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Stellenbosch Economic Working Papers: 01/15

KEYWORDS: TEACHER CONTENT KNOWLEDGE, CORRELATED RANDOM ERRORS MODEL, WITHIN-STUDENT, SOUTH AFRICA
JEL: C30, I21, I24

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A WORKING PAPER OF THE DEPARTMENT OF ECONOMICS AND THE
BUREAU FOR ECONOMIC RESEARCH AT THE UNIVERSITY OF STELLENBOSCH

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ABSTRACT

This paper assesses the impact of teacher subject knowledge on student performance using a nationally representative dataset of grade 6 students in South Africa. Test scores in two subjects and correlated random error models are used to identify within-pupil across subject variation in performance. Teacher knowledge is estimated to have a positive impact on performance across both the poorer and wealthier subsets of schools once controlling for teacher unobservables. The results suggest that consideration needs to be given to contextual factors such as the quality of teacher training and the working environment within schools and their relationship to the manner in which teacher knowledge is transferred to students.

Keywords: teacher content knowledge, correlated random errors model, within-student, South Africa
JEL codes: C30, I21, I24

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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). 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 (Taylor and Vinjevoild, 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. Recent research has shown that variation in teacher quality is a significant determinant of variation in student outcomes (Hanushek, Kain, O'Brien and Rivkin, 2005; Hanushek and Rivkin, 2006). Yet, 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 and Rivkin, 2006: 3). Empirical evidence has yet to find strong evidence in support of a relationship between teacher characteristics typically "purchased" by schools - such as a teacher's qualification attained and level of experience – and student achievement. In cases where experience and level of qualification are found to matter, the circumstances tend to be very specific; for example, only the first few years of experience may matter and the effect of teacher qualification may depend on the subject-specificity of the qualification (Goldhaber and Anthony, 2007). Although evidence is somewhat mixed, characteristics such as teacher knowledge and recentness of education are more often than not found to be significantly associated with high student performance in both developed country (Hanushek, 1971; Hanushek, 1986; Monk, 1994; Hanushek, 1997; Wayne and Youngs, 2003; Hill, Rowan and Ball, 2005; Rivkin, Hanushek and Kain, 2005) and developing country contexts (Kingdon, 1996; Mullens, Murnane and Willett, 1996; Tan, Lane and Coustere, 1997; Bedi and Marshall, 2002; Behrman, Ross and Sabot, 2008; Altinok, 2013). The use of, for example, teacher experience and teacher education as policy levers for improving school performance is therefore limited.

The literature has adopted two main approaches to identify the effectiveness of individual teachers in enhancing student performance. These may broadly be classified as value-added or gains models and mixed models. One of the important challenges facing studies attempting to estimate the causal effect of teacher characteristics on student performance is the non-random sorting and selection of students 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. This issue may be addressed through the use of student and teacher fixed effects, although this requires the availability of longitudinal datasets. However, this assumes that students are assigned to teachers on the basis of their time-invariant characteristics rather than time-varying, unobservable characteristics (Ladd, 2008).

This study makes use of a within-pupil between-subject methodology used by Metzler and Woessmann (2012) to estimate the effect of teacher subject content knowledge on grade 6 student test scores in South Africa. This methodology is an extension of the first differencing technique proposed by Dee (2005, 2007) that 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 (Ammermüller and Dolton, 2006; Clotfelter, Ladd and Vigdor, 2006, 2010; Dee, 2005, 2007; T. Dee and West, 2008; Eren and Henderson, 2011; Lavy, 2010; Schwerdt and Wuppermann, 2011). Identification here relies on variation across teachers in different subjects, as well as student fixed effects across subjects to correct for between and within school sorting of students. This paper adopts a correlated random errors model that allows for the over-identification restriction that is implicit in the fixed-effects model to be tested. We further restrict the sample to students who are taught by the same teacher in the two subjects in order to correct for potential bias due to teacher unobservables.

Two recently compiled case studies in the Gauteng (Carnoy and Chisholm, 2008) and North West provinces (Carnoy and Arends, 2012) of South Africa have provided evidence of a positive relationship between teacher knowledge and student performance. However, stronger positive effects are estimated for quality of teaching,[3] opportunity to learn and teaching institution attended. This study hopes to build on the findings of these studies using the

[3] Quality of teaching is measured through classroom surveillance.

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 student 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. Policy context and previous findings in South Africa

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 (Department of Basic Education, 2000: 47) regarded teachers who had obtained a three-year post-school qualification, or REVQ13,[4] 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

[4] 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.

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.[5] Furthermore, the majority of teachers currently in the 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 (Mda and Erasmus, 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.[6] In videotaped observations of mathematics teachers in the Gauteng Province, Carnoy and Chisolm (2008) 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.

Evidence on the impact of teacher knowledge on student outcomes in South Africa is largely unclear. This is mainly due to the fact that teacher subject content knowledge has rarely

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[5] At least within the context of the expectations set by the new schools' curriculum and the Norms and Standards for Teachers.

[6] The Intermediary Phase level is defined as grades 4 to 7.

been captured in large-scale, nationally representative surveys of student 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. Employing the SACMEQ 2007 dataset to estimate education production functions of student performance, Spaull (2011) finds statistically significant coefficients on teacher content knowledge of 0.074 and 0.048 for reading and mathematics scores, respectively. These estimates are similar to those estimated by Altinok (2013) using multivariate multilevel analysis of the same dataset. These analyses were, however, performed using cross-section least squares methodologies that did not correct for potential bias due to non-random sorting and omitted variables. Additionally, neither teacher education nor teacher experience was included in the regression models; the impact of these teacher quality variables after controlling for teacher knowledge is unclear. Utilising the NSES panel data, Taylor (2011) finds substantial gains in student learning when teacher knowledge is combined with time on task.[7] However, this only occurs at a very high level of knowledge, indicating a non-linear relationship between teacher knowledge and student performance. The strongest finding by Taylor (2011) is the significant positive relationship between student outcomes and curriculum coverage. Reeves (2005) similarly found that opportunity to learn as measured by curriculum coverage was significantly related to student gain scores in mathematics in a sample of 24 schools in the Western Cape Province.

Two recently conducted South African case studies have paid specific attention to the effect of teacher knowledge on student outcomes. Their methodological approaches further account for non-random sorting across and within schools through the use of value-added modelling. In both studies the authors differentiate between two types of knowledge: content knowledge and pedagogical content knowledge. Shulman (1986) distinguishes between these two forms as knowledge as the former being principally obtained through a teacher's formal pre-service training, and the latter referring to the manner in which content knowledge is applied for teaching and is typically obtained through practice or highly skilled training programs. The

[7] The shortness of the teacher tests conducted under the NSES (English teachers were given a comprehension test comprising of 7 questions, and mathematics teachers a 5 mark test) means that this survey provides limited, and potentially noisy, measures of teacher knowledge.

notion of pedagogical content knowledge has gained wide appeal as it links content knowledge and the practice of teaching and arguably has the greatest ties to effective teaching (Ball et al, 2008). However, 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.

Carnoy and Chisholm (2008) attempt to estimate the contributions of various classroom and teaching factors to learning gains in mathematics of Grade 6 students using a sample of 40 schools in the Gauteng Province. The teacher instrument was designed to include questions that provided measures of content knowledge and pedagogical content knowledge. The findings of Carnoy and (2008) indicated that teachers employed at historically African and coloured schools were observed to score lower in both content knowledge and pedagogical content knowledge than teachers employed within Independent and former white schools where student ability is also relatively higher. Only in the case of the two highest levels of student socio-economic status was performance found to be related to teacher knowledge. Pedagogical content knowledge was strongly positively related to the quality of a teacher's training institution, suggesting that the institution of training may have some direct influence on quality of teaching. Conversely, content knowledge was not found to be significantly related to teaching quality. Value-added modelling of student performance indicated a significant positive effect of teaching quality on test score gains and a positive, but statistically insignificant, coefficient on pedagogical content knowledge. A negative, but statistically insignificant, effect of content knowledge was estimated. This may be driven by the fact that students taught by teachers with higher content knowledge may have experienced lower average gains given higher base test scores. It should be mentioned that value added models were only based on a 25 percent sub-sample of students and t is difficult to say whether the results are upwardly or downwardly biased as the original report gives no details as to how this sub-sample compared to the full sample.

A more recent study by Carnoy and Arends (2012) exploits a natural experiment based on the geographical closeness of South-eastern 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 and Chisholm (2008) study that includes schools from different former departments, the sixty schools selected for this sample are all no-fee (i.e. low wealth) 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 and Chisholm (2008) and Reeves (2005), teacher quality and opportunity to learn [8] were estimated to have positive and significant effects on learner gains in mathematics test scores. However, the effect size of teacher quality was small at 0.05 percent.[9] Teacher mathematics knowledge was not significantly related to 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 selection 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 teacher qualification.

