The impact of teacher subject knowledge on learner performance in South Africa: A within-pupil across-subject approach

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Abstract

This paper assesses the impact of teacher subject knowledge on learner performance using a nationally representative dataset of grade 6 students in South Africa. Learner test scores in two subjects are used to identify within-pupil across subject variation in performance. Teacher knowledge is only estimated to have a significant positive impact on performance when considering the wealthiest quintile of schools. The effect is removed once controlling for teacher unobservables. The results suggest that a deep knowledge and understanding of subject matter taught are important, but of more importance is the ability to transfer that information in a meaningful way to learners.

JEL Code: C31, I21

Keywords: teacher content knowledge, test performance, inequality, South Africa

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1. Introduction

Almost two decades after the end of apartheid, it is claimed that as many as 90 percent of South African schools "can be labeled as dysfunctional" (Cohen and Seria, 2010). Recently, the World Economic Forum ranked South Africa 137th out of 139 countries in terms of mathematics and science education. This is in spite of the fact that education gets the biggest share of the country's budget and spending per learner far exceeds that of any other African country. The dismal state of affairs has in part been ascribed to poor teacher education, as well as a broad national concern over the poor state of teachers' knowledge, particularly their subject content knowledge. The President's Education Initiative research project (1999) concluded that the limited conceptual knowledge of teachers – including poor grasp of subject - was the most important challenge facing teacher education in South Africa.

Stakeholders in education consider teacher quality to be the most important determinant of learner performance. According to the 2009 General Household Survey (GHS), of the South African households who do not send their children to the nearest available education institution, approximately 13 percent cited "poor quality of teaching" as the reason for doing so. An additional third of households surveyed cite that their school of choice is better than the nearest available one. This is likely to be strongly correlated to teacher quality. Yet the emphasis on teachers largely conflicts with empirical research into teacher quality and effectiveness. There is little agreement on what the characteristics of a high quality teacher are, as well as the relative importance of teacher quality for explaining learner performance (Hanushek & Rivkin, 2006: 3). Teacher characteristics typically "purchased" by schools, such as experience and education, have been found to be less important for achievement than characteristics such as teacher knowledge and recentness of education. These findings hold true in both developed country (c.f. Hanushek 1971, 1986, 1997; Monk, 1994; Monk and King, 1994; Wayne and Youngs, 2003; Hanushek et al, 2005) and developing country contexts (Glewwe et al, 1995; Kingdon, 1996; Tan et al, 1997).

The biggest challenges facing studies that attempt to estimate the causal effect of teacher characteristics on learner performance are omitted student, school and teacher characteristics and non-random sorting and selection of learners and teachers into classrooms and schools. For example, parents with a preference for achievement will select their children into schools and/or classrooms with high quality, better motivated and knowledgeable teachers. Furthermore, high quality teachers tend to be those teachers who are both highly motivated and accumulate more subject knowledge. The former trait is typically unobserved in survey datasets. Cross-sectional analyses that fail to address the issue of non-random assignment will produce biased estimates of teacher effects. This study makes use of a within-pupil between-subject methodology by Dee (2005, 2007) to estimate the effect of teacher subject content knowledge on grade 6 learner performance in South Africa. This first differencing technique has been applied quite extensively to eliminate bias from unobserved non-subject-specific student characteristics in order to identify the impact of various teacher and classroom factors such as the teaching style, certification, race and gender of the teacher (c.f. Dee 2005; 2007; Ammermüller and Dolton 2006; Dee et al, 2008; Clotfelter, Ladd, and Vigdor 2010; Metzler and Woessmann, 2010; Schwerdt and Wuppermann, 2011; Eren and Henderson, 2011). Identification here relies on variation across teachers in different subjects, as well as fixed pupil effects across subjects to correct for between and within school sorting of students. Estimation is furthermore restricted to a sample of learners that are taught by the same teacher in the two subjects in order to correct for teacher unobservables.

Two recently compiled case studies in the Gauteng (Carnoy et al, 2010) and North West provinces (Carnoy and Arends, 2012) of South Africa have provided evidence of a positive relationship between teacher knowledge and learner performance. However, stronger positive effects are estimated for quality of teaching, opportunity to learn and teaching institution attended. This study hopes to build on the findings of these studies using the methodology described above and a nationally representative dataset – the 2007 wave of the Southern and Eastern African Consortium for Monitoring Educational Quality (SACMEQ). This dataset is unique in that teachers were asked to complete subject specific tests. To the knowledge of the author, this is the first study to use a nationally representative data set to estimate the effect of teacher subject content knowledge on learner performance in South Africa whilst attempting to correct for omitted variable and selection bias. This study also goes further in testing for heterogeneity in the effect of teacher and classroom factors.

The remainder of the paper is structured as follows. Section 2 reviews the literature on teacher knowledge and student performance. Section 3 presents the data and basic descriptives and section 4 describes the estimation strategy. The main model results and robustness checks are presented in Section 5. Section 6 concludes.

2. Background and literature review

2.1 Policy Context

The education system inherited by the newly elected democratic government in 1994 was one characterised by high levels of racial segregation and inequality. The general view was that the apartheid curriculum served to prepare black students with inferior levels of knowledge, understanding and skills in comparison to their white counterparts. The first-ever national audit of teachers in South Africa in 1995 found high numbers of un- and under-qualified teachers as well as fragmented provision of teacher education and training. In attempts to return equality of opportunity to the education system, the current generation of teachers have had to face a number of challenges, including formation of a single national system, the introduction of new curricula and radically changing classroom compositions in terms of language, demography and culture.

The Norms and Standards for Educators (DoE, 2000: 47) regarded teachers who had obtained a three-year post-school qualification, or REVQ13,[1] as adequately qualified. The minimum requirement has since been updated to a four-year degree or equivalent qualification (REVQ14) as stated in the 2007 National Policy Framework for Teacher Education. However, a REVQ13 remains to be the norm as an adequate qualification level. In 2004, only 48 percent of teachers met the minimum qualification of a REVQ14. In-service programs offered by universities have allowed teachers to upgrade their qualifications to the necessary level. This is reflected in the rising proportion of annual graduates in Education that are teachers upgrading their existing qualifications. According to the Quarterly Labour Force Surveys (QLFS, Statistics South Africa) of 2010, the proportion of secondary and primary school teachers with REVQ14 and higher was 78.9 and 36.0 percent respectively (68.7 percent together). A further 18 percent are adequately qualified at an REVQ13 level. This implies that in 2010, 13.3 percent, or approximately 55000, of Basic Education teachers, remained under-qualified even by the more lenient requirements that applied in 2000.

The quality of content of initial and further training of teachers may vary dramatically given that the current curriculum decisions for pre- and in-service training programs are made independently by individual institutions[2]. Furthermore, the majority of teachers currently in the

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[1] The Relative Education Qualification Value (REQV) is a relative value attached to an education qualification that is based primarily on the number of recognised prescribed full-time years of study. Completion of school (matric or Grade 12) is an REQV of 10; each additional year of recognized post-school education or training adds one point to the REQV.

[2] Within the context of the expectations set by the new schools' curriculum and the Norms and Standards for Teachers (Sayed, 2004).

teaching profession would have received training prior to 1994 when education was racially and ethnically sub-divided and the curriculum was not centralised. A mere 5.4 percent of all practising teachers in 2005 were under the age of 30, which implies that only a limited proportion of teachers are prepared for the new curriculum (Erasmus and Mda, 2008). Some teacher training institutions teach mathematics only up to the level which the teachers would be teaching, which would not provide teachers with an adequate depth of content knowledge or understanding necessary to teach at an Intermediary Phase level. In videotaped observations of mathematics teachers in the Gauteng Province, Carnoy et al (2010) find that some teachers employ methods that point towards formal training in the use of highly effective methods that require both a deep understanding of the mathematical concepts and pedagogical skills. However, the majority of teachers observed were found to use a limited range of teaching methods that were indicative of the rigidity of training received.

