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

Debra Lynne Shepherd

[DRAFT VERSION – DO NOT QUOTE]

Abstract

This paper assesses the impact of teacher subject knowledge specifically, amongst other teacher characteristics, on student performance using a nationally representative dataset of grade 6 students in South Africa. Differences in student test scores are used to identify within-pupil across-subject variation in performance. Teacher subject knowledge is only estimated to have a significant positive impact for student learning when considering the subset of 20 percent richest schools and students taught by the same teacher in mathematics and English. However, there is evidence to suggest that this effect may be due to teacher unobservables and/or subject-varying student and school unobservables. There is therefore insufficient evidence to suggest that teacher subject knowledge has a positive impact on student performance.

JEL Code: C31, I21

Keywords: teacher knowledge, student performance, South Africa

[a] African Micro Econometric Research Unit (AMERU), University of the Witwatersrand
email: debrashepherd@sun.ac.za

1. Introduction

Teacher quality may be considered the most important determinant of learner performance by stakeholders in education, not least due to the fact that teacher salaries make up the largest individual component of total expenditure on education. South Africa is no exception where teacher salaries make up approximately 75 percent of the education budget. In the 2009 General Household Survey (GHS), of the group of South African households who report not sending their children to the nearest available education institution, approximately 13 percent cited "poor quality of teaching" as the reason for doing so.[1] However, the emphasis on teachers largely conflicts with empirical research into teacher quality, as 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). Increasing attention has been given to teacher subject knowledge, particularly as this measure of teacher quality has been shown to be more often significantly correlated with learner performance than other measurable characteristics such as teacher experience and qualifications (see Hanushek, 1997). In the South African context, where the vast majority of learners perform at a level that subpar both internationally and regionally, it is of vital importance 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, 2007: 3).

This study makes use of the 2007 wave of the Southern and Eastern African Consortium for Monitoring Educational Quality (SACMEQ) in order to estimate a reduced form education production function. This nationally representative dataset is unique in that teachers were asked to complete subject specific tests. This allows us to identify the impact of teacher knowledge on pupil performance in a given subject. As is well documented in the education production function literature, selection on unobservables is a particular problem that plagues model identification. In order to address this issue, the within-pupil between-subject methodology per Dee (2005, 2007) is employed. Identification here relies on variation across subject-specific teachers, as well as fixed pupil and school characteristics across subjects to correct for between and within school sorting of students. However, identification may still be related to selection on teacher unobservables. The methodology per Altonji et al (2005) is employed in order to assess the potential bias due to selection on unobservables once accounting for selection based on subject-invariant pupil and school characteristics.

Empirical results find that teacher test score has a positive yet statistically insignificant impact on learner performance. The impact is further found to be robust to different model specifications and results based on sub-samples. Estimation of the model separately for the poorest 80 percent of schools and the richest 20 percent of schools finds divergent impacts of teacher knowledge for learner outcomes. Teacher knowledge remains statistically insignificant for learner performance in the case of poorer schools, yet leads to a significant increase in average learner test

[1] A third of these households choose a further institution as they believe it to be better than the nearest available alternative, and another 11 percent cited lack and resources and/or equipment.

scores of 9 percent for a 1 standard deviation in teacher test score in the case of rich schools. Restriction of the sample to students taught by the same teacher in both English and math finds a similar result. Employing the technique per Altonji et al (2005) for measuring the potential bias due to selection on observables relative to selection on unobservables indicates that relatively small shifts in unobservables may account for the estimated coefficients on specifically teacher knowledge and teacher education. Therefore, it may not be possible to attribute the estimated positive impact on learner performance wholly to these variables.

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. Section 4 describes the estimation strategy. The main model results are presented in Section 5, while Section 6 provides robustness checks. Section 7 concludes.

2. Literature: teacher knowledge and learner performance

In an early study analysing the link between teacher characteristics and achievement gains, Hanushek (1971) finds that those teacher characteristics typically “purchased” by schools, such as experience and education, are less important for achievement than characteristics such as performance on a verbal facility test and recentness of education. He further finds a difference in the impact of teacher characteristics for students from different socio-economic backgrounds, with teacher verbal skills playing a larger role in determining outcomes of students from less affluent homes. Measurable teacher and classroom characteristics are found to explain only a limited portion of the variation in the performance of affluent children. In two subsequent reviews of the existing literature, Hanushek (1986, 1997) finds far more evidence in favour of teacher test score as having positive impacts on learner performance as opposed to teacher experience and education.

Recent analyses have largely confirmed these earlier findings. In their analysis of the impact of teachers and schools on gains scores in Texas, Hanushek et al (2005) find that although teachers have strong impacts on learner performance in mathematics and reading, observable school and teacher characteristics explain little of the within-school between-classroom variation in gains scores. Controlling for school rather than teacher fixed effects results in a substantial reduction in the model explanatory power. This suggests that much of the variation in teacher quality exists within rather than between schools. They further find no significant impact of master’s degree on teacher effectiveness. In a review of studies that have examined the impact of teacher characteristics on learner gains scores, Wayne and Youngs (2003) conclude that college ratings and test scores have positive impacts for learner performance, whilst the effects of degrees, coursework and qualifications are less conclusive. They further point out that despite substantial variation in teacher effectiveness as evidenced by student performance across teachers, this variation is little driven by differences in teacher qualifications. In a recent study based on state administrative data for elementary schools, Clotfelter et al (2007) find positive effects of teacher test score on achievement have, with stronger findings emerging for mathematics. This finding is consistent with studies by Monk (1994) and Monk and King (1994) who find that teacher preparation translates into higher student test scores in math, with similar effects not observed in other subjects.

The studies outlined above have largely been compiled in a developed country context. Comparisons to the South African case may be better drawn with findings of the link between teacher quality and achievement in developing countries. In an analysis of student performance in reading and mathematics in Jamaican primary schools, Glewwe et al (1995) find largely insignificant impacts of teacher variables for determining achievement. The only teacher variable found to have a positive significant effect was that of teacher training within the past 3 years, with the effect limited to mathematics. Kingdon (1996) finds a positive significant impact of teacher test scores on grade 8 performance in reading and mathematics in Indian private schools. In contrast to the findings of studies in developed countries, teacher education is found to have a positive significant impact that is separate from the impact of teacher knowledge. However, once controlling for selection into schools, the positive impact of teacher knowledge disappears and the impact of teacher education is decreased. A positive significant impact of teacher knowledge on reading and mathematics scores is also found by Tan et al (1997) using a dataset of first grade students in the Philippines. They estimate a 12 percent of a standard deviation and a 10 percent of a standard deviation increase in student reading and mathematics scores respectively for a one standard deviation increase in teacher subject knowledge. Neither teacher possessing a master's degree nor teacher experience was found to have statistically significant impacts on achievement.

Evidence on the impact of teacher knowledge on learner outcomes in South Africa is largely unclear. This is mainly due to the fact that it has rarely been captured in large-scale, nationally representative surveys of student achievement. However, 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 (employed by this study) have provided information on teacher knowledge through teacher test scores. The NSES administered testing of both mathematics and English teachers. However, the shortness of these tests (English teachers were given a comprehension test comprising of 7 questions, and mathematics teachers a 5 mark test) means that they provide limited measures of teacher knowledge. An interesting finding relating teacher knowledge to student performance is found by Taylor (2011) using the NSES dataset. Students taught by teachers who scored 100 percent on the teacher test for numeracy perform significantly better on average than students taught by teachers who scored less than 100 percent. Conditioning further on time spent teaching per week, Taylor (2011: 27) finds no significant difference in average student performance between teachers scoring 100 percent versus those scoring less than 100 percent among the group of teachers reporting to teach for less than 18 hours a week. However, the difference becomes large and statistically significant when comparing teachers who scored 100 percent versus those who scored less than 100 percent among teachers who report to teach for more than 18 hours a week. This hints that, when combined with time on task, teacher knowledge leads to substantial gains in student learning. When controlling for teacher subject knowledge as well as other measurable pupil, classroom, teacher and school characteristics in multivariate regression models of performance in English and mathematics, teacher knowledge was found to be not significantly associated with student achievement. Only in the case of the mathematics teacher scoring 100 percent on the numeracy test was a positive impact (significant at the 10 percent level) observed. Regarding other measures of teacher quality, teacher experience was only found to have positive and significant impact on learner performance for students taught by teachers with more than 20 years of experience.