3. Data and Descriptive Statistics

The data used in this study is the third wave of the SACMEQ survey conducted in 2007. Student knowledge in three subject areas - numeracy, literacy and health - was tested using multiple-choice questionnaires and performance 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. [10] In addition to testing, a full array of information regarding home, classroom, and school environments was collected, as well as demographic information on students, parents, teachers and principals. Teachers were also required to complete the health

[8] Here opportunity to learn was defined by content coverage (the number of topics taught during the year) and content emphasis (the number of lessons taught on each topic). These two factors of OTL may have both a direct and an indirect (through quality of teaching) association with student learning gains.

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

[10] Other countries surveyed were Botswana, Kenya, Lesotho, Mauritius, Malawi, Mozambique, Namibia, Seychelles, Swaziland, Tanzania, Uganda, Zambia and Zimbabwe.

test, as well as subject-specific tests in mathematics and English.[11] This is the first nationally representative education survey in South Africa where teachers' subject knowledge was tested.

Although content knowledge may be related to pedagogical content knowledge, for simplicity's sake this study considers the teacher test score to be a measure of the former. Whilst there was some commonality in questions across the teacher and student tests, 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.[12] Altogether 9083 6 grade learners were sampled from 392 schools in South Africa. The large size of the dataset makes SACMEQ III 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).[13] 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 were observed to teach the same students in both subjects.[14]

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[11] 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.

[12] Learner performance on the health test was not considered for this study as performance was significantly higher than performance in numeracy and literacy, and there was no significant difference in the health test scores of mathematics and reading teachers.

[13] 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. The third wave was in this respect a major improvement.

[14] A large proportion of the missing data is due to 15 percent of teachers declining to take the subject-specific tests. Controlling for missing teacher test score as a dummy in the analysis does not significantly alter the results presented in this paper. However, is it probable that the teachers who refused to write the tests are likely to be those with poor subject knowledge. This limits the generalizability of the results around teacher test scores.

Table A.1 of the appendix reports descriptives of the final sample. Both the student and teacher scores have been standardised to have a mean of zero and standard deviation equal to one. The estimated model coefficients are therefore expressed as the effect size, or a standard deviation of student performance per standard deviation of teacher subject knowledge. We can compare the estimated effect size to an international benchmark which equates an average learning gain from one year of primary schooling to roughly 30-50 percent of a standard deviation of student achievement (Hill, Bloom, Black and Lipsey, 2008). On average, students performed better in the numeracy test than the literacy test. This may be related to the language of the test as all students were required to write both tests in English.[15] Test scores were found to be positively related to borrowing books outside of school, high household socio-economic status and tertiary education of parents. Both students and teachers performed better in classrooms that were in general better resourced. Test performance of teachers and students were further negatively related to strike activity by teachers and positively related to higher teacher qualifications.

Table A.2 summarises subject-specific differences in teacher and classroom characteristics. In general, teacher and classroom characteristics were fairly similar across the two subjects. 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. Classrooms in which mathematics teachers taught tended to be better resourced, whilst there was a greater availability of textbooks in English classrooms. Further descriptive analysis (not shown here) revealed that girls performed significantly better in both numeracy and literacy, with a larger 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

[15] Given that the scores on the two tests are standardised across all SACMEQ countries, language may only account for a small part of the difference.

literacy.[16] 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 dummy controls.

4. Estimation strategy: correlated random errors model

We consider an educational production function that places explicitly focuses on teacher subject content knowledge:

$$Y_{1i} = \beta_1 Q_{1j_1} + \gamma' T_{1j_1} + \theta' C_{1j_1} + \delta' X_i + \mu_i + \tau_{1j_1} + \varepsilon_{1i} \quad [1]$$

$$Y_{2i} = \beta_2 Q_{2j_2} + \gamma' T_{2j_2} + \theta' C_{2j_2} + \delta' X_i + \mu_i + \tau_{2j_2} + \varepsilon_{2i} \quad [2]$$

where Y_{1i} and Y_{2i} are test scores of student i in subject s, $s \in (1,2)$ with $s = 1$ and $s = 2$ representing mathematics and reading, respectively. Students are taught by teachers j who are characterized by their score on the subject-specific test Q_{sj_s}, other non-subject-specific teacher characteristics T_{sj_s} and subject-specific classroom characteristic C_{sj_s}. Teacher characteristics besides subject-specific knowledge will differ across the two equations only if a student is taught by different teachers in the two subjects. X_i represents non-subject-specific student (and school) characteristics. The error term is comprised of a student-specific component μ_i, a teacher-specific component τ_{sj_s} and a subject-specific student component ε_{si}.

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 student effects in the error terms. We are able to correct for non-random selection of students into and within schools through conditioning for unobservable time-invariant characteristics of students (such as ability or motivation) that could be correlated with teacher observables including subject knowledge.[17] Following Metzler and

[16] In cases where the same teacher teaches both subjects, classroom controls were subject-variant whilst teacher controls such as age, experience, qualification, strike activity and hours of preparation were subject-invariant.

[17] In panel models where multiple observations per student are observed over *time*, educational outcomes can be explicitly modelled as a cumulative process. In order to avoid biased coefficients on characteristics of teacher quality/effectiveness, one or more lagged test scores should be included in the model to account for the prior knowledge/learning that the student brings to the classroom. An analogous approach in the context of a cross-subject model would be to represent a student's knowledge at the beginning of the school year through subject-specific test scores taken prior to the beginning of the period of instruction (Clotfelter et al., 2010). Initial test

Woessmann (2012), the potential correlation of the unobserved student fixed effect μ_i with the observed inputs can be modeled as:

$$\mu_i = \eta_1 Q_{1j_1} + \eta_2 Q_{2j_2} + \kappa_1{}' T_{1j_1} + \kappa_2{}' T_{2j_2} + \lambda_1{}' C_{1j_1} + \lambda_2{}' C_{2j_2} + \phi' X_i + \varpi_i \qquad [3]$$

The residual term ϖ_{ij} is assumed to be uncorrelated with the explanatory variables. The parameters η, κ and λ are permitted to vary over subjects, but the parameters on student characteristics, ϕ, are assumed to be the same. Substituting [3] into [1] and [2] yields the following reduced-form equations:

$$Y_{1i} = (\beta_1 + \eta_1) Q_{1j_1} + \eta_2 Q_{2j_2} + (\gamma + \kappa_1)' T_{1j_1} + \kappa_2{}' T_{2j_2} + (\theta + \lambda_1)' C_{1j_1} + \lambda_2{}' C_{2j_2}$$
$$+ (\delta + \phi)' X_i + \tau_{1j_1} + \varepsilon_{1i}^{'} \qquad [4]$$

$$Y_{2i} = (\beta_2 + \eta_2) Q_{2j_2} + \eta_1 Q_{1j_1} + (\gamma + \kappa_2)' T_{2j_2} + \kappa_1{}' T_{1j_1} + (\theta + \lambda_2)' C_{2j_2} + \lambda_1{}' C_{1j_1}$$
$$+ (\delta + \phi)' X_i + \tau_{2j_2} + \varepsilon_{2i}^{'} \qquad [5]$$

where $\varepsilon_{si}^{'} = \varepsilon_{si} + \varpi_i$.

Equations [4] and [5] comprise an exactly identified model with correlated random effects that are easily estimable using ordinary least squares. Note that teacher subject-content knowledge in each subject enters both equations. The magnitude of the η coefficients capture the extent to which estimated teacher knowledge effects are biased due to omitted student characteristics, while the β coefficients represent the structural effect of teacher subject knowledge (Metzler and Woessmann, 2012). Following estimation of the above correlated random errors model, the implied effect of teacher subject knowledge on test performance, β_s, is calculated as the difference between the estimated coefficient on Q_{sj_s} in the equation of student test performance in subject s and the estimated coefficient on Q_{sj_s} in the equation of student test performance in the other subject.

This model specification allows us to test the over-identification restrictions implicit in fixed-effects models (Ashenfelter and Zimmerman, 1997). The within-student across-subject estimator by Dee (2005) implicitly assumes that teacher effects are the same across multiple subjects. This makes the model over-identified. Following estimation of equations [4] and [5] it

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scores of students are not available in the case of this study. Therefore, we make the assumption that a student's initial knowledge in a subject is negligible and any overall ability will be captured by the student fixed effect.

is straightforward to test whether $\beta_1 = \beta_2 = \beta$ and $\eta_1 = \eta_2 = \eta$. If these overidentification restrictions cannot be rejected, we can specify a model that equates the β and η coefficients across equations [4] and [5] which, given $\lambda_1 = \lambda_2$ and $\kappa_1 = \kappa_2$, will yield the conventional fixed effects model that eliminates bias from student unobservables through differencing within students, across subjects. This illustrates that unrestricted reduced-form estimates for the correlated random effects model will always allow the estimation of the fixed effects model.

