Africa's Skill Tragedy: Does Teachers' Lack of Knowledge Lead to Low Student Performance?*

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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 bias due to unobserved student heterogeneity, we exploit variation within students across math and reading. We find that teacher subject knowledge has a modest impact on student performance on average. However, this effect is substantially larger for students with access to textbooks, which indicates important complementarities between teacher knowledge and school resources. Results are robust to adding teacher fixed effects and not driven by sorting.

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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 also 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

[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.

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 reading, thus eliminating any unobserved student heterogeneity that is constant across subjects. The specifications additionally control for several subject-specific teacher characteristics and school resources.

We find that teacher subject knowledge has a positive and significant impact on student performance. Our student fixed-effects results indicate that increasing teacher subject knowledge by one standard deviation (SD) raises student performance by about 0.03 SD. 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 20% of the variation in teachers' overall effectiveness.[3]

By far the most popular policy in developing countries for increasing student performance is to provide additional resources, in particular, more textbooks. Contrary to popular belief,[4] however, rigorous evaluation studies from Sub-Saharan Africa which randomized textbook provision have shown that textbooks have little impact on student achievement on average. For example, Glewwe et al. (2009) find that providing free textbooks to primary schools in Kenya does not improve the performance of the average student, but benefits those students who performed well before the

[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.

[3]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, 2015).

[4]For instance, the World Bank regularly publishes reports which emphasize that providing textbooks to all students is essential to improving the quality of learning in Sub-Saharan Africa (most recently, Fredriksen et al., 2015).

intervention. Rationalizing this finding, the authors argue that the English-language textbooks were too difficult to read for most students. Similarly, Sabarwal et al. (2014) find no impact on student performance from the provision of textbooks to schools in Sierra Leone. The authors attribute this zero effect to implementation problems since only few textbooks were actually distributed to students (but instead kept in storage).[5]

We suspect that providing textbooks might fail to improve students' performance because many teachers lack the (subject) knowledge necessary to make productive use of them. We investigate this hypothesis by interacting teacher subject knowledge with the availability of subject-specific textbooks during class. To identify a causal interaction effect, we exploit within-student across-subject variation in both teacher knowledge and textbook availability. We find that textbook availability increases student performance only when students are taught by teachers with high subject knowledge, indicating that teacher knowledge and textbook availability are complements in educational production.[6] In contrast, and consistent with the existing literature, textbook availability is ineffective in raising student performance for the average teacher.[7]

Several robustness checks support a causal interpretation of both the main effect of teacher subject knowledge and its interaction with textbook availability. For instance, results are 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. We can also restrict our analysis to schools with only one sixth-grade classroom, excluding the possibility that students are assigned to teachers based on teachers' specific knowledge in one subject. Results are furthermore qual-

[5]A zero impact of textbooks on student performance is also found in non-experimental work exploiting within-student variation (Kuecken and Valfort, 2013) and not limited to Sub-Saharan Africa (Das et al., 2013). In particular, the latter study finds no overall effect on student performance of a randomly-assigned school grant (which was mostly spent on books and other materials) in India, arguing that households have offset the intervention by reducing their own spending on these inputs.

[6]This finding is in line with Abeberese et al. (2014), who find significantly positive effects of a reading program in the Philippines that provided age-appropriate reading material to fourth-graders *and* trained teachers to use the textbooks in their class (and also supported these measures with a 31-day reading marathon).

[7]Note that this result cannot be explained by a failure of distributing textbooks to students because we use the actual availability of textbooks during class, as reported by students.

itatively similar if we focus on rural schools, suggesting that they are not driven by across-school sorting of students or teachers.

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, holding everything else constant. Our back-of-the-envelope calculation suggests that these effects would be modest in all countries (at most 0.05 SD). However, given that teacher knowledge and textbooks are complements in educational production, simultaneously increasing teacher knowledge and textbook availability (to the level of the country with the best textbook endowment) leads to substantially larger improvements in student performance (up to 0.20 SD). Both the increase in teacher knowledge and in textbook availability assumed in our simulation analysis seem feasible. First, the average level of teacher performance appears to be very low in all Sub-Saharan African countries compared to developed economies. Second, recent estimates by the UNESCO suggest that the current number of textbooks available in Sub-Saharan Africa could be tripled without an increase in government funds if efficiency in textbook procurement was improved (UNESCO, 2016).

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).[8] Hanushek et al. (2014) also find positive effects of teacher cognitive skills on student achievement across OECD economies. However, in contrast to

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

this paper, the authors do not observe the skills of individual teachers, but instead rely on country-level measures of teacher skills. Moreover, our measures of teacher subject knowledge reflect the knowledge that is essential for teaching the material included in the curriculum, and therefore differ considerably from more general teacher ability measures that most of the previous literature has used.

In the context of developing countries, several studies have found positive correlations between teacher test scores and student achievement.[9] 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. In contrast to our study, the authors focus only on a single country and do not investigate the interplay between teacher quality and school resources.[10]

This study 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. Furthermore, we are the first to identify a complementarity between teacher knowledge and textbooks, a frequently emphasized input in the educational process in developing countries. This finding yields new insights for both researchers and policymakers. On the one hand, it helps to understand why existing evaluation studies have found zero average effects of textbooks on student performance. On the other hand, given that the subject knowledge of many teachers in Sub-Saharan Africa is very poor, it suggests that increasing the availability of textbooks without

[9]See, for example, Santibañez (2006) for Mexico, Marshall (2009) for Guatemala, and Behrman et al. (2008) for Pakistan. In the context of Kenya, Duflo et al. (2015) study the impact of teacher incentives on student performance. 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.

[10]Three 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. Hein and Allen (2013) focus primarily on other teacher characteristics such as experience.

simultaneously improving teacher quality may not be effective as a strategy for promoting student learning in Sub-Saharan Africa.

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 the results regarding the effect on student learning of teacher subject knowledge and its complementarity with textbook availability and other school resources. Section 5 reports results from robustness checks, addressing potential biases from omitted teacher traits and non-random sorting across and within schools. 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-sectional and longitudinal correlations between student performance and teacher subject knowledge at the country level.

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 randomly, and the teachers who taught math and reading to these students were tested. In the third wave, 25 students per school were sampled randomly, and the math and reading teachers of the three largest classes in each school were tested.[11] 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.

Importantly, 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 as well as 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.[12] 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. Using 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 other teacher

[11]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.

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

test scores, 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 wave 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.[13] We further exclude from the sample 5,428 students who could not be linked to a teacher in any subject, 4,018 students who had at least one teacher with missing test scores, and 225 students with missing test scores.[14] 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.[15]

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, in math, students in Kenya score on average more than 1.4 international SD higher than students in Zambia. Similarly, in reading, students in the Seychelles score more than 1.5 international SD higher than their peers in Malawi. Interestingly, the cross-country

[13]Opting out (by either students or teachers) was not possible in any other country. Results are robust to retaining South Africa in the sample.

[14]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.

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

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.[16] 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, in the pooled 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 substantial 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) $x < 14$, (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.[17]

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

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

[17] 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 18% in Zanzibar to 88% in Kenya.

1995 assessment, eighth-grade students were asked to solve the same math question described above ("$x/2 < 7$ is equivalent to"). In 19 out of 39 mostly developed countries, eighth-grade students 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.[18]

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.

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]

[18] These comparisons even overestimate 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.

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

The cross-sectional correlation between teacher subject knowledge and student performance might of course be driven by numerous unobserved factors that are correlated with teacher subject knowledge at the country level, such as the overall quality of the education system. As a first step to mitigate the influence of such correlated unobservables, we exploit the availability of two waves of the SACMEQ assessment and plot changes in teacher subject knowledge between 2000 and 2007 against the analogous changes in student performance. Figure 2 shows for both math and reading that student performance tends to improve in those countries where the subject knowledge of teachers increases. The figure also reveals that student performance improved in most countries during this seven-year period, which is also true for teachers' knowledge in reading (but less so in math).

Overall, Figures 1 and 2 suggest that teacher subject knowledge is an important determinant of student performance. We assess this hypothesis more rigorously in Section 4 using student-level regressions.