Spaull (2011) uses the SACMEQ 2007 dataset to estimate education production functions for learner performance in mathematics, English and health. The multivariate regression results indicate a statistically significant impact of teacher knowledge on learner test scores, with a larger impact observed for reading.[2] The estimated impacts are smaller than those observed in other studies, with a 1 standard deviation increase in teacher test score leading to a 7.1 percent, 4.8 percent and 6.5 percent increase in student performance in English, mathematics and health respectively. Noting that the empirical model used does not correct for potential bias due to non-random sorting of students and teachers, as well as omitted variable bias, these estimates become even less convincing of a positive impact of teacher knowledge on performance in South African primary schools. Spaull (2011) further finds divergent impacts of teacher knowledge once conditioning on school wealth; that is, teacher knowledge is found to have a larger significant impact on student test scores in reading and health in the richer subset of schools, while teacher test score is estimated to have no significant impact on mathematics scores in the subset of poor schools.[3]

In should be noted that virtually all education production function studies face the limitation of a small number of observed characteristics with which to capture school and teacher quality. The most commonly available characteristics, such as teacher education and experience, are clearly important variables to consider, mainly because of the role they play in teacher pay. Yet, as discussed, they explain little of the actual variation in teacher effectiveness. Even when more detailed information regarding other characteristics such as quality of qualifications and scores on standardised tests are available, much of the variation in learner performance remains unexplained. Given that teacher quality variables tend to be inter-related, the impact of one variable may be absorbed by other quality measures. Omitted variable bias is a great concern in estimating education production function, not only at the level of the teacher, but also at the level of the student, classroom and school. Non-random sorting of students and teachers both between and within schools that cannot be controlled for via observable characteristics creates further bias in the model estimates. For example, 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.

Studies that have attempted to estimate the impact of teacher knowledge on student achievement have largely failed to overcome the biases caused by omitted variables and nonrandom sorting. However, a recent study by Woessmann and Metzler (2010) takes steps towards identifying the impact of teacher knowledge using a nationally representative dataset of 6th grade students in Peru and a correlated random effects technique (which reduces to a within-student fixed effects approach). Through restricting the sample to students taught by the same

[2] This result is further corroborated by this study.

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

teacher in both subjects in schools with only one classroom, the authors are able to fully correct for potential bias due to teacher unobservables and nonrandom sorting between teachers within schools. An additional correction is made for measurement error in the teacher test score. They find a one standard deviation increase in teacher subject knowledge results in approximately a 10 percent of a standard deviation increase in pupil performance.

3. Data

The data used in this study is the third wave of the SACMEQ conducted in 2007. Learner knowledge in three subject areas, namely mathematics, English and health, was tested using multiple-choice questionnaires. Test scores are standardised on a scale of mean 500 and a standard deviation 100. In addition to testing of learners, a full array of information regarding home, classroom, and school environments was collated, as well as specific demographic information on students, parents, teachers and principals. Teachers were further required to complete the Health test, as well as a subject-specific test in the case of mathematics and English teachers.[4] As this is the first nationally representative education survey in South Africa where teachers' subject knowledge was tested, there is scope to better understand the impact of teacher-knowledge on student performance.[5] For the most part, teachers and students wrote the same tests, with the former required to answer additional challenging questions in mathematics and English. To account for differences in difficulty across questions, teacher test scores are transformed using Rasch scaling into values that are directly comparable with student test-scores (Rasch, 1960). For purposes of this study, only scores on English and mathematics are considered. In order to make use of the within-pupil difference in test performance as the dependent variable, the z-score of achievement in each subject is used. The z-scores are calculated by taking the student's test score in a subject less the sample mean test score in that subject, divided by the standard deviation of the subject test score. Therefore, the z-scores in any subject are standardized on a scale of mean 0 and standard deviation 1.

In the process of choosing model covariates, two new variables were generated, namely: a household socio-economic index (SES) and the average SES of the school student body. There is much support for using asset-based indices to represent wealth or income and they perform well in education production functions (see for example Filmer & Pritchett, 2001). Both of these socio-economic indices were generated from 31 possession items using the first principal component (PCA). The measure of pupil SES was further standardised to have a mean of 0 and a standard deviation of 1. The average socio-economic status of the students in a school was similarly standardised to have a mean of 0 and a standard deviation of 1. Although some studies have chosen

4 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.

5 The National School Effectiveness Survey (NSES) also included a teacher test, although the test was different to that completed by students, and comprised of 5 questions in the case of mathematics and 7 questions in the case of English literacy. The NSES further does not include the Gauteng province, making it not nationally representative.

to group parental education with possession items in the SES variable, it has been found that parental education has a significant impact on child learning that is independent of household wealth. For the purposes of this analysis parental education has been treated separately with dummy variables for mother completed secondary education, father completed secondary education, mother post-matric education, father post-matric education, mother possessing university degree or higher and father possessing university degree or higher.

In the case of South Africa, 9083 6th grade learners were sampled from 392 schools, taught by 498 literacy and mathematics teachers, and 492 health teachers. The large size of the dataset makes SACMEQ III highly advantageous for analysing educational outcomes and their determinants in South Africa. This is especially given the large intraclass correlation coefficient that is typically observed in school performance data in South Africa (Van der Berg, 2007). Not all students, teachers and schools completed the questionnaire, resulting in missing data. So as to not lose a large number of observations, a number of imputations were performed. Missing data on household possession items were dealt with by recoding missing values as “not possessed”. Thus, for instance, if a child did not answer whether their household owned a TV, it was assumed that they did not. Missing values on parent education were imputed using the modal parental education by school (parent education was recorded in very broad attainment categories). Indicators for missing values on categorical variables at the student level were included separately in the model. In most cases, the coefficients on these variables were found not to be significantly different from the reference category. Consequently, missing data on categorical variables were grouped with the reference category. Given the comparatively smaller number of missing data at the school level, schools with missing data were dropped from the sample. Dealing with missing data at the teacher level proved more challenging. The issue was addressed in a similar manner as missing data at the student/household level, that is, including a separate category for missing/unspecified data. 6996 students in 325 schools with 711 teachers (357 reading teachers and 354 maths teachers, where 59 teachers teach both subjects) remain in the sample.[6] Stratification was done by province and school size. The 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 (SACMEQ, 2010: 4). The sample design is taken into account in the analysis. Due to the nested nature of the data, heteroskedastic robust standard errors are calculated.

Table A.1 of the appendix reports the descriptive statistics on observable teacher and classroom characteristics separately for mathematics and English, with differences in means presented in the final column of the table. Teachers and classrooms are fairly comparable across the two subjects, although significant differences between the two groups are observed on several variables. Mathematics teachers are more likely to be younger and possess post-matriculation qualifications, whereas English teachers are more likely to be female, tertiary educated, and have completed more in-service courses in the past three years. With regards to classroom resources and processes, classrooms in which mathematics teachers teach tend to be more equipped, whilst there is a greater availability of textbooks in English classrooms. All observable variables listed in table 1 are included as controls in the empirical analysis.

[6] Robustness checks will be performed excluding missing data on pupil and teacher level variables.