The above model specification does not prohibit the possibility of student sorting between subjects. Any unobserved subject-specific student characteristics (such as subject-specific proclivity for performance) will be captured in ε_{si} and any unobserved teacher characteristics that may be related to teacher test score will be captured in τ_{sj_s}. For example, unobserved teacher quality may differ in some consistent way between the subjects taught, or students with an aptitude for mathematics may be assigned to teachers with greater subject knowledge.

A direct test of the hypothesis that the relative student ability in the two subjects is uncorrelated with relative teacher subject knowledge is not available for the SACMEQ data. However, the National School Effectiveness Survey (NSES) collected over three years between 2007 and 2009 can be used to infer the underlying relationship. The mathematics and reading scores of a panel of approximately 8400 students in grade 3, grade 4 and grade 5 are observed. As mentioned in section 2, the NSES conducted subject knowledge testing of Grade 4 and 5 mathematics and reading teachers using short multiple choice tests. Although these tests are likely to be imperfect measures of teacher subject knowledge, they will serve for the purpose at hand. Following the approach taken by Clotfelter et al (2010), we run a regression of student relative ability (measured as the difference between third grade mathematics and reading test performance) on a dependent variable of the difference between the subject-specific test score of fifth grade mathematics and reading teachers. The model further controls for school fixed effects. Taking student relative ability in reading and mathematics as a proxy for the subject-specific component of the error term, we find that we cannot reject the null hypothesis that there is no relationship between student relative ability and relative teacher subject knowledge. Therefore, the NSES data provides no reason to question the assumption that the ε_{si} term in a model with student fixed effects is uncorrelated with the explanatory variable of interest. Although subsequent discussion refers to β as the effect of student knowledge, the author of this study does not wish to infer causality. Rather, β is a measure of the relationship between subject-specific teacher knowledge and student 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 students taught by the same teacher in both subjects. In this case, $\mathrm{T}_{1\mathrm{j}_1} = \mathrm{T}_{2\mathrm{j}_2} = \mathrm{T}_\mathrm{j}$ and $\tau_{1\mathrm{j}_1} = \tau_{2\mathrm{j}_2} = \tau_\mathrm{j}$ and the education production function simplifies to:

$$Y_{1i} = (\beta_1 + \eta_1)Q_{1j} + \eta_2 Q_{2j} + (\gamma + \kappa_1 + \kappa_2)'T_j + (\theta + \lambda_1)'C_{1j} + \lambda_2{}'C_{2j} + (\delta + \phi)'X_i + \tau_j + \varepsilon'_{1i} \quad [6]$$

$$Y_{2i} = (\beta_2 + \eta_2)Q_{2j} + \eta_1 Q_{1j} + (\gamma + \kappa_2 + \kappa_1)'T_j + (\theta + \lambda_2)'C_{2j} + \lambda_1{}'C_{1j} + (\delta + \phi)'X_i + \tau_j + \varepsilon'_{2i} \quad [7]$$

Restricting $\beta_1 = \beta_2 = \beta$ and $\eta_1 = \eta_2 = \eta$ and taking the first-difference of the two equations gives:

$$Y_{1i} - Y_{2i} = \beta\left(Q_{1j} - Q_{2j}\right) + \theta'\left(C_{1j} - C_{2j}\right) + \varepsilon'_{1i} - \varepsilon'_{2i} \quad [8]$$

This specification is equivalent to including student and teacher fixed effects in a pooled regression. 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-specific knowledge. Due to the limited sample of students taught by the same teacher in both subjects – only 15 percent of the original sample – estimation using this group will serve as a specification check to the main results based on the full sample.

5. Results

5.1 Results from full sample

In order to provide some continuity with the earlier literature, table 1 presents conventional cross-sectional regression estimates based on equations [1] and [2]. All regression analysis takes the sampling design of the data into account and standard errors are clustered at the classroom level.[18] Standardized test performance in numeracy and reading are used as the dependent variable in all regressions. Given the purpose of the analysis, only coefficient estimates for the variable of interest (teacher subject knowledge) are reported.[19] The OLS specifications presented in columns 1 – 8 control for varying sets of explanatory variables and the final two columns present the results of a seemingly unrelated regression (SUR) that ignores modelling of correlated random errors. The estimates in columns 1 – 4 indicate a significant positive effect of teacher subject knowledge on student test scores in both subjects that is substantially reduced - from 0.43 to 0.175 and 0.132 percent of a standard deviation in mathematics and reading, respectively - after controlling for a full set of student and home background characteristics. The coefficient on teacher knowledge is more than halved after the addition of school, teacher and classroom controls, yet remains statistically significant. There therefore appears to be evidence of (i) substantial correlation between teacher subject-knowledge and observable and unobservable school characteristics and (ii) self-selection of higher quality students and teachers into higher quality schools. Furthermore, even with a fuller set of controls the estimates on teacher knowledge in columns 9 and 10 of table 1 are similar to those estimated by Spaull (2011).

Table 2 presents the results of the correlated random errors model of equations [4] and [5]. We begin by estimating a SUR of test performance that allows for the coefficients on all controls across equations [4] and [5] to vary. Following this, we were able to test for equivalence

[18] 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. A minimum cluster size of 25 students was randomly sampled from all grade 6 classes in cases where the total number of enrolled grade 6 students exceeded 25; otherwise all students were included in the sample. Clustering at the classroom level accounts for any correlation of errors associated with the common experience of students in a given classroom environment. The inclusion of student fixed effects makes the case for clustering errors at the student level less compelling.

[19] It can, however, be noted that the estimated coefficients on learner/family background and school covariates 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, the proportion of non-permanent teaching staff and school SES are significantly positively related to performance.

of coefficients across equations [1] and [2].[20] The findings suggest that assuming equivalent effects of T and C across the production functions for mathematics and reading scores may be restrictive, as there is no a priori reason to suppose that the relationship between, for example, teacher qualification and test performance will be the same for both mathematics and reading.[21]

The final model specification was chosen such that δ and ϕ are constrained to be the same across the two subject equations, but γ, θ, κ and λ are permitted to vary. The effect of teacher subject knowledge on student performance in mathematics, β_1, is given by the difference between the regression coefficient on the teacher math test score in the math equation and the regression coefficient on the teacher math test score in the reading equation; and similarly for β_2. The results from column 2 indicate a larger positive estimate on teacher subject knowledge in reading than in mathematics. However, the implied coefficients on teacher knowledge in both subjects are not significantly different from zero. Tests of the over-identification restrictions do not reject the hypothesis that the effect of teacher knowledge is the same in both subjects.

Therefore, column 3 presents the results from SUR estimation that restricts $\beta_1 = \beta_2$ and $\eta_1 = \eta_2$.[22] The estimate of η in the final restricted model is found to be highly significantly different from zero, indicating positive selection effects. A model specification that failed to account for this would yield an upward biased estimate of the effect of teacher subject-knowledge on student performance. The implied coefficient on teacher subject knowledge predicts that an increase in teacher test scores by 1 standard deviation increase is expected to increase student performance by 1.3 percent of a standard deviation. This result is not significantly different from zero.

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[20] Results of these equivalence tests are available from the author by request.

[21] A SUR model that constrains γ and θ to be equivalent across equations [1] and [2] does not yield significantly different results with regards to the estimated coefficients on teacher same subject (β_s) and teacher other subject test scores (η_s). However, given that this study is also interested in the effect of other observable teacher and classroom characteristics, such a teacher qualification, a model that constrains γ and θ to be the same could lead to erroneous conclusions regarding the returns to these characteristics.

[22] This model is equivalent to estimating a first-difference model that allows for differing coefficients across other teacher and classroom characteristics besides teacher subject knowledge in the two subjects.

Table 1: Cross-sectional regressions

	Ordinary Least Squares								Seemingly unrelated regression	
	Maths	Reading	Maths	Reading	Maths	Reading	Maths	Reading	Maths	Reading
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Teacher test score	0.433***	0.426***	0.175***	0.132***	0.102***	0.059***	0.076***	0.065***	0.064***	0.051***
	(0.028)	(0.031)	(0.023)	(0.022)	(0.024)	(0.023)	(0.022)	(0.023)	(0.021)	(0.019)
Student/home background controls	-	-	X	X	X	X	X	X	X	X
Classroom controls	-	-	-	-	-	-	X	X	X	X
Teacher controls	-	-	-	-	-	-	X	X	X	X
School controls	-	-	-	-	X	X	X	X	X	X
Adjusted R-squared (OLS)	0.18	0.175	0.399	0.508	0.442	0.563	0.461	0.583		
Observations (students)	6996	6996	6996	6996	6996	6996	6996	6996	6996	
Classrooms (clusters)	686	686	686	686	686	686	686	686	686	
Number of schools	325	325	325	325	325	325	325	325	325	

Note: Dependent variable is the standardized learner test score in numeracy and literacy. Robust standard errors adjusted for clustering at class level shown in parentheses. Clustered standard errors in the SUR models are estimated by maximum likelihood. Significance at *** 1% level ** 5% level * 10% level.

