Section 3 lays out the estimation strategy. Section 4 presents our main results and provides evidence on heterogeneous effects, including interactions between teacher subject knowledge and school resources. Section 5 reports results from robustness checks and discusses measurement-error correction. Section 6 presents simulations of the effect on student performance of increasing teacher subject knowledge to the level of the best-performing country. Section 7 concludes.

2 Data and Descriptive Statistics

In this section, we first introduce the data. We then describe our sample selection and provide descriptive statistics, including cross-country correlations between student performance and teacher subject knowledge.

2.1 The SACMEQ Assessments

The empirical analysis draws on data from the Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ), a collaborative network of 15 Sub-Saharan African Ministries of Education and the UNESCO International Institute for Educational Planning (IIEP). The network periodically conducts international assessments of the math and reading knowledge of sixth-grade primary-school students and their teachers. By means of student, teacher, and principal questionnaires, it also collects detailed background information on student and teacher characteristics as well as on classroom and school resources. The first of the three waves of the assessment conducted to date took place in seven countries in 1995, the second wave in 14 countries in 2000, and the third wave in 15 countries in 2007. In this paper, we use data from the last two waves because teachers were not tested in the first wave.

SACMEQ employs a two-stage clustered sampling design to draw nationally representative samples of sixth-grade students for each participating country. Schools are sampled within pre-defined geographical strata in the first stage, and a simple random sample of students is drawn from each selected school in the second stage. In the second wave, 20 students per school were sampled, and the teachers who taught math and reading to these students were tested. In the third wave, 25 students per school were sampled, and the math and reading teachers of the three largest classes in each school were tested.[10] While all students are tested in both math and reading, teachers are tested only in the subject they teach. However, both math and reading scores are available for a subsample of teachers who teach sampled students in both subjects. Throughout our analysis, we use student sampling weights to account for this complex sampling design.

The student assessments are designed to reflect the elements common to the math and language curricula in the participating countries. The multiple-choice tests contain items developed by SACMEQ and items from other international student assessments such as the Trends in International Mathematics and Science Study (TIMSS). Students in all participating countries are administered the same tests at the end of sixth grade.[11] The teacher tests include items from the student assessment and additional, more difficult questions. Both student and teacher tests are graded centrally in each country under the auspices of the IIEP. By employing Item Response Theory, all test scores are placed on a common scale with mean 500 and standard deviation 100 across students participating in the second SACMEQ wave. Because of the overlapping items, test scores are directly comparable between students and teachers as well as between the two assessment waves. The similarity between student and teacher tests also means that teacher test scores in SACMEQ reflect knowledge that is likely highly relevant for teaching math and reading; therefore, these curriculum-based measures of teacher knowledge differ noticeably from, for instance, SAT and ACT scores in the United States, which reflect teachers' general cognitive ability.

2.2 Sample Selection and Descriptive Statistics

We pool the data from the second and third waves of the SACMEQ assessment. From initially 15 countries, we exclude Mauritius because it did not test teachers. Furthermore, teachers in South Africa were not tested at all in the second wave and could opt out of the assessment in the third wave, which 18% of the sampled teachers did. As this might lead to an unrepresentative sample, we also exclude South Africa from the analysis.[12] We further exclude from the sample 5,428 students who could not be linked to a teacher in any

[10] The sampling design of the third wave implies that teacher test scores are missing for students who did not attend any of the three largest classes. As described in Section 2.2, all students with missing teacher test scores are excluded from the sample.

[11] Tests are translated into the local language of instruction if it is different from English.

[12] In none of the other countries opting out (by either students or teachers) was possible. Results are robust to retaining South Africa in the sample.

subject, 4,018 students who had at least one teacher with missing test scores, and 225 students with missing test scores.[13] The final estimation sample consists of 74,708 students with 8,742 teachers in 3,939 schools in the following 13 countries: Botswana, Kenya, Lesotho, Malawi, Mozambique, Namibia, Seychelles, Swaziland, Tanzania (mainland), Uganda, Zambia, Zanzibar (semi-autonomous region of Tanzania), and Zimbabwe.[14]

Table A-1 reports descriptive statistics of student performance and teacher subject knowledge for the pooled sample and separately for each country. There are striking differences in student performance between countries. For example, students in Kenya score on average more than 1.4 international SD higher than students in Zambia in math. Similarly, in reading, students in the Seychelles score more than 1.5 international SD higher than their peers in Malawi. Interestingly, the cross-country differences in teacher subject knowledge are even larger. Teachers in Kenya, for example, outperform teachers in Zanzibar by 2.2 international SD in math; the variation in teacher reading knowledge is of a similar magnitude.[15] Figures A-1 and A-2 further illustrate these large cross-country differences by plotting each country's distribution of teacher test scores and, as a benchmark, the average test score of teachers in the best-performing country (separately for math and reading).

To put the observed variation in teacher subject knowledge into perspective, we compare it to the subject-knowledge variation between teachers with different levels of education. For instance, across all countries in our sample, the average math test score is 734 points for teachers with only primary education and 822 points for teachers with tertiary education. This difference is equivalent to 0.8 international SD in teacher subject knowledge in math. In other words, the difference in teacher math knowledge between the country with the best-performing teachers and the country with the worst-performing teachers is almost three times as large as the difference between teachers with tertiary education and teachers with primary education (in reading, this ratio is about two). Another way to illustrate the differences in teacher subject knowledge across countries is to consider individual test items. For instance, teachers participating in SACMEQ were asked to answer the following math question: "$x/2 < 7$ is equivalent to (a) $x > 14$, (b)

[13] As usual, some background variables have missing values. Since we consider a large set of explanatory variables and since a portion of these variables is missing for a relatively large fraction of students, dropping all student observations with any missing value would result in substantial sample reduction. We therefore imputed missing values for control variables by using the country-by-wave means. To ensure that imputed data are not driving our results, all our regressions include an indicator for each variable with missing data that equals 1 for imputed values and 0 otherwise.

[14] All these countries participated in the second and third SACMEQ waves, except for Zimbabwe, which participated only in the third wave.

[15] As expected, in each country, the average teacher significantly outperforms the average student in both math and reading. However, the best students outperform the worst teachers in all countries in our sample.

$x < 14$, (c) $x > 5$, or (d) $x < 7/2$?" 83% of teachers in Kenya answered this question correctly, but only 43% of teachers in Lesotho did so.[16]

These large cross-country differences notwithstanding, teachers in Sub-Saharan Africa appear to possess dramatically less knowledge than teachers in developed countries. While there is no dataset that would allow a direct comparison between African teachers and teachers in developed countries, we can compare the math knowledge of teachers in Sub-Saharan Africa to that of eighth-grade students in developed countries. In the TIMSS 1995 assessment, eighth-grade students were asked to solve the same math question mentioned above ("$x/2 < 7$ is equivalent to"). In 19 out of 39 mostly developed countries, eighth graders did as well or even better than teachers in the worst-performing Sub-Saharan country (Lesotho) and in four countries they did even better than the average teacher in Sub-Saharan Africa. Moreover, 47% of eighth-grade students in the United States could solve this math question, and—judging by this item alone—are therefore at the level of teachers in Botswana and Namibia.[17]

2.3 Relationship Between Student Performance and Teacher Subject Knowledge at the Country Level

To get a first sense of the importance of teacher subject knowledge for student performance, we plot average student test scores against average teacher test scores at the country level. The upper panel of Figure 1 reveals a positive association between teacher subject knowledge and student performance in both math and reading. Students in countries with highly knowledgeable teachers tend to perform better than their peers in countries with teachers who have less of a command of the material they are teaching.[18]

The availability of both student and teacher performance measures is a unique feature of the SACMEQ assessments. Other international student assessments contain at best coarse measures of teacher quality such as teachers' educational attainment. To provide suggestive evidence that teacher subject knowledge is a better predictor of student performance than teachers' educational credentials, the bottom panel of Figure 1 plots a country's average student performance against the share of teachers with a college degree. Unlike subject knowledge, educational credentials appear to explain little if any of the cross-country variation in student performance in math or reading.[19] Overall,

[16]Even bigger cross-country differences arise for the following item: "If the height of a fence is raised from 60cm to 75cm, what is the percentage increase in height: (a) 15%, (b) 20%, (c) 25%, or (d) 30%?" Here, the spectrum of correct answer rates ranges from 88% in Kenya to 18% in Zanzibar.

[17]This is even an overestimation of the relative performance of teachers in Sub-Saharan Africa because they faced only four different answer options in the SACMEQ assessment, whereas the eighth-grade students in TIMSS had to choose among five possible answers.

[18]We also find that changes in teacher subject knowledge between 2000 and 2007 are strongly correlated with changes in student performance over the same period (results available upon request).

[19]A qualitatively similar picture emerges if we instead use the share of teachers who completed at least secondary school.