2.2 Teacher content knowledge and learner outcomes

Shulman (1986) distinguishes between four broad kinds of knowledge that an effective teacher should possess: general pedagogical knowledge; content knowledge (CK); pedagogical content knowledge (PCK); and curricular knowledge. Pedagogical knowledge is generally obtained formally through pre- and in-service training and informally through trial-and-error in their own classrooms and through observing their peers (Carnoy et al, 2010). CK is principally obtained through a teacher's former pre-service training, and may be further subdivided into common or specialised CK. PCK refers to the manner in which CK is applied for teaching others and is obtained through practice or highly skilled training programs. The notion of PCK has gained wide appeal as it links content knowledge and the practice of teaching (Ball et al, 2008). A natural question to ask would be "which is most important?" It can be argued that pedagogical content knowledge (PCK) is likely to have the greatest ties to effective teaching as well as to directly influence a teacher's ability to develop curriculum. Shulman (1987) notes that someone who assumes the role of teacher must first demonstrate knowledge of their subject matter before being able to help learners to learn with understanding.

Evidence on the impact of teacher knowledge on learner outcomes in South Africa is largely unclear. This is mainly due to the fact that teacher subject content knowledge has rarely been captured in large-scale, nationally representative surveys of learner achievement. Furthermore, empirical analysis has largely been limited to mathematics. Two recently collated datasets, namely the National School Effectiveness Survey (NSES), a panel dataset covering 3 years of primary schooling, and the 2007 SACMEQ survey provide information on teacher content knowledge through subject-specific teacher test scores. The shortness of the teacher tests conducted under the NSES[3] means that this survey provides limited, and potentially noisy, measures of teacher knowledge. In an attempt to relate teacher content knowledge to student performance in the NSES, Taylor (2011) finds that, when combined with time on task, teacher knowledge leads to substantial gains in student learning. However, this only occurs at a very high level of knowledge, indicating a non-linear relationship between teacher knowledge and learner performance. The strongest finding by Taylor (2011) is the significant positive relationship between learner outcomes and curriculum coverage. Using a sample of 24 schools in the Western Cape Province, Reeves (2005) similarly finds that opportunity to learn as measured by curriculum coverage is significantly related to learner gains in mathematics. Employing the SACMEQ 2007 dataset, Spaull (2011) estimates education production functions for learner performance in mathematics, English and health. The results indicate a statistically significant relationship between teacher content knowledge and learner test scores. The estimated coefficients are, however, smaller than those observed in other developing country studies. Spaull (2011) further finds the relationship between teacher knowledge and performance to be stronger for a subset of wealthier schools.[4] These analyses were, however, performed using cross-section least squares methodologies that do not correct for potential bias due to non-random sorting of students and teachers across schools, as well as omitted variable bias. Therefore the results cannot be interpreted as causal.

Of more relevance are the findings of two case studies that have paid specific attention to the effect of teacher knowledge on learner outcomes. These studies further adopt value-added approaches which account for non-random sorting of learners and teachers across schools and classrooms. In a pilot study of forty schools in the Gauteng Province, Carnoy et al (2010) attempt to estimate the contributions of various classroom and teaching factors to learning gains in mathematics of Grade 6 learners. The teacher instrument was designed to include questions that provide measures of CK and PCK.[5] Teachers from historically African and coloured schools were observed to score lower in both CK and PCK than teachers from the Independent and former white schools, with larger differences observed in the latter. Only in the case of the two highest levels of SES was learner performance found to be closely related to teacher knowledge. Mathematics

[3] English teachers were given a comprehension test comprising of 7 questions, and mathematics teachers a 5 mark test.

[4] Neither teacher education nor teacher experience was included in the regression models of Spaull (2011), therefore the impact of these teacher quality variables after controlling for teacher knowledge is unclear.

[5] Three of the questions on the test measured CK, whilst the remaining seven questions were about a "big" idea or concept that is rooted in a teaching situation; that is, it measures a teacher's ability to apply CK to the job of teaching. The limited number of questions used may provide quite noisy measures of knowledge.

teachers with higher CK and PCK were predominantly found in wealthier schools where learner ability is also higher, indicating a non-random sorting of teachers to schools and learners. Teacher PCK was found to be weakly but significantly related to teacher quality ratings based on videotaped classroom sessions. A stronger relationship was estimated between PCK and the institution where training was received, with substantial differences in levels of PCK observed between those teachers who attended rural and urban African or coloured colleges and those who attended Indian and white institutions or universities. This suggests that the institution of training may have some direct influence on quality of teaching that is unrelated to the relationship between the quality of training and PCK. CK was not found to be significantly related to teaching quality. Estimates from a value-added model of learner performance in mathematics indicate a significant positive effect of teaching quality on test score gains and a positive, but statistically insignificant, coefficient on PCK. However, approximately 25 percent of the original sample took part in the second test, therefore the result may suffer from selection bias.[6] A negative, but statistically insignificant, effect of CK was estimated. This may be driven by the fact that learner gains were negatively related to initial learner score. Learners taught by teachers with higher CK may therefore have experienced lower average gains given higher base test scores. The findings of the study by Carnoy et al (2010) provide empirical support for that hypothesis that PCK is important for learning.

A more recent study by Carnoy and Arends (2012) exploits a natural experiment based on geographical closeness of Southeastern Botswana and the North West (NW) Province in order to estimate the contributions of classroom and teaching factors to student gains in mathematics. Unlike the Carnoy et al (2010) sample that includes schools from different former departments, this study selected sixty schools from a sample of no-fee (i.e. low SES) public sector schools in the NW. These are likely to have fallen under the former African school department. Teachers from the NW sample were found to have less content and pedagogical knowledge than their Botswana counterparts. Teacher knowledge was found to have a strong positive relationship to ratings of teacher quality and opportunity to learn in the NW schools. As in Carnoy et al (2010) and Reeves (2005), teacher quality and opportunity to learn were estimated to have positive and significant effects on learner gains in mathematics test scores. However, the coefficient on a one standard deviation increase in teacher quality was small at 0.05 percent of a standard deviation, i.e. the "effect size" was 0.05.[7] Teacher mathematics knowledge was not significantly related to

[6] It is difficult to say whether the result is upwardly or downwardly biased as the original report gives no details as to how the sample that wrote the second test compares to the overall sample.

[7] In education, when both dependent and independent variables are measures in standard deviations, the coefficient is referred to as the "effect size".

achievement gains, possibly due to its positive correlation with teaching quality and opportunity to learn.

In summary, the findings in the South African context seem to suggest that teachers with higher content knowledge, specifically PCK, are more likely to be teaching in wealthier schools that are Independent or fell under the former white and Indian school departments. Therefore, correction for non-random is necessary in order to identify the impact of teacher and classroom factors. Teacher knowledge has been found to be positively related to factors associated with effective teaching, such as high teacher quality, opportunity to learn and quality of training, but not to level of education.