Table 2: correlated random effects models

	Unrestricted model: All coefficients differ over equations (4) and (5)		Restricted model: $\delta_1 = \delta_2, \phi_1 = \phi_2$		Restricted model $\delta_1 = \delta_2, \phi_1 = \phi_2$ $\beta_1 = \beta_2, \eta_1 = \eta_2$
	(1)		(2)		(3)
	Maths	Reading	Maths	Reading	
Implied β_s	0.015	-0.008	0.001	0.021	0.013
χ^2 ($\beta_s = 0$)	0.99	0.20	0.01	1.90	0.99
Prob > χ^2	0.321	0.654	0.940	0.168	0.320
Regression estimates:					
Teacher test score in same subject	0.044**	0.039	0.036*	0.047**	0.044***
	(0.021)	(0.022)	(0.021)	(0.022)	(0.014)
Teacher test score in other subject	0.047**	0.029	0.026	0.035*	0.031***
	(0.019)	(0.020)	(0.018)	(0.020)	(0.012)
$\chi^2(\eta_1 = \eta_2)$	0.32		0.08		-
Prob > χ^2	0.570		0.779		-
$\chi^2(\beta_1 = \beta_2)$	1.32		0.96		-
Prob > χ^2	0.251		0.326		-
Observations (students)	6996		6996		6996
Classrooms (clusters)	686		686		686
Number of schools	325		325		325

Note: Dependent variable is the standardized learner test score in numeracy and literacy. Regressions are estimated using seemingly unrelated regressions (SUR). Implied β_s is calculated as the difference in the coefficient on teacher test score in subject s between the equation of the student test score in the respective subject and the equation of the student test score in the other subject. Standard errors adjusted for clustering at class level shown in parentheses. Clustered standard errors, shown in parentheses and clustered at the classroom level, are estimated by maximum likelihood. Regressions control for all student, classroom, teacher and school characteristics defined in tables A1 and A2 of the appendix. Significance at *** 1% level ** 5% level * 10% level.

5.2 Heterogeneous effects across student sub-groups

The majority of students in the South African schooling system are not first-language English speakers. In addition, these students are likely to be taught by teachers who are themselves not first-language English speakers and are from the same ethnic group as their students. This is particularly true for historically African schools. In addition, access to quality schools is often determined by the affluence of a student's home background. The estimated effect from column 3 of table 2 may mask heterogeneity in the effect of teacher subject knowledge across different sub-samples of students. Table 3 presents results from estimation of the correlated random effects model for various student sub-groups: students who speak English frequently at home (column 2), students who speak English rarely at home (column 3), students who come from above average SES home backgrounds (column 4) and students who come from below average SES home backgrounds (column 5). Table 3 further includes estimates from a model specification that allows for non-linear returns to teacher subject-knowledge through a spline set at above average teacher test scores (column 1).

A larger positive effect size of mathematics teacher subject knowledge on mathematics test scores of 5.5 and 3.9 is estimated for the sub-groups of students who speak English often at home and come from high SES backgrounds, respectively. The results of column 1 further provide evidence of a significant non-linear effect of teacher subject-knowledge on student performance. Specifically, students taught by mathematics teachers who performed 1 (2) standard deviations above average in the teacher math test are estimated to score 6.1 (12.1) percent of a standard deviation higher than students taught by average performing teachers. Similarly, students taught by reading teachers who performed 1 (2) standard deviations above average in the teacher reading test are estimated to score 6.5 (13) percent standard deviations higher than students taught by reading teachers who scored at the mean. Given that English speaking and above average SES students have a higher likelihood of attending former White and Indian schools that (i) perform notably better on average than former African and Coloured schools (see Van der Berg, 2008) and (ii) are able to afford better quality teachers, [23] the results of table 3 are believed to provide evidence of potentially divergent effects of teacher subject knowledge across different sectors of the South African primary school system.

The bimodal nature of performance within the South African schooling system is a well-documented finding in the South African education literature (Gustafsson, 2005; Fleisch, 2008; Taylor, 2011; Spaull, 2013). By this it is meant that the overall test score distribution disguises 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).

[23] 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.

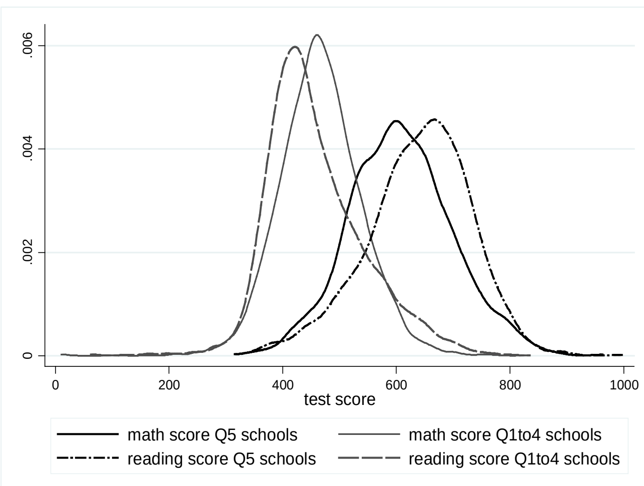
Table 3: correlated random effects models across sub-samples

	Teacher test score level (1)		Student speaks English often (2)		Student speaks English rarely (3)		Household SES above average (4)		Household SES below average (5)	
	Maths	Reading	Maths	Reading	Maths	Reading	Maths	Reading	Maths	Reading
Implied β_s			0.055	0.017	0.001	0.013	0.039*	0.030	-0.024	-0.008
Prob > χ^2			0.124	0.548	0.949	0.401	0.056	0.104	0.293	0.738
Implied β_s (below average teacher score)	-0.074***	-0.027								
Prob > χ^2	0.010	0.372								
Implied β_s (above average teacher score)	0.061***	0.065**	-	-	-	-	-	-	-	-
Prob > χ^2	0.006	0.021	-	-	-	-	-	-	-	-
Observations (students)	6996		895		6101		3313		3683	
Classrooms (clusters)	686		351		676		646		584	
Number of schools	325		224		323		311		304	

Note: Dependent variable is the standardized learner test score in numeracy and literacy. Regressions are estimated using seemingly unrelated regressions (SUR). Implied β_s is calculated as the difference in the coefficient on teacher test score in subject s between the equation of the student test score in the respective subject and the equation of the student test score in the other subject. In all models, the coefficients on student and school characteristics are constrained, with $\delta_1 = \delta_2$ and $\phi_1 = \phi_2$. Clustered standard errors, shown in parentheses and clustered at the classroom level, are estimated by maximum likelihood. Regressions control for all student, classroom, teacher and school characteristics defined in tables A1 and A2 of the appendix. Significance at *** 1% level ** 5% level * 10% level.

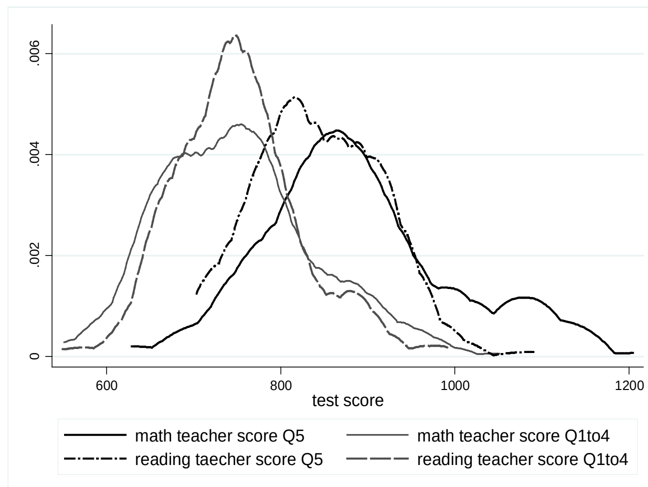
Figures 1 and 2 show the distributions of student and teacher test scores across school wealth quintiles based on school average SES, where the top 20 percent SES schools (Q5 schools) have been separated from the bottom 80 percent (Q1to4 schools).[24] It is clear that the students in the Q5 schools perform more than an international standard deviation (100 points) above the SACMEQ average of 500, whilst students in the poorest schools perform below average. The picture is similar for teacher test scores in that teachers employed within the wealthier subset of schools perform significantly better on average in both subjects. These findings are in agreement with those of Carnoy and Chisholm (2008).