Figure 1 suggests that teacher subject knowledge is an important determinant of student performance, a suggestion that we assess more rigorously using student-level regressions in Section 4.

3 Estimation Strategy

In the baseline OLS model, we estimate the following education production function:

$$y_{ikcs} = \alpha + \beta T_{ikcs} + \gamma_1 X_{ics} + \gamma_2 X_{cs} + \gamma_3 X_s + \delta Z_{kcs} + \mu_{country} + \varepsilon_{ikcs}, \tag{1}$$

where y_{ikcs} is the test score of student i in subject k (math or reading) in classroom c in school s; T_{ikcs} is the test score of student i's teacher in subject k; X_{ics} is a vector of student-level controls measuring student and family background; X_{cs} is a vector of subject-invariant classroom and teacher characteristics; and X_s is a vector of school characteristics. Z_{kcs} contains classroom and teacher characteristics that vary across subjects (e.g., the availability of a teacher's guide in math or reading).[20] $\mu_{country}$ denotes country fixed effects which absorb any country-specific differences in student performance. ε_{ikcs} is an error term with mean zero.

Interpreting the OLS estimate of β as the causal effect of teacher subject knowledge on student performance is problematic because of omitted variables that might be correlated with both student and teacher test scores. For instance, the estimated β would be biased upward if high-educated parents select schools or classrooms with better teachers and also foster their children's learning in other ways. Similarly, student sorting across or within schools would lead to biased estimates, for example, if students with high (unobserved) academic ability are more likely to attend schools with highly knowledgeable teachers. To overcome these sources of bias, we exploit the fact that students were tested in two subjects and ask whether *differences* in teacher knowledge between math and reading are systematically related to *differences* in student performance between the same two subjects. This implies that we identify the effect of teacher subject knowledge only from variation between the math and reading performance within the same student. We thus estimate the following first-differenced model:

$$\begin{aligned} y_{ics,math} - y_{ics,read} &= \beta(T_{ics,math} - T_{ics,read}) + \delta(Z_{cs,math} - Z_{cs,read}) \\ &\quad +(\varepsilon_{ics,math} - \varepsilon_{ics,read}). \end{aligned} \tag{2}$$

[20] See Table A-2 for a complete list of control variables.

This model, which we implement by adding student fixed effects to Equation 1, controls for the influence of any student-level performance determinants that are not subject-specific, such as family background, overall academic ability, or general motivation. It also eliminates the impact of school resources that do not differ across subjects, such as availability of black boards, chairs, and computers. Therefore, estimates from the student fixed-effects model are not biased by student sorting across or within schools, as long as such sorting is not subject-specific. In robustness checks, we provide evidence that our estimates are also unlikely to be biased by subject-specific sorting.[21]

While the within-student model in Equation 2 ensures that the estimates are not confounded by any subject-invariant student characteristics, unobserved teacher traits could still bias the coefficient on teacher subject knowledge. For example, if teachers with high subject knowledge are also more motivated (a trait not observed in the data), a positive estimate of β might partly reflect the impact of higher motivation. The fact that about one-third of the students in our sample were taught by the same teacher in math and in reading allows us to rigorously address this issue in a robustness check. Specifically, by restricting the sample to students taught in both subjects by the same teacher (*same-teacher sample*), we can control for any teacher traits that affect students' math and reading performance in the same way.[22] The corresponding results suggest that our student fixed-effects estimates are not biased by correlated teacher traits.

While we control for any differences between teachers that are similar across subjects—most importantly, motivation and pedagogical skills—our results might still be affected by subject-specific teacher traits (e.g., particularly high motivation in math) if these subject-specific traits are correlated with subject knowledge. It seems likely, however, that non-subject-specific teacher traits (e.g., general pedagogical skills) differ much more across teachers than do subject-specific traits within teachers. Nevertheless, our results should be interpreted as the impact of teacher subject knowledge and any subject-specific trait correlated with it (see also Metzler and Woessmann, 2012).

4 Results

We start the discussion of our results by documenting a positive association between student performance and teacher subject knowledge at the individual level. We then present the estimates from our student fixed-effects model, in which the effect of teacher subject knowledge is identified only from the variation within students across subjects. Finally, we provide evidence that the impact of teacher subject knowledge systematically

[21]In contrast to the OLS model, the impact of teacher subject knowledge in the fixed-effects model is "net" of teacher knowledge spillovers across subjects.

[22]Using the same-teacher sample is equivalent to adding teacher fixed effects in Equation 2, thus exploiting only variation within students and within teachers.

differs with various school characteristics, particularly with the availability of school resources such as textbooks.

4.1 Ordinary Least Squares Results

Table 1 reports estimates of the association between student performance and teacher subject knowledge in math (Panel A) and reading (Panel B) based on the model in Equation 1. In addition to an increasing set of control variables at the student, classroom, school, and teacher level, all specifications include country fixed effects, which absorb any country-specific differences in student performance and teacher subject knowledge.[23] To facilitate interpretation of effect sizes, both student and teacher test scores are standardized with a mean of 0 and a standard deviation of 1 across countries and waves. Throughout our analysis, we cluster standard errors at the school level to account for possible correlations in the error structure within schools.

The results in Table 1 show a strong positive association between teacher subject knowledge and student performance in both math and reading, which is in line with the positive country-level correlation illustrated in Figure 1. In the most parsimonious specification which includes only country fixed effects, a one SD increase in teacher subject knowledge is associated with a 0.11 SD increase in student performance in both subjects (Column 1). This association becomes somewhat weaker when student, classroom, and school characteristics are added as controls but remains highly statistically significant (Columns 2–4). Interestingly, the coefficient on teacher subject knowledge changes only little when teacher characteristics, such as educational attainment and experience, are also controlled for (Column 5). In this most restrictive specification, a one SD increase in teacher subject knowledge is associated with a 0.07 (0.05) SD increase in student performance in math (reading).

Table A-2 reports the estimated coefficients on the remaining control variables from the regressions in Column 5 of Table 1. Covariates generally enter the regressions with the expected signs. For instance, female students perform worse than male students in math but not in reading, and students with highly-educated parents perform better in both subjects. Furthermore, student performance is negatively related to class size and positively related to an index of school facilities, which measures the availability of resources such as classroom boards, chairs, tables, and libraries. In line with existing evidence on the detrimental effects of teacher absenteeism (e.g., Duflo et al., 2012), teacher absence is negatively associated with student performance.[24] Finally, several teacher characteristics

[23]Note that since the regressions in Table 1 use only within-country variation, the coefficients do not correspond to the cross-country correlations in the upper panel of Figure 1.

[24]To construct the teacher absence index, we combine information from school principals on how often teachers in their school (i) arrive late, (ii) skip classes, and (iii) are not present at all. We take the simple average across the three indicators, with answers 'never', 'sometimes', and 'often' coded as 0, 1, and 2, respectively. Descriptive statistics of our index show that teacher absenteeism is a pervasive phenomenon

are significantly associated with student performance. For example, female teachers and teachers with higher education levels tend to have better-performing students. We also observe a positive association between student performance and teachers having at least some subject-specific training, whereas teacher experience is unrelated to student performance.[25]

4.2 Student Fixed-Effects Results

As discussed in Section 3, the OLS estimates in Table 1 are likely biased due to omitted variables and non-random sorting across or within schools. Therefore, we now turn to the student fixed-effects models that identify the impact of teacher subject knowledge only from within-student variation between math and reading. The results, shown in Table 2, indicate that teacher subject knowledge has a positive and statistically highly significant impact on student performance. However, the coefficients in the fixed-effects model are substantially lower than the corresponding OLS coefficients: when controlling for subject-specific classroom and teacher characteristics, a one SD increase in teacher subject knowledge raises student performance by 0.026 SD (Column 3).[26]

The smaller coefficient on teacher subject knowledge in the fixed-effects model compared to the OLS model suggests that there are unobserved student characteristics that are correlated with both student and teacher test scores which bias the OLS estimates upward. Another possible explanation is that attenuation bias due to measurement error in teacher subject knowledge is aggravated in the student fixed-effects model (see Angrist and Krueger, 1999, Chapter 4). We address the issue of measurement error in Section 5.3. Under some assumptions detailed there, we find that the effect of teacher subject knowledge increases by almost 50% after correcting for measurement error.

Figure 2 shows a non-parametric version of the regression in Column 3 of Table 2. To create this binned scatterplot, we first regress student and teacher test scores on the student fixed effects and the other control variables. We then divide the residualized teacher test scores into 20 equal-sized groups and plot the mean value of the residualized teacher test scores in each bin against the mean value of the residualized student test scores. The binned scatterplot shows that the conditional expectation of student performance appears to be linear throughout the distribution of teacher subject knowledge.

in Sub-Saharan Africa: almost 95% of schools in our sample suffer from at least some teacher absence, and in 8% of schools, all three dimensions of teacher absence occur 'often'. See also Spaull (2011) for a discussion of teacher absenteeism in Sub-Saharan Africa.