It is of further interest to note whether student and school characteristics differ by teacher test performance, as this may indicate whether there is selection of better teachers into specific schools and/or pupil groups. These descriptives are shown in table A.2 (see appendix). Teachers are split into two groups: above-average performing teachers and below-average performing teachers, where teacher performance is standardised at mean zero. It is obvious that average pupil and school characteristics between above- and below-average performing teachers differ significantly. It is clear that above average performing teachers are found in better equipped and wealthier schools, with higher community support, and a higher density of non-permanent and tertiary educated teaching staff. Notably, teachers with better subject knowledge are found more predominantly in urban located schools (55 percent versus 36 percent), as well as schools where teacher salaries are subsidized by the community (48 percent versus 27 percent). Furthermore, the average learner taught by above-average performing teachers is better performing, and comes from wealthier and better educated households in which more emphasis on learning activities, *inter alia* frequency of homework and reading, is placed. More than half of students taught by above-average scoring teachers report borrowing books outside of the school, whilst only 30 percent of students taught by below-average scoring teachers report similar activities. It is interesting to note that a higher proportion of students taught by below-average scoring teachers report to receive help with their homework at home. This may reflect a need for more support at home due to the possibly poorer learning environment at school. Given the high likelihood of selection of better teachers into potentially better functioning schools, all analysis controls for observable and, to an extent, unobservable, learner and school traits.

Teacher performance may further be related to other teacher and classroom traits that lead to augmented learner performance. Table A.3 (see appendix) summarises mean differences in teacher and classroom traits conditional on teacher performance. Above-average scoring teachers teach in better resourced classrooms, have more access to teaching aides, and are more likely to test their students on a weekly basis. Above-average performing teachers are also observed to be 40 years or younger, better educated (more than half possess a university degree as compared to 36 percent of below-average scoring teachers), lose fewer teaching days due to strike activity, spend more time teaching per week, and have 6 to 15 years of experience. There is no significant difference in time spent on preparation for class and the number of in-service courses completed in the last 3 years when conditioning on teacher performance.

4. Estimation strategy

In order to estimate the impact of teacher qualifications on test performance, a standard education production function is estimated as:

$$Y_{ijk} = a_j + F'_{ijk}\beta_j + S'_{ijk}\gamma + T'_{ijk}\delta + D'_{ijk}\theta +' \varepsilon_{ijk} \tag{1}$$

where the test score Y_{ijk} of student i in subject j in school k is determined by student and family background characteristics, F_{ijk}, school characteristics,S_{ijk}, and classroom/teacher characteristics, T_{ijk}, and the standardised teacher test score D_{ijk}. The error term, ε_{ijk}, captures the impact of all unobservable determinants of student test performance, where:

$$\varepsilon_{ijk} = \mu_i + \xi_j + \nu_k + \psi_{ijk} \tag{2}$$

with μ_i, ξ_j and ν_k the effects of unobservable student, teacher and school characteristics respectively. The remaining unobservables are in the error term ψ_{ijk}, and it is potential correlation between these unobservables and the observables, particularly at the teacher and classroom level, that is key to being able to identify a causal effect from teacher knowledge on achievement. Ordinary least squares estimation of the coefficients of equation (1) will necessarily lead to biased results if the observed characteristics F, S, T and D are correlated with the unobserved determinants of test scores. For example, high ability students and good quality teachers may select themselves into certain schools given better management, a strong learning culture, and so forth, which may be included in ν_k, but are correlated with F, T and D. In order to eliminate the effects of school sorting, we can control for school fixed effects, represented by Q_k, that exclude any systematic between-school variation in performance or teaching practice:

$$Y_{ijk} = a_j + F'_{ijk}\beta_j + Q_k + S'_{ijk}\gamma + T'_{ijk}\delta + D'_{ijk}\theta + \mu_i + \xi_j + \psi_{ijk} \tag{3}$$

The estimates of (3) could still be biased by within-school sorting. By differencing between subjects, we are able to eliminate the influence on constant student characteristics:

$$\Delta Y_i = a_m - a_l + F'_i(\beta_m - \beta_l) + S'_i(\gamma_m - \gamma_l) + T'_{im}\delta_m - T'_{il}\delta_l + D'_{im}\theta_m - D'_{il}\theta_l + \eta_i \tag{4}$$

where $Y_i = Y_{im} - Y_{il}$ and $\eta_i = \xi_m - \xi_l + \psi_{im} - \psi_{il}$. Following Schwerdt et al (2011) and Dee et al (2005), the assumption is made that coefficients for F and S are equal across the two subjects, such that the final model to be estimated becomes:

$$\Delta Y_i = \Delta T'_i\delta + \Delta D'_i\theta + \eta_i \tag{5}$$

The assumption of homogenous effects across subjects of all variables is a rather strong one to make. Therefore, as a robustness check, equation (4) will be estimated allowing for different coefficients across subjects, after which statistically significant differences in coefficients can be tested. The impact of teacher qualification on student test performance as estimated by (5) will not be biased due to differences in between and within school sorting of students as a result of unobservable student characteristics. However, if D_i is correlated with η_i (that is, unobservable teacher characteristics that directly influence student performance are related to the teacher's test score), then θ will be biased. Similarly, θ will be biased if $\eta_i$contains subject-varying school and/or pupil unobservables that are related to D_i. For example, student ability may vary across subjects, and this may be related to observable teacher characteristics such as teacher knowledge, rendering the coefficient estimates biased. As omitted variables may be correlated both with D_i and with Y_i, we hesitate to interpret θ as a causal effect, but rather interpret it as a measure of the relationship between teacher knowledge and student performance that is not driven by student sorting, but may be partly driven by sorting of teachers.

In order to deal with the issue of selection on unobservables, the methodology per Altonji et al (2005) is employed to assess the potential size of bias in the estimated model coefficients due to unobservables. Let $\Delta T'_i\delta$ and $\widetilde{\Delta D_i}$ represent the predicted value and residuals of a regression of ΔD_i on ΔT_i so that $\Delta D_i = \Delta T_i'\beta + \widetilde{\Delta D_i}$. Then:

$$\Delta Y_i = \theta\widetilde{\Delta D_i} + \Delta T'_i(\delta + \theta\beta) + \eta_i \tag{6}$$

By construction $\widetilde{\Delta D_i}$ and ΔT_i are orthogonal in (6), and the potential bias in θ is:

$$plim\hat{\theta} \simeq \theta + \frac{Cov(\widetilde{\Delta D_i},\eta_i)}{Var(\widetilde{\Delta D_i})} = \frac{Cov(\Delta D_i,\eta_i)}{Var(\widetilde{\Delta D_i})} \tag{7}$$

as ΔT_i is orthogonal to η_i. The condition per Altonji et al (2005) that "selection on the unobservables" is the same as selection on observables is equivalent to the condition that:

$$\frac{Cov(\eta_i,\Delta D_i)}{Var(\eta_i)} = \frac{Cov(\delta\Delta T_i,\Delta D_i)}{Var(\delta\Delta T_i)} \tag{8}$$

The bias can then be estimated by noting that:

$$\frac{Cov(\eta_i,\Delta D_i)}{Var(\widetilde{\Delta D_i})} = \frac{Cov(\eta_i,\Delta D_i)}{Var(\delta\Delta T_i,\Delta D_i)}\frac{Var(\delta\Delta T_i)}{Var(\eta_i)}\frac{Cov(\delta\Delta T_i,\Delta D_i)}{Var(\delta\Delta T_i)}\frac{Var(\eta_i)}{Var(\widetilde{\Delta D_i})} \tag{9}$$

and

$$\frac{Cov(\eta_i,\Delta D_i)}{Var(\widetilde{\Delta D_i})} = \frac{Cov(\delta\Delta T_i,\Delta D_i)}{Var(\delta\Delta T_i)}\frac{Var(\eta_i)}{Var(\widetilde{\Delta D_i})} \tag{10}$$

where (10) follows from (9) using (8). In the analysis, the bias estimated using (10) is reported. The estimated bias represents the impact of teacher knowledge we would estimate even if the true effect was zero when selection on unobservable is as strong as selection on observables. In addition to the bias, we can calculate the ratio of the estimate of θ and the estimated bias. This ratio provides an indication of how large selection on unobservable would have to be relative to selection on observables in order to explain the entire estimated effect of teacher knowledge; that is, it measures the size of the shift in the distribution of the unobservables necessary to explain away the estimated effect of teacher knowledge.