3. Data and Descriptive Statistics

The data used in this study is the third wave of the SACMEQ survey conducted in 2007. Learner knowledge in three subject areas - numeracy, literacy and health - was tested using standardized multiple-choice questionnaires. Performance on the individual tests was standardized to a regional average of 500 points and a standard deviation of 100 points. Of the 15 countries surveyed, South Africa ranked 10th for reading and 8th in mathematics. In addition to testing, a full array of information regarding home, classroom, and school environments was collated, as well as demographic information on students, parents, teachers and principals. Teachers were required to complete the health test, as well as subject-specific tests in mathematics and English.[8] This is the first nationally representative education survey in South Africa where teachers' subject knowledge was tested. Although it has been shown that content knowledge is related to pedagogical content knowledge, the claim in this paper is not that the teacher test score is reflective of the latter but rather that it is a measure of the former.[9] For simplicity, teacher test score will be considered as a measure of teacher subject knowledge. For the most part, teachers and students wrote the same tests, although teachers were required to answer additional "challenging" questions. To account for differences in difficulty across questions, teacher test scores were transformed using the Rasch scaling (Rasch, 1960) so to be directly comparable with student test-scores. For purposes of this study, only scores on literacy and numeracy are considered. Altogether 9083 6th grade learners were sampled from 392 schools in South Africa. The large size of the dataset makes SACMEQ III

[8] Although the SACMEQ II questionnaire did contain a teacher-test, due to South African teacher-union objections, South Africa was one of the few SACMEQ countries that did not complete the teacher-test section of the SACMEQ II survey. This being said, in SACMEQ III teachers were allowed to refuse to write the tests, which some of them did.

[9] One concern for the analysis is that teacher knowledge may be measured with noise. This would understate the effect of teacher knowledge.

highly advantageous for analysing educational outcomes and their determinants in South Africa. This is especially true given the large intraclass correlation coefficient that is typically observed in school performance data in South Africa (Van der Berg, 2007).[10] After accounting for missing data, the final sample is comprised of 6996 learners in 325 schools taught in 686 classrooms by 357 reading teachers and 354 mathematics teachers, where 57 teachers taught the same learners in both subjects.

Table A.1 of the appendix reports descriptives of the final sample. Both the learner and teacher scores have been normalized to have a mean of zero and standard deviation equal to one.[11] On average, learners performed better in the numeracy test than the literacy test. This may be related to the language of the test as all learners were required to write both tests in English.[12] Only 13 percent of learners were observed to speak English often at home; these learners, as well as their teachers, further had higher average test performance. Learner performance was positively related to borrowing books outside of school, high household socio-economic status and tertiary education of parents. Both learners and teachers performed better in classrooms that were in general better resourced. Test performance of teachers and learners was further positively related to little strike activity by teachers and higher teacher qualifications.

Table A.2 summarises subject-specific differences in teacher and classroom characteristics. Teacher and classroom characteristics were fairly similar across the two subjects, although significant differences between the two groups were observed on several variables. Mathematics teachers were more likely to be younger and possessed post-matriculation qualifications, whereas English teachers were more likely to be female, tertiary educated, and had completed more in-service courses in the past three years. With regards to classroom resources and processes, classrooms in which mathematics teachers taught tended to be better equipped, whilst there was a greater availability of textbooks in English classrooms. Further descriptive analysis (not shown here) reveals that girls performed significantly better in both numeracy and literacy, with a larger

[10] In calculating the required sample sizes, the first and second waves of the SACMEQ survey erroneously assumed that the intra-class correlation (rho) for the group of countries under investigation would be in the range of 0.3 to 0.4. However, the true rho values in South African fall within the range 0.6 to 0.75, resulting in the samples drawn being too small to obtain the desired significance (Ross et al, 2005). The third wave was in this respect a major improvement.

[11] Therefore, the estimated model coefficients can be interpreted as fractions of a standard deviation.

[12] Language may only account for a small part of the difference. The scores on the two tests are standardised across all SACMEQ countries. This implies that performance in each of the subjects reveals something of the relative performance in a SACMEQ context.

difference observed for literacy. Teachers with at least a university degree performed better in literacy but not significantly different in mathematics when compared with teachers with only a post-matric but non-degree qualification. When compared to teachers with complete high school or less, teachers with university degrees performed significantly better in both numeracy and literacy. All variables listed in tables A.1 and A.2 were included as explanatory variables in the empirical analysis, as well as a set of provincial dummies.

4. Estimation strategy: first-difference specification

The design of the SACMEQt III surveys implies that we contemporaneously observe two measures of learner outcomes along with our variable of interest, the corresponding teacher test score for each subject. This makes it possible to construct within-learner comparisons that eliminate selection bias due to the influence of subject-invariant learner and school unobservables. We are also able to eliminate the influence of teacher unobservables that may be correlated with our variable of interest through limiting the sample to only those learners who were taught by the same teacher in both subjects.

It is assumed that the observed numeracy test score for learner *i* who is taught by teacher *j* in subject 1 (mathematics) is a function of learner characteristics (including home background), X_i, observable teacher and the classroom variables that are subject-variant, T_{1j_1}, and teacher test score, Q_{ij_1}:

$$Y_{1ij_1} = \alpha_1 + \delta' X_i + \beta Q_{1ij_1} + \gamma' T_{1j_1} + \mu_i + \tau_{1j_1} + \varepsilon_{1i} + \varpi_{ij} \quad (1)$$

The error term comprises of a learner component, μ_i, *while* τ_{1j_1} and ε_{1i} represent the unobserved characteristics of the teacher and the subject respectively, and ϖ_{ijk} is the remaining unobserved error term. The learner fixed effect, μ_i, captures family background, underlying ability and other constant underlying non-cognitive skills. Note that in combination with exploiting within-leaner variation between subject test scores, controlling for learner fixed effects results in controlling for school fixed effects.

It is further assumed that a similar specificaion exists for learner test scores in literacy:

$$Y_{2ij_2} = \alpha_2 + \delta' X_i + \beta Q_{2ij_2} + \gamma' T_{2j_2} + \mu_i + \tau_{2j_2} + \varepsilon_{2i} + \varpi_{ij} \quad (2)$$

Least squares estimation of β and γ in (1) and (2) will lead to biased results due to the presence of confounding unobservable teacher and learner effects in the error terms. We are able to correct for non-random selection of learners into and within schools through conditioning for learner fixed effects. First-differencing (1) and (2) results in:

$$Y_{1ij_1} - Y_{2ij_2} = (\alpha_1 - \alpha_2) + \beta\left(Q_{1ij_1} - Q_{2ij_2}\right) + \gamma'\left(T_{1j_1} - T_{2j_2}\right) + \left(\tau_{1j_1} - \tau_{2j_2}\right) + (\varepsilon'_{1i} - \varepsilon'_{2i}) \qquad (3)$$

where $\varepsilon'_{1i} = \varepsilon_{1i} + \varpi_{ij}$ and $\varepsilon'_{2i} = \varepsilon_{2i} + \varpi_{ij}$.

Several points need to be made with regard to the identification strategy outlined above. First, the effect of teacher knowledge is "net" of teacher knowledge spillovers across subjects; that is, teacher subject knowledge in mathematics might influence learners' test scores in English.[13] Second, the specification in (3) imposes that teacher effects are the same across subjects. This is quite a strong assumption given that the effect of, say, teacher subject knowledge on learner performance could be related to the specific subject matter being taught. We allow for heterogeneity in the impact of teacher subject knowledge through allowing for different β's across equations (1) and (2) as follows:

$$Y_{1ij_1} = \alpha_1 + \delta' X_i + \beta_1 Q_{1ij_1} + \gamma' T_{1j_1} + \mu_i + \tau_{1j_1} + \varepsilon_{1i} + \varpi_{ij} \qquad (4)$$

$$Y_{2ij_2} = \alpha_2 + \delta' X_i + \beta_2 Q_{2ij_2} + \gamma' T_{2j_2} + \mu_i + \tau_{2j_2} + \varepsilon_{2i} + \varpi_{ij} \qquad (5)$$

First-differencing equations (4) and (5) to remove the learner fixed effect yields:

$$Y_{1ij_1} - Y_{2ij_2} = (\alpha_1 - \alpha_2) + \beta_1 Q_{1ij_1} + \beta_2 Q_{2ij_2} + \gamma'\left(T_{1j_1} - T_{2j_2}\right) + \left(\tau_{1j_1} - \tau_{2j_2}\right) + (\varepsilon'_{1i} - \varepsilon'_{2i}) \qquad (6)$$

Following estimation of (6), we can test for rejection of the hypothesis $\beta_1 = \beta_2$. Similarly, we can allow for differences in γ across the two subject equations.