Figure 1: Student performance by school SES quintile



Note: based on own calculations from SACMEQ III (2007)

Figure 2: Teacher performance by school SES quintile



Note: based on own calculations from SACMEQ III (2007)

Table 4 presents the estimated results from correlated random effects models estimated separately for the two school wealth groups. Students test scores across the Q5 and Q1to4 samples have been normalized based on the mean and standard deviation of the respective sub-group. In the case of the Q5 schools, we are able to reject the restriction $\eta_1 = \eta_2$ but not $\beta_1 = \beta_2$ (see column 1). Neither of the over-identification restrictions can be rejected for the sample of relatively poorer schools (see column 3). Using restricted models for each school sample

[24] This grouping is chosen based on other studies which have shown no significant difference in performance across the three bottom school SES quantiles (see for example Taylor, 2011; Spaull, 2013). This division is further closely related to the historical separation of formerly black/homeland (African) schools and formerly white, coloured and Indian schools.

(columns 2 and 4), a significant positive effect of mathematics teacher subject knowledge on student achievement of 11.5 percent of a standard deviation, and a *negative* effect (-0.05) of reading teacher knowledge on student achievement that is not significantly different from zero are estimated. The finding that mathematics and not reading teacher knowledge has an effect on student performance is not surprising given that unlike mathematics, a substantial amount of learning in reading occurs at home.[25] In the case of Q1to4 schools, we find a small negative effect (-0.019) of teachers' subject knowledge that is not significantly different from zero. The estimates for η across the two school samples indicate significant positive selection in Q1to4 schools driven by student unobservables.

The presence of potential non-linearities in the returns to teacher subject knowledge is assessed using a model specification that controls for dummy variables representing teacher test score quintiles defined relative to the school wealth group. Figures 3 and 4 illustrate the estimated coefficients on the teacher knowledge quintiles across subjects and school wealth samples. The coefficients are plotted against the average test score of the respective quintile and normalized relative to a zero coefficient for quintile 1 of teacher performance. It is immediately clear that irrespective of the ranking of teacher performance, there is no pattern of increasing returns to teacher subject knowledge in Q1to4 schools. Statistical testing confirms that the hypothesis that returns to teacher knowledge are not significantly different from zero at all quintiles of teacher subject knowledge cannot be rejected. Hence, it cannot be concluded that a student's performance in the poorer subset of schools is significantly better or worse depending on the relative ability of the mathematics and reading teachers.

Conversely, the estimates indicate a strong non-linear return to teacher knowledge in Q5 schools. Students taught by the most knowledgeable mathematics teachers perform significantly higher on average, scoring 70 percent of a standard deviation more than students taught by teachers performing at quintile 1. The returns to reading teacher subject knowledge in Q5

[25] This is, however, dependent on whether or not learning takes place at home. For example, Spaull (2013) finds that the frequency of speaking English at home and mother's education are positively and significantly associated with reading scores. Gustafsson, van der Berg, Shepherd and Burger (2010) find that the literacy of parents displays a large association with student literacy in South Africa, with the magnitude of parent factors - relative to that of other factors – being arguably larger than is commonly believed.

schools rises dramatically when moving from a teacher ranked in the bottom 40 percent of performance to a teacher at the 3rd quintile. Although the returns appear to decline at the 4th and 5th quintiles of reading teacher knowledge, the coefficients are not statistically significantly different from that observed at the 3rd quintile.

Table 4: correlated random effects models across different school sub-systems

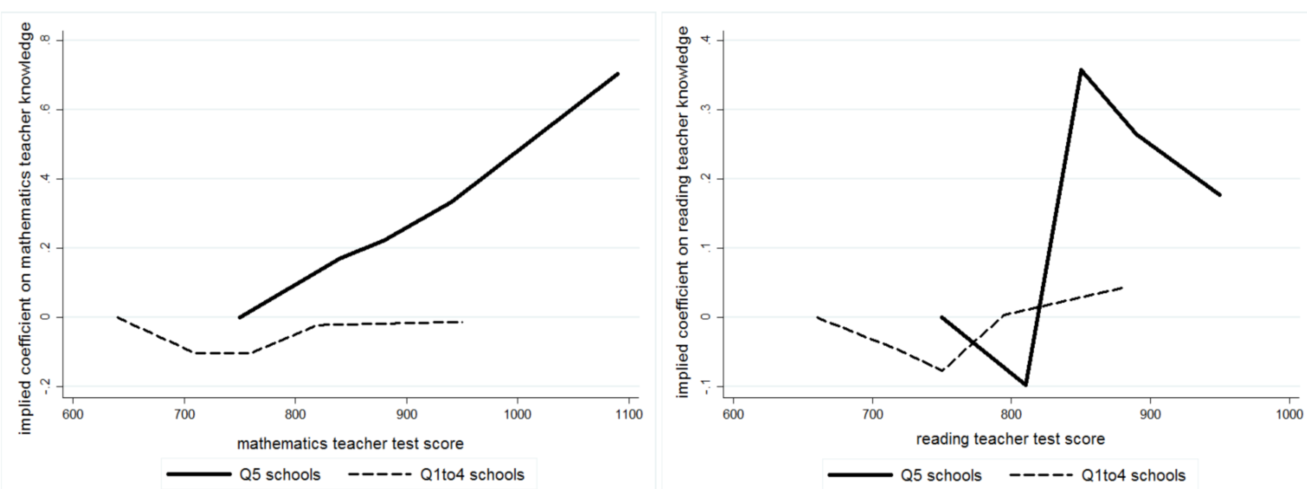
	20% wealthiest schools				80% poorest schools			
	$\beta_1 \neq \beta_2, \eta_1 \neq \eta_2$		$\beta_1 \neq \beta_2, \eta_1 = \eta_2$		$\beta_1 \neq \beta_2, \eta_1 \neq \eta_2$		$\beta_1 = \beta_2, \eta_1 = \eta_2$	
	(1)		(2)		(3)		(4)	
	Maths	Reading	Maths	Reading	Maths	Reading	Maths	Reading
Implied β_s	0.110**	-0.042	0.115**	-0.050	-0.028	-0.006	-0.019	
χ^2 ($\beta_s = 0$)	4.91	0.52	5.43	0.77	1.29	0.05	0.82	
Prob > χ^2	0.027	0.471	0.020	0.379	0.256	0.823	0.366	
Regression estimates:								
Teacher test score in same subject	0.177***	-0.087	0.130***	-0.035	0.070**	0.040	0.054**	
	(0.068)	(0.075)	(0.048)	(0.060)	(0.035)	(0.034)	(0.022)	
Teacher test score in other subject	-0.045	0.067	0.015		0.046	0.098***	0.072***	
	(0.065)	(0.069)	(0.040)		(0.028)	(0.037)	(0.021)	
$\chi^2(\eta_1 = \eta_2)$	1.07		-		0.01		-	
Prob > χ^2	0.301		-		0.908		-	
$\chi^2(\beta_1 = \beta_2)$	6.22**		8.61***		0.14		-	
Prob > χ^2	0.013		0.003		0.709		-	
Observations (students)	1317				5679			
Classrooms (clusters)	163				523			
Number of schools	65				260			

Note: Dependent variable is the standardized student test score in numeracy and literacy calculated using the mean and standard deviation of the respective school sub-sample. Student test scores are normalized relative to the school sub-sample mean and standard deviation. Regressions are estimated using seemingly unrelated regressions (SUR). Implied β_s is calculated as the difference in the coefficient on teacher test score in subject s between the equation of the student test score in the respective subject and the equation of the student test score in the other subject. In all models, the coefficients on student and school characteristics are constrained, with $\delta_1 = \delta_2$ and $\phi_1 = \phi_2$. Clustered standard errors, shown in parentheses and clustered at the classroom level, are estimated by maximum likelihood. Regressions control for all student, classroom, teacher and school characteristics defined in tables A1 and A2 of the appendix. Significance at *** 1% level ** 5% level * 10% level.

It is clear that there are great discrepancies in the role that teacher subject knowledge plays across the poorer and wealthier school sub-systems. Even in cases where teachers in Q1to4 schools possess high levels of subject knowledge that are comparable to that of teachers in Q5 schools, this is not realized in the form of student performance gains. It should be acknowledged that the estimates on teacher knowledge in the Q5 sample may be upwardly biased by a correlation with unobservable teacher quality. Similarly, we may question whether or not the results for the group of Q1to4 schools may be driven by a *negative* correlation with teacher unobservables. Closer inspection of the data reveals that the test score variation of students taught by the least knowledgeable mathematics and reading teachers (scoring below 600 points) is the smallest. This might be indicative of effective teaching if it is believed that good teachers produce more equitable test outcomes. For example, a highly dedicated and enthusiastic teacher may not necessarily be the most knowledgeable teacher in terms of subject content, but he/she may more effectively transfer the knowledge they do possess, albeit small, to students. It could also be hypothesised that the working environment of teachers with adequate subject knowledge may be such that the benefits to teacher quality are not able to be realized.

Taylor and Taylor (2013) differentiate between three patterns of teacher knowledge in the SACMEQ III data, loosely named transmission, knowledge impedance and complex impedance. Transmission identifies those items in the test that both teachers and their students scored well on; hence teachers may well be affecting learning in these knowledge areas. Conversely, knowledge impedance and complex impedance patterns identify cases where teachers found it difficult to transmit knowledge, the first being due to a lack of knowledge on the part of teachers and the second due to an inability to convey knowledge. Correction for teacher unobservables will be explored in section 5.4.