5. Results

The main results for learner test performance are presented in Table 1 below which pool mathematics and literacy scores together. The first column of table 1 is an OLS education production function that controls for a complete set of learner and family background variables, teacher and class controls, school characteristics, as well as subject and province dummies. The second column show results of a pooled model with school fixed effects that also controls for student and family background. The third column presents the final model results of a between subjects differences approach. Given the focus of this study on the impact of teacher characteristics on learner outcomes, only estimates of the coefficients on teacher and various classroom characteristics are reported.

Under the OLS regression model, teacher knowledge is estimated to have a positive and significant impact on test scores, all else constant, increasing learner test scores 5 percent of a standard deviation given a one standard deviation increase in teacher test score. Further positive and significant effects on learner achievement are estimated on the availability of textbooks in the classroom, where two or fewer students per textbook brings larger positive impacts for learning, as well as on teacher qualifications and the number of in-service training courses completed within the past three years. Negative and significant impacts on test scores are observed for learners taught by female teacher, teachers between the ages of 31 and 50 (relative to teachers older than 50), teachers who are absent due to strike activity, and taught in classrooms with fewer writing spaces than there are learners. However, these results may be biased by between school sorting of students on unobservable characteristics. This may be especially true of the coefficients on teacher knowledge and qualifications, as higher ability students are likely to sort themselves into certain schools that attract a higher quality teaching staff.

In order to address the issue of between school sorting of learners, the model is rerun with the inclusion of school fixed effects. When moving to the school fixed effects model, there are notable changes in the coefficient estimates. The impact of teacher knowledge is more than halved, yet still significantly different from zero at the 5 percent level. A similar decline is observed on teacher qualifications. This hints towards the fact that sorting of high ability students and/or high quality teachers into schools may exist. The significant negative impact of female teacher, teacher absence due to striking and fewer writing spaces than learners disappears once controlling for school fixed effects, suggesting that these characteristics may be related to subject-invariant school unobservables. However, positive and significant effects of teachers with less than 6 years of experience and hours spent on lesson preparation are now observed.

Although the impact of teacher knowledge and qualifications remains to be positive and significant moving from OLS to school fixed effects estimation, within school selection may be driving this. For example, teacher knowledge and qualifications may be related to student unobservables such as classroom effort and average learner ability. The across-subject within-student estimation works to alleviate this problem, although, as mentioned earlier, potential bias from subject-varying teacher unobservables that are related to teacher observables may persist.

Taking first-differences across subjects within students, the impact of teacher knowledge as represented by the teacher's test score has decreased and is not statistically different from zero. The impact of textbook availability remains statistically significant, but the impact has decreased substantially. This indicates that within school sorting may matter for the estimation of teacher and classroom level traits. However, teacher qualifications continues to have a positive and significant impact on learner test scores, with coefficient that indicates a 6 percent of a standard deviation increase in learner test score if taught by a teacher with a university degree or higher. The coefficients on the remaining teacher and classroom variables have remained fairly robust when moving from the school fixed effects to the pupil fixed effects model.

Table 1: Education production function (OLS, FE and first difference)

Variable	OLS	School FE	First difference (pupil FE)
Only the teacher has a textbook	0.0921**	0.1040**	0.0805*
	(0.043)	(0.042)	(0.049)
Textbook shared between >2 learners	0.0382	0.0618	0.0919
	(0.044)	(0.046)	(0.066)
Textbook shared between two learners	0.1989***	0.2139***	0.0994**
	(0.040)	(0.038)	(0.048)
Learners have their own textbook	0.1757***	0.1277***	0.0888*
	(0.037)	(0.034)	(0.049)
Teacher female	-0.0435*	0.0109	0.0161
	(0.024)	(0.024)	(0.024)
Teacher 30 or younger	-0.0284	-0.0277	-0.0398
	(0.089)	(0.073)	(0.073)
Teacher 31 to 40 years old	-0.0911*	-0.0255	-0.028
	(0.054)	(0.049)	(0.050)
Teacher 41 to 50 years old	-0.0429	-0.0281	-0.0258
	(0.045)	(0.040)	(0.040)
Teacher has university degree or higher	**0.0766*** **	**0.0602** **	**0.0601** **
	(0.029)	**(0.026)**	**(0.026)**
Teacher has post matric qualifications	**0.0343**	**-0.0108**	**-0.0221**
	(0.036)	**(0.034)**	**(0.033)**
Teacher has 0-5 years experience	**0.0693**	**0.1374***	**0.1343***
	(0.091)	**(0.073)**	**(0.076)**
Teacher has 6-15 years experience	**-0.0034**	**-0.0138**	**-0.024**
	(0.075)	**(0.066)**	**(0.068)**
Teacher has 16-30 years experience	**-0.0627**	**-0.0076**	**-0.0205**
	(0.067)	**(0.062)**	**(0.064)**
Hours teacher prepares for lesson a week	**-0.0015**	**0.0024**	**0.0031** **
	(0.002)	**(0.002)**	**(0.001)**
Number of in-service courses completed in last 3 years	**0.0041***	**0.0044***	**0.004**
	(0.002)	**(0.003)**	**(0.003)**
Access to teaching aids	0.0076	-0.0045	-0.005
	(0.008)	(0.009)	(0.009)
Classroom resources	0.0082	-0.0248	-0.0284
	(0.013)	(0.021)	(0.021)

Teaching minutes per week	0.0000	-0.0000*	0.0000
	(0.000)	(0.000)	(0.000)
Days lost due to strike activity	-0.0454**	0.0136	0.001
	(0.021)	(0.023)	(0.023)
Parents required to sign homework	0.0099	0.0083	0.0037
	(0.027)	(0.023)	(0.021)
Tests given once a semester	-0.0256	-0.0005	-0.0209
	(0.035)	(0.033)	(0.033)
Tests given 2-3 times a month	-0.0585	0.0283	-0.0081
	(0.041)	(0.040)	(0.040)
Tests given almost weekly	0.0208	0.0191	0.0092
	(0.046)	(0.046)	(0.045)
Standardised teacher test score	0.0498***	0.0255	0.0186
	(0.016)	(0.015)	(0.015)
Subject dummies	Yes	Yes	-
Pupil variables	Yes	Yes	-
School variables	Yes	-	-
Observations	13992	13992	6996
R-squared	0.5423	0.6041	0.0208
Estimation bias on teacher degree			3.144
Ratio[a]			0.019

Note: All models are pooled samples of literacy and numeracy test scores. Dependent variable is the standardised test score (mean 0, standard deviation 1). Pupil level controls include learner gender, overage and underage dummies, frequency of homework, frequency of reading activity in the home (both with an adult and alone), assistance with homework, household SES, parent education, dummy variable for more than 10 books in the household and a dummy variable for borrowing library books outside of school. School level controls include location dummies, average school SES, community involvement (specifically subsidising teacher salaries), learner absenteeism, feeding programme present in the school, proportion of tertiary educated teachers, proportion of non-permanent teachers, and a school resource index. Heteroskedastic robust standard errors shown in parentheses.

** $p < 0.10$*

*** $p < 0.05$*

**** $p < 0.01$*

[a] *This is the ratio of the coefficient on standardised teacher test score and the estimated bias*

There may be reason to suspect that the estimate on teacher qualification may be biased due to teacher selection on unobservables. Adopting the methodology of Altonji et al (2005) as outlined in section 4, we calculate the potential estimation bias teacher degree due to selection on unobservables, as well as the ratio of this bias to the estimated coefficient. These are shown in the final two rows of Table 1. The estimated bias is found to be substantially larger than the point estimate of the impact of teacher qualification on learner test scores. The ratio of 0.019 therefore indicates that a fairly small shift in the distribution of unobservable/s suffices to explain away the entire effect of teacher qualification. Therefore, we cannot interpret the coefficient on teacher qualifications as causal, as the positive significant impact of this variable may also reflect a positive relationship between other unobserved desirable teacher characteristics that are related to higher teacher education and better learner performance. Given the size of the estimated bias, we may suspect that the true impact of teacher education on learner performance is in fact negative.