Finally, the fixed effect framework does not prohibit the possibility that learner sorting occurs between subjects based on subject knowledge of the teachers. Unobserved subject-specific

[13] The fact that the data used here is cross-sectional and test performance is only available for two subjects makes it difficult to test for spillover effects whilst controlling for learner fixed effects. See Dee (2005, 2007) and Eren and Henderson (2011) for examples of tests for spillover effects of teacher characteristics across related subjects using cross sectional data and test scores on more than two subjects. Least squares estimates of teacher subject scores in mathematics on learner performance in literacy shows a positive and significant relationship. This may be evidence of knowledge spillovers. However, this may be driven by a positive correlation between the quality of mathematics teacher and unobservable school quality.

learner and teacher or classroom traits that may be related to teacher test score and other observables captured in T may be present. For example, unobserved teacher quality may differ in some consistent way between the subject taught, or learners with an aptitude for mathematics may be assigned to teachers with greater subject knowledge. The assumption that $(\tau_{j1} - \tau_{j2}) + (\varepsilon'_{i1} - \varepsilon'_{i2})$ is uncorrelated with either Q or T may be quite strong. Therefore, we refrain from interpreting β as a causal effect and rather interpret it as a measure of the relationship between teacher subject knowledge and learner performance that is not driven by between- or within-school sorting of students. In order to correct for bias due to unobservable teacher characteristics, we can restrict the sample to learners taught by the same teacher in both subjects. In this case, $T_{1j_1} = T_{2j_2} = T_j$ and $\tau_{1j_1} = \tau_{2j_2} = \tau_j$ such that (3) will simplify to:

$$Y_{1ij} - Y_{2ij} = (\alpha_1 - \alpha_2) + \beta\big(Q_{1j} - Q_{2j}\big) + (\varepsilon'_{i1} - \varepsilon'_{i2}) \qquad (7)$$

Although this specification makes it impossible to identify the impact of subject-invariant teacher inputs such as gender and race, it does eliminate bias from unobservable teacher characteristics variables when estimating the effect of teacher subject knowledge. Due to the limited sample of learners taught by the same teacher in both subjects, estimation using only this group will serve as a robustness check to the main results using the full sample.

In addition to first difference (FD) estimates based on equations (3) and (6), pooled versions of equations (1) and (2) that control for school fixed effects instead of student fixed effects will be estimated. These more conventional OLS estimates provide some continuity with the earlier literature by examining whether unobserved student traits could impart a bias to the estimated effect of teacher subject-knowledge. All regression analysis takes the sampling design of the data into account.[14] Due to the nested nature of the data, inferences are based on robust standard errors that are clustered at the level of the school.

5. Baseline results

Table A3 presents the baseline specification estimates using least squares and learner fixed-effects estimation. The least squares specifications (columns 1 – 4) control for different sets of explanatory variables over a pooled data set of the two subjects. Column (4) further controls for school fixed effects. The normalized test score outcomes (in both subjects) are used as the

[14] A sampling method of probability proportional to size (PPS) was used to select schools within provinces, and simple random sampling was used to select students within schools.

dependent variable in all the least squares regressions. Given the purpose of the analysis, only estimated coefficients for the variable of interest, teacher subject-knowledge, and typical variables of teacher quality such as education and experience are reported.[15] The final four columns of table A3 present the results of FD specifications that condition on student fixed effects and teacher/classroom characteristics. The difference in the normalized subject scores forms the dependent variable in all FD model estimations.

5.1 Uniform returns to teacher subject knowledge across subjects

The estimates in columns (1) - (3) of table A3 indicate a significant positive effect of teacher subject knowledge on learner test scores that is substantially reduced (from 0.43 to 0.15 of a standard deviation) after controlling for a full set of learner and household background characteristics. The coefficient is reduced by a further 30 percent after the addition of teacher and classroom controls, yet remains statistically significant. However, these findings may be confounded by within- and between-school sorting based on unobservable characteristics of learners as neither school nor learner fixed effects are controlled for. After the addition of school fixed effects in column (4), the coefficient on teacher test score remains positive albeit small at 0.026, but turns statistically insignificant. There therefore appears to be evidence that teacher knowledge is positively related to observable and unobservable school characteristics and that there is a self-selection of higher quality learners and teachers into higher quality schools. Estimation of a FD model as in equation (3) that controls for learner fixed effects serves as a means of dealing with these potential biases. The results of these are shown in columns (6) and (7). Both models predict a small positive and statistically insignificant effect of teacher subject test score.

5.2 Subject-specific returns to teacher subject knowledge

Thus far the effect of teacher subject knowledge has been restricted to be the same across both subjects. A schools fixed effects model that allows for different returns indicates a smaller return to mathematics teachers' subject knowledge. This difference is not statistically significant. Extending the model specification to control for learner fixed effects as in equation (6) we find that the coefficients on teacher subject knowledge drop (column 8 of table A3). The coefficient of 0.033

[15] It can, however, be noted that the estimated coefficients on learner/family background and school covariates not shown in table A3 indicate that female learners perform significantly better on average, as well as learners who speak English on a regular basis at home. Mother's education (particularly higher education), household SES, urban school location, community subsidization of teacher salaries, the proportion of non-permanent teaching staff and school SES are significantly positively related to performance.

on English teacher test score is weakly statistically significant (at the 10 percent level). An F-test for equal effects across the two subjects is rejected at the 10 percent level of significance.

5.3 Non-linear returns to teacher subject knowledge

The base model specification allowed only for a linear effect of teacher subject knowledge. In column (9) of table A3 the coefficients for a more flexible specification that allows for a non-linear effect of teacher test score are reported. The model estimates indicate that there may indeed be a non-linear effect of teacher knowledge, with a statistically significant and positive quadratic effect estimated for teacher subject knowledge across both subjects. The non-linear effect may be linked to the type of school attended by the learners. Spaull (2011) finds a stronger positive effect of teacher test score for performance for a wealthier subset of schools in his analysis of the SACMEQ III data. The non-linear effect may therefore be driven by the higher content knowledge and quality of teachers found in wealthier schools in South Africa. This conjecture is tested in the next section.

5.4 Heterogeneous effects of teacher subject knowledge

A potential concern for the analysis is that the majority of learners in the South African schooling system are not first-language English speakers. In addition, these learners are likely to be taught by teachers who are themselves not first-language English speakers and are likely to be from the same ethnic group as their learners. This is particularly true for historically black and homeland schools in South Africa. Columns (1) – (2) of table A4 shows results from estimation of a FD model for groups of learners with varying frequency of spoken English at home. The effect of teacher knowledge is not restricted to being uniform across subjects. Column (1) shows results for a sample of learners who speak English regularly at home, whilst column (2) shows results for the sample of learners who rarely or never speak English at home. The effect of teacher test score in both subjects is estimated to be positive for both groups. However, only the effect of English teacher test score in the sample of frequent English speaking learners is weakly statistically significant. The estimated coefficient of 0.059 is larger than the baseline result for the whole sample, although not significantly so. Columns (3) and (4) of table A4 repeat the analysis for a sample of above average household SES learners and a sample of below average household SES learners. A significant quadratic effect of teacher test score is estimated for both subjects in the sample of above average SES learners, whereas no significant linear (or quadratic) effect of teacher test scores is found for the sample of below average SES learners. The results in column (3) very closely mirror those seen in the final column of table A3, suggesting that the strong positive quadratic effect of teacher subject knowledge may be related to the types of schools in which particular learners groups are found, as well as the quality of teacher that is attracted to those schools.