3 Estimation Strategy

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

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

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 subject-invariant school characteristics. Z_{kcs} contains classroom and teacher characteristics that vary across subjects (e.g., the availability of teacher guides in math or reading).[20] $\mu_{country}$ denotes country fixed effects which absorb any country-

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

specific differences in student performance.[21] ε_{ikcs} is an error term with mean zero.[22]

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, $\hat{\beta}$ 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 if students with high (unobserved) academic ability are more likely to attend schools or classrooms 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 teacher math and reading knowledge within the same student.[23] We thus estimate the following first-differenced model:

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

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

[21] The country fixed effects also control for potential cross-country differences in school curricula or in the timing of national examinations.

[22] Additionally, we include a wave dummy in all specifications. To simplify notation, we drop the wave dummy and the wave subscripts in all equations.

[23] Within-student across-subject variation has been exploited in previous studies (e.g., Dee, 2005, 2007; Clotfelter et al., 2010; Lavy, 2015).

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.[24]

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 (not observed in the data), a positive estimate of β might partly reflect the impact of high 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.[25] The corresponding results suggest that our student fixed-effects estimates are not biased by correlated teacher traits.[26]

4 Results

We first document a positive association between student performance and teacher subject knowledge at the individual level. We then present the estimates from the student fixed-effects model, which identifies the effect of teacher subject knowledge only from variation within students across subjects. Finally, we provide evidence that the impact of teacher subject

[24] 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.

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

[26] 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 one subject) if correlated with subject knowledge. However, it seems likely that non-subject-specific teacher traits differ much more between teachers than do subject-specific traits within teachers. Still, as in Metzler and Woessmann (2012), our results should be interpreted as the impact of teacher subject knowledge and any subject-specific trait correlated with it.

knowledge systematically differs with school resources, particularly with the availability of subject-specific 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 in 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.[27] To facilitate interpretation of effect sizes, both student and teacher test scores are standardized with mean 0 and standard deviation 1 across countries and waves. Throughout our analysis, we cluster standard errors at the school level to account for potential correlation of the error term 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 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 slightly 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.

[27]Note that because 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.

Furthermore, student performance is negatively related to class size and positively related to the availability of subject-specific textbooks during class. In line with existing evidence on the detrimental effects of teacher absenteeism, teacher absence is negatively associated with student performance.[28] Finally, several teacher characteristics 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.[29]

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. As expected, the coefficients in the fixed-effects models are substantially smaller than the corresponding OLS estimates: 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).[30]

The smaller estimate in the fixed-effects model compared to the OLS model suggests that there are unobserved student characteristics correlated

[28]See Banerjee and Duflo (2006) and Chaudhury et al. (2006) for overviews on absenteeism in the education and health sector, and Spaull (2011) for a discussion of teacher absenteeism in Sub-Saharan Africa. Duflo et al. (2012) provide evidence that paying teachers bonuses for attending school significantly reduces teacher absenteeism, which in turn increases student performance.

[29]Due to the large number of control variables, and for ease of exposition, we do not report coefficients on ten family resources in Table A-2 (all coefficients have the expected signs). Results are available on request.

[30]Besides teacher subject knowledge, the only statistically significant explanatory variables are a dummy for female teachers and a dummy for teachers having access to a teaching guide for their subject; the coefficients on both variables are positive.

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 fixed-effects model (see Angrist and Krueger, 1999, Chapter 4). In the Appendix, we show how the reliability ratios of the teacher math and reading tests can be used to correct for measurement error. We find that the measurement-error-corrected coefficient on teacher subject knowledge is almost 50% larger than the baseline estimate (0.039 SD instead of 0.026 SD). However, a caveat of this correction procedure is that it hinges on several (strong) assumptions, for example, that measurement errors in math and reading are uncorrelated. While the measurement error correction suggests that our baseline coefficient on teacher subject knowledge is likely downward biased, due to these (strong) assumptions it is hard to pin down the exact magnitude of this bias. Therefore, we prefer reporting only the uncorrected, more conservative, estimates throughout the paper.

Figure 3 displays 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 indicates that the conditional expectation of student performance appears to be linear throughout the distribution of teacher subject knowledge.[31]

One important question concerning the interpretation of these results is whether our estimate captures the impact of teacher subject knowledge of only a single school year or rather the cumulative effect over 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

[31] In Table A-3, we explore whether the effect of teacher subject knowledge on student performance depends on the gender of the student or teacher. The results suggest that particularly students who are taught by a teacher of the same gender benefit from higher teacher subject knowledge, which is in line with Metzler and Woessmann (2012). We also find that, conditional on subject knowledge, both male and female teachers are more effective at teaching students of their own gender; this is consistent with evidence from India reported in Muralidharan and Sheth (Forthcoming).

ample evidence that teacher turnover in Sub-Saharan Africa is high, with annual attrition rates ranging between 5 and 30 percent (Mulkeen et al., 2007). Moreover, a study from two Malawian school districts finds that almost 50 percent of 188 teachers who began the school year were not teaching the same class nine months later (IEQ, 2000).[32] 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 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 Complementarity between Teacher Subject Knowledge and School Resources

The most popular education policies in developing countries involve the provision of additional resources such as textbooks. However, rigorous evaluation studies have shown that such policies often fail to improve student learning (for an overview, see Murnane and Ganimian, 2014). One candidate explanation for this finding is the prevalence of low-quality teachers in developing countries, who lack the necessary knowledge and skills to make productive use of these resources. Containing information on a variety of school inputs, the SACMEQ data allow to rigorously examine the potential complementarity between teacher subject knowledge and school resources in Sub-Saharan Africa. To do so, we add the respective school resource both as main term and interacted with teacher subject knowledge to the model in Equation (2). The results are presented in Table 3.

The most important school resource is textbook availability during class, a crucial education input that is often lacking in Sub-Saharan Africa.[33] Since each student reports the availability of textbooks separately for math

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

[33] In our sample, for example, about 40% of students report that they either have no textbook at all or have to share a textbook with two or more classmates.

and reading, we exploit within-student across-subject variation in both teacher knowledge and textbook availability to identify a causal interaction effect between both education inputs.[34] Column 1 of Table 3 shows that the student performance increase resulting from a 1 SD increase in teacher subject knowledge is more than twice as large when textbooks are available during class compared to when textbooks are not available. This indicates that teacher knowledge and textbooks are important complements in the education production function. In line with existing evaluation studies, textbooks have no impact on student performance for the average teacher (i.e., teachers with average subject knowledge). This finding suggests that low teacher quality might explain why providing physical inputs by themselves have often proven to be so little effective in raising student performance.

In Columns 3 to 5 of Table 3, we consider the complementarity between teacher subject knowledge and other school resources. The results on these interactions are, however, only suggestive because these resource variables are not subject specific and are furthermore measured at the school level only. Since identification relies on variation across schools, these interaction effects may be driven by differences in school management or in school quality more generally. Against this background, it is worth noting that the interaction between teacher subject knowledge and a *school*-level measure of textbook availability—averaged across math and reading—is also positive and statistically significant as is the well-identified interaction that exploits within-student between-subject variation (Column 2).[35]

[34]In the SACMEQ background questionnaire, students were asked "How are the *math* textbooks used in your classroom during the lessons?", with five answer categories: (1) There are no math textbooks; (2) Only the teacher has a math textbook; (3) I share a math textbook with two or more pupils; (4) I share a math textbook with one pupil; (5) I use a math textbook by myself. The analogous question was asked about *reading* textbooks. In line with Glewwe et al. (2009), we group students who use a textbook by themselves and students who share a textbook with only one other student because all these students can effectively use a textbook during class (in this case, our binary textbook variable equals 1; 0 otherwise). This categorization is also consistent with experimental evidence from the Philippines that providing one textbook for every two students and providing one textbook for each student has very similar effects on test scores (Heyneman et al., 1984). The sample mean of our binary textbook variable is 0.56 for math and 0.58 for reading.

[35]To facilitate interpretation of results, we normalize all school-level variables to have mean 0 and standard deviation 1, such that the main effect of teacher subject knowledge reflects the impact at the sample mean of the respective resource variable. Therefore, the

The SACMEQ data contain information on the availability of a large variety of school resources (reported by principals), 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. In line with the complementarity between teacher knowledge and textbook availability, Column 3 suggests that the effectiveness of teacher knowledge is enhanced by such resources.