However, this seems highly implausible given the lack of both theoretical and empirical evidence to support this. Therefore, adopting a prudent interpretation of the model results, there is little evidence to suggest that higher teacher education and/or knowledge has a negative effect on student learning, although there is insubstantial evidence to suggest the contrary.

The previously outlined models are rerun for different sub-samples, specifically, the poorest 80 percent of schools and the richest 20 percent of schools separately (based on average school socio-economic status). The bimodal nature of school performance within the South African school system suggests that quite different production processes are at work across two groups of schools: the better functioning, more affluent schools (largely the ex-white and –Indian school systems under the apartheid regime, now referred to as Model C schools); and the largely failing poorer schools, mainly confined to the ex-black and homeland schools (see, for example: Van der Berg, 2008; Fleisch, 2008; Shepherd, 2011). Information regarding the ex-department of schools is not provided in the dataset, therefore we are unable to make a clear distinction between these school groups. However, there is a significant overlap between these groups and school socio-economic status; therefore, we resolve to make the distinction along these lines.

Estimation results for the three models estimated for the two groups separately are indicated in Table 2. It is immediately clear that there are differences in the impacts of teacher and classroom characteristics across these two school groups. The availability of textbooks is estimated to have a positive and significant impact on learner outcomes in the poorest schools, yet has no significant impact on learning in the richer schools once controlling for school and pupil fixed effects. Teacher qualifications are estimated to have a positive and significant impact across both school groups, yet the impact is substantially larger for the group of rich schools where teacher possessing a university degree, or at least some post-matric qualification, leads to roughly a 30 percent of a standard deviation improvement in learner test scores. The estimated impact of teacher education increases as the model controls for school and pupil fixed effects. This indicates a negative correlation between teacher education and school and pupil subject invariant unobservables. In the case of teacher subject knowledge, no significant impact is found in poor schools, yet a positive and significant impact is observed in rich schools. The estimated coefficient remains fairly robust even when controlling for school and pupil fixed effects. A one standard deviation increase in teacher test score is estimated to increase learner test score by 9 percent of a standard deviation. This statistic is of a similar magnitude found in a recent study that adopts a similar methodology to assess the impact of teacher knowledge on student outcomes in developed countries (Metzler & Woessmann, 2010). Further differences across the two school groups are found with respect to the impact of teacher preparation and training. Hours of preparation is estimated to have a positive and significant impact on learner performance in poorer schools, whilst a higher index of classroom resources and number of in-service courses completed has a positive and significant impact in rich schools.

The final two rows of Table 2 indicate the estimated bias on teacher knowledge and teacher qualifications, as well as the ratio of the estimated coefficient and bias. The estimated bias of 2.72 and ratio of 0.019 for the coefficient on teacher having a university degree or higher in the sample of poor schools indicates that the impact of teacher qualifications is likely to be driven by unobservables, as selection on unobservables that is only 0.019 times stronger than selection on observables would be enough to explain away the estimated coefficient. In the case of the coefficients on teacher education and teacher knowledge in the sample of rich schools, the estimated biases are 0.9088 and 0.9090 respectively. This translates to a bias to unrestricted estimated coefficient ratio of 0.33 on teacher degree and 0.10 on teacher test score. Therefore, there is reason to suspect that the coefficients on these variables for the sample of rich schools are also partly driven by selection on unobservables.

Table 2: Education production function (OLS, FE and first difference), by school SES

	80% poorest schools			20% richest schools		
Variable	OLS	School FE	First difference (pupil FE)	OLS	School FE	First difference (pupil FE)
Learners have their own textbook	0.1867***	0.1324***	0.1071*	0.2789**	0.2948**	0.1031
	(0.400)	(0.380)	(0.057)	(0.134)	(0.140)	(0.057)
Textbook shared between 2 learners	0.2368***	0.2228***	0.1259**	-0.2407	-0.2618	-0.0869
	(0.042)	(0.042)	(0.055)	(0.151)	(0.163)	(0.083)
Textbook shared between > 2 learners	0.0745	0.073	0.1084	0.0848	0.1239	-0.0213
	(0.048)	(0.049)	(0.075)	(0.094)	(0.097)	(0.112)
Only the teacher has a textbook	0.0906**	0.0786**	0.0813	0.0864	0.0559	-0.0029
	(0.041)	(0.039)	(0.052)	(0.071)	(0.082)	(0.134)
Teacher female	-0.0127	0.0326	0.0343	-0.1581***	-0.1126*	-0.1329*
	(0.027)	(0.025)	(0.026)	(0.049)	(0.066)	(0.067)
Teacher 30 or younger	-0.0437	-0.0674	-0.0528	-0.0405	0.1843	-0.0253
	(0.116)	(0.089)	(0.090)	(0.114)	(0.135)	(0.139)
Teacher 31 to 40 years old	-0.1125*	-0.0164	-0.0098	-0.052	-0.0037	-0.0234
	(0.062)	(0.048)	(0.051)	(0.081)	(0.092)	(0.093)
Teacher 41 to 50 years old	-0.0672	-0.0313	-0.0227	-0.076	-0.1596*	-0.1959**
	(0.051)	(0.040)	(0.041)	(0.071)	(0.080)	(0.076)
Teacher has university degree or higher	0.0766**	0.0467*	0.0508*	0.1198*	0.2348***	0.3030***
	(0.030)	(0.026)	(0.026)	(0.063)	(0.075)	(0.063)
Teacher has post matric qualifications	0.0604	-0.0411	-0.0494	0.0521	0.1848*	0.2995***
	(0.039)	(0.034)	(0.032)	(0.077)	(0.105)	(0.097)
Teacher has 0-5 years experience	0.0972	0.0931	0.0721	0.1022	0.0396	0.0678
	(0.098)	(0.080)	(0.085)	(0.126)	(0.138)	(0.146)
Teacher has 6-15 years experience	0.026	-0.0449	-0.0699	-0.0197	0.0575	0.1416
	(0.087)	(0.072)	(0.077)	(0.106)	(0.133)	(0.141)
Teacher has 16-30 years experience	-0.023	-0.0259	-0.0525	-0.1005	0.0606	0.0647
	(0.076)	(0.069)	(0.074)	(0.072)	(0.126)	(0.129)
Hours teacher prepares for lesson a week	-0.0022	0.0017	0.0025*	0.0039	0.005	0.0091
	(0.002)	(0.002)	(0.001)	(0.004)	(0.006)	(0.006)
Number of in-service courses completed	0.0004	-0.0028	-0.0032	0.0052**	0.0116***	0.0082**
in last 3 years	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Access to teaching aids	0.0066	0.0041	0.0046	0.0201	-0.0225	-0.0278
	(0.009)	(0.009)	(0.009)	(0.032)	(0.043)	(0.048)
Classroom resources	0.0031	-0.0267	-0.0295	0.0674**	0.0724	0.1108***
	(0.014)	(0.021)	(0.022)	(0.027)	(0.048)	(0.036)
Teaching minutes per week	0.000	-0.0000*	0.0000	-0.0001	-0.0003**	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Days lost due to strike activity	-0.0382*	-0.007	-0.0085	-0.0242	0.0493	-0.0817
	(0.023)	(0.024)	(0.109)	(0.040)	(0.066)	(0.076)
Parents required to sign homework	0.0225	0.0257	0.0207	-0.0462	0.0263	0.0069
	(0.028)	(0.023)	(0.022)	(0.051)	(0.061	(0.056)
Tests given once a semester	-0.0408	-0.0122	-0.0293	0.0465	0.0052	-0.0825
	(0.038)	(0.033)	(0.033)	(0.081)	(0.080)	(0.105)
Tests given 2-3 times a month	-0.0821*	0.0175	-0.0126	0.0252	0.1406	0.0793
	(0.045)	(0.043)	(0.042)	(0.094)	(0.089)	(0.117)
Tests given almost weekly	-0.0293	-0.0033	-0.0181	0.0992	0.0726	0.0052
	(0.056)	(0.051)	(0.049)	(0.091)	(0.090)	(0.097)
Standardised teacher test score	0.0416**	0.0061	0.0045	0.1076***	0.0973***	0.0912**
	(0.020)	(0.017)	(0.017)	(0.027)	(0.029)	(0.038)
Subject dummies	Yes	Yes	-	Yes	Yes	-
Pupil variables	Yes	Yes	-	Yes	Yes	-
School variables	Yes	-	-	Yes	-	-
Observations	11464	11464	5732	2528	2528	1264
R-squared	0.2747	0.3747	0.0231	0.4032	0.4409	0.0818
Estimated bias						
Teacher degree			2.7199			0.9088
Teacher test score			-			0.9090
Ratio[a]			0.019			0.330
Ratio[b]			-			0.100