Native English speaking learners as well as those leaners from more affluent home backgrounds are more likely to attend former White and Indian schools that perform notably better on average than former black and coloured schools (c.f. Van der Berg, 2008) and these schools are able to afford better quality teachers.[16] These results provide cursory evidence that there are potentially divergent effects of teacher subject knowledge across different sectors of the South African primary school system. The bi-modal nature of performance within the South African schooling system is a well-documented finding in the South African education literature (c.f. Gustafsson, 2005; Fleisch, 2008; Taylor, 2011; Spaull, 2012). By this it is meant that the overall test score distribution masks two separate distributions that correspond to two quite divergently performing subsets of the South African school system that are embedded in the formerly separate administration of education for each race group (Fleisch, 2008).

Table 1 presents distribution statistics of learner and teacher test scores across school wealth quintiles based on school SES. The top 20 percent SES schools (from this point forward referred to as Q5 schools) are separated from the bottom 80 percent (below referred to as Q1to4 schools).[17] It is clear that the Q5 schools perform more than an international standard deviation (100 points) above the SACMEQ average of 500, whilst the Q1to4 schools perform below the average. It is further evident that the Q1to4 schools perform better on average in numeracy than in literacy whilst the opposite is true for the Q5 schools. This may be a reflection of the low proportion of first-language speaking English learners found in the former.[18] The picture is similar for teacher test scores. Teachers in Q5 schools perform significantly better on average in both subjects. These findings are in agreement with those of Carnoy et al (2010).

[16] Even though the salary of the teachers a school appoints (the value of which is based on their experience and qualifications) is paid by the state, schools that manage to attract better quality teachers receive larger state subsidies for teacher costs, ceteris paribus. Schools can use fees to appoint additional teachers that may furthermore be of a higher quality.

[17] This grouping is chosen based on other studies which have shown no significant difference in performance across the three bottom school SES quartiles (c.f. Taylor, 2011; Spaull, 2012). This division is further closely related to the historical separation of formerly black/homeland schools and formerly white, coloured and Indian schools.

[18] 34 percent of learners in Q5 schools are first language English speakers. This is compared to 8 percent of learners in Q1to4 schools.

Table 1: learner and teacher test score performance by school wealth

	20% wealthiest schools		80% poorest schools		
	Mean	s.d.	Mean	s.d.	Difference
Learner scores:					
Numeracy	608.2	90.3	466.2	71.6	142.0***
Literacy	639.3	91.3	458.7	85.1	180.6***
Teacher scores:					
Mathematics teacher numeracy score	896.3	116.1	739.5	87.4	155.8***
English teacher literacy score	847.6	73.2	742.6	68.8	105.0***

Note: Significance at *** 1%, ** 5%, * 10%.

The baseline specifications are estimated separately for the two school wealth groups. The results of these are shown in columns (7) – (11) of table A4.[19] The results here indicate quite divergent impacts of teacher subject knowledge across different subsets of the schooling system. The impact of teacher subject knowledge is not estimated to be statistically significant from zero for the group of Q1to4 schools for all specifications of the base model that allow for both uniform and divergent returns across subjects (see the final three columns of table A4). Assuming uniform returns to teacher test scores in Q5 schools (column 7) teacher subject knowledge is estimated to have a positive significant effect of 7.1 percent of a standard deviation (6 points) increase in learner test scores for a 1 standard deviation increase in teacher test score. With divergent returns permitted across the two subjects (column 8), a strong positive effect of mathematics teacher test score of 12.8 percent of a standard deviation is estimated. No discernible linear effect of English teacher test score is estimated for the Q5 schools. Allowing for non-linear returns, we find evidence of increasing returns to English teacher subject knowledge in the Q5 schools, although the overall effect remains substantially smaller than that of mathematics teacher knowledge. The findings here support the notion of bimodality in the South African schooling system.

5.5 Achievement effects of other teacher and classroom characteristics

Table A5 presents the estimated returns to other teacher and classroom characteristics. For comparative purposes, coefficients from least squares and school fixed effects models are shown in columns (1) and (2). Coefficients estimated using the baseline specification allowing for quadratic effects on teacher test score are shown in column (3). It is interesting to note that the coefficient on less than 6 years of teaching experience more than triples and turns statistically significant after

[19] So as not to bias the results, learner and teacher test scores have been re-standardised to have a standard deviation of 1 and mean of zero with respect to each groups' respective test score distribution.

controlling for school fixed effects. This indicates that, when compared to other teachers within the same school, learners taught by less experienced teachers perform significantly better on average (26.4 percent of a standard deviation or approximately 25 points) than learners taught by teachers with more than 5 years of experience, all else equal. This may reflect a higher quality of teachers that have recently entered the profession given that they are required to have a minimum of four years of tertiary education and may be better prepared to take on the curriculum. The significant positive coefficient on continuous experience in column (3) indicates a convex returns to teaching experience. The change in the coefficient on teacher degree moving from the LS to school fixed effects model indicates a positive correlation of this variable to school unobservables. Controlling for learner fixed effects, a university qualification has a statistically significant impact of 0.05 percent of a standard deviation. It is worth nothing that teaching experience has a larger effect on learner performance than both teacher subject knowledge and a tertiary education. Textbook availability and number of recently completed in-service courses are further estimated to have a weakly significant and positive effect on learner outcomes.

Columns (4) and (5) show estimates from a flexible model that allows for different returns on all teacher and classroom characteristics across the two subjects. The results suggest that the experience and education of mathematics teachers have a large and significant impact on learner performance. For example, learners in classrooms taught by a mathematics teacher with 5 years of experience and a university degree would perform 75 points higher on average, all else equal. The same does not hold for the experience and education of English teachers. Textbook availability in English classrooms as well as in-service courses completed by English teachers have stronger positive effects on learner test scores than in mathematics classrooms.

The final two columns of table A5 show estimated returns for the sample of Q5 and Q4to1 schools separately. Learners in Q5 school classrooms taught by teachers with higher education perform between 18 and 23 points higher, ceteris paribus. No significant effect of teacher education is estimated for the sample of Q1to4 schools. Continuous teacher experience is estimated to have a significant positive effect on learner test scores in the group of Q1to4 schools; learners taught in classrooms by teachers with less than 6 years of experience have an additional significant return to their performance of 0.35 standard deviations (25 points). Hours of preparation by the teacher is estimated to positive impact learner performance in both school samples, although this effect is only weakly significant in the case of Q1to4 schools. The number of in-service courses completed by teachers has a positive and significant effect of 0.9 percent of a standard deviation on test scores in Q5 schools, although taking into consideration that the majority (90 percent) of teachers have taken less than 10 courses in the past 3 years, this effect is small. Finally, textbook availability has a positive and significant effect in Q1to4 schools.

What is immediately clear from the results discussed above is that the effect of teacher subject knowledge is smaller than that of most observable teacher and classroom characteristics. It should be noted, however, that the results displayed in table A5 may be biased by a correlation of these observables with the $(\tau_{j1} - \tau_{j2})$ component of the error term. For example, the estimated returns to higher education and experience of teachers may be upwardly biased due to a positive correlation of these teacher characteristics with unobservable teacher quality.