In addition to physical resources, we also investigate the interaction between teacher knowledge and other school inputs. We find no significant interaction between teacher subject knowledge and class size, suggesting that teachers with the same level of subject knowledge are as effective in large classrooms as in small ones (Column 4). The negative interaction between teacher knowledge and a school-level index of teacher absenteeism suggests that the impact of teacher subject knowledge is weaker among teachers who are regularly absent from the classroom (Column 5).[36] This makes intuitive sense: higher teacher subject knowledge can translate into more student learning only if teachers are actually teaching their students.[37]

Overall, the results in Table 3 yield a consistent picture: the transmission of knowledge from teachers to students is facilitated by the presence of educational resources such as textbooks. Therefore, improving both teacher knowledge and simultaneously adding resources might lead to substantial improvements in student performance.

magnitudes of the interaction terms in Columns 1 and 2 are not directly comparable. Because the school-level variables do not vary across subjects, their main effects on student performance cannot be estimated.

[36]To construct this 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 this index show that teacher absenteeism is a pervasive phenomenon 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'.

[37]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.

5 Robustness Checks

The student fixed-effects model identifies the impact of teacher subject knowledge from variation between math and reading within students. Therefore, the model accounts for any sorting of students across and within schools that is based on subject-invariant factors such as overall ability. However, the estimates in Section 4 might still be biased if students (or teachers) sort 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, the teacher knowledge impact would be biased upward if school principals tend to assign proficient math students to teachers with high math knowledge. To examine whether our estimates are biased due to subject-specific sorting, we perform several robustness checks, reported in Table 4.

We first address the potential bias due to sorting *across* schools by restricting the sample to students living in rural areas, where 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 statistically significant. This indicates that non-random sorting of students across schools is unlikely to affect our results.

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, which implies that students cannot choose 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;[38] this school-level measure of teacher knowledge also shows an effect very similar to our baseline estimate (Col-

[38]For this analysis, all other teacher characteristics have been aggregated to the school level as well.

umn 3). In sum, these results strongly suggest that our estimates do not suffer from any meaningful bias due to sorting across or within schools.

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 therefore based only on variation in subject knowledge between math and reading within the same teacher. Hence, all subject-invariant teacher traits, such as pedagogical skills or absenteeism, 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 are 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.[39]

The interaction effect between teacher subject knowledge and student-level subject-specific textbooks might suffer from the same potential biases as the main teacher knowledge effect. Therefore, we conduct the same checks as in Tables 4 and 5 to assess the robustness of this complementarity. Results are presented in Table 6. In Column 1, we replicate the baseline estimate (from Column 1 of Table 3) as a reference. Restricting the sample to students taught both math and reading by the same teacher

[39]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.

leads to an even stronger complementarity between teacher knowledge and textbook availability (Column 2). Focusing on students in rural areas, where students have little school choice, yields an interaction coefficient of very similar magnitude as the baseline estimate (Column 3). This also holds when we focus on schools with only one sixth-grade classroom (Column 4). Finally, aggregating teacher subject knowledge (and all other teacher characteristics) to the school level leads to a somewhat smaller, but statistically significant interaction effect (Column 5). These results suggest that the estimated complementarity between teacher subject knowledge and textbook availability does not suffer from any meaningful bias due to omitted teacher characteristics or subject-specific sorting across or within schools.

One potential remaining concern regarding the complementarity result arises when parents are responsible for providing textbooks. If parents have limited resources and can afford to buy only one textbook, they may purchase the textbook for the subject they deem more important. But at the same time these parents may support their children's learning—specifically in the preferred subject—also in other ways (e.g., through helping with homework). If this was the case, the coefficient on the interaction term would be biased upward. However, this concern seems to have little empirical support, given that we find a precisely estimated zero effect of textbook availability on student performance (see Column 1 of Table 6). Moreover, the main source of textbook funding in Sub-Saharan Africa in primary school is the government (i.e., purchases by schools with government funding or free government supply to schools), while parental provision becomes more prevalent in secondary school (Fredriksen et al., 2015).

6 Simulation Analysis

Our results indicate that better teacher subject knowledge—by itself and also in combination with a higher textbook availability in class—significantly improves student performance in Sub-Saharan Africa. In this section, we first 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. Second, we simulate the impact on student performance of simultaneously raising each country's teacher subject knowledge (as before) *and* its textbook availability (to the level of the country with the best textbook endowment, that is, Swaziland in both subjects).[40]

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 5 reports the analogous difference for reading). Column 2 (Column 6) 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, evaluated at the current level of textbook availability in that country. For countries with already highly knowledgeable teachers, such as Zimbabwe, this would have only a weak impact (student-performance improvements of 0.01 SD in math and 0.02 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 Lesotho and Zanzibar) would amount to about 0.05 SD in both math and reading.

Column 3 reports the difference in math textbook availability between the indicated country and the country with the highest availability of math textbooks (Column 7 reports the analogous difference for reading textbooks). There is huge variation in textbook availability across countries.

[40] The impact on student performance of the simulated increases in teacher knowledge and textbooks is calculated as follows. Ignoring other control variables and omitting subscripts for simplicity, we estimate the simple interaction model $y = \beta_0 + \beta_1 TSK + \beta_2 books + \beta_3 (TSK \times books) + u$, where y denotes student performance, TSK denotes teacher subject knowledge, and *books* denotes textbook availability. The total impact on student performance of increasing both teacher knowledge and textbook availability then is: $\Delta y = (\beta_1 + \beta_3 books)\Delta TSK + (\beta_2 + \beta_3 TSK)\Delta books + \beta_3 \Delta TSK \times \Delta books$. For calculating the impact on student performance of an increase in teacher knowledge alone, $\Delta books = 0$ and *books* equals the average textbook availability in the respective subject and country (see Columns 2 and 6). For calculating the impact of simultaneously increasing teacher knowledge and textbooks, we set $\beta_2 = 0$ because of the precisely estimated zero effect of textbook availability on student performance (see Columns 4 and 8). The calculations in Table 7 are based on the coefficients in Column 1 of Table 3.

While almost all students in Swaziland have access to a subject-specific textbook, not even every third student in Tanzania, Uganda, and Zimbabwe does. In light of these substantial differences in textbook availability across Sub-Saharan African countries, increasing textbook availability—together with teacher knowledge—is likely to have considerable leverage in improving student performance.

The results of the counterfactual exercise of simultaneously increasing teacher knowledge and textbooks are shown in Columns 4 (math) and 8 (reading). The simulation suggests sizable improvements in student performance in many countries. For example, the estimated math performance increase in Zimbabwe would now be 0.13 SD (as compared to 0.01 SD for an increase in teacher math knowledge alone), reflecting the poor textbook endowment of Zimbabwean schools. Although its teacher knowledge is at the international average, Tanzania would experience the largest student performance increase because textbook availability is by far the lowest among all countries. Generally, the estimated impact on student performance is much larger than before because two additional effects add to the effect from improving teacher knowledge alone. First, teachers at their current knowledge level get more effective because more textbooks are available; and, second, the increase in teacher knowledge also becomes more effective because the availability of textbooks in the country improves.

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. A similar argument can be made regarding the availability of textbooks in this region. For example, a recent report by the UNESCO estimates that by simply re-organizing the procurement process for textbooks, the total number of textbooks available in Sub-Saharan Africa can be tripled, from currently 72 million to 258 million

(UNESCO, 2016). In our sample across all countries, this would imply that *all* students could share a textbook with at most one other student, which indicates that our simulated improvement in textbook availability is realistic.

These back-of-the-envelope calculations suggest that just increasing teacher subject knowledge is unlikely to lead to large improvements in student performance in Sub-Saharan Africa. However, raising teacher knowledge and at the same time providing textbooks to (almost) all students may yield considerable improvements in student performance in many Sub-Saharan African countries.