Note: All models are pooled samples of literacy and numeracy test scores. Dependent variable is the standardised test score (mean 0, standard deviation 1). Pupil level controls include learner gender, overage and underage dummies, frequency of homework, frequency of reading activity in the home (both with an adult and alone), assistance with homework, household SES, parent education, dummy variable for more than 10 books in the household and a dummy variable for borrowing library books outside of school. School level controls include location dummies, average school SES, community involvement (specifically subsidising teacher salaries), learner absenteeism, feeding programme present in the school, proportion of tertiary educated teachers, proportion of non-permanent teachers, and a school resource index. Heteroskedastic robust standard errors shown in parentheses.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

[a] *This is the ratio of the coefficient on teacher having a university degree or higher and the estimated bias*

[b] *This is the ratio of the coefficient on standardised teacher test score and the estimated bias*

6. Robustness checks

This section tests the sensitivity of the main model results presented in the previous section with respect to specifications allowing for heterogenous effects across subjects and sub-samples of the dataset. The results of the robustness checks are presented in tables 3 and 4 below.

Two versions of equation (4) were run that allow for differing impacts of teacher and classroom variables across the two subjects; that is, coefficients on covariates were not restricted to being equal for the mathematics and English. It should be noted that as all English variables enter as negatives on the right-hand side of equation (4), a negative effect on variables for English represent a true positive effect on average test score. The first estimation allows for only teacher and classroom controls, while the second allows further for pupil controls.[7] We control for pupil and household characteristics as any significant difference in the impact of these across the two subjects will necessarily bias the estimates on the teacher and classroom variables if they are omitted and thus incorporated in the error term. Analysis was further performed by school SES.

Table 3: Robustness checks: heterogeneity

	Whole sample		80% poorest schools		20% richest schools	
	Excl. pupil and school controls	Excl. school controls	Excl. pupil and school controls	Excl. school controls	Excl. pupil and school controls	Excl. school controls
Std. teacher test score (math)	0.0088	0.0153	-0.0062	0.0009	0.1338***	0.0955*
	(0.019)	(0.018)	(0.021)	(0.021)	(0.049)	(0.050)
Std. teacher test score (English)	-0.0214	0.0000	-0.0177	-0.0008	-0.0036	-0.0234
	(0.017)	(0.016)	(0.018)	(0.019)	(0.053)	(0.049)
Teacher degree (math)	0.0750***	0.0685**	0.0680**	0.0679**	0.1430	0.1737*
	(0.033)	(0.032)	(0.033)	(0.032)	(0.1117)	(0.1028)
Teacher degree (English)	-0.0107	0.0000	0.0002	0.0120	-0.2529**	-0.1578
	(0.033)	(0.033)	(0.0362)	(0.036)	(0.103)	(0.114)
Teacher post-matric (math)	0.0194	0.0213	-0.0097	-0.0095	0.3050***	0.3329***
	(0.039)	(0.038)	(0.042)	(0.045)	(0.127)	(0.111)
Teacher post-matric (English)	0.0706*	0.0690	0.1000**	0.1138***	-0.2890**	-0.1748*
	(0.043)	(0.042)	(0.042)	(0.040)	(0.135)	(0.123)
Observations	6996	6996	5732	5732	1264	1264
R-squared	0.049	0.0752	0.0792	0.0541	0.1301	0.2096

Note: All models are pooled samples of literacy and numeracy test scores. Dependent variable is the standardised test score (mean 0, standard deviation 1). Pupil level controls include learner gender, overage and underage dummies, frequency of homework, frequency of reading activity in the home (both with an adult and alone), assistance with homework, household SES, parent education, dummy variable for more than 10 books in the household and a dummy variable for borrowing library books outside of school. School level controls include location dummies, average school SES, community involvement (specifically subsidising teacher salaries), learner absenteeism, feeding programme present in the school, proportion of tertiary educated teachers, proportion of non-permanent teachers, and a school resource index. Heteroskedastic robust standard errors shown in parentheses.

* $p < 0.10$
** $p < 0.05$
*** $p < 0.01$

The results of the first column 1 are in keeping with those of the main model results in table 1. Teacher knowledge as represented by test score does not have a significant impact on learner scores. When the sample is split by school SES, the results indicate that in the group of rich schools, there is evidence to suggest that the impact of teacher knowledge is stronger in mathematics than

[7] The coefficients on the school level variables of the education production function run separately for math and English were not found to be significantly different from each other. Significantly different coefficients were, however, found on several pupil and household level variables.

in English. The decrease in the coefficient after controlling for pupil controls indicates some positive correlation between teacher knowledge and pupil observables. In the case of teacher education, teacher degree is estimated to have a positive and significant impact on learner performance in the case of mathematics, yet no significant impact in English. This positive effect holds across both poor and rich schools, yet the impact is more significant in the case of the former. The significant impact of teacher degree on learner performance in English in the richest schools falls away once controlling for pupil observables. This may be related to the language competency of students attending these schools (about a third of students attending the richest schools speak English at home most/all of the time). Teacher post-matric is estimated to have a significant *negative* effect on learner performance in English in the poorest schools, whilst similar teacher qualifications are found to have a significant positive effect in both English and mathematics in the richest schools.

We may also be concerned that controlling for missing values on pupil and teacher traits may have had some impact on the model estimates. Making exclusions for missing observations has no noticeable impact on the coefficient on teacher test score. In fact, all model coefficients on teacher and classroom variables remain robust to missing observation exclusions, with the exception of in-service courses completed that is now estimated to have a positive and significant impact on learner scores (not shown here). As mentioned earlier, the coefficient on teacher test score cannot be interpreted as a causal effect if we suspect that students are non-randomly assigned to teachers, particularly if this is based on " subject-specific propensity for achievement" (Metzler & Woessmann, 2011: 6). Furthermore, the results may be biased if teacher unobservables such as pedagogical skills and motivation, that are included in the error term are related both to teacher observables such as teacher knowledge and student performance. Metzler and Woessman (2011) suggest avoiding this bias through only running the analysis for students who are taught by the same teacher in both subjects. This assumes, however, that teacher unobservables are constant across the two subjects. The results of this are shown in column 3 of table 4. We find that, once controlling for the same teacher, the impact of teacher knowledge is significant suggesting an 8.4 percent increase in learner test score for a 1 standard deviation increase in teacher test score. However, it should be noted that this estimate is based on a very small sample.

Overall, a positive yet insignificant impact of teacher test score on learner performance is observed. However, this impact is positive and significant when considering the group of rich schools and students taught by the same teacher in both subjects. There is evidence to support heterogenous effects of teacher knowledge and education across the two subjects, which may contribute to the estimates presented in the previous section.