5.6. Robustness checks

In order to correct for bias related to teacher unobservables the analysis is for this purpose now restricted to the group of learners who are taught by the same teacher for both subjects as in Metzler and Woessman (2011). This sample is referred to as the ST sample. Only 15 percent of the full sample is taught by the same teacher in both subjects. Therefore, this group may not be a non-random subset of the full sample. Amongst the ST sample, 31 percent and 43 percent are employed within the Q1 schools and the Q5 schools respectively, with the remaining 26 percent of teachers employed in Q2, Q3 and Q4 schools. This is compared to the overall sample where approximately 18 and 22 percent of teachers are found in the Q5 and Q1 schools respectively. A comparison with schools where learners are taught by different teachers across subjects indicates Q1to4 schools within the ST sample to be mostly rural, relatively poorer as well as smaller in size. On the other hand, the ST sample of Q5 schools are relatively wealthier, urban and employ teachers with significantly higher levels of education.[20] This suggests that poorer schools in which teachers are found to teach both subjects may do so out of necessity or lack of resources. The opposite may be true of the Q5 schools that possibly attract highly educated teachers specialized to teach numerous subjects.

The results of estimating equation (6) are shown in table A6. Specifying a uniform impact of teacher subject knowledge across subjects, a positive and weakly significant coefficient of 0.075 (9 points) is estimated. Allowing for differing returns to teacher knowledge, a positive effect of 8 percent of a standard deviation (9 points) and 6.5 percent of a standard deviation (7 points) is estimated on English and mathematics teacher test score respectively. Although these point

[20] All but one of the teachers in the group of ST sample of Q5 schools has at least a university degree. This is compared to 43 percent of teachers in the non ST sample of Q5 schools.

estimates are significantly larger than the baseline estimates of table A3, they are not statistically significant from zero.[21] An F-test of equivalence of coefficients cannot be rejected. Columns (3) and (4) show results from estimation of equation (6) separately for Q1to4 and Q5 schools. Teacher knowledge is estimated to have a positive effect of 4.4 percent (4 points) and 11.6 percent (10 points) of a standard deviation in the sample of Q5 and Q1to4 schools respectively. The effect is only estimated to be statistically significant at the 10 percent level for the sample of Q1to4 schools. The results from columns (1) and (2) may therefore mask a difference in impact across school wealth sub-samples. No significantly different or non-linear effect of teacher knowledge across subjects is found for either of the school samples (results not shown here).

Given the relatively small size of this group, the results are not generalizable.[22] However, the results of table A6 and their comparison to the overall sample are nevertheless interesting. The higher returns to teacher subject knowledge on the sample of Q1to4 schools once accounting for teacher unobservables indicate a negative selection bias; that is, teacher test score is negatively correlated to unobserved teacher quality. This is not to say that lower quality teachers perform better on the teacher test, but rather that teacher knowledge in itself does not provide an accurate reflection of effective teaching amongst Q1to4 schools. This is similar to the findings of Carnoy et al (2010) who do not find a clear positive relationship between teacher knowledge and learner test scores in mathematics across the lower levels of school SES. The opposite is true of the sample of Q5 schools in the ST group. Comparing the coefficient on teacher knowledge in table A6 with that estimated using the full sample of Q5 schools suggests a *positive* correlation of teacher knowledge with unobservable teacher quality, particularly that of mathematics teachers. This finding is further in keeping with the study of Carnoy et al (2010), where higher levels of content and pedagogical knowledge of teachers of Independent and former white and Indian schools were observed to be positively related to teaching quality and quality of education received.

6. Conclusion

In the South African context, where the vast majority of learners perform at a level that is subpar both internationally and regionally, it is vitally important that we begin to understand the role that teachers play in schooling outcomes, and what the characteristics of high quality teachers

[21] The estimated effect on English teacher test score is weakly significant at the 10 percent level.

[22] However, a comparison of the results of least squares models that regress learner test score on learner and home background characteristics indicates no significantly different coefficient on teacher knowledge across ST and non ST samples. We are unable to control for teacher, classroom and school variables given the small sample size within the ST sample

are. Similarly, a better understanding is needed of the policy levers that will not only raise teacher quality in general, but also create a more equitable distribution of high quality teachers across the education system (Clotfelter et al, 2007: 3). The international empirical literature has demonstrated that teachers do indeed have an effect on student performance, as evidenced by variation in student achievement across teachers. The evidence on the teacher characteristics that are directly related to high quality teaching is less clear. It is apparent, however, that the teacher characteristics traditionally thought to be a signal of quality such as higher education, experience and training are increasingly found to have little significant impact on student outcomes. This is unlike teacher subject knowledge as captured by teacher test scores, which has been consistently found to have a positive and significant impact on student performance (Hanushek, 1986; Hanushek and Rivkin, 2006; Hanushek, 2007). The aim of this study was to add to the debate of the determinants of student performance in South Africa through identifying the impact of teacher content knowledge on learner test scores. In order to identify the impact of teachers on student performance, a learner fixed-effects approach was adopted.

Taking all the results together, a number of important empirical findings stand out. First, it is vital when estimating the impact of teacher and classroom factors on learner outcomes that we control for unobservable school and learner characteristics, as in the absence of these controls positive selection biases are observed on the estimates of teacher content knowledge. Accounting for selection biases on learner and school unobservables, teacher content knowledge is estimated to have no impact on learner outcomes. This finding holds across both mathematics and English. This is similar to the findings of Carnoy et al (2010) and Carnoy and Arends (2012) who find no significant effect of teacher content knowledge on learner gains in mathematics. A significant non-linear effect of teacher content knowledge across both subjects is estimated, indicating that teacher knowledge only has an impact at higher level of content knowledge. It is postulated that this result is linked to the type of school attended and the quality of teacher found within different schools. This brings us to the second important empirical finding, that the impact of teacher knowledge is not homogenous across different sub systems of the South African education system. Carnoy et al (2010) do not find the distribution of teachers to be random across former departments and household wealth/capital. High quality teachers are typically observed to be teaching in Independent and former white and Indian schools that also fall within the top school wealth quintiles. Using average school SES as a proxy for former department and school wealth quintile, a strong positive effect of mathematics teacher content knowledge and a significant positive quadratic effect of English teacher content knowledge for the wealthiest quintile of schools are found. No significant effect of teacher knowledge is estimated for the poorest four school wealth quintiles.

The final key result pertains to the correlation of teacher content knowledge with other factors associated with teacher quality. Correcting for teacher unobservables indicates negative selection bias for the estimates on teacher knowledge for the sample of poorest 80 percent of schools (based on average school SES) and a positive selection bias for the sample of wealthiest 20 percent of schools. This seems to suggest that, in the context of the less wealthy schools, teacher content knowledge alone does not necessarily augment learning. This may be due to a lack of other aspects related to of effective teaching such as better quality training, pedagogical skill and opportunity to teach that are more present in wealthier schools. Clearly, not all teachers with poor content knowledge are ineffective teachers, and not all teachers with good content knowledge are effective teachers. As in the international empirical literature, teacher education and education are not especially found to have significant and large effects for learner outcomes. The significant positive effect of higher education of teachers in wealthier schools may be driven by a positive relationship to teacher unobservables, as too may be the case of less experienced teachers in poorer schools.

The findings of this study echo the point made by Shulman (1986) that “mere content knowledge is likely to be as useless pedagogically as content free skill”. If the results of this study can be taken as valid, they suggest that a deep knowledge and understanding of subject matter are important, but of more importance is the ability to transfer that information in a meaningful way to learners. The results therefore suggest that teacher content knowledge needs to be augmented by higher level training in pedagogical skills such that subject matter is not only taught by those who know more about it but also know how to teach it. The author would agree with Carnoy et al (2010) that the quality of teacher training and adequate curriculum preparation are crucial for explaining differences in learner performance. In spite of headway made in upgrading the qualifications of teachers in South Africa, this does not appear to have improved the teaching capacity of teachers. There needs to be a shift in policy emphasis from measurable credentials as indicators of teacher quality toward other contributors to teacher effectiveness such as opportunity to learn and pedagogical content knowledge that may only be determined through classroom or school observation. It is encouraging that the work of Carnoy et al (2010), Carnoy and Aremds (2012) and Reeves (2005) takes us further in terms of understanding the characteristics of effective teaching and classroom practices and the role that these play in determining learning. Furthermore, the systematic difference with which high quality teachers are distributed across schools should also be of concern to policy. Large performance gaps observed across school wealth quintiles may be mitigated through improving the overall effectiveness of teachers across the entire school system. Nevertheless, improving the overall quality of teachers in the South African education system is and always will be an arduous task.