Figure 3: returns to teacher knowledge by performance quintile and school wealth group



Note: based on own calculations from SACMEQ III (2007) dataset

5.3 Returns to teacher and classroom characteristics

Table 5 presents the estimated returns to other teacher and classroom characteristics aside from teacher content knowledge. Students attending a Q5 school taught by math and reading teachers with a university degree or post matric (diploma) qualification perform approximately 20 to 40 percent of a standard deviation higher compared to students taught by teachers with less than higher education. A smaller positive effect of math teacher university education (11% of a standard deviation) is estimated for the sample of Q1to4 schools.

Surprisingly, a negative and statistically significant coefficient is estimated for diploma qualification of reading teachers in Q1to4 schools. Summary statistics indicate that reading teachers employed within Q1to4 schools with post-matriculation diplomas are older (significantly so) and more experienced than teachers with higher qualifications. It is likely that these teachers were trained under the former colleges of education that offered mainly diploma courses and have, since 1996, been absorbed into universities and other tertiary education institutions such as technikons. The majority of the students attending these colleges would not have obtained a matriculation exemption which would have allowed them access to a university degree. Many of the colleges were described as "glorified high schools" seen to be largely "underperforming and problematic in terms of turning out quality teachers" (Chisholm, 2009). Obviously this explanation for the negative diploma coefficient is conjecture. Clotfelter et al (2010) similarly find a negative effect size for teachers who invest in a postgraduate degree later into their teaching. This may be related to the recent provision of teacher qualification upgrades through the Advanced Certificate in Education (ACE). Unfortunately, the data does not provide information regarding the timing of receiving the diploma; it is therefore impossible to separate the causal effect of getting a diploma from the selection effect of the decision to get one.

The return to mathematics teacher experience is estimated to be 0.56 and 0.31 standard deviations for Q1to4 teachers with less than 5 years of experience and 6 to 15 years of experience, respectively. Similarly large effect sizes are found for mathematics teachers in Q5 schools, although they are less precisely estimated (possibly due to small sample sizes). The finding that the effect of teacher experience is highest in the first five years of teaching is in keeping with other research (Clotfelter et al, 2006, 2007) and may reflect the relative high quality of mathematics teachers who have recently entered the teaching profession following completion of formal training. Another interpretation is that very effective young, and therefore less experienced, teachers may opt out of teaching in government schools. The estimated coefficients on reading teacher experience are not estimated to be significantly different from zero for both school groups.

One of the most significant findings is the large positive and statistically significant effect of textbook availability on student achievement in poorer schools. Students having access to their own or a shared reading textbook has an estimated effect of 22 to 29 percent of a standard deviation increase in achievement, more than twice the effect size of being taught by a mathematics teacher with a university degree. Similarly, similarly high student access to mathematics textbooks is expected to increase math performance by 12 to 15 percent of a standard deviation in Q1to4 schools. This stresses the importance of adequate access to learning resources and teaching aids in South African classrooms, particularly for those students who are from disadvantaged socio-economic backgrounds.

5.4 Correction for teacher unobservables

When we compare the results of table 5 to the estimated teacher knowledge effects discussed in section 5.2, it is immediately evident that the estimated effect of teacher subject knowledge for the sample of Q1to4 schools is substantially smaller than that of other observable teacher and classroom characteristics. However, the estimates on teacher (and classroom) characteristics may be biased due to a correlation with the $(\tau_{1j_1} - \tau_{2j_2})$ component of the error term. For example, the large effect sizes of teacher qualification and teacher experience, as well as teacher subject knowledge in the Q5 sample, may be related to the quality of education and training received by teachers as was suggested by the findings of Carnoy and Chisholm (2008).

In order to correct for bias related to teacher unobservables, we can control for teacher fixed effects through restricting the analysis to the group of students who are taught by the same teacher for both subjects. The size of the same-teacher (referred to from this point onwards as ST) sample comprises of only 15 percent of the original student sample, which raises concern about the randomness of this sample. Inspection of the data reveals that schools within the ST sample are comprised of mostly rural, relatively poorer and smaller schools on the one hand (Q1to4), and relatively wealthier, urban and well-resourced schools on the other (Q5). This suggests that poorer schools in which teachers are observed to teach both subjects may do so out of necessity or lack of resources, whilst the opposite may be true of the wealthier school system that is able to attract highly educated teachers who are trained to teach several different subjects.

Table 5: Returns to other teacher and classroom characteristics

	20% wealthiest schools		80% poorest schools	
	Implied coef.	Prob > χ^2	Implied coef.	Prob > χ^2
	(1)		(2)	
Math teacher has university degree	0.393***	0.001	0.100**	0.017
Reading teacher has university degree	0.339***	0.002	0.005	0.900
Math teacher has post-matric diploma	0.232*	0.082	0.010	0.861
Reading teacher has post-matric diploma	0.203	0.166	-0.161***	0.002
Math teacher has <5 years teaching experience	0.450	0.157	0.252**	0.045
Reading teacher has < 5 years teaching experience	0.124	0.593	0.016	0.882
Math teacher has 6-15 years teaching experience	0.220	0.462	0.117	0.337
Reading teacher has 6-15 years teaching experience	-0.038	0.847	-0.080	0.460
Textbook shared between 2 students in math class	-0.139	0.183	0.119*	0.062
Students have their own textbooks in math class	-0.088	0.259	0.149**	0.019
Textbook shared between 2 students in reading class	0.127	0.283	0.289**	0.027
Students have their own textbooks in reading class	0.107	0.253	0.220*	0.087
Observations	1317		5679	
Clusters	163		523	
Schools	65		260	

Note: Dependent variable is the standardized learner test score in numeracy and literacy calculated using the mean and standard deviation of the respective sample. Regressions are estimated using seemingly unrelated regressions (SUR). Implied coefficients are calculated as the difference in the coefficient on the respective variable in subject s from the equation of the student test score in subject s and the equation of the student test score in the other subject. In all models, the coefficients on student and school characteristics are constrained, with $\delta_1 = \delta_2$ and $\phi_1 = \phi_2$. Clustered standard errors in the SUR models are estimated by maximum likelihood. Regressions control for all student, classroom, teacher and school characteristics defined in tables A1 and A2 of the appendix. Significance at *** 1% level ** 5% level * 10% level.

Comparisons of the student and teacher test score distributions of the Q5 ST sample to the Q5 non-ST sample reveals significantly higher performance in the former. In the case of Q1to4 schools, the ST sample of students and teachers performs significantly lower than the non-ST sample. In addition, students in the Q5 ST sample are significantly more likely to come from English speaking homes with more educated parents (particularly fathers) and more likely to be taught by younger, less experienced and more qualified teachers (all of which have been shown to have large positive effect sizes) than students within the Q5 non-ST sample. Conversely, students within the Q1to4 ST sample are significantly more likely to come from poorer homes with less educated parents and are taught in less resourced classrooms than the Q1to4 non-ST sample. However, teachers within the former sample are more likely to possess a university degree and spend significantly more time preparing for class (self-reported).

The results of estimating equations [6] and [7] are shown in table 6. The estimated effect sizes on teacher knowledge should be free from bias driven by teacher unobservables, at least subject-invariant ones. This, however, comes at the cost of lower precision given the smaller sample sizes. In both school ST samples we were not able to reject the over-identification restrictions and the final model was estimated with restrictions $\beta_1 = \beta_2$ and $\eta_1 = \eta_2$. The estimates for the ST sample of Q5 schools indicate an effect size of 5.4 percent of a standard deviation increase in student performance for a one standard deviation above average teacher subject knowledge, which is half that estimated for the whole sample of Q5 schools. A statistically significant effect size of teacher knowledge of 0.13 is estimated for the ST sample of Q1to4 schools. Whilst statistically insignificant, these effect sizes are in no way trivial.

The larger positive effect of teacher test score estimated for the Q1to4 schools when moving to the ST sample is suggestive of negative correlation between teacher subject knowledge and teacher unobservable characteristics. This is not to say that lower quality teachers necessarily perform better on the teacher test. Given that we know this group to be a relatively poorer subset of the whole Q1to4 sample, and hence also the overall South African school sample, we can expect the working environment to be such that the transmission of teacher knowledge to students may be hindered by a lack of teacher capacity; this may be linked on the one hand to poor formal training and a lack of strongly developed pedagogical skills, and on the other factors such as poor school leadership, overcrowded classrooms, absence of a learning culture and lack of community involvement (Bush, Joubert, Kiggundu and van Rooyen, 2010). If we further consider that the presence of the aforementioned factors are expected to be less prevalent (if not absent) in the Q5 ST sample that is likely to be representative of the wealthiest and best performing schools, then it stands to reason that the smaller positive coefficient on teacher knowledge is indicative of a positive correlation between teacher knowledge and teacher quality unobservables.