7 Conclusion

Student performance in Sub-Saharan Africa is dramatically low. This might partly explain the poor economic performance of this region, given that the cognitive skills of a population are an important driver of economic growth (Hanushek and Woessmann, 2012). We investigate the role of teacher quality in explaining the low student performance, focusing on teacher subject knowledge as a central dimension of teacher quality. Our measures for teacher knowledge in math and reading are curriculum-based, thus reflecting the subject knowledge required for teaching. To identify a causal effect of teacher subject knowledge, we exploit within-student variation across math and reading. We find that a one SD increase in teacher subject knowledge raises student performance by 0.03 SD. Results are robust to including teacher fixed effects and are not driven by sorting of students or teachers.

In Sub-Saharan Africa, policymakers frequently try to improve student learning by providing additional school resources, in particular textbooks. However, rigorous evaluation studies have shown that textbooks have at best small effects on student performance. Consistent with this evidence, we find that textbooks have no impact on student performance on average. This result might be explained by the poor subject knowledge of many teachers, which prevents a productive use of textbooks. In line with this argument, textbook availability does raise student performance when students are taught by teachers with high knowledge. This complementarity between teacher quality and resources in educational production suggests that simultaneously improving both inputs might be an effective strategy for policymakers to overcome Africa's skill tragedy.

References

Abeberese, Ama Baafra, Todd J. Kumler, and Leigh L. Linden. 2014. "Improving Reading Skills by Encouraging Children to Read in School: A Randomized Evaluation of the Sa Aklat Sisikat Reading Program in the Philippines." *Journal of Human Resources*, *49*, 611–633.

Altinok, Nadir. 2013. "The Impact of Teacher Knowledge on Student Achievement in 14 Sub-Saharan African Countries." Mimeo.

Angrist, Joshua D. and Alan B. Krueger. 1999. "Empirical Strategies in Labor Economics." in David Card and Orley Ashenfelter, eds., *Handbook of Labor Economics*, Vol. 3 Part A, Elsevier, pp. 1277–1366.

Azam, Mehtabul and Geeta Kingdon. 2015. "Assessing Teacher Quality in India." *Journal of Development Economics*, *117*, 74–83.

Banerjee, Abhijit and Esther Duflo. 2006. "Addressing Absence." *Journal of Economic Perspectives*, *20*, 117–132.

Behrman, Jere R. 2010. "Investment in Education: Inputs and Incentives." in Dani Rodrik and Mark Rosenzweig, eds., *Handbook of Development Economics*, Vol. 5, Elsevier, pp. 4883–4975.

Behrman, Jere R., David Ross, and Richard Sabot. 2008. "Improving Quality Versus Increasing the Quantity of Schooling: Estimates of Rates of Return from Rural Pakistan." *Journal of Development Economics*, *85*, 94–104.

Chaudhury, Nazmul, Jeffrey Hammer, Michael Kremer, Karthik Muralidharan, and F. Halsey Rogers. 2006. "Missing in Action: Teacher and Health Worker Absence in Developing Countries." *Journal of Economic Perspectives*, *20*, 91–116.

Clotfelter, Charles T., Helen F. Ladd, and Jacob L. Vigdor. 2006. "Teacher-Student Matching and the Assessment of Teacher Effectiveness." *Journal of Human Resources*, *41*, 778–820.

Clotfelter, Charles T., Helen F. Ladd, and Jacob L. Vigdor. 2010. "Teacher Credentials and Student Achievement in High School: A Cross-Subject Analysis with Student Fixed Effects." *Journal of Human Resources*, *45*, 655–681.

Das, Jishnu, Stefan Dercon, James Habyarimana, Pramila Krishnan, Karthik Muralidharan, and Venkatesh Sundararaman. 2013. "School Inputs, Household Substitution, and Test Scores." *American Economic Journal: Applied Economics*, *5* (2): 29–57.

Dee, Thomas S. 2005. "A Teacher like Me: Does Race, Ethnicity, or Gender Matter?" *American Economic Review, Papers and Proceedings*, *95*, 158–165.

Dee, Thomas S. 2007. "Teachers and the Gender Gaps in Student Achievement." *Journal of Human Resources*, *42*, 528–554.

Duflo, Esther, Pascaline Dupas, and Michael Kremer. 2015. "School Governance, Teacher Incentives, and Pupil-Teacher Ratios: Experimental Evidence from Kenyan Primary Schools." *Journal of Public Economics*, *123*, 92–110.

Duflo, Esther, Rema Hanna, and Stephen P. Ryan. 2012. "Incentives Work: Getting Teachers to Come to School." *American Economic Review*, *102*, 1241–1278.

Eide, Eric, Dan Goldhaber, and Dominic Brewer. 2004. "The Teacher Labour Market and Teacher Quality." *Oxford Review of Economic Policy*, *20*, 230–244.

Fredriksen, Birger, Sukhdeep Brar, and Michael Trucano. 2015. *Getting Textbooks to Every Child in Sub-Saharan Africa: Strategies for Addressing the High Cost and Low Availability Problem*, Washington DC: World Bank.

Glewwe, Paul, Eric A. Hanushek, Sarah Humpage, and Renato Ravina. 2013. "School Resources and Educational Outcomes in Developing Countries: A Review of the Literature from 1990 to 2010." in

Paul Glewwe, ed., *Education Policy in Developing Countries*, University of Chicago Press, pp. 13–64.

Glewwe, Paul, Michael Kremer, and Sylvie Moulin. 2009. "Many Children Left Behind? Textbooks and Test Scores in Kenya." *American Economic Journal: Applied Economics*, *1*, 112–135.

Goldhaber, Dan. 2007. "Everyone's Doing It, But What Does Teacher Testing Tell Us About Teacher Effectiveness?" *Journal of Human Resources*, *42*, 765–794.

Hanushek, Eric A. 1986. "The Economics of Schooling: Production and Efficiency in Public Schools." *Journal of Economic Literature*, *24*, 1141–1177.

Hanushek, Eric A. and Ludger Woessmann. 2012. "Do Better Schools Lead to More Growth? Cognitive Skills, Economic Outcomes, and Causation." *Journal of Economic Growth*, *17*, 267–321.

Hanushek, Eric A. and Steven G. Rivkin. 2006. "Teacher Quality." in Eric A. Hanushek and Finis Welch, eds., *Handbook of the Economics of Education*, Vol. 2, Elsevier, pp. 1051–1078.

Hanushek, Eric A., Marc Piopiunik, and Simon Wiederhold. 2014. "The Value of Smarter Teachers: International Evidence on Teacher Cognitive Skills and Student Performance." NBER Working Paper 20727.

Harris, Douglas and Tim R. Sass. 2006. "Value-Added Models and the Measurement of Teacher Quality." Mimeo.

Hein, Christopher F. and Rebecca Allen. 2013. "Teacher Quality in Sub-Saharan Africa: Pupil-fixed Effects Estimates for Twelve Countries." DoQSS Working Papers 13-08. Department of Quantitative Social Science, University College London.

Heyneman, Stephen P., Dean T. Jamison, and Xenia Montenegro. 1984. "Textbooks in the Philippines: Evaluation of the Pedagogical Impact of Nationwide Investment." *Educational Evaluation and Policy Analysis*, *6*, 139–150.

IEQ. 2000. "What Happened to the Teachers? Follow-Up on Teacher Mobility in Two Malawi Districts." Technical Report, Improving Educational Quality undertaken by: American Institutes for Research in collaboration with Academy for Educational Development, Education Development Center, Inc., Juárez and Associates, Inc., and University of Pittsburgh. Washington, D.C.

Jackson, C. Kirabo, Jonah E. Rockoff, and Douglas O. Staiger. 2014. "Teacher Effects and Teacher-Related Policies." *Annual Review of Economics*, *6*, 801–825.

Kuecken, Maria and Marie-Anne Valfort. 2013. "When Do Textbooks Matter for Achievement? Evidence from African Primary Schools." *Economics Letters*, *119*, 311–315.

Lavy, Victor. 2015. "Do Differences in Schools' Instruction Time Explain International Achievement Gaps? Evidence from Developed and Developing Countries." *Economic Journal*, *125*, F397–F424.

Lewin, Keith M. 2002. "The costs of supply and demand for teacher education: dilemmas for development." *International Journal of Educational Development*, *22*, 221–242.