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Appendix

Table A1: Descriptive Statistics of selected variables (full sample)

		Mean	Std dev	Min	Max	Test score if indicator = 1[23] Student	Test score if indicator = 1[23] Teacher
Student test score							
Numeracy (matscore)		0	1	-5.153	5.017		
Literacy (lanscore)		0	1	-3.853	4.518		
Difference		0	1.392	-6.279	6.048		
Teacher test score							
Numeracy (tmatscore)		0	1	-1.980	3.976		
Literacy (tlanscore)		0	1	-2.607	4.122		
Student/family characteristics							
female	dummy variable 1 = female; 0 = male	0.506	0.500	0	1	0.074	0.014
overage	dummy variable 1 = overage; 0 = otherwise	0.437	0.496	0	1	-0.373	-0.202
underage	dummy variable 1 = underage; 0 = otherwise	0.069	0.253	0	1	-0.064	-0.100
speak	dummy variable 1 = speak English often; 0 = otherwise	0.128	0.334	0	1	0.618	0.548
repeat1	dummy variable 1 = never repeated a grade; 0 = otherwise	0.711	0.453	0	1	0.167	0.075
repeat2	dummy variable 1 = repeated a grade once; 0 = otherwise	0.209	0.407	0	1	0.780	0.943
repeat3	dummy variable 1 = repeated a grade twice; 0 = otherwise	0.053	0.225	0	1	-0.609	-0.253
repeat4	dummy variable 1 = repeated a grade > twice; 0 = otherwise	0.027	0.161	0	1	-0.605	-0.308
borrow	dummy variable 1 = borrow books outside school; 0 = otherwise	0.451	0.498	0	1	0.421	0.341
homework1	dummy variable 1 = does homework every day; 0 = otherwise	0.545	0.498	0	1	0.174	0.164
homework2	dummy variable 1 = does homework 1-2 times a week; 0 = otherwise	0.322	0.467	0	1	-0.124	-0.202
books	dummy variable 1 = > 10 books in the household; 0 = otherwise	0.287	0.453	0	1	0.530	0.393
hhchores	index of household chores	0	1	-1.773	3.446	-0.307	-0.240
hhses*	Household SES	0	1	-2.206	2.450	0.383	0.306
mothermatric	dummy variable 1 = mother has matric qualification; 0 = otherwise	0.175	0.380	0	1	0.176	0.188
fathermatric	dummy variable 1 = father has matric qualification; 0 = otherwise	0.206	0.404	0	1	0.074	0.092

[23] Or above 1 (above average) in the case of continuous variables

Table A1 continued: Descriptive Statistics of selected variables (full sample)

motherpostm	dummy variable 1 = mother has post-matric qualification; 0 = otherwise	0.133	0.340	0	1	0.454	0.293
fatherpostm	dummy variable 1 = father has post-matric qualification; 0 = otherwise	0.153	0.360	0	1	0.351	0.238
mothertert	dummy variable 1 = mother has tertiary qualification; 0 = otherwise	0.094	0.292	0	1	0.880	0.595
fathertert	dummy variable 1 = father has tertiary qualification; 0 = otherwise	0.118	0.323	0	1	0.659	0.467
hmkhelp1	dummy variable 1 = help with homework sometimes; 0 = otherwise	0.569	0.495	0	1	0.129	0.083
hmkhelp2	dummy variable 1 = help with homework most of the time; 0 = otherwise	0.343	0.475	0	1	-0.154	-0.116
Classroom and teacher characteristics							
textbook1	dummy variable 1 = only the teacher has a textbook; 0 = otherwise	0.110	0.314	0	1	-0.128	-0.033
textbook2	dummy variable 1 = textbook shared between > 2 learners; 0 = otherwise	0.139	0.346	0	1	-0.394	-0.232
textbook3	dummy variable 1 = textbook shared between 2 learners; 0 = otherwise	0.266	0.442	0	1	-0.023	-0.059
textbook4	dummy variable 1 = learners have their own textbooks; 0 = otherwise	0.404	0.491	0	1	0.250	0.158
pwratio	dummy variable 1 = fewer writing spaces than learners; 0 = otherwise	0.676	0.468	0	1	-0.160	-0.167
access	index of access to teaching aides	0	1	-2.397	1.458	0.346	0.303
cresources	index of classroom resources	0	1	-3.009	0.983	0.176	0.144
tests1	dummy variable 1 = class tests given once a semester; 0 = otherwise	0.462	0.499	0	1	-0.005	0.032
tests2	dummy variable 1 = class tests given 2-3 times a month; 0 = otherwise	0.235	0.424	0	1	-0.078	-0.150
tests3	dummy variable 1 = class tests are given weekly; 0 = otherwise	0.152	0.359	0	1	0.204	0.133
tfemale	dummy variable 1 = teacher is female; 0 = teacher is male	0.592	0.491	0	1	0.037	-0.001
tyoung	dummy variable 1 = teacher 30 years or younger; 0 = otherwise	0.042	0.200	0	1	0.664	0.657
t31to40	dummy variable 1 = teacher 31 to 40 years; 0 = otherwise	0.412	0.492	0	1	-0.072	0.004
t41to50	dummy variable 1 = teacher 41 to 50 years; 0 = otherwise	0.381	0.486	0	1	-0.094	-0.084
tdegree	dummy variable 1 = teacher has a university degree; 0 = otherwise	0.438	0.496	0	1	0.143	0.193
tpostm	dummy variable 1 = teacher has post-matric qualification; 0 = otherwise	0.169	0.375	0	1	0.048	0.182
texperience1	dummy variable 1 = teacher has < 6 years of experience; 0 = otherwise	0.117	0.322	0	1	0.021	-0.190
texperience2	dummy variable 1 = teacher has 6-15 years of experience; 0 = otherwise	0.369	0.482	0	1	-0.007	0.079

Table A1 continued: Descriptive Statistics of selected variables (full sample)

texperience3	dummy variable 1 = teacher has 16-25 years of experience; 0 = otherwise	0.439	0.496	0	1	-0.046	-0.026
hoursprep	number of hours teacher spends preparing per week	10.146	7.699	0	25	0.080	-0.004
courses	number of in-service courses completed in last 3 years	3.983	5.614	0	61	0.075	0.014
teachmin	teaching minutes per week	1189.69	528.21	0	3000	0.174	0.177
strike	days lost due to strike activity	11.989	8.556	0	31	-0.323	-0.261

Note: Household SES generated using principal component analysis on household possession items and standardized to have a mean of 0 and a standard deviation of 1; average school SES calculated as average of household SES within each school and standardized to have a mean of 0 and a standard deviation of 1.