[25]Due to the large number of control variables, and for ease of exposition, we do not report coefficients on ten family resources (all coefficients have the expected signs). Results are available on request.

[26]In addition to teacher subject knowledge, the only statistically significant control variables are a dummy for female teachers and a dummy for teachers having access to a teaching guide for their subject. Coefficients on both variables are positive.

One important question concerning the interpretation of our results is whether our estimate captures the impact of teacher subject knowledge of just a single school year or the cumulative effect of several school years. Unfortunately, as is the case for other international assessments like PISA or TIMSS, the SACMEQ data do not contain information about how long each teacher has been teaching a particular class. However, there is ample evidence that teacher turnover in Sub-Saharan Africa is very high, with annual attrition rates ranging between 5 and 30 percent (Mulkeen et al., 2007). Moreover, a study from two Malawi school districts estimated that of 188 teachers who began the school year, almost 50 percent were not teaching the same class nine months later (IEQ, 2000).[27] Given this high turnover in the teacher workforce, our estimate likely captures a short-run effect of teacher subject knowledge on student performance. Importantly, if our estimate indeed reflects such a short-run effect, the improvements in student performance from raising the subject knowledge of teachers across *all* grade levels will likely be substantially larger than our modest point estimate indicates.

4.3 Heterogeneous Effects

The most popular education policies in developing countries involve the provision of additional resources to schools, whether in the form of more teaching materials, better (physical) facilities, or smaller class sizes (see Murnane and Ganimian, 2014). However, providing more resources alone may not be effective if teacher knowledge and skills are limited. We therefore examine whether teacher subject knowledge systematically interacts with different types of school resources in improving student performance.[28] To facilitate interpretation of results, we normalize all interaction variables to have a mean of 0 and a standard deviation of 1, such that the main effect of teacher subject knowledge reflects the impact at the sample mean of the respective interaction variable.

We first explore the role of textbook access for the impact of teacher subject knowledge on student learning. Access to textbooks is very limited in Sub-Saharan Africa: more than 40% of students in our sample either have no access to textbooks or have to share a textbook with more than one classmate. Column 1 of Table 3 suggests that the lack of such basic school material may substantially impede the transmission of knowledge in the classroom: for example, the impact of a one SD increase in teacher subject knowledge is reduced from 0.027 SD to 0.01 SD in schools where access to textbooks is one standard

[27] One reason for these high attrition rates is that primary-school teachers often enroll in upgrading programmes, which allow them to advance to secondary-school teaching or to move to other careers. Moreover, prevalence of HIV/AIDS in a region may increase teacher attrition (Lewin, 2002).

[28] All variables interacted with teacher subject knowledge in Table 3 are school-specific averages. Due to a lack of between-subject variation in these variables, we cannot estimate their main effects on student performance. Note that we average textbook access across subjects here because there is very limited variation between math and reading.

deviation below the sample average.[29] Conversely, this result implies that teachers with higher subject knowledge may be particularly effective in raising student learning when students can follow the material in a textbook.

We now consider the interaction between teacher subject knowledge and overall physical school resources. The SACMEQ data contain information on the availability of a large variety of resources, ranging from classroom endowments with boards, chairs, and tables to access to drinking water. We combine all 31 school resources surveyed in SACMEQ into a single index by counting the number of available resources. Column 2 suggests that the presence of school resources improves teacher effectiveness: a one SD increase in the school-facilities index, which corresponds to six more available resources, is associated with a 1.6 percentage point higher impact of teacher subject knowledge. This suggests that higher subject knowledge is more productive in better-endowed schools.

Despite a negative association between student performance and class size (see Table A-2), we find no significant interaction between teacher subject knowledge and class size (Column 3). Thus, teachers with a given level of subject knowledge are as effective in large classrooms as they are in small ones.

Next, we investigate the role of teacher absenteeism as measured by our absenteeism index (see footnote 24). We find that the impact of teacher subject knowledge is weaker for teachers who are regularly absent from the classroom: a one SD increase in teacher absenteeism is associated with a 1 percentage point smaller effect of teacher subject knowledge (Column 4). This suggests that higher teacher subject knowledge is beneficial for student learning only if teachers are regularly teaching their class.[30]

Column 5 of Table 3 reports estimates of the interaction between teacher subject knowledge and the share of students with highly educated parents, that is, students who have at least one parent with secondary or higher education. The interaction suggests that a one SD (24%) increase in the share of students with highly-educated parents almost doubles the effect of teacher subject knowledge. One interpretation of this result is that classrooms with more students from highly-educated families might have a more learning-friendly atmosphere. Alternatively, highly-educated parents might complement the subject knowledge of teachers, for instance, by encouraging their children to complete school-related tasks. This interpretation is supported by unreported regressions showing that teacher subject knowledge also interacts significantly with an indicator of high parental education measured at the student level.[31]

[29] There is evidence suggesting that providing one textbook per student or one textbook for every two students leads to very similar test-score gains (e.g., Heyneman et al., 1984).

[30] SACMEQ also contains information on the number of days students were absent from school during the month before the survey. As expected, we find that students who are more often absent benefit less from highly knowledgeable teachers. Results are available on request.

[31] A possible concern with the results in Table 3 is that the school-level variables may simply pick up country effects if school characteristics (e.g., resources) differ across countries. Therefore, we added interactions of teacher subject knowledge with a full set of country dummies as control variables. All

Overall, the results in Table 3 yield a consistent picture: the transmission of knowledge from teachers to students is greatly facilitated in schools of higher quality, as measured, for instance, by the availability of resources. This suggests that simultaneously enhancing teacher subject knowledge and resources might lead to substantial improvements in student performance in Sub-Saharan Africa.[32]

5 Robustness Checks and Measurement-Error Correction

In this section, we first show that our results are unlikely to be confounded by subject-specific student sorting across or within schools and that they are robust to adding teacher fixed effects. We then correct our baseline estimates for measurement error.

5.1 Sorting

Our baseline model identifies the effect of teacher subject knowledge only from the variation between math and reading within students. Therefore, the model accounts for any sorting of students across or within schools based on subject-invariant factors such as overall ability. The estimates in Section 4 could still be biased, however, if students sort (or are matched to teachers) on the basis of subject-specific factors. For example, if students who are particularly interested in math manage to attend schools with particularly good math teachers, the estimated impact of teacher subject knowledge would be biased upward. Similarly, an upward bias in the teacher-subject-knowledge estimate would also occur if school principals tended to assign proficient math students to teachers with high math knowledge. In Table 4, we address these potential concerns in several ways.

We first address the potential bias due to sorting across schools by restricting the sample to students living in rural areas, in which students likely have little choice between different schools. Column 1 shows that the coefficient on teacher subject knowledge decreases somewhat compared to our baseline estimate in Table 2 but remains highly statistically significant. This indicates that non-random sorting of students between schools is unlikely to affect our results.

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results remain robust in this more demanding specification that uses only within-country variation in school-level characteristics (results available on request).

[32]Furthermore, Table A-3 explores whether the effect of teacher subject knowledge on student performance depends on the gender of the student or teacher. The results suggest that students who are taught by a teacher of the same gender especially benefit from his or her subject knowledge. This is in line with results by Metzler and Woessmann (2012), who find that transmission of subject knowledge is facilitated when students and teachers in Peru are of the same gender.

Even in the absence of sorting *across* schools, matching of students to teachers *within* schools based on subject-specific factors might bias our results. One way to address this concern is to restrict the analysis to schools with only one sixth-grade classroom, meaning that students cannot select their teachers and principals cannot assign students to teachers based on relative subject performance. This yields a coefficient of similar magnitude as the baseline estimate (Column 2). An alternative way of accounting for potential within-school sorting is to aggregate teachers' subject knowledge to the school level;[33] this school-level measure of teacher knowledge also shows an effect very similar to our baseline estimate (Column 3). In sum, these results strongly suggest that our estimates do not suffer from any meaningful bias due to sorting across or within schools.

5.2 Correlated Teacher Characteristics

Another concern is that our baseline estimate reflects not only the impact of teacher subject knowledge, but also other, unobserved teacher characteristics correlated with subject knowledge. For example, teachers with high subject knowledge might also have better pedagogical skills than their peers with low subject knowledge, thus biasing the coefficient of interest upward. We address this concern by restricting the sample to students taught both math and reading by the same teacher. This analysis is equivalent to including teacher fixed effects in the full sample. Identification in the same-teacher sample is thus based only on variation in subject knowledge between math and reading within each teacher, which means that all subject-invariant teacher traits that might affect student performance are controlled for.