Marshall, Jeffery H. 2009. "School Quality and Learning Gains in Rural Guatemala." *Economics of Education Review*, *28*, 207–216.

Metzler, Johannes and Ludger Woessmann. 2010. "The Impact of Teacher Subject Knowledge on Student Achievement: Evidence from Within-Teacher Within-Student Variation." IZA Discussion Paper 4999.

Metzler, Johannes and Ludger Woessmann. 2012. "The Impact of Teacher Subject Knowledge on Student Achievement: Evidence from Within-Teacher Within-Student Variation." *Journal of Development Economics*, *99*, 486–496.

Mulkeen, Aidan, David W. Chapman, Joan G. DeJaeghere, and Elizabeth Leu. 2007. *Recruiting, Retaining, and Retraining Secondary School Teachers and Principals in Sub-Saharan Africa*, Washington DC: World Bank.

Muralidharan, Karthik and Ketki Sheth. Forthcoming. "Bridging Education Gender Gaps in Developing Countries: The Role of Female Teachers." *Journal of Human Resources.*

Murnane, Richard J. and Alejandro J. Ganimian. 2014. "Improving Educational Outcomes in Developing Countries: Lessons from Rigorous Evaluations." NBER Working Paper 20284.

Rockoff, Jonah E., Brian A. Jacob, Thomas J. Kane, and Douglas O. Staiger. 2011. "Can You Recognize an Effective Teacher When You Recruit One?" *Education Finance and Policy*, *6*, 43–74.

Sabarwal, Shwetlena, David Evans, and Anastasia Marshak. 2014. "The Permanent Input Hypothesis: The Case of Textbooks and (No) Student Learning in Sierra Leone." Policy Research Working Paper 7021, Washington, DC: World Bank Group.

Santibañez, Lucrecia. 2006. "Why We Should Care if Teachers Get A's: Teacher Test Scores and Student Achievement in Mexico." *Economics of Education Review*, *25*, 510–520.

Shepherd, Deborah L. 2015. "Learn to Teach, Teach to Learn: A Within-Pupil Across-Subject Approach to Estimating the Impact of Teacher Subject Knowledge on South African Grade 6 Performance." Stellenbosch Economic Working Papers 01/15.

Spaull, Nicholas. 2011. "Primary School Performance in Botswana, Mozambique, Namibia, and South Africa." SACMEQ Working Paper 8.

UNESCO. 2016. "Every Child Should Have a Textbook." Global Education Monitoring Report, Policy Paper 23.

A 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). In this appendix, we assess the importance of measurement error for our estimates and propose a way of correcting the corresponding attenuation bias.

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 $T_{ik} = T^*_{ik} + e_{ik}$.[1] Assuming classical measurement error, $E(e_{ik}) = 0$ and $Cov(T^*_{ik}, e_{ik}) = 0$. In a bivariate model, the true effect of teacher subject knowledge on student performance, y_{ik}, will then be asymptotically biased towards zero:

$$y_{ik} = \beta\lambda_k T_{ik} + \varepsilon_{ik}, \quad \text{where } \lambda_k = \frac{Var(T^*_{ik})}{Var(T^*_{ik}) + Var(e_{ik})}. \tag{A.1}$$

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, i.e., a student fixed-effects model, the attenuation bias due to measurement error is likely aggravated. Intuitively, teachers' math and reading knowledge 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):

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

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

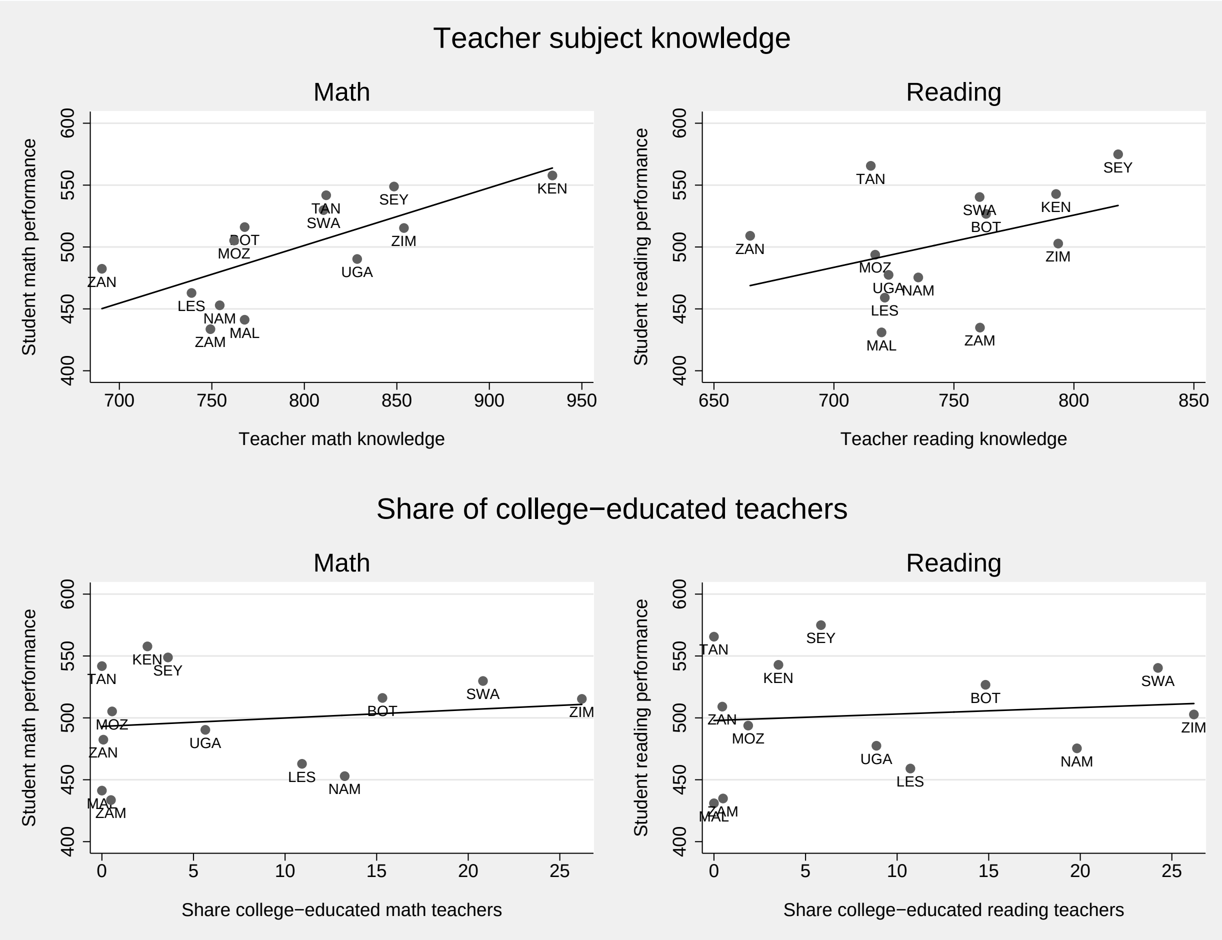
Note that the only unknown quantities in Equation (A.2) are λ_m and λ_r, while the variances and covariances of teacher subject knowledge can easily be computed from the data. Therefore, if the reliability ratios of the teachers' math and reading assessments were known, we could correct our baseline estimate for measurement error by multiplying the estimated coefficient with $1/\lambda_\Delta$.

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) by using teachers' answers to all individual test items.[2] The estimated reliability ratios are $\widehat{\lambda_m} = 0.83$ for math and $\widehat{\lambda_r} = 0.75$ for reading. Together with $Var(T_{im}) = Var(T_{ir}) = 1$ (due to our normalization of test scores) 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. For our baseline coefficient of 0.026 SD, this implies a corrected effect of 0.039 SD.

[2] 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, 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.