Table 4: Robustness checks – missing observations and teacher samples

	Excl. missing pupil	Excl. missing teacher & pupil	Same teacher	Different teacher
Std. teacher test score	0.0228	0.0217	0.084**	0.0113
	(0.017)	(0.017)	(0.041)	(0.016)
Observations	5070	4785	847	6149
R-squared	0.024	0.023	0.018	0.023

Note: All models are pooled samples of literacy and numeracy test scores. Dependent variable is the standardised test score (mean 0, standard deviation 1). Pupil level controls include learner gender, overage and underage dummies, frequency of homework, frequency of reading activity in the home (both with an adult and alone), assistance with homework, household SES, parent education, dummy variable for more than 10 books in the household and a dummy variable for borrowing library books outside of school. School level controls include location dummies, average school SES, community involvement (specifically subsidising teacher salaries), learner absenteeism, feeding programme present in the school, proportion of tertiary educated teachers, proportion of non-permanent teachers, and a school resource index. Heteroskedastic robust standard errors shown in parentheses.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

7. Conclusion

The 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 quality, specifically teacher subject knowledge and education, on student test scores. The 2007 SACMEQ dataset of grade 6 test scores in mathematics and English is employed to estimate education production functions of student performance controlling for various student, school, classroom and teacher characteristics. In order to identify the impact of teachers on student performance, it is important to address potential bias due to omitted variables and non-random sorting of students and teachers. This is especially relevant if it is suspected that student, school and teacher unobservables, as well as the selection processes between and within schools, are related to teacher quality and student performance. Testing of students across multiple subjects meant that a within-pupil between-subject model that controls for pupil and school fixed effects could be estimated, such that the estimated impact of teacher characteristics on student performance is not biased by student sorting. However, the model is unable to solve for potential bias due to omitted teacher characteristics that are related to student performance and teacher quality, for example, teacher motivation. Similarly, any subject-varying school and/or pupil unobservables that are related to teacher quality will further bias the estimates on teacher characteristics. The technique per Altonji et al (2005) that assesses the potential bias due to selection on unobservables is employed.

Using ordinary least squares, teacher knowledge is estimated to increase student performance by 5 percent of a standard deviation for a 1 standard deviation improvement in teacher knowledge. However, a noticeable decline in this estimate and a loss of statistical significance is observed when accounting for fixed effects. This suggests sorting of high quality students and teachers across and within schools in South Africa, which may be related to student and school unobservables that can lead to bias in the estimates on teacher and classroom characteristics. Robustness analyses indicate that this result is robust to specifications that allow for heterogeneous effects across subjects (although there is some evidence that the impact of teacher knowledge is stronger in English than in mathematics), as well as the exclusion of missing observations on students and teachers. Unlike teacher subject knowledge, teacher education is estimated to have a positive and significant impact on student performance. However, this estimate may be biased by omitted teacher characteristics, as well as subject-varying school and student level unobservables. Application of the method per Altonji et al (2005) demonstrates that a fairly small shift in unobservables would serve to explain away the effect of teacher education. Therefore, we are unable to say with certainty that higher teacher education has a positive and significant impact on student performance.

Given prior evidence of bimodality in the South African education system, the impact of teacher subject knowledge and education was estimated separately for rich and poor schools. The availability of textbooks is estimated to have a positive and significant impact on student performance in the group of poor schools, yet has no significant impact in rich schools remains once controlling for fixed effects. This stresses the importance of resources and their use in classrooms in poor schools. The converse is observed in the case of teacher subject knowledge, where no discernible impact of teacher knowledge is found in poor schools, yet a positive and significant impact is found in rich schools. A noteworthy finding is that the estimated coefficient remains robust to the inclusion of fixed effects, suggesting that the impact of teacher knowledge is not related to constant student and school unobservables. However, this effect may be driven by teacher unobservables or subject-varying pupil and school unobservables. Robustness checks allowing for heterogeneous effects indicate a significant positive impact of teacher knowledge in mathematics for the richer schools, as opposed to no impact in English. Similarly, teacher education is found to have a stronger positive impact on student performance in mathematics than in English among the sample of rich schools.

References

Altonji, J.G., Elder, T.E. & Taber, C.R. 2005. Selection on observed and unobserved variables: assessing the effectiveness of catholic schools. *Journal of Political Economy*, 113(1): 151-184.

Clotfelter, C.T., Ladd, H.F. & Vigdor, J.L. 2007. *Teacher credentials and student achievement in high school: a cross-subject analysis with student fixed effects*. National Centre for Analysis of Longitudinal Data in Education Research, Working Paper 11.

Dee, T.S. 2005. A teacher like me: does race, ethnicity, or gender matter? *American Economic Review,* 95 (2): 158-165.

Dee, T.S. 2007. Teachers and the gender gaps in student achievement. *Journal of Human Resources,* 42 (3): 528-554.

Filmer, D. & Pritchett, L.H. (2001). Estimating wealth effect without expenditure data – or tears: an application to educational enrolments in states of India. *Demography*, 38: 115-32.

Fleisch, B. 2008. *Primary Education in Crisis: Why South African schoolchildren underachieve in reading and mathematics*. Cape Town, Juta.

Glewwe, P., Grosh, M., Jacoby, H. & Lockhead, M. 1995. An eclectic approach to estimating the determinants of achievement in Jamaican primary education. *World Bank Economic Review*, 9 (2): 231-258.

Hanushek, E.A. 1971. Teacher characteristics and gains in student achievement: estimation using micro data. *The American Economic Review*, 61 (2): 280-288.

Hanushek, E.A. 1986. *The economics of schooling: production and efficiency in public schools*. Journal of Economic Literature, 24 (3): 1141-1177.

Hanushek, E.A. 2007. Assessing the effects of school resources on student performance: an update. *Educational Evaluation and Policy Analysis*, 19 (2): 141-162.

Hanushek, E.A. & Rivkin, S.G. 2006. Teacher quality. *Handbook of the Economics of Education*, Elsevier.

Kingdon, G. 1996. The quality and efficiency of public and private schools: a case study of urban India. *Oxford Bulletin of Economics and Statistics*, 58 (1): 55-80.

Kingdon, G. & Teal, F. (2010). Teacher unions, teacher pay and student performance in India: A pupil fixed effects approach. *Journal of Development Economics*, 91: 278-288.

Metzler, J. & Woessmann, L. (2010). *The impact of teacher subject knowledge on student achievement: Evidence from within teacher within-student variation*. CESIFO Working paper no. 311.

Rasch, G. 1960. *Studies in mathematical psychology: I. Probabilistic models for some intelligence and attainment tests*. Oxford, England: Nielsen & Lydiche

Schwerdt, G. & Wuppermann, A.C. (2011). Is traditional teaching really all that bad? A within student between-subject approach. *Economics of Education Review*, 30: 365-379.

Shepherd, D.L. 2011. *Constraints to school effectiveness: what prevents poor schools from delivering results?* Stellenbosch Economic Working Papers 05/11.

Spaull, N. 2011. *A preliminary analysis of SACMEQ III South Africa*. Stellenbosch Economic Working Paper 11/11.

Tan, J., Lane, J. & Coustere, P. 1997. Putting inputs to work in elementary schools: what can be done

in the Philippines. *Economic Development and Cultural Change*, 45 (4): 857-879.
Taylor, S. 2011*. Uncovering indicators of effective school management in South Africa using the National School Effectiveness Study.* Stellenbosch Economic Working Papers 10/11.
Van der Berg, S. & Louw, M. 2007. *Lessons learnt from SACMEQII: South African student Performance in regional context*. Stellenbosch Economic Working Papers 16/07.
Van der Berg, S. 2008. *How effective are poor schools? Poverty and educational outcomes in South Africa*, Centre for European, Governance and Economic Development Research (cege) Discussion Papers 69.
Wayne, A.J. & Youngs, P. 2003. Teacher characteristics and student achievement gains: a review. *Review of Educational Research*, 73 (1): 89-122.