Table 5 reports results from regressions based on the same-teacher sample. In the simple OLS models, the coefficients on teacher subject knowledge become only slightly smaller than those in the full sample (Columns 1 and 2). Similarly, adding teacher fixed effects leaves our baseline student fixed-effects results almost unchanged: when controlling for subject-specific classroom characteristics, a one SD increase in teacher subject knowledge is estimated to raise student performance by 0.024 SD (Column 4). These results indicate that unobserved subject-invariant teacher characteristics are unlikely to bias our baseline estimates.[34]

[33] For this analysis, all teacher characteristics have also been aggregated to the school level.

[34] We prefer estimating the effect of teacher subject knowledge in the full sample because the extent to which sixth-grade students are taught by the same teacher in both subjects varies widely across countries. For example, all students in Zimbabwe are taught by the same teacher in both subjects, but only less than 1% of students in Mozambique are. Across all countries in our sample, 35% of students are taught by the same teacher in both subjects.

5.3 Measurement Error

Like in any performance assessment, teacher subject knowledge in SACMEQ is likely measured with error. As is well known, measurement error in the explanatory variable may lead to a downward bias in the estimated coefficient, and this bias may be aggravated in the student fixed-effects models (Angrist and Krueger, 1999, Chapter 4). Therefore, we now assess the importance of measurement error for our estimates and propose a way of correcting the corresponding attenuation bias. Addressing this issue is particularly important to be able to gauge the extent to which country-level differences in teacher subject knowledge can explain cross-country differences in student performance in Sub-Saharan Africa (see Section 6).

We begin our analysis by assuming that teacher subject knowledge is measured with random noise. Let T^*_{ik} denote the true knowledge of student i's teacher in subject k and let the observed teacher test score be denoted by $T_{ik} = T^*_{ik} + e_{ik}$.[35] Under classical measurement error, $E(e_{ik}) = 0$ and $Cov(T^*_{ik}, e_{ik}) = 0$ hold. In a bivariate model, the true effect of teacher subject knowledge on student performance, y_{ik}, will then be asymptotically biased towards zero:

$$y_{ik} = \beta\lambda_k T_{ik} + \varepsilon_{ik}, \quad \text{where } \lambda_k = \frac{Var(T^*_{ik})}{Var(T^*_{ik}) + Var(e_{ik})}. \tag{3}$$

The factor λ_k indicates how much the true effect β is attenuated and is often referred to as the reliability ratio or signal-to-noise ratio.

In a first-differenced model (or, equivalently, in a student fixed-effects model), the attenuation bias due to measurement error is likely to be aggravated. Intuitively, the reason for this is that teacher knowledge levels in math and reading are more strongly correlated than the measurement errors in these variables, such that differencing the observed test scores decreases the signal-to-noise ratio. More formally, consider the case where the measurement errors are uncorrelated across subjects, that is, $Cov(e_{im}, e_{ir}) = Cov(T^*_{im}, e_{ir}) = Cov(e_{im}, T^*_{ir}) = 0$. In this case, the reliability ratio for the first-differenced model can be derived as (see Metzler and Woessmann, 2010):

$$\begin{aligned} \lambda_\Delta &= \frac{Var(\Delta T^*_i)}{Var(\Delta T^*_i) + Var(\Delta e_i)} \qquad (4) \\ &= \frac{\lambda_m Var(T_{im}) + \lambda_r Var(T_{ir}) - 2Cov(T_{im}, T_{ir})}{Var(T_{im}) + Var(T_{ir}) - 2Cov(T_{im}, T_{ir})}. \end{aligned}$$

Note that the only unknown quantities in Equation 4 are λ_m and λ_r, while the variances and covariances of teacher subject knowledge can easily be computed from the data. Therefore, if the reliability ratios of the teachers' math and reading assessments were

[35] For conciseness, we ignore the classroom and school subscripts in this discussion.

known, we could correct our baseline estimate for measurement error by multiplying the estimated coefficient by the factor $1/\lambda_\Delta$.

Referring to psychometric test theory, Metzler and Woessmann (2012) argue that Cronbach's α is a natural estimate for λ_k in the context of teacher subject knowledge. We compute Cronbach's α for the math and reading tests (which are not reported by SACMEQ) ourselves by using teachers' answers to all individual test items.[36] The estimated reliability ratios are $\widehat{\lambda_m} = 0.83$ for math and $\widehat{\lambda_r} = 0.75$ for reading. Together with $Var(T_{im}) = Var(T_{ir}) = 1$ (by construction) and the estimated covariance $\widehat{Cov}(T_{im}, T_{ir}) = 0.34$, we obtain $\widehat{\lambda_\Delta} = 0.68$ as an estimate for the reliability ratio for the differenced teacher test scores. Therefore, under the assumptions set out in the previous paragraphs, multiplying our baseline coefficient by the factor $1/0.68 = 1.46$ will provide the measurement-error-corrected estimate of the effect of teacher subject knowledge on student performance.

Table 6 reports the measurement-error-corrected coefficients for both the OLS and fixed-effects models. Column 1 shows that a one SD increase in teacher subject knowledge is associated with 0.088 SD higher student math performance. Column 2 reports the corresponding effect size of 0.067 SD for reading. Finally, Column 3 shows that after correcting for measurement error, an increase in teacher subject knowledge by one SD improves student performance by 0.04 SD in the student fixed-effects models. Assuming that the variation in teacher effectiveness in Sub-Saharan Africa is similar to that in the United States and India, where student performance increases by about 0.15 SD for a one SD increase in teacher value-added (Jackson et al., 2014; Azam and Kingdon, Forthcoming), teacher subject knowledge thus explains about 25% of the variation in teachers' overall effectiveness.

6 Simulation Analysis

Our results indicate that teacher subject knowledge has a significant effect on student performance in Sub-Saharan Africa. In this section, we provide back-of-the-envelope calculations of the impact of raising each country's average teacher subject knowledge to the level of knowledge in the country with the most knowledgeable teachers, that is, Kenya in math and the Seychelles in reading. These calculations will help in assessing the extent to which differences in teacher subject knowledge are responsible for the large cross-country differences in student performance observed in the data.

[36]Cronbach's α is a function of the number of test items and the covariances between all possible item pairs; see Metzler and Woessmann (2010) and Metzler and Woessmann (2012) as well as references therein. We use Stata's `alpha` command to compute Cronbach's α for the teacher math and reading tests in SACMEQ.

Column 1 of Table 7 reports the difference in average teacher subject knowledge in math between the indicated country and the country with the best-performing teachers (Column 3 reports the difference for reading). Column 2 (Column 4) shows the corresponding increase in student math (reading) performance if the country enhanced its teachers' knowledge to the level held by the best-performing teachers.[37] For countries with already highly knowledgeable teachers, such as Zimbabwe, this would have only a weak impact (student-performance improvements of 0.03 SD in math and 0.01 SD in reading). For other countries, however, improvements would be more substantial, albeit not large. For instance, our simulations indicate that the largest improvements (for students in Zanzibar) would amount to about 0.08 SD in both math and reading.

To get an idea of how difficult it would be for teachers to catch up to the best-performing country, consider again the math question "$x/2 < 7$ is equivalent to" from Section 2. Only 58% of the teachers in Sub-Saharan Africa were able to answer this simple math question correctly. Moreover, only half the teachers could correctly answer the question "If the height of a fence is raised from 60cm to 75cm, what is the percentage increase in height?", with correct-answer rates below 20% in some countries. Given the abysmal level of teacher subject knowledge suggested by these two items, there is likely substantial room for policy to improve teacher skills in Sub-Saharan Africa.

While the simulation results in Table 7 suggest rather modest improvements in student performance when average teacher subject knowledge in a country increases, it is important to remember that teacher knowledge appears to be complementary to school resources in the education production function (see Table 3). Therefore, simultaneously enhancing teacher subject knowledge and resources (such as availability of textbooks) can be expected to lead to considerably larger improvements in student performance than those suggested in Table 7. However, due to a lack of exogenous variation in school resources, we cannot credibly assess the magnitude of these counterfactual performance gains.

7 Conclusion

We provide the first rigorous evidence on the effects of teacher subject knowledge on student performance for a large group of developing countries with very low-performing students. Our teacher-skill measures for math and reading are curriculum-based, thus reflecting subject knowledge required for teaching sixth-grade students. To identify a causal effect of teacher subject knowledge, we exploit only within-student variation across math and reading. We find that a one SD increase in teacher subject knowledge raises

[37] The calculations in Table 7 are based on the measurement-error-corrected coefficient in Column 3 of Table 6.

student performance by 0.04 SD. Results are robust to including teacher fixed effects and are not driven by non-random sorting.