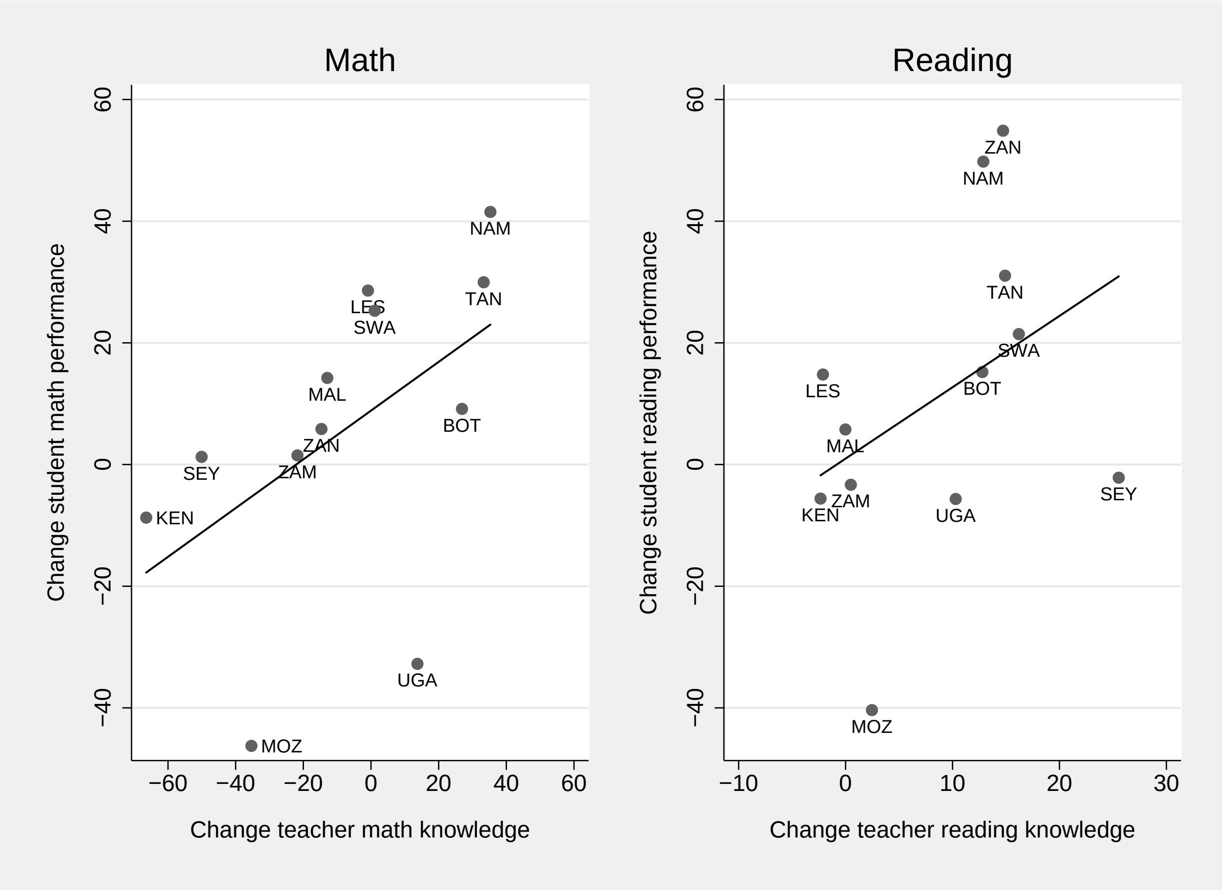
Figures and Tables

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



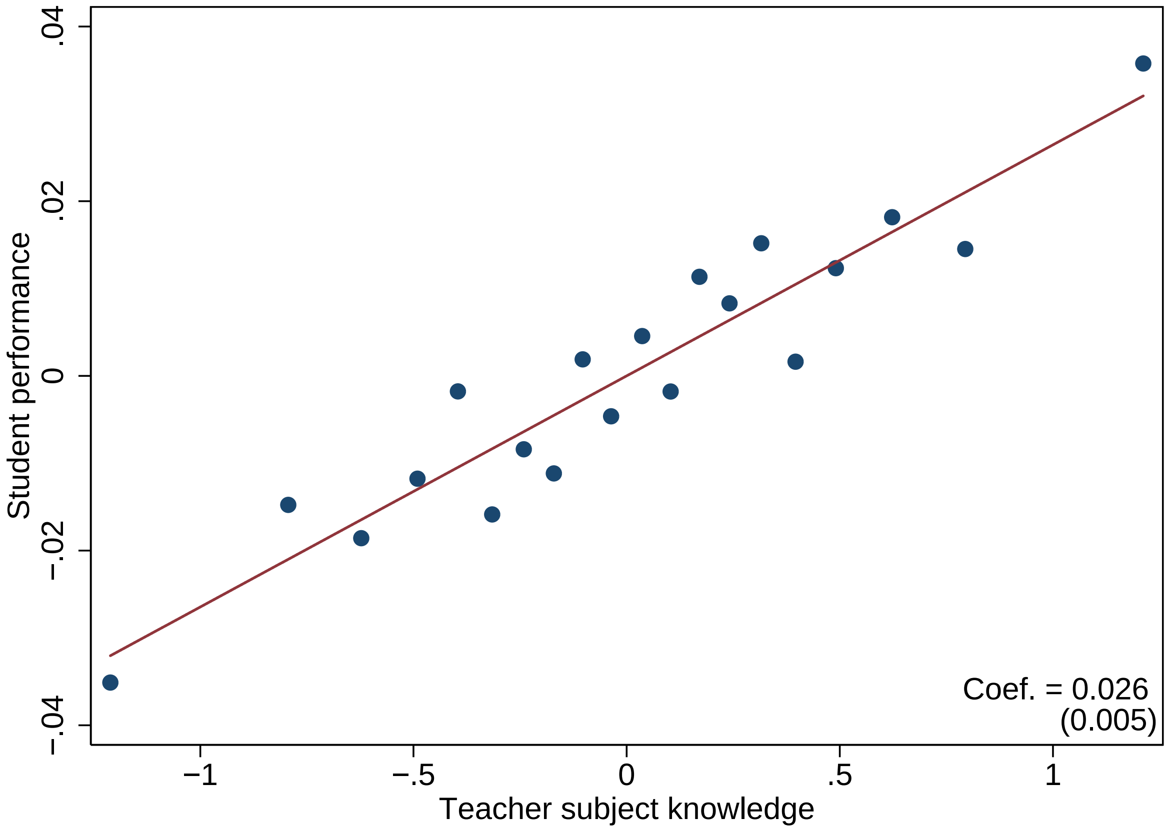
Notes: Solid lines fit a linear relationship between student performance and teacher subject knowledge in the top panel and between student performance and the share of college-educated teachers in the bottom panel. Share of college-educated teachers is the share of sixth-grade teachers with a college 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: Changes in Student Performance and Teacher Subject Knowledge between 2000 and 2007



Notes: Solid lines fit a linear relationship between changes in student performance and changes in teacher subject knowledge between 2000 and 2007. 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. Zimbabwe did not participate in the second SACMEQ wave and is therefore excluded in this figure.

Figure 3: Effect of Teacher Subject Knowledge on Student Performance



Notes: The figure displays a binned scatterplot corresponding to the student fixed-effects model 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, including student fixed effects. 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***	0.074***	0.073***
	(0.013)	(0.011)	(0.011)	(0.010)	(0.010)
Adj. R2	0.22	0.30	0.30	0.32	0.32
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***	0.077***	0.057***	0.052***
	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)
Adj. R-squared	0.22	0.35	0.35	0.38	0.38
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 coefficients on 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: Complementarity Between Teacher Subject Knowledge and School Resources (Student Fixed-Effects Model)

Dependent variable: student performance					
	Student-level resources	Resources measured at school level			
	(1)	(2)	(3)	(4)	(5)
Teacher subject knowledge	0.015**	0.027***	0.026***	0.027***	0.027***
	(0.007)	(0.005)	(0.006)	(0.006)	(0.005)
× textbook availability	0.020**	0.017***			
	(0.008)	(0.005)			
× school facilities (index)			0.016***		
			(0.005)		
× average class size				–0.002	
				(0.006)	
× teachers absent from classroom					–0.010*
					(0.006)
Textbook availability	0.005				
	(0.011)				
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	149,416	146,310	149,416