Appendix

Table A.1: Descriptive statistics – teacher and classroom variables

Variable	Math		English		Difference
	Mean	SD	Mean	SD	
Classroom resources					
Only the teacher has a textbook	0.163	0.369	0.059	0.236	0.103***
Textbook shared between >2 learners	0.122	0.327	0.163	0.370	-0.041***
Textbook shared between 2 learners	0.239	0.427	0.293	0.455	-0.054***
Learners have own textbooks	0.362	0.481	0.437	0.496	-0.075***
Access to teaching aides	0.308	2.469	0.262	2.376	0.046*
Classroom resource index	0.257	1.503	0.207	1.424	0.050**
Classroom processes					
Parents asked to sign homework	0.654	0.476	0.650	0.477	0.003
Tests given once a semester	0.471	0.499	0.447	0.497	0.024*
Tests given 2-3 times a month	0.234	0.423	0.240	0.427	-0.006
Tests given almost weekly	0.146	0.353	0.156	0.363	-0.010
Teacher variables					
Teacher female	0.517	0.500	0.664	0.472	-0.147***
Teacher <31 years old	0.043	0.203	0.029	0.168	0.014***
Teacher 31 to 40 years old	0.432	0.495	0.414	0.493	0.018
Teacher 41 to 50 years old	0.382	0.486	0.387	0.487	-0.005
Teacher has at least university degree	0.415	0.493	0.444	0.497	-0.029**
Teacher has post matric qualification	0.170	0.376	0.146	0.353	0.024***
Teacher has <6 years experience	0.119	0.324	0.103	0.304	0.016*
Teacher has 6 to 15 years experience	0.381	0.486	0.383	0.486	-0.001
Teacher has 16 to 25 years experience	0.436	0.496	0.426	0.495	0.010*
Number of hours preparation per week	9.951	7.598	10.154	7.851	-0.203*
In service courses completed in last 3 years	3.426	4.550	4.210	6.428	-0.784***
Teaching minutes per week	1144.73	531.54	1201.58	526.35	-56.85***
Days lost due to strike activity	0.186	0.946	0.147	0.958	0.040
Standardised teacher test score	-0.058	0.958	-0.031	0.957	-0.027

Note: teacher and classroom variables are weighted by the number of children taught.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

Table A.1: Student, household and school variables by teacher test score

Variable	Std. teacher test score > 0		Std. teacher test score ≤ 0		Difference
	Mean	SD	Mean	SD	
Pupil variables:					
Learner test score	0.294	1.072	-0.373	0.754	0.667***
Female	0.512	0.500	0.502	0.500	0.011
Overage	0.353	0.478	0.504	0.500	-0.151***
Underage	0.085	0.279	0.090	0.286	-0.005***
Speak English all/most of the time	0.227	0.419	0.080	0.271	0.147***
Repeated a grade once	0.177	0.381	0.218	0.413	-0.041***
Repeated a grade/s twice	0.039	0.193	0.062	0.242	-0.024***
Repeated a grade/s > twice	0.022	0.148	0.032	0.176	-0.010***
Borrow books from outside school	0.538	0.499	0.299	0.458	0.240***
Does homework most days	0.625	0.484	0.484	0.500	0.141***
Does homework 1-2 times a week	0.267	0.442	0.369	0.483	-0.103***
Household variables:					
Live with parents	0.769	0.421	0.696	0.460	0.074***
>10 books at home	0.379	0.485	0.198	0.399	0.181***
Index of household chores	-0.164	0.953	0.275	1.006	-0.440***
Household SES	0.256	1.052	-0.382	0.860	0.638***
Mother has matric	0.201	0.401	0.151	0.358	0.050***
Father has matric	0.235	0.424	0.209	0.407	0.026***
Mother has post-matric	0.177	0.382	0.105	0.306	0.072***
Father has post-matric	0.184	0.388	0.130	0.336	0.054***
Mother has at least university degree	0.132	0.339	0.059	0.236	0.073***
Father has at least university degree	0.155	0.362	0.087	0.282	0.068***
Eat a daily meal at school	0.672	0.469	0.853	0.354	-0.181***
Receives help at home with homework most of the time	0.305	0.460	0.377	0.485	-0.072***
School variables:					
Rural	0.193	0.395	0.355	0.479	-0.162***
Suburban	0.254	0.436	0.277	0.488	-0.023
Urban	0.550	0.498	0.356	0.479	0.206***
Learner absenteeism serious problem	0.326	0.469	0.384	0.487	-0.058
Index of school resources	1.936	2.697	0.492	2.902	1.444***
Lack of community involvement	0.468	0.500	0.474	0.500	-0.006
Community subsidises teacher salaries	0.483	0.500	0.265	0.442	0.218***
Proportion of non-permanent teaching staff	0.134	0.154	0.094	0.122	0.040***
Feeding programme at school	0.683	0.466	0.838	0.369	-0.155***

Proportion of tertiary educated teaching staff	0.319	0.326	0.265	0.277	0.054***
School average SES	0.539	1.006	-0.051	0.873	0.590***
Proportion schools in school quintile 1	0.068	0.253	0.164	0.370	-0.096***
Proportion schools in quintile 2	0.140	0.347	0.216	0.412	-0.076***
Proportion schools in schools quintile 3	0.182	0.386	0.277	0.448	-0.095***
Proportion schools in school quintile 4	0.243	0.429	0.216	0.412	0.037
Proportion schools in school quintile 5	0.367	0.483	0.128	0.334	0.239***
Province:					
Western Cape	0.182	0.387	0.106	0.308	0.076***
Eastern Cape	0.049	0.287	0.083	0.277	-0.034***
Northern Cape	0.118	0.323	0.111	0.314	0.007
Free State	0.139	0.347	0.115	0.319	0.024
Kwa-Zulu Natal	0.146	0.354	0. 139	0.346	0.007
North West	0.100	0.300	0.094	0.293	0.006
Gauteng	0.161	0.368	0.169	0.375	-0.008*
Mpumalanga	0.049	0.215	0.116	0.320	-0.067***
Limpopo	0.056	0.230	0.067	0.251	-0.011

Note: school level variables weighted by school size.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

Table A.3: Teacher and classroom variables by teacher test score

Variable	Teacher test score > average		Teacher test score ≤ average		Difference
	Mean	SD	Mean	SD	
Classroom resources:					
Learners have own textbooks	0.445	0.497	0.366	0.482	0.079***
2 learners share a textbook	0.247	0.431	0.280	0.449	-0.033***
>2 learners share a textbook	0.118	0.322	0.161	0.368	-0.043***
Only the teacher has a textbook	0.113	0.316	0.110	0.312	0.003
Access to teaching aides	0.987	2.428	-0.239	2.285	1.226***
Classroom resource index	0.583	1.344	-0.030	1.494	0.612***
Classroom processes:					
Parents asked to sign homework	0.642	0.479	0.660	0.474	-0.018
Tests given once a semester	0.443	0.497	0.469	0.499	-0.027
Tests given 2-3 times a month	0.213	0.409	0.254	0.436	-0.041***
Tests given almost weekly	0.172	0.378	0.135	0.342	0.037***
Teacher variables:					
Female	0.581	0.493	0.598	0.490	-0.017
<31 years old	0.062	0.241	0.017	0.129	0.045***
31 to 40 years old	0.450	0.498	0.402	0.490	0.048***
41 to 50 years old	0.329	0.470	0.426	0.495	-0.097***
At least a university degree	0.518	0.500	0.363	0.481	0.155***
Post-matric qualifications	0.187	0.390	0.136	0.343	0.051***
<6 years experience	0.098	0.297	0.121	0.326	-0.023***
6 to 15 years experience	0.416	0.493	0.356	0.479	0.060***
16 to 25 years experience	0.406	0.491	0.452	0.498	-0.046***
Hours of preparation a week	10.148	7.157	9.965	8.117	0.183
In-service courses completed in last 3 years	3.924	5.218	3.735	5.828	0.188
Teaching minutes per week	1256.01	487.96	1109.77	551.77	146.25***
Days lost due to strike activity	-0.113	0.986	0.375	0.870	-0.489***

Note: teacher and classroom variables are weighted by the number of children taught.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$