This paper complements recent findings by Carneiro et al. (2015) who provide evidence that investing in teacher training is more effective in raising student test scores than investing in school materials. We additionally show that teacher knowledge and school resources are complements in the education production function. This finding suggests that a lack of teacher skills might explain why resources, in and of themselves, have often proved to be an ineffective means of improving student performance.

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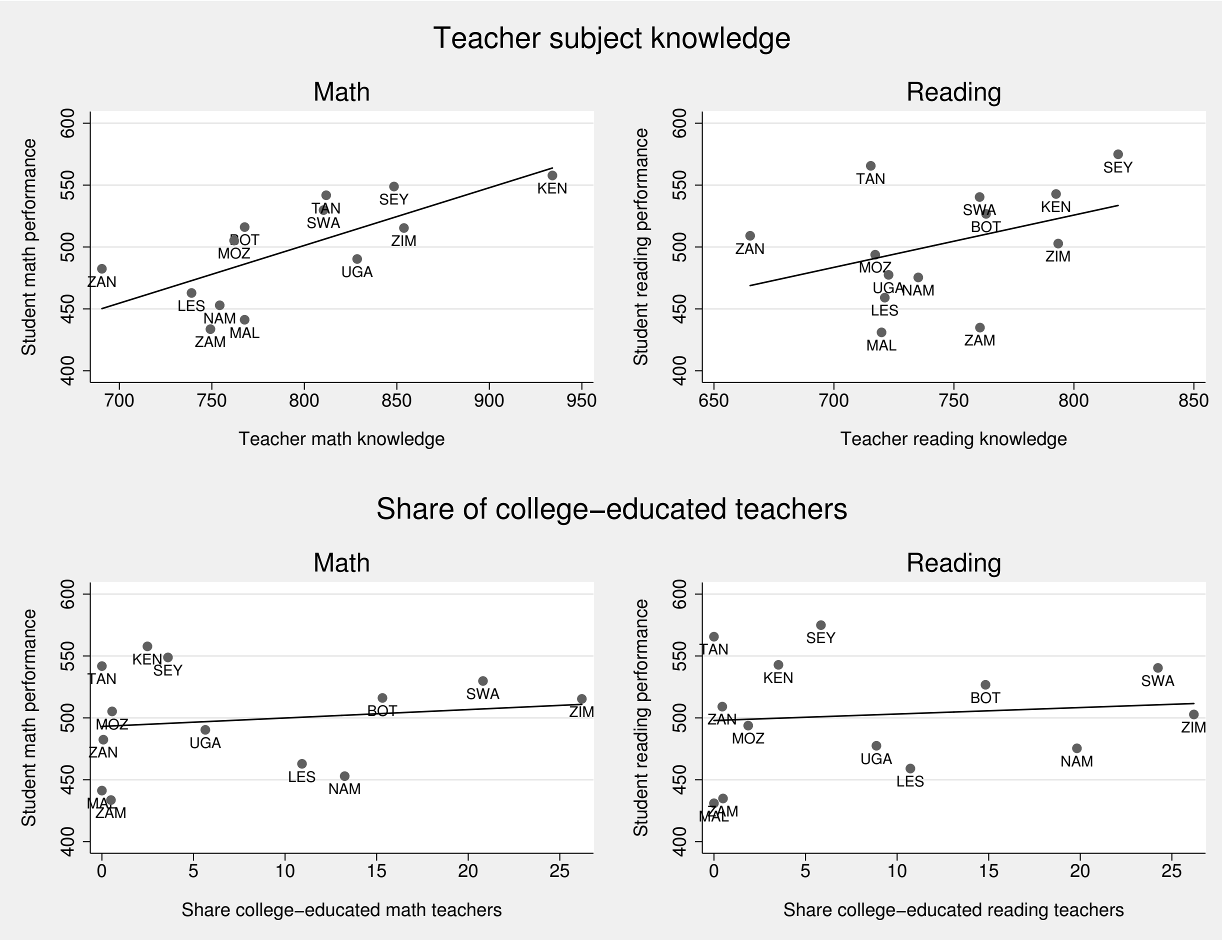
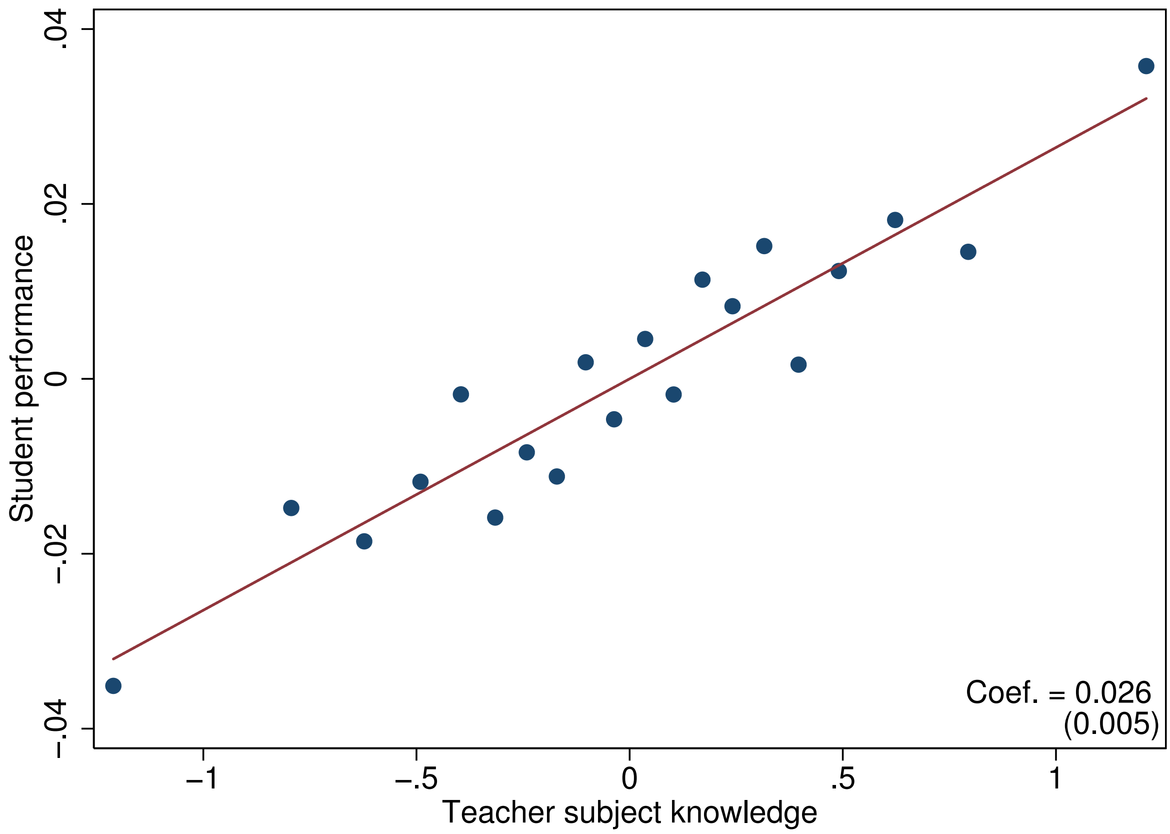
Figures and Tables

Figure 1: Potential Determinants of Cross-Country Differences in Student Performance



Notes: Solid lines fit a linear relationship between student performance and teacher subject knowledge in the top panel and between student performance and the share of college-educated teachers in the bottom panel. Share of college-educated teachers is the share of sixth-grade teachers with a college degree (based on SACMEQ data). Country abbreviations: BOT=Botswana, KEN=Kenya, LES=Lesotho, MAL=Malawi, MOZ=Mozambique, NAM=Namibia, SEY=Seychelles, SWA=Swaziland, TAN=Tanzania, UGA=Uganda, ZAM=Zambia, ZAN=Zanzibar, ZIM=Zimbabwe.

Figure 2: Effect of Teacher Subject Knowledge on Student Performance



Notes: The figure displays a binned scatterplot corresponding to the student fixed-effects estimate in Column 3 of Table 2; see notes to Table 2 for list of control variables. To construct the figure, we first regress math and reading test scores of students and teachers separately on all control variables and student fixed effects using OLS regressions. We then divide the teacher test score residuals into 20 ranked equal-sized groups and plot the mean of the student test score residuals against the mean of the teacher test score residuals in each bin. The best-fit line, the coefficient, and the standard error (clustered at the school level) are calculated from regressions on the micro data.