Notes: Fixed-effects estimations weighted by students' inverse sampling probability. Dependent variable: student performance in math and reading. In Column 1, teacher subject knowledge is interacted with a student-level indicator of whether subject-specific textbooks are available during math and reading class, respectively. In the remaining columns, teacher subject knowledge is interacted with school-level measures of share of students with subject-specific textbooks (Column 2), school facilities (Column 3), class size (Column 4), and teacher absenteeism (Column 5). To facilitate interpretation of coefficient magnitudes, the resource variables in Columns 2–5 are z-standardized across countries and waves. *Textbook availability*: binary variable that equals 1 if a student shares his or her subject-specific textbook with exactly one other student or has own textbook; 0 otherwise. In Column 2, *textbook availability* is aggregated to the school level and measures the share of students at school who share subject-specific textbook with at most one other student (averaged across math and reading). *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 in sixth grade. 3,106 student observations are missing because some school principals did not report the number of sixth-grade students at school. *Teachers absent from classroom*: overall indicator of teacher absence combining 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? (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. The main effects of the school-level resources in Columns 2–5 cannot be estimated because these variables do not vary across subjects. Classroom and teacher characteristics are the same as in Column 3 of 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**	0.017*	
	(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 Student Fixed-Effects Models)

Dependent variable: student performance	OLS		Student fixed effects	
	Math	Reading	Math & Reading	
	(1)	(2)	(3)	(4)
Teacher subject knowledge	0.064***	0.039***	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. In the student fixed-effects model, 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; teacher characteristics are also excluded as they 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: Complementarity Between Teacher Subject Knowledge and Subject-Specific Textbooks (Robustness Checks)

Dependent variable: student performance					
	Baseline	Same-teacher sample	Rural schools	One-classroom schools	School-level variables
	(1)	(2)	(3)	(4)	(5)
Teacher subject knowledge	0.015**	0.005	0.008	0.009	0.030***
	(0.007)	(0.015)	(0.009)	(0.012)	(0.006)
× textbook availability	0.020**	0.035***	0.017*	0.016	0.013**
	(0.008)	(0.013)	(0.009)	(0.012)	(0.005)
Textbook availability	0.005	0.019	0.003	–0.012	–0.003
	(0.011)	(0.016)	(0.013)	(0.017)	(0.012)
Effect of teacher knowledge for students with textbooks	0.035***	0.040***	0.025***	0.025**	0.044***[(a)]
(linear combination of main effect and interaction)	(0.006)	(0.012)	(0.008)	(0.011)	(0.008)
Student fixed effects	X	X	X	X	X
Classroom characteristics (2)	X	n.a.	X	X	X
Teacher characteristics (6)	X	n.a.	X	X	X
Observations	149,416	46,888	92,968	63,204	149,416

Notes: Fixed-effects estimations weighted by students' inverse sampling probability. Dependent variable: student performance in math and reading. Column 1 replicates Column 1 of Table 3. In Column 2, 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. In Column 3, the sample includes only schools in rural areas. In Column 4, all schools with more than one sixth-grade classroom are excluded. In Column 5, teacher test scores, subject-specific textbooks, access to teaching guide, and all teacher characteristics are collapsed at the school level. Thus, the textbook availability variable in Column 5 measures the share of students at school who share a textbook with one other student or have own textbook (separately for math and reading); this variable is z-standardized across countries and waves. Classroom and teacher characteristics are the same as in Table 2 (without the textbooks variable); these variables are excluded in Column 2 because they 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: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

[(a)] Effect size is not directly comparable to magnitudes in Columns 1–4 because of a different standardization of the textbook variable.

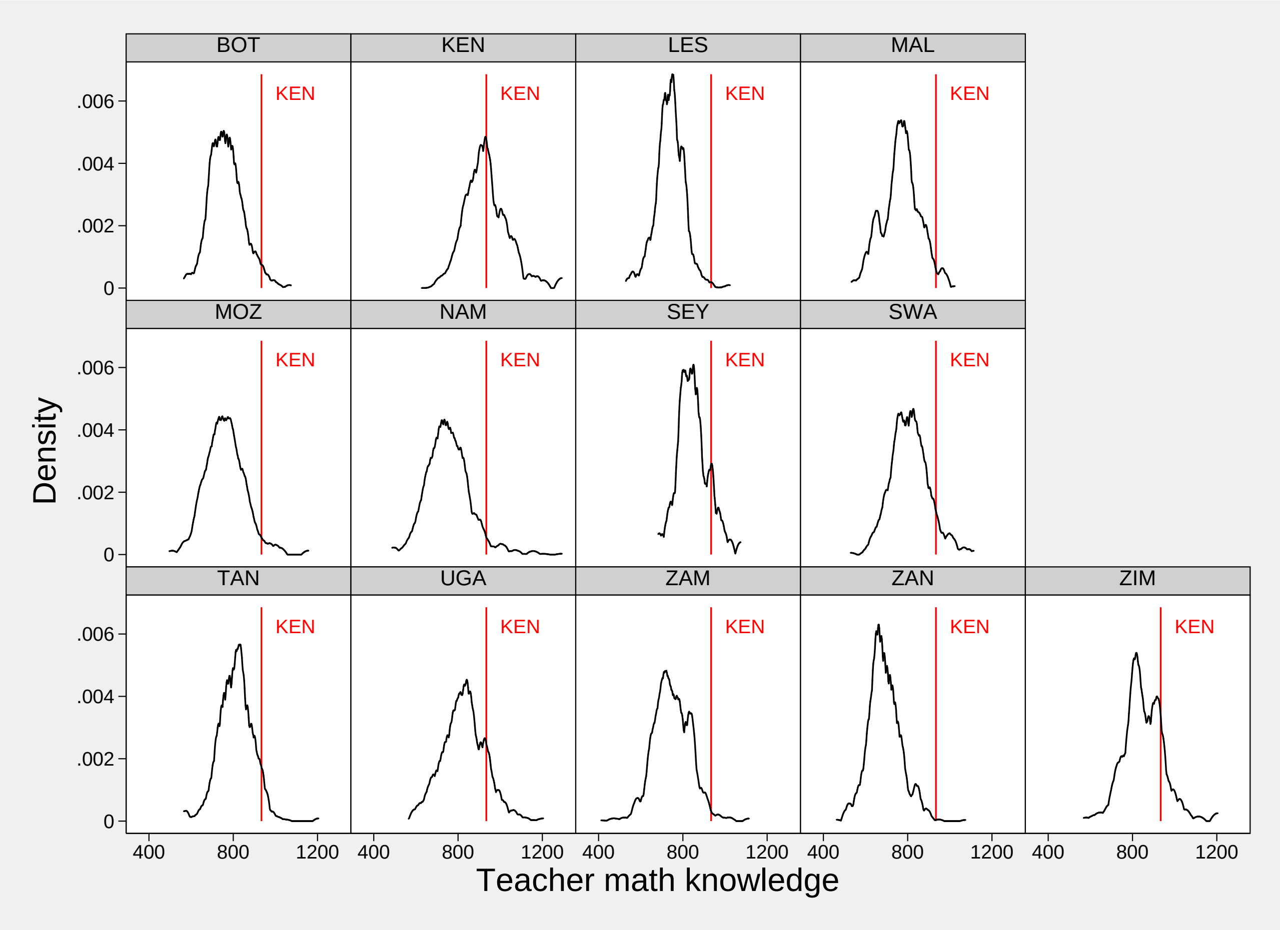
Table 7: Simulation Analysis: Raising Teacher Subject Knowledge and Subject-Specific Textbooks