Table 6: correlated random error model results using the ST sample

	20% wealthiest schools	80% poorest schools
	(1)	(2)
	$\beta_1 = \beta_2, \eta_1 = \eta_2$	$\beta_1 = \beta_2,\ \eta_1 = \eta_2$
	Maths Reading	Maths Reading
Implied β_s	0.054	0.130
χ^2 ($\beta_s = 0$)	1.06	1.73
Prob > χ^2	0.303	0.188
Regression estimates:		
Teacher test score in same subject	0.109***	0.303**
	(0.041)	(0.215)
Teacher test score in other subject	0.055	0.173***
	(0.043)	(0.187)
Observations (students)	225	622
Classrooms (clusters)	25	34
Number of schools	14	32

Note: Dependent variable is the standardized learner test score in numeracy and literacy calculated using the mean and standard deviation of the respective sample. Regressions are estimated using seemingly unrelated regressions (SUR). Implied coefficients are calculated as the difference in the coefficient on the respective variable in subject s from the equation of the student test score in subject s and the equation of the student test score in the other subject. In all models, the coefficients on student and school characteristics are constrained, with $\delta_1 = \delta_2$ and $\phi_1 = \phi_2$. Clustered standard errors (shown in parentheses) in the SUR models are estimated by maximum likelihood. Regressions control for all student, classroom, teacher and school characteristics defined in tables A1 and A2 of the appendix. Significance at *** 1% level ** 5% level * 10% level.

5.5 Fixed effects estimation

A number of the correlated random errors models estimated by this study have indicated that the over-identification restrictions are not rejectable. Does this then prescribe the use of a fixed effects model? The author would argue, not necessarily. The use of students as their own controls (as in the case of a fixed effects model) requires adequate within-student variability in the teacher and classroom characteristic. If variability is low (often referred to as sluggish covariates) then fixed effects estimation will lead to a fair amount of the share of variance in exposure to teacher content knowledge being removed and inflated standard errors. Both fixed effects and correlated random errors models are able to eliminate the bias in parameter estimates stemming from endogenous unobserved effects. As mentioned it is difficult to argue that the error term $\tau_j + \varepsilon'_{si}$ will not contain some unobservable characteristics that are correlated with inter alia teacher subject knowledge, therefore we can expect some bias in the estimates regardless of estimation strategy chosen.[26] If, however, our intention is to estimate the effect of subject-invariant observable characteristics rather than to only control for them, then correlated random error modelling is the appropriate method.

In order to assess the appropriateness of the methodological strategy adopted by this study the estimates from the correlated random error models are contrasted with those from student fixed effects estimation; these are summarised in table 7. Despite being slightly larger, the model parameters on teacher subject knowledge are in general robust to those estimated using correlated random errors. It is expected that the coefficient on teacher knowledge for the sample of ST Q1to4 schools would be estimated with smaller standard error when fixed effect estimation is used. Sample-specific descriptives on the between- and within-student variation in teacher subject knowledge for the same samples considered in table 7 are presented in table 8. The within-student variation in teacher subject knowledge increases when the whole sample is sub-divided into the two school wealth groups. However, limiting the school wealth samples to those students taught by the same teacher in both subjects reduces the within-student variation in teacher knowledge. Although student fixed effect estimation appears to be a fair choice of methodological approach, and indeed provides results that are similar to that of a correlated random errors model, it is the opinion of the author that the latter approach is more adaptable when interest lies in estimating divergent effect sizes of teacher quality characteristics across different subjects.

6. Conclusion

In the South African context, where the vast majority of students 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 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, 2008: 3). The aim of this study was to add to the debate of the determinants of student performance in South Africa through identifying the

[26] Fixed effects estimation assumes omitted variables to have time-invariant, or in this case subject-invariant, values as well as subject-invariant effects.

impact of teacher content knowledge and other teacher and classroom factors on grade 6 student performance in reading and mathematics. To this end, the 2007 SACMEQ dataset and correlated random effects model estimation were employed.

Table 7: Student fixed effects estimation results

	Whole sample	20% wealthiest schools		80% poorest schools	
		All Q5 schools	ST Q5 schools	All Q1to4 schools	ST Q1to4 schools
	(1)	(2)	(4)	(6)	(8)
Teacher test score	0.019	0.085**	0.063	-0.0002	0.152**
	(0.015)	(0.037)	(0.053)	(0.022)	(0.065)
Adjusted R-squared	0.020	0.091	0.039	0.021	0.025
Observations (students)	6996	1317		5679	
Classrooms (clusters)	686	163		523	
Number of schools	325	65		260	

Note: Dependent variable is the standardized learner test score in numeracy and literacy calculated using the mean and standard deviation of the respective sample. Robust standard errors clustered at the classroom level are shown in parentheses. Regressions control for all student, classroom, teacher and school characteristics defined in tables A1 and A2 of the appendix. Significance at *** 1% level ** 5% level * 10% level.

Table 8: Standard deviations of teacher subject knowledge by sub-samples

	Observations (students)	S.D.	Within-student S.D.	Fraction of variance across students
Whole sample	6996	1.000	0.729	0.468
Q5 sample	1317	0.961	0.887	0.148
Q1to4 sample	5679	0.836	0.687	0.325
Same-teacher Q5 sample	225	0.937	0.700	0.443
Same-teacher Q1to4 sample	622	0.722	0.482	0.554

Note: the fraction of variance across students is calculated as $\{SD^2\text{-(Within-student SD)}^2\}/SD^2$.

A number of important empirical findings emerge from this study and are discussed in turn. First, it is vital when estimating the impact of teacher and classroom factors on student outcomes that we control for unobservable school and student 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 these unobservables, teacher knowledge is estimated to have no significant effect on student outcomes. This is similar to the findings of Carnoy and Chisholm (2008) and Carnoy and Arends (2012) who find no significant effect of teacher content knowledge on student gains in mathematics. However, this may mask differences in impact across student sub-groups. This leads into the second important empirical finding that the impact of teacher knowledge is not homogenous across the South African education system. High quality teachers are typically observed to teach in Independent and former white and Indian schools that are likely to fall within the top school wealth quintile (Carnoy and Chisholm, 2008). Using average school SES as a proxy for former department and school wealth quintile, significant positive non-linear effects of teacher subject knowledge is estimated for the wealthiest quintile of schools. However, no significant effect of teacher knowledge is estimated for the poorest four school wealth quintiles. Teacher qualifications are estimated to have significant and large effects for student outcomes in wealthier schools, though this may be driven by a positive relationship to teacher unobservables. The same may be true of the large and highly significant effect size of young and inexperienced teachers in poor schools, which may signal an improvement in the training of those that have most recently entered the teaching profession.

Restricting the analysis to those students who are taught by the same teacher in both subjects removes any bias driven by a relationship between teacher unobservables and measurable teacher characteristics. Whilst the results for this sample may not be generalizable to the school system as a whole, they are likely to represent the two extremes of the South African education system; that is, the wealthiest of the Q5 schools and the poorest of the Q1to4 schools. The results indicate a positive effect size of teacher knowledge on performance of approximately 13-15 percent of a standard deviation and 5-6 percent of a standard deviation for the poorer subset and wealthier subset of South African schools, respectively. These estimates are in line with international findings that adopt similar techniques for estimating teacher effects. The most comparable of these studies is that of Metzler and Woessman (2012) who adopt an identical approach to that of this study in their assessment of the effect of teacher knowledge on grade 6 performance in Peru.[27] Metzler and Woessman's (2012) estimated effect size of 0.10 is very similar to that estimated for Q1to4 schools, as is that of Tan et al (1997) who find an estimated

[27] A number of similarities can be drawn between South Africa and Peru. For example, the average performance of Peruvian students on international achievement tests also tends to be dismal when compared to developed countries. Furthermore, similar to the ranking of South African grade 6 students in SACMEQ III, Peruvian 6th grade students ranked 9 and 10 in mathematics and reading, respectively, amongst a comparative study of 16 Latin American countries from the Latin American Laboratory for Assessment of the Quality of Education (LLECE) in 2008.

effect of teacher test scores of 0.10-0.12 on first grade learning gains in the Philippines. This illustrates that the findings for Q1to4 schools are largely in line with those of other developing country estimates. Conversely, the estimated effect size of teacher knowledge in Q5 schools is more comparable to the estimates found in developed country contexts, particularly the United States where estimates range between 0.01 and 0.06 (Hill et al, 2005; Goldhaber, 2007; Clotfelter et al , 2007).