Table 1: Ordinary Least Squares Results

	(1)	(2)	(3)	(4)	(5)
Panel A: student math performance					
Teacher math knowledge	0.112***	0.091***	0.091***	0.075***	0.074***
	(0.013)	(0.011)	(0.011)	(0.010)	(0.010)
Adj. R-squared	0.22	0.30	0.30	0.32	0.33
Observations (students)	74,708	74,708	74,708	74,708	74,708
Clusters (schools)	3,939	3,939	3,939	3,939	3,939
Panel B: student reading performance					
	(1)	(2)	(3)	(4)	(5)
Teacher reading knowledge	0.106***	0.078***	0.076***	0.056***	0.051***
	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)
Adj. R-squared	0.22	0.35	0.36	0.39	0.39
Observations (students)	74,708	74,708	74,708	74,708	74,708
Clusters (schools)	3,939	3,939	3,939	3,939	3,939
Control variables in Panels A + B					
Country fixed effects	X	X	X	X	X
Socio-economic characteristics (18)		X	X	X	X
Classroom characteristics (4)			X	X	X
School characteristics (5)				X	X
Teacher characteristics (6)					X

Notes: Least squares regressions weighted by students' inverse sampling probability. Dependent variable: student performance in math (Panel A) and in reading (Panel B). Student and teacher test scores are z-standardized at the individual level across countries and waves. Socio-economic controls include three student characteristics and 15 family background measures. Classroom controls contain four classroom resources and school resource controls include five measures of school resources and location. Teacher controls include six teacher characteristics. Table A-2 reports results for these control variables. All regressions include imputation dummies and a dummy indicating the SACMEQ wave. Robust standard errors, adjusted for clustering at the school level, are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 2: Student Fixed-Effects Results

Dependent variable: student performance			
	(1)	(2)	(3)
Teacher subject knowledge	0.027***	0.026***	0.026***
	(0.005)	(0.005)	(0.005)
Student fixed effects	X	X	X
Classroom characteristics (3)		X	X
Teacher characteristics (6)			X
Observations	149,416	149,416	149,416

Notes: Fixed-effects estimations weighted by students' inverse sampling probability. Dependent variable: student performance in math and reading. Student and teacher test scores are z-standardized at the individual level across countries and waves. Compared to Table 1, among classroom characteristics, class size is excluded because it does not vary across subjects for the same student. All regressions include subject fixed effects and imputation dummies. Robust standard errors, adjusted for clustering at the school level, are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Heterogeneous Effects (Student Fixed-Effects Model)

Dependent variable: student performance					
	(1)	(2)	(3)	(4)	(5)
Teacher subject knowledge	0.027***	0.026***	0.027***	0.027***	0.025***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
× sharing textbook w/ at most one student	0.017***				
	(0.005)				
× school facilities (index)		0.016***			
		(0.005)			
× average class size			–0.002		
			(0.006)		
× teachers absent from classroom				–0.010*	
				(0.006)	
× % students w/ highly educated parents					0.023***
					(0.005)
Student fixed effects	X	X	X	X	X
Classroom characteristics (3)	X	X	X	X	X
Teacher characteristics (6)	X	X	X	X	X
Observations	149,416	149,416	146,310	149,416	149,416

Notes: Fixed-effects estimations weighted by students' inverse sampling probability. Dependent variable: student performance in math and reading. Specifications include all control variables as Column 3 of Table 2. Teacher subject knowledge is interacted with school-level measures of share of students with subject-specific textbooks (Column 1), facilities (Column 2), class size (Column 3), teacher absenteeism (Column 4), and share of students with highly educated parents (Column 5). All variables are z-standardized across countries and waves. *Sharing textbook w/ at most one student*: share of students at school who share subject-specific textbook with one other student or who have own textbook. *School facilities (index)*: counts the availability of all 31 school resources reported in SACMEQ: board, cafeteria, chairs, chalk, charts, classroom library, community hall, computer, drinking water, duplicator, electricity, fax, fence, first aid kit, garden, locker, overhead projector, photocopier, playground, radio, school library, separate office for school head, shelves, storeroom, tables, tape recorder, teacher room, telephone, TV, typewriter, and VCR. *Average class size:* average number of students per classroom (sixth grade). 3,106 student observations are missing because school principal did not report the number of sixth-grade students at school. *Teachers absent from classroom*: overall indicator of teacher absence using the following three questions answered by the school principal: (1) How often do teachers arrive late at school? (2) How often do teachers skip classes? and (3) How often are teachers unjustifiably absent? Each answer is coded as follows: 0: never; 1: sometimes; 2: often. The index is the simple average across the three answers. *% students w/ highly educated parents*: share of students at school with at least one parent with secondary or tertiary education. Main effects in Columns 1–5 cannot be estimated because school-level variables do not vary across subjects for the same student. Classroom and teacher characteristics are the same as in Table 2. All regressions include subject fixed effects and imputation dummies. Robust standard errors, adjusted for clustering at the school level, are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Sorting (Student Fixed-Effects Model)

Dependent variable: student performance	Rural schools	One-classroom schools	School level
	(1)	(2)	(3)
Teacher subject knowledge (indiv. level)	0.017**	0.019**	
	(0.007)	(0.009)	
Teacher subject knowledge (school level)			0.030***
			(0.006)
Student fixed effects	X	X	X
Classroom characteristics (3)	X	X	X
Teacher characteristics (6)	X	X	X
Observations	92,968	63,204	149,416

Notes: Fixed-effects estimations weighted by students' inverse sampling probability. Dependent variable: student performance in math and reading. Student and teacher test scores are z-standardized at the individual level across countries and waves. In Column 1, the sample includes only schools in rural areas. In Column 2, all schools with more than one sixth-grade classroom are excluded. In Column 3, teacher test scores and all teacher characteristics are collapsed at the school level. Classroom and teacher characteristics are the same as in Table 2. All regressions include subject fixed effects and imputation dummies. Robust standard errors, adjusted for clustering at the school level, are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Same-Teacher Sample (OLS and FE Models)

Dependent variable: student performance	OLS		Student fixed effects	
	Math	Reading	Math & Reading	
	(1)	(2)	(3)	(4)
Teacher subject knowledge	0.064***	0.040***	0.025**	0.024**
	(0.016)	(0.014)	(0.012)	(0.012)
Socio-economic characteristics (18)	X	X	n.a.	n.a.
Classroom characteristics (4)	X	X		X
School characteristics (5)	X	X	n.a.	n.a.
Teacher characteristics (6)	X	X	n.a.	n.a.
Student fixed effects			X	X
Observations	23,444	23,444	46,888	46,888

Notes: Estimations weighted by students' inverse sampling probability. Same-teacher sample includes only students who are taught in both math and reading by the same teacher; this is equivalent to adding teacher fixed effects in the full sample. Dependent variable: student performance in math (Column 1), in reading (Column 2), and in math and reading (Columns 3 and 4). Student and teacher test scores are z-standardized at the individual level across countries and waves. The specifications in Columns 1 and 2 are analogous to those in Column 5 of Table 1. In the student fixed-effects estimations in Columns 3 and 4, socio-economic characteristics, school characteristics, class size, and the wave indicator are excluded because variables do not vary across subjects for the same student; all teacher controls are also excluded because these variables do not vary within the same teacher. All regressions include subject fixed effects and imputation dummies. Robust standard errors, adjusted for clustering at the school level, are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Measurement-Error Correction (OLS and FE Models)

Dependent variable: student performance	OLS		Student fixed effects
	Math	Reading	Math & Reading
	(1)	(2)	(3)
Teacher subject knowledge (baseline)	0.074***	0.051***	0.026***
	(0.010)	(0.009)	(0.005)
Teacher subject knowledge (corrected)	0.088***	0.067***	0.039***
Socio-economic characteristics (18)	X	X	n.a.
Classroom characteristics (4)	X	X	X
School characteristics (5)	X	X	n.a.
Teacher characteristics (6)	X	X	X
Student fixed effects			X
Observations	74,708	74,708	149,416

Notes: Estimations weighted by students' inverse sampling probability. Dependent variable: student performance in math (Column 1), in reading (Column 2), and in math and reading (Column 3). Student and teacher test scores are z-standardized at the individual level across countries and waves. Baseline coefficients are the same as in Column 5 of Table 1 (OLS) and in Column 3 of Table 2 (FE). See main text for description of measurement-error correction. In Column 3, socio-economic characteristics, school characteristics, class size, and the wave indicator are excluded because variables do not vary across subjects for the same student. All regressions include subject fixed effects and imputation dummies. Robust standard errors, adjusted for clustering at the school level, are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