	Math				Reading			
	Δ TSK to Kenia (SACMEQ points)	Δ stud. perf. TSK increases (in SD)	Δ books to Swaziland (in p.p.)	Δ stud. perf. TSK&books increase (in SD)	Δ TSK to Seychelles (SACMEQ points)	Δ stud. perf. TSK increases (in SD)	Δ books to Swaziland (in p.p.)	Δ stud. perf. TSK&books increase (in SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Botswana	157	0.05	10	0.06	54	0.02	7	0.04
Kenya	0	0	55	0.09	28	0.01	50	0.12
Lesotho	185	0.05	26	0.09	98	0.04	22	0.09
Malawi	159	0.04	45	0.11	100	0.03	44	0.13
Mozambique	166	0.04	27	0.09	100	0.04	25	0.10
Namibia	164	0.04	26	0.09	79	0.03	24	0.08
Seychelles	78	0.02	7	0.04	0	0	13	0.03
Swaziland	118	0.04	0	0.04	58	0.03	0	0.03
Tanzania	112	0.02	83	0.16	103	0.03	81	0.20
Uganda	96	0.02	72	0.14	94	0.03	64	0.17
Zambia	178	0.04	63	0.14	58	0.02	50	0.13
Zanzibar	229	0.05	51	0.14	154	0.05	51	0.16
Zimbabwe	71	0.01	69	0.13	24	0.01	63	0.15

Notes: Column 1 (Column 5) shows the difference in teacher subject knowledge between the indicated country and Kenya (the Seychelles), i.e., the country with the highest average teacher knowledge in math (reading). Column 2 (Column 6) shows by how much student performance in math (reading) would increase if teacher knowledge in math (reading) was raised to the level in Kenya (the Seychelles). Column 3 (Column 7) shows the percentage-point difference in the average availability of math (reading) textbooks between the indicated country and Swaziland, i.e., the country with the highest availability of math and reading textbooks. Column 4 (Column 8) shows by how much student performance in math (reading) would increase if teacher knowledge and textbooks in math (reading) were raised to the level of Kenya (the Seychelles) in teacher knowledge and to the level of Swaziland in textbook availability. These simulations are based on the coefficients in Column 1 of Table 3; see also footnote 39.

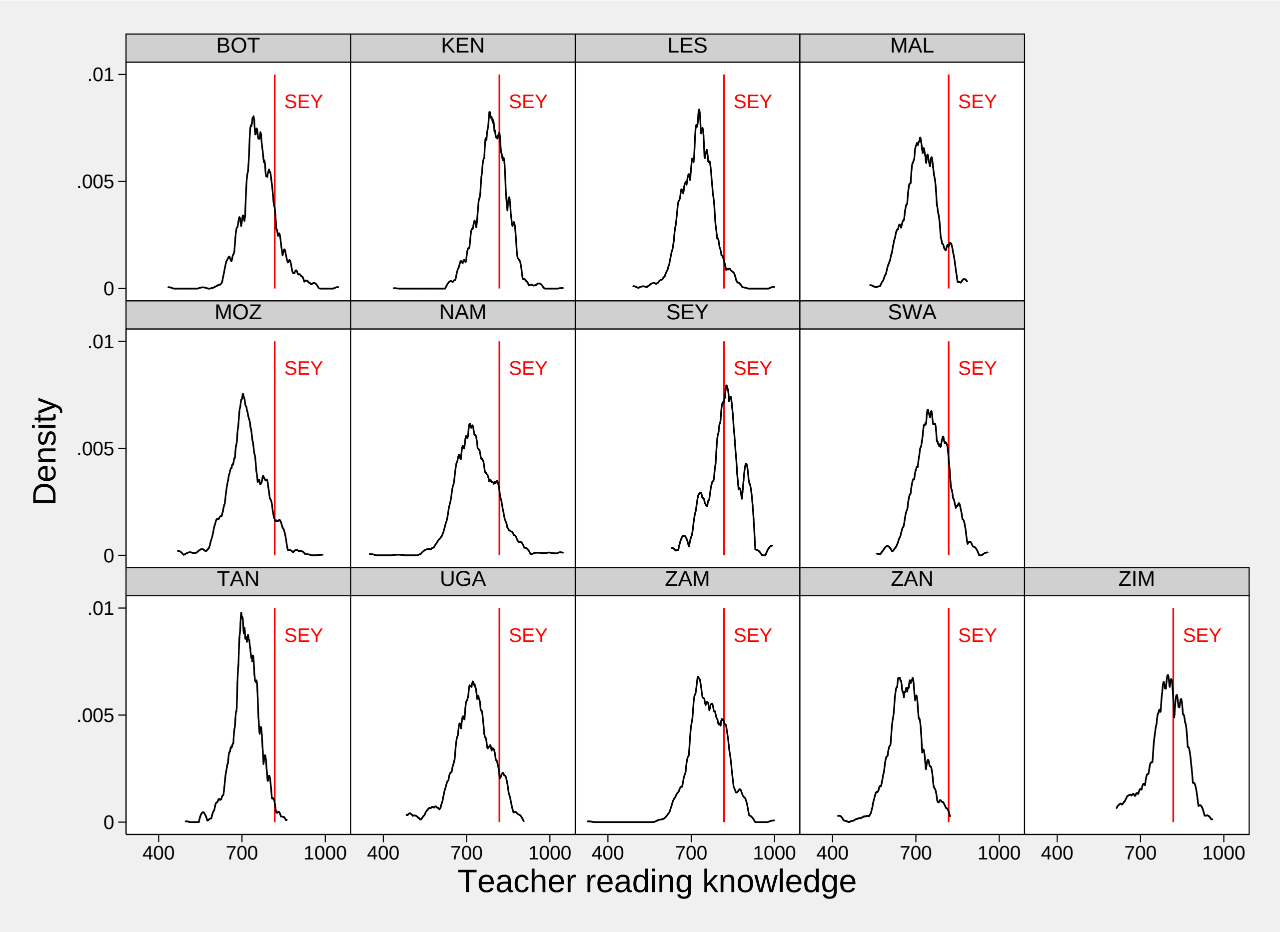
Appendix

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	–0.032***	–0.041***
	(0.003)	(0.003)
Female	–0.128***	0.004
	(0.009)	(0.008)
Mother's education		
Unknown	–0.022	0.009
	(0.017)	(0.016)
Some primary	–0.001	0.033**
	(0.017)	(0.015)
Primary	–0.001	0.033**
	(0.017)	(0.015)
At least some secondary	0.022	0.077***
	(0.018)	(0.016)
More than secondary	0.134***	0.199***
	(0.021)	(0.020)
Father's education		
Unknown	0.042**	0.104***
	(0.018)	(0.016)
Some primary	0.044**	0.098***
	(0.018)	(0.017)
Primary	0.070***	0.103***
	(0.018)	(0.017)
At least some secondary	0.083***	0.146***
	(0.019)	(0.016)
More than secondary	0.203***	0.275***
	(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***	0.233***
	(0.024)	(0.024)

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Table A-2 (continued)

Dependent variable: student performance	Math	Reading
Classroom characteristics		
Access to teaching guide	–0.057***	0.002
	(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)
Textbook availability	0.047***	0.077***
	(0.013)	(0.013)
School characteristics		
School facilities (index)	0.153***	0.184***
	(0.012)	(0.012)
Private school	0.139***	0.116***
	(0.029)	(0.027)
Rural school	–0.143***	–0.191***
	(0.019)	(0.018)
Teachers absent from classroom	–0.032***	–0.016*
	(0.009)	(0.008)
Number of students in school (/100)	–0.003*	–0.003
	(0.002)	(0.002)
Teacher characteristics		
Teacher female	0.034**	0.037**
	(0.017)	(0.015)
Education		
Junior secondary	0.015	0.021
	(0.030)	(0.030)
Senior secondary	0.049*	0.070***
	(0.026)	(0.025)
A-level	0.034	0.061**
	(0.028)	(0.029)
Tertiary	0.143***	0.125***
	(0.039)	(0.036)
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**	0.078
	(0.048)	(0.050)
1 year	0.153***	0.025
	(0.054)	(0.051)
2 years	0.069*	0.061*
	(0.036)	(0.036)
3 years	0.042	0.094**
	(0.036)	(0.039)
>3 years	0.097**	0.103**
	(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	0.32	0.38
Observations (students)	74,708	74,708
Clusters (schools)	3,939	3,939

Notes: The table reports results on 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 categories of teacher characteristics: *primary education*; and *no training*. *Textbook availability*: binary variable which equals 1 if a student shares his or her subject-specific textbook with one other student or has own textbook; 0 otherwise. *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 combining 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? (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. 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			
Gender:	Student	Teacher	Student-teacher
	(1)	(2)	(3)
Teacher subject knowledge	0.028***	0.031***	0.014**
	(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.