The relationship between teacher knowedge and teacher unobservables further needs to be acknowledged. The analysis of this study suggests that teacher knowledge is positively related to teacher unobservable quality in Q5 schools, which we would expect. On the other hand, teacher knowledge appears to be negatively correlated to teacher (and school) unobservables in the poorest schools. This may be due to a lack of factors contributing to effective teaching such as high quality training, pedagogical skill and opportunity to teach that are more present in wealthier schools. It may also suggest a correlation with factors that hinder the transmission of knowledge to students such as mismanagement, poor instructional leadership and poor teacher collaboration. Clearly, not all teachers with poor content knowledge are ineffective teachers, and not all teachers with good content knowledge are effective teachers.

Many important policy conclusions arise from this study. First, the provision of textbooks and other teaching aids in poor schools is of utmost importance given the consistent finding by this study that the availability of textbooks to all students is associated with a large positive effect on performance. Furthermore, the effect size on textbook provision outweighs that of all other observable teacher and classroom characteristics identified in this study. The finding that the estimated effect size of teacher knowledge is of twice the magnitude in the poorest subset of schools reflects the relative importance of teacher knowledge for learning across the school system. Circumstance, both in the background of the teacher and the immediate working environment, will however dictate whether or not the benefits to teacher knowledge are able to be fully realized. The author would agree with Carnoy and Chisholm (2008) that the quality of teacher training and adequate curriculum preparation are crucial for explaining differences in student performance. Furthermore, the systematic differences with which high quality teachers are distributed across schools need to be addressed, if we consider this to be a driving factor behind the large performance gaps observed across school-wealth quintiles. School hiring practices need to take into account the long-term investment involved when selecting teachers, given their near-permanent employment statuses.

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Appendix

Table A1: Descriptive statistics (weighted) of selected variables (full sample)

Variable	Variable type	Mean	Standard deviation	Minimum	Maximum	Test score if indicator = 1[a] Student	Teacher
Student test score							
Unstandardised:							
Numeracy	continuous	490.2	93.4	10.3	962.9		
Literacy	continuous	489.3	112.4	62.9	996.5		
Standardised:							
Numeracy	continuous	0	1	-5.153	5.017		
Literacy	continuous	0	1	-3.853	4.518		
Difference		0	1.392	-6.279	6.048		
Teacher test score							
Numeracy		0	1	-1.980	3.976		
Literacy		0	1	-2.607	4.122		
Student/family characteristics							
Female	dummy variable	0.506	0.500	0	1	0.074	0.014
Overage	dummy variable	0.436	0.496	0	1	-0.373	-0.202
Underage	dummy variable	0.088	0.283	0	1	-0.064	-0.100
Speak English most/all of the time	dummy variable	0.146	0.353	0	1	0.618	0.548
Never repeated	dummy variable	0.721	0.448	0	1	0.167	0.075
Repeated once	dummy variable	0.199	0.400	0	1	0.780	0.943
Repeated twice	dummy variable	0.052	0.222	0	1	-0.609	-0.253
Repeated > twice	dummy variable	0.028	0.164	0	1	-0.605	-0.308
Borrow books outside of school	dummy variable	0.406	0.491	0	1	0.421	0.341
Homework everyday	dummy variable	0.547	0.498	0	1	0.174	0.164
Homework 1-2 times/week	dummy variable	0.323	0.468	0	1	-0.124	-0.202
More than 10 books at home	dummy variable	0.279	0.449	0	1	0.530	0.393
Index of household chores	continuous	0	1	-1.773	3.446	-0.307	-0.240

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

Variable	Variable type	Mean	Standard deviation	Minimum	Maximum	Test score if indicator = 1[a] Student	Teacher
Household socio-economic status*	continuous	0	1	-2.206	2.450	0.383	0.306
Mother has a matric qualification	dummy variable	0.174	0.379	0	1	0.176	0.188
Father has a matric qualification	dummy variable	0.220	0.415	0	1	0.074	0.092
Mother has higher level diploma	dummy variable	0.137	0.344	0	1	0.454	0.293
Father has higher level diploma	dummy variable	0.154	0.361	0	1	0.351	0.238
Mother has tertiary education	dummy variable	0.092	0.289	0	1	0.880	0.595
Father has tertiary education	dummy variable	0.118	0.322	0	1	0.659	0.467
Parents help with homework sometimes	dummy variable	0.567	0.496	0	1	0.129	0.083
Parents help with homework most of the time	dummy variable	0.345	0.475	0	1	-0.154	-0.116
School characteristics:							
School located in a town	dummy variable	0.181	0.385	0	1	0.146	0.028
School located in a city	dummy variable	0.293	0.455	0	1	0.600	0.521
School has a moderate absenteeism problem	dummy variable	0.327	0.469	0	1	-0.243	-0.072
School resource index	continuous	0	1	-2.083	1.579	0.488	0.420
Lack of community involvement a problem	dummy	0.328	0.470	0	1	-0.109	-0.178
School average socio-economic status	continuous	0	1	-2.512	2.654	0.577	0.500
Classroom and teacher characteristics							
Only the teacher has a textbook	dummy variable	0.119	0.324	0	1	-0.128	-0.033
Textbook shared between > 2 learners	dummy variable	0.142	0.349	0	1	-0.394	-0.232
Textbook shared between 2 learners	dummy variable	0.264	0.441	0	1	-0.023	-0.059
Learners have their own textbook	dummy variable	0.394	0.489	0	1	0.250	0.158
Writing space to learner ratio less than 1	dummy variable	0.704	0.457	0	1	-0.160	-0.167
Class testing a few times term	dummy variable	0.467	0.499	0	1	-0.005	0.032
Class testing done 2-3 times a month	dummy variable	0.240	0.427	0	1	-0.078	-0.150
Class testing done weekly	dummy variable	0.142	0.349	0	1	0.204	0.133
Teacher female	dummy variable	0.611	0.488	0	1	0.037	-0.001
Teacher younger than 30 years	dummy variable	0.038	0.190	0	1	0.664	0.657
Teacher 31-40 years	dummy variable	0.438	0.496	0	1	-0.072	0.004
Teacher 41-50 years	dummy variable	0.372	0.483	0	1	-0.094	-0.084

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

Variable	Variable type	Mean	Standard deviation	Minimum	Maximum	Test score if indicator = 1[a] Student	Teacher
Teacher has university degree	dummy variable	0.438	0.496	0	1	0.143	0.193
Teacher has a postmatric diploma	dummy variable	0.166	0.372	0	1	0.048	0.182
Teacher has 0-5 years teaching experience	dummy variable	0.119	0.324	0	1	0.021	-0.190
Teacher has 6-15 years teaching experience	dummy variable	0.386	0.487	0	1	-0.007	0.079
Teacher has 16-25 years teaching experience	dummy variable	0.421	0.494	0	1	-0.046	-0.026
Numbers of hours spent on preparation/week	continuous	10.117	7.669	0	25	0.080	-0.004
Number of in-service courses competed in last 3 years	continuous	3.533	5.121	0	61	0.075	0.014
Teaching minutes per week	continuous	1138.9	528.1	0	3000	0.174	0.177
Days lost due to strike activity	continuous	12.473	8.536	0	31	-0.323	-0.261

[a] For continuous variables these are mean standardised test scores for cases that are above the average, as given by the mean value of the continuous variable.

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
Only the teacher has a textbook	0.162	0.368	0.059	0.236	0.102***
Textbook shared between > 2 learners	0.120	0.326	0.158	0.365	0.037***
Textbook shared between 2 learners	0.243	0.429	0.288	0.453	0.046***
Learners have their own textbook	0.366	0.482	0.442	0.497	0.076***
Writing space to learner ratio less than 1	0.668	0.471	0.684	0.465	0.016**
Class testing once a term	0.470	0.499	0.455	0.498	-0.015*
Class testing done 2-3 times a month	0.232	0.422	0.239	0.426	0.007
Class testing done weekly	0.156	0.363	0.148	0.355	-0.009
Teacher female	0.513	0.500	0.672	0.470	0.158***
Teacher younger than 30 years	0.047	0.212	0.037	0.188	-0.010***
Teacher 31 to 40 years	0.414	0.493	0.411	0.492	-0.003
Teacher 41 to 50 years	0.382	0.486	0.380	0.485	-0.003
Teacher has university degree	0.429	0.495	0.447	0.497	0.018**
Teacher has a postmatric diploma	0.178	0.383	0.160	0.367	-0.018***
Teacher has 0-5 years teaching experience	0.122	0.327	0.113	0.316	-0.009*
Teacher has 6-15 years teaching experience	0.363	0.481	0.374	0.484	0.011
Teacher has 16-25 years teaching experience	0.446	0.497	0.432	0.495	-0.014*
Numbers of hours spent on preparation/week	10.019	7.617	10.272	7.778	0.253*
Number of in-service courses competed in last 3 years	3.657	4.699	4.308	6.384	0.652***
Teaching minutes per week	1160.70	529.56	1218.68	525.30	57.98***
Days lost due to strike activity	12.110	8.462	11.868	8.648	-0.243*

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