Table A2: Classroom and teacher variables by subject

	Numeracy		Literacy		
Variable	Mean	Std dev	Mean	Std dev	Difference
textbook1	0.162	0.368	0.059	0.236	0.102***
textbook2	0.120	0.326	0.158	0.365	0.037***
textbook3	0.243	0.429	0.288	0.453	0.046***
textbook4	0.366	0.482	0.442	0.497	0.076***
pwratio	0.668	0.471	0.684	0.465	0.016**
access	0.016	1.015	-0.016	0.985	-0.032*
cresources	0.0177	1.023	-0.018	0.976	-0.036**
tests1	0.470	0.499	0.455	0.498	-0.015*
tests2	0.232	0.422	0.239	0.426	0.007
tests3	0.156	0.363	0.148	0.355	-0.009
tfemale	0.513	0.500	0.672	0.470	0.158***
tyoung	0.047	0.212	0.037	0.188	-0.010***
t31to40	0.414	0.493	0.411	0.492	-0.003
t41to50	0.382	0.486	0.380	0.485	-0.003
tdegree	0.429	0.495	0.447	0.497	0.018**
tpostm	0.178	0.383	0.160	0.367	-0.018***
texperience1	0.122	0.327	0.113	0.316	-0.009*
texperience2	0.363	0.481	0.374	0.484	0.011
texperience3	0.446	0.497	0.432	0.495	-0.014*
hoursprep	10.019	7.617	10.272	7.778	0.253*
courses	3.657	4.699	4.308	6.384	0.652***
teachmin	1160.70	529.56	1218.68	525.30	57.98***
strike	12.110	8.462	11.868	8.648	-0.243*

Note: significance at *** 1%, ** 5%, * 10%.

Table A3: Least squares and first-difference estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
tscore	0.429***	0.153***	0.110***	0.026*	0.038**	0.009	0.019		
	(0.031)	(0.019)	(0.019)	(0.015)	(0.018)	(0.016)	(0.015)		
tscore*math dummy					-0.027				
					(0.018)				
tmatscore								0.002	-0.013
								(0.017)	(0.017)
tmatscore squared									0.025***
									(0.009)
tlanscore								-0.033*	-0.025
								(0.018)	(0.018)
tlanscore squared									-0.018**
									(0.009)
p-value ($\beta_1 = \beta_2$)								0.085	
Learner/family controls	No	Yes	Yes	Yes	Yes	No	No	No	No
Teacher/classroom controls	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes
School fixed effects	No	No	No	Yes	Yes	No	No	No	No
Learner fixed effects	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	13992	13992	13992	13992	13992	6996	6996	6996	6996
Clusters (schools)	325	325	325	325	325	325	325	325	325
R-squared	0.177	0.450	0.502	0.604	0.604	0.000	0.022	0.023	0.026

Note: Dependent variable: difference in standardized test scores in numeracy and literacy. Robust standard errors adjusted for clustering at school level. All other teacher and classroom controls defined in table A1 are included in the model specification. Significance at *** 1%, ** 5%, * 10%.

Table A4: Heterogeneity across sub-samples

	Learner observables				Q5 schools			Q1to4 schools	
	(1)	(2)	(3)	(4)	(7)	(8)	(9)	(11)	(12)
tscore					0.071**			-0.008	
					(0.035)			(0.020)	
tmatscore	0.035	0.005	-0.011	-0.015		0.128***	0.123***		-0.024
	(0.029)	(0.017)	(0.022)	(0.025)		(0.034)	(0.031)		(0.022)
tmatscore squared			0.034***				0.013		
			(0.010)				(0.015)		
tlanscore	-0.059*	-0.018	-0.049**	0.006		0.010	0.029		-0.007
	(0.026)	(0.019)	(0.019)	(0.029)		(0.042)	(0.032)		(0.027)
tlanscore squared			-0.002				-0.040**		
			(0.011)				(0.011)		
p-value ($\beta_1 = \beta_2$)	0.388	0.534		0.783		0.002			0.260
Learner/family controls	No	No	No	No	No	No	No	No	No
Teacher/classroom controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School fixed effects	No	No	No	No	No	No	No	No	No
Learner fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	895	6101	3313	3683	1317	1317	1317	5679	5679
Clusters (schools)	224	323	311	304	65	65	65	260	260
R-squared	0.075	0.019	0.040	0.032	0.091	0.102	0.106	0.023	0.024

Note: Dependent variable: difference in standardized test scores in numeracy and literacy. Robust standard errors adjusted for clustering at school level. All other teacher and classroom controls defined in table A1 are included in the model specification. Significance at *** 1%, ** 5%, * 10%.

Table A5: Achievement effects of teacher and classroom characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
tdegree	0.079***	0.059**	0.050**	0.083***	0.003	0.201***	0.062*
	(0.030)	(0.026)	(0.025)	(0.032)	(0.032)	(0.071)	(0.032)
tpostm	0.038	-0.009	0.000	0.048	-0.056	0.304***	-0.037
	(0.037)	(0.035)	(0.032)	(0.039)	(0.043)	(0.088)	(0.043)
texperience1	0.083	0.305***	0.264***	0.706***	-0.066	0.031	0.335***
	(0.130)	(0.099)	(0.086)	(0.148)	(0.128)	(0.214)	(0.118)
texperience2	0.005	0.106	0.096	0.454***	-0.086	-0.012	0.130
	(0.105)	(0.081)	(0.071)	(0.114)	(0.100)	(0.153)	(0.097)
texperience3	-0.062	0.055	0.065	0.280***	-0.057	-0.010	0.088
	(0.078)	(0.064)	(0.057)	(0.079)	(0.073)	(0.111)	(0.075)
texperience	(0.001)	0.007**	0.006***	0.020***	-0.002	-0.001	0.010**
	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.006)	(0.004)
textbook3	0.197***	0.218***	0.128**	0.071	0.183**	-0.059	0.198***
	(0.041)	(0.040)	(0.050)	(0.043)	(0.076)	(0.084)	(0.074)
textbook4	0.177***	0.127***	0.096*	0.086**	0.126	-0.074	0.171**
	(0.038)	(0.036)	(0.052)	(0.041)	(0.077)	(0.067)	(0.076)
hours_prep	-0.001	0.003*	0.002	0.001	0.003*	0.002	0.003*
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
courses	0.004*	0.005*	0.004*	0.003	0.004**	0.009***	-0.003
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
strike	-0.005**	0.002	0.000	-0.003	0.001	-0.018**	-0.002
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.007)	(0.003)
Learner/family controls	Yes	Yes	Yes	Yes		Yes	Yes
Teacher/classroom controls	Yes	Yes	Yes	Yes		Yes	Yes
School fixed effects	No	Yes	No	No		No	No
Learner fixed effects	No	No	Yes	Yes		Yes	Yes
Observations	13992	13992	6996	6996		1317	5679
Clusters (schools)	325	325	325	325		65	260
R-squared	0.542	0.604	0.048	0.068		0.150	0.042

Note: Dependent variable: difference in standardized test scores in numeracy and literacy. Robust standard errors adjusted for clustering at school level. All other teacher and classroom controls defined in table A1 are included in the model specification. Significance at *** 1%, ** 5%, * 10%.

Table A6: Robustness checks

	(1)	(2)	(3)	(4)
tscore	0.075*		0.044	0.116*
	(0.042)		(0.051)	(0.059)
tmatscore		0.065		
		(0.058)		
tlanscore		-0.080*		
		(0.040)		
p-value ($\beta_1 = \beta_2$)		0.734	0.269	0.952
Teacher/classroom controls	Yes	Yes	Yes	Yes
Learner fixed effects	Yes	Yes	Yes	Yes
Teacher fixed effects	Yes	Yes	Yes	Yes
Observations	847	847	225	622
Clusters (schools)	46	46	14	32
R-squared	0.036	0.035	0.056	0.043

Note: Dependent variable: difference in standardized test scores in numeracy and literacy. Robust standard errors adjusted for clustering at school level. All other teacher and classroom controls defined in table A1 are included in the model specification. Significance at *** 1%, ** 5%, * 10%.