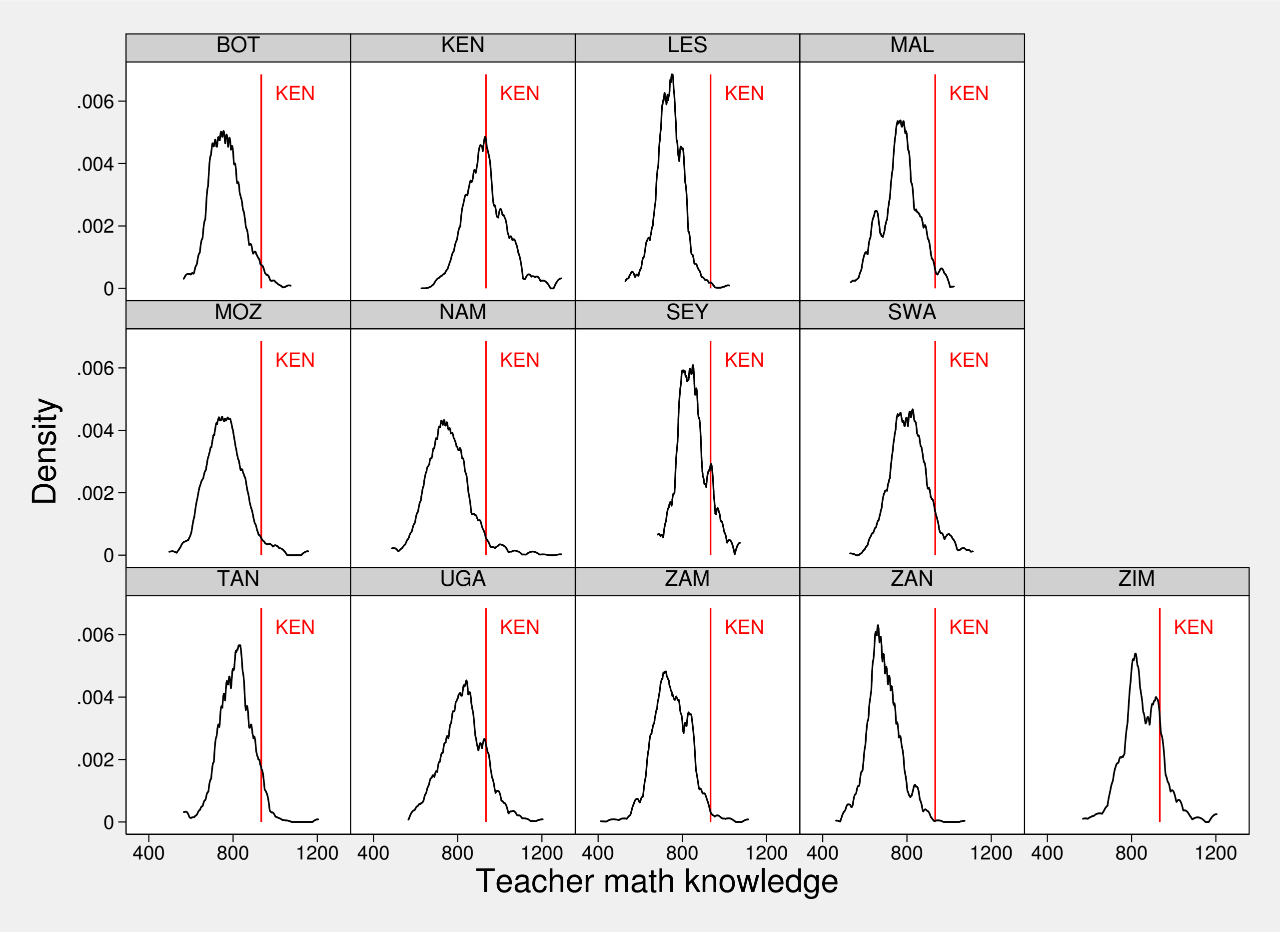
Table 7: Simulation Analysis:
Raising Teacher Subject Knowledge to the Level of the Country with Top-Performing Teachers

	Math		Reading	
	Δ teacher knowledge to Kenya (SACMEQ points)	Δ student performance (% int'l SD)	Δ teacher knowledge to Seychelles (SACMEQ points)	Δ student performance (% int'l SD)
	(1)	(2)	(3)	(4)
Botswana	157	5.6	54	2.9
Kenya	0	0	28	1.5
Lesotho	185	6.7	98	5.3
Malawi	159	5.7	100	5.4
Mozambique	166	6.0	100	5.4
Namibia	164	5.9	79	4.2
Seychelles	78	2.8	0	0
Swaziland	118	4.2	58	3.1
Tanzania	112	4.0	103	5.5
Uganda	96	3.4	94	5.0
Zambia	178	6.4	58	3.1
Zanzibar	229	8.2	154	8.3
Zimbabwe	71	2.6	24	1.3

Notes: Column 1 (Column 3) shows difference in teacher subject knowledge between indicated country and Kenya (Seychelles), i.e., the country with the highest average teacher subject knowledge in math (reading). Columns 2 and 4 show by how much student performance in math (reading) would increase if teacher subject knowledge in math (reading) was raised to the level in Kenya (Seychelles). Estimations are based on the measurement-error-corrected estimate in Column 3 of Table 6.

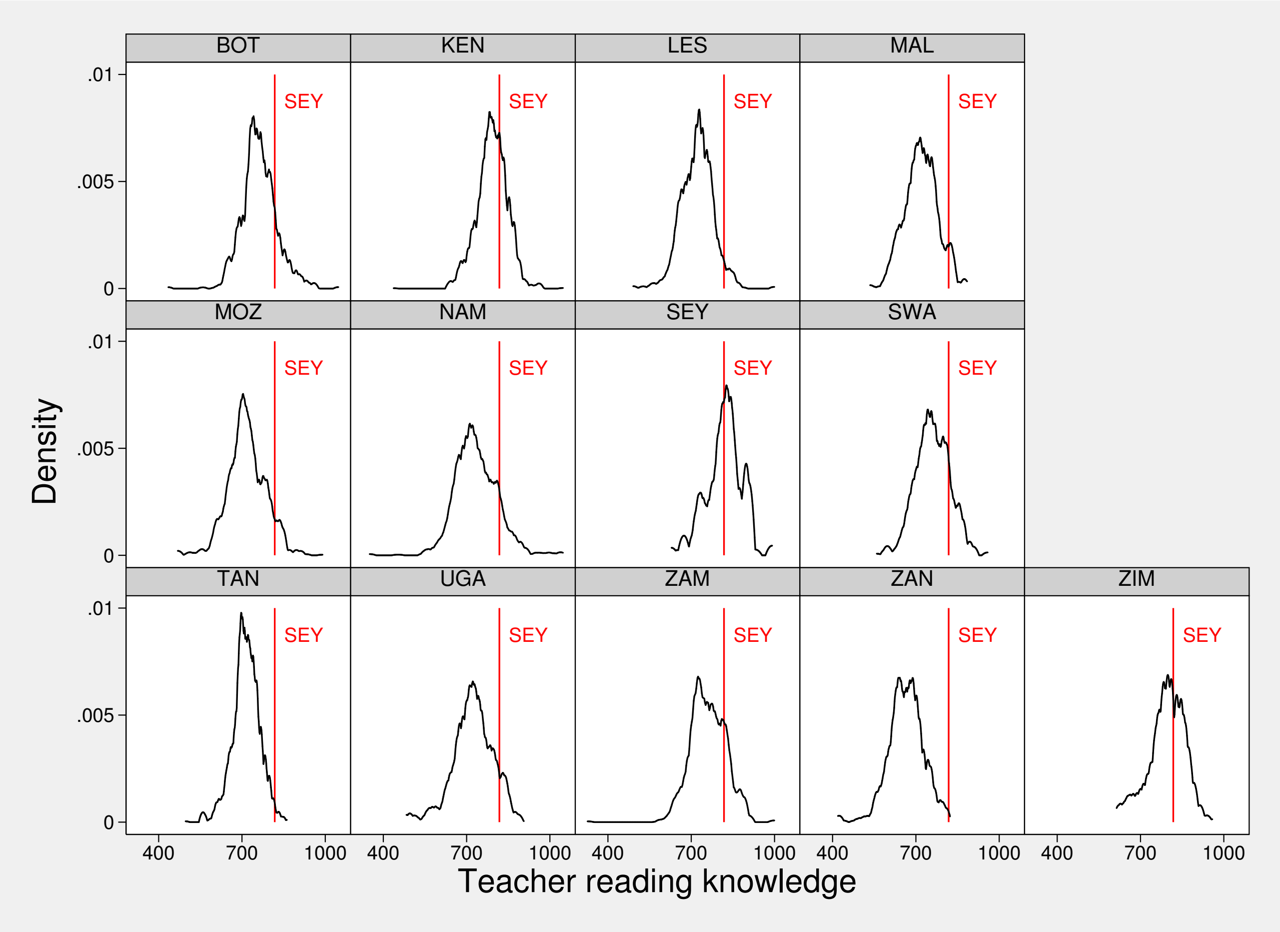
Appendix

Figure A-1: Distribution of Teacher Math Knowledge by Country



Notes: Kernel density plots of teacher math knowledge separately for each country. Vertical red lines indicate the average math knowledge of teachers in Kenya, the country with the highest average teacher math knowledge in our sample. Country abbreviations: BOT=Botswana, KEN=Kenya, LES=Lesotho, MAL=Malawi, MOZ=Mozambique, NAM=Namibia, SEY=Seychelles, SWA=Swaziland, TAN=Tanzania, UGA=Uganda, ZAM=Zambia, ZAN=Zanzibar, ZIM=Zimbabwe.

Figure A-2: Distribution of Teacher Reading Knowledge by Country



Notes: Kernel density plots of teacher reading knowledge separately for each country. Vertical red lines indicate the average reading knowledge of teachers in the Seychelles, the country with the highest average teacher reading knowledge in our sample. Country abbreviations: BOT=Botswana, KEN=Kenya, LES=Lesotho, MAL=Malawi, MOZ=Mozambique, NAM=Namibia, SEY=Seychelles, SWA=Swaziland, TAN=Tanzania, UGA=Uganda, ZAM=Zambia, ZAN=Zanzibar, ZIM=Zimbabwe.

Table A-1: Summary Statistics of Student Performance and Teacher Subject Knowledge

	Pooled	Botswana	Kenya	Lesotho	Malawi	Mozambique	Namibia
				Students			
Math performance	496	516	558	463	441	505	453
	(88)	(81)	(86)	(66)	(60)	(69)	(82)
Reading performance	501	527	543	459	431	494	475
	(94)	(94)	(92)	(65)	(51)	(73)	(90)
# Students	74,708	6,375	6,778	6,895	4,733	5,308	10,365
				Teachers			
Math knowledge	792	768	934	739	768	762	754
	(110)	(83)	(106)	(70)	(89)	(95)	(105)
Reading knowledge	742	763	793	721	720	717	735
	(73)	(63)	(55)	(58)	(61)	(68)	(78)
# Math teachers	5,421	730	474	422	278	586	587
# Reading teachers	5,466	725	480	421	288	603	561

	Seychelles	Swaziland	Tanzania	Uganda	Zambia	Zanzibar	Zimbabwe
				Students			
Math performance	549	530	542	490	434	482	515
	(100)	(65)	(87)	(88)	(70)	(64)	(95)
Reading performance	575	540	566	477	435	509	503
	(122)	(67)	(90)	(79)	(78)	(86)	(99)
# Students	2,820	6,700	6,455	6,498	4,745	4,317	2,719
				Teachers			
Math knowledge	848	810	812	829	749	691	854
	(75)	(91)	(81)	(103)	(89)	(78)	(96)
Reading knowledge	818	761	715	723	761	665	793
	(65)	(62)	(49)	(73)	(64)	(64)	(67)
# Math teachers	91	336	397	355	534	362	269
# Reading teachers	105	336	398	359	534	387	269

Notes: Means and standard deviations (in parentheses) reported. The pooled sample includes 8,742 teachers in total, some of them teaching both math and reading. Statistics are based on individual-level observations weighted with inverse sampling probabilities.

Table A-2: OLS Estimations: Results on Other Covariates

Dependent variable: student performance	Math	Reading
Socio-economic characteristics		
Age	–0.031***	–0.041***
	(0.003)	(0.003)
Female	–0.128***	0.003
	(0.009)	(0.008)
Mother's education		
Unknown	–0.022	0.007
	(0.017)	(0.016)
Some primary	–0.002	0.029*
	(0.017)	(0.015)
Primary	0.008	0.050***
	(0.018)	(0.016)
At least some secondary	0.020	0.072***
	(0.018)	(0.016)
More than secondary	0.132***	0.194***
	(0.021)	(0.020)
Father's education		
Unknown	0.039**	0.100***
	(0.018)	(0.016)
Some primary	0.042**	0.094***
	(0.018)	(0.016)
Primary	0.067***	0.099***
	(0.018)	(0.017)
At least some secondary	0.082***	0.143***
	(0.019)	(0.016)
More than secondary	0.201***	0.272***
	(0.020)	(0.018)
Repeated grade	–0.191***	–0.231***
	(0.010)	(0.009)
Books at home		
11-50 books	0.093***	0.102***
	(0.015)	(0.013)
More than 50 books	0.177***	0.234***
	(0.024)	(0.024)

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Table A-2 (continued)

Dependent variable: student performance	Math	Reading
Classroom characteristics		
Access to teaching guide	–0.059***	–0.000
	(0.019)	(0.020)
Number of books in class (/10)	–0.001	–0.001**
	(0.001)	(0.001)
Class size	–0.002***	–0.001***
	(0.001)	(0.001)
Subject-specific textbooks		
Only teacher has textbook	0.002	0.021
	(0.045)	(0.028)
Student shares textbook w/ >=2 other students	0.118***	0.214***
	(0.043)	(0.026)
Student shares textbook w/ at most one student	0.129***	0.245***
	(0.042)	(0.025)
School characteristics		
School facilities (index)	0.154***	0.185***
	(0.012)	(0.012)
Private school	0.140***	0.115***
	(0.029)	(0.027)
Rural school	–0.143***	–0.192***
	(0.019)	(0.018)
Teachers absent from classroom	–0.033***	–0.015*
	(0.009)	(0.008)
Number of students in school (/100)	–0.003*	–0.003*
	(0.002)	(0.002)
Teacher characteristics		
Teacher female	0.035**	0.035**
	(0.017)	(0.015)
Education		
Junior secondary	0.015	0.021
	(0.030)	(0.030)
Senior secondary	0.047*	0.067***
	(0.026)	(0.025)
A-level	0.031	0.057**
	(0.028)	(0.029)
Tertiary	0.142***	0.123***
	(0.039)	(0.035)
Work experience	0.000	0.001
	(0.001)	(0.001)

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Table A-2 (continued)

Dependent variable: student performance	Math	Reading
Years of subject-specific training		
<1 year	0.120**	0.083*
	(0.048)	(0.050)
1 year	0.154***	0.027
	(0.054)	(0.050)
2 years	0.067*	0.062*
	(0.036)	(0.036)
3 years	0.041	0.096**
	(0.036)	(0.038)
>3 years	0.095**	0.106**
	(0.040)	(0.042)
Weekly teaching time	–0.002**	–0.002**
	(0.001)	(0.001)
How often teacher meets parents	0.004	0.002
	(0.009)	(0.008)
Family resources (10)	X	X
Adj. R-squared	0.33	0.39
Observations (students)	74,708	74,708
Clusters (schools)	3,939	3,939

Notes: The table reports results on all other covariates of the ordinary least squares estimations with the full set of control variables, corresponding to Column 5 of Table 1 (Panel A: math, Panel B: reading). Omitted categories of student characteristics: *mother no education*; *father no education*; and *0-10 books*. Omitted category of classroom characteristics: *no textbook*. Omitted categories of teacher characteristics: *primary education*; and *no training*. *School facilities (index)*: counts the availability of all 31 school resources reported in SACMEQ: board, cafeteria, chairs, chalk, charts, classroom library, community hall, computer, duplicator, electricity, fax, fence, first aid kit, garden, locker, overhead projector, photocopier, playground, radio, school library, separate office for school head, shelves, storeroom, tables, tape recorder, teacher room, telephone, TV, typewriter, VCR, and drinking water. *Teachers absent from classroom*: overall indicator of teacher absence using the following three questions answered by the school principal: (1) How often do teachers arrive late at school? (2) How often do teachers skip classes? and (3) How often are teachers unjustifiably absent? Each answer is coded as follows: 0: never; 1: sometimes; 2: often. The index is the simple average across all three answers. *School facilities (index)* and *Teachers absent from classroom* are z-standardized across countries and waves. Detailed results for *family resources* are available on request. All regressions include subject fixed effects and imputation dummies. Robust standard errors, adjusted for clustering at the school level, are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A-3: Heterogeneity by Student and Teacher Gender

Dependent variable: student performance	Student	Teacher	Student-teacher
	(1)	(2)	(3)
Teacher subject knowledge	0.028***	0.032***	0.015**
	(0.006)	(0.007)	(0.006)
× female student	–0.004		
	(0.006)		
× female teacher		–0.009	
		(0.009)	
× same-gender teacher			0.022***
			(0.005)
Female teacher		0.039***	
		(0.013)	
Same-gender teacher			0.046***
			(0.008)
Student fixed effects	X	X	X
Classroom characteristics (3)	X	X	X
Teacher characteristics (6)	X	X	X
Observations	148,174	148,174	148,174

Notes: Fixed-effects estimations weighted by students' inverse sampling probability. Four students with missing gender information and 617 students with missing information on their teacher's gender are excluded from the sample. All regressions include subject fixed effects and imputation dummies. Robust standard errors, adjusted for clustering at the school level, are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.