How effective are poor schools? Poverty and educational outcomes in South Africa

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ABSTRACT

Massive differentials on achievement tests and examinations reflect South Africa's divided past. Improving the distribution of educational outcomes is imperative to overcome labour market inequalities. Historically white and Indian schools still outperform black and coloured schools in examinations, and intraclass correlation coefficients (rho) reflect far greater between-school variance compared to overall variance than for other countries.

SACMEQ's rich data sets provide new possibilities for investigating relationships between educational outcomes, socio-economic status (SES), pupil and teacher characteristics, school resources and school processes. As a different data generating process applied in affluent historically white schools (test scores showed bimodal distributions), part of the analysis excluded such schools, sharply reducing rho. Test scores were regressed on various SES measures and school inputs for the full and reduced sample, using survey regression and hierarchical (multilevel) (HLM) models to deal with sample design and nested data. This shows that the school system was not yet systematically able to overcome inherited socio-economic disadvantage, and poor schools least so. Schools diverged in their ability to convert inputs into outcomes, with large standard deviations for random effects in the HLM models. The models explained three quarters of the large between-school variance but little of the smaller within-school variance. Outside of the richest schools, *SES had only a mild impact on test scores, which were quite low in SACMEQ context.*

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[1] Revised version of paper delivered at SACMEQ International Invitational Research Conference, Paris, September 2005. The author wishes to thank Derek Yu for technical assistance with the data and Megan Louw, Ronelle Burger, Kenneth Ross and Neville Postlethwaite for useful comments.

How effective are poor schools? Poverty and educational outcomes in South Africa[2]

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Introduction

Massive differentials on achievement tests and examinations reflect South Africa's divided past. Despite narrowing attainment differentials, unprecedented resource transfers to black schools and large inflows of black pupils to historically white schools, studies have shown that historically white and Indian schools still far outperform black and coloured schools in matriculation examinations and performance tests at various levels of the school system. Moreover South African educational quality lags far behind even much poorer countries, as has been demonstrated by a number of international tests, including MLA, TIMSS and now SACMEQ II. Educational quality in historically black schools – which constitute 80 per cent of enrolment and are thus central to educational progress – has not improved significantly since political transition. Inadequate educational progress constrains

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both black upward mobility in the labour market and the skills required for economic growth in a middle-income country.

Thus a better understanding is required of the factors that inhibit performance in poorer, mainly black or coloured schools. This paper attempts to improve understanding of the role of socio-economic status (SES) and other factors in determining educational performance at the Grade 6 level. Such performance affects drop-outs, transitions between grades and quality of educational performance up to matriculation and beyond.

Studies have shown high variability in school performance (large residuals) <u>after controlling for SES and teacher inputs</u> that may be indicative of varying efficiency, hinting at managerial problems in many schools (Crouch and Mabogoane 1998). Because of data limitations, education production function studies thus far have had to use school examination performance for matriculation (Grade 12) and have largely ignored non-teacher school inputs and processes. SACMEQ II's rich individual and school level data provide new possibilities for investigating interactions between educational outcomes, SES, school resources and teacher inputs, thus moving towards an understanding of how and under which conditions resources improve outcomes. As it appears that quite different processes may determine learning outcomes in affluent schools (bimodal distributions of test scores provide evidence of separate data generating processes) and the focus here lies predominantly on the performance of the resource-scarce formerly black school system, part of the analysis excludes affluent schools. Test scores will be regressed on SES, pupil characteristics, school inputs, school processes and location for the full and reduced sample, using Stata's survey regression and hierarchical (multilevel) (HLM) models to deal with sample design and nested data. This should help to advance understanding of the conditions required for resources to have an optimal impact, as earlier work indicated that resources mattered only conditionally on school efficiency (the ability to convert resources into educational performance, whilst controlling for SES),), which varied widely amongst schools.

The paper proceeds in the following way: First, South African educational inequality between schools is discussed and placed in international perspective, to show that such inequality is indeed a large part of the education challenge in this country. The paper then turns to a brief discussion of the SACMEQ II South African data. Thereafter, an analysis of performance is attempted by focusing on both school and pupil performance, using OLS (ordinary least-square) regressions but allowing for clustering effects in sample design. The next step is an analysis of performance of poorer schools (a reduced sample), to try to exclude most formerly white schools that could perhaps best be seen as functioning on the basis of a different data generating process. This procedure assists in capturing the relationships amongst individuals in schools that were not formerly advantaged, so that the coefficients can better be interpreted as applying amongst such schools. If the same analysis was applied to all schools, then the coefficients would instead reflect differences between historically white and historically black schools. Next, quantile regression is used for the same purpose, viz. to model the differences between performance of children in well and weakly performing schools. School rather than individual performance is briefly modelled next, as a prelude to the final modelling. The final form of analysis employed here is the estimation of a two-level HLM which attempts to incorporate the effects of both individual and school characteristics, focusing particularly on the role of SES. The paper closes with an overall conclusion.

Inequality between schools

The intraclass correlation coefficient rho (ρ) – which expresses the variance in performance between schools as a proportion of overall variance – is extremely high in South Africa. The Kenya SACMEQ II report (SACMEQ 2005: Ch.8, p.14) quotes Willms and Somers' (2001) finding that the intraclass correlation coefficient ranged from 19.5 per cent to 41.2 per cent for mathematics achievement for Grade 3 and 5 pupils in 13 Latin American countries. Rumberger and Palardy (2003: 14) report a value of 25 per cent to be "within the range that Coleman found in his 1996 study and the range found in other recent studies of student achievement using similar models". In calculating required sample sizes, SACMEQ II erroneously assumed that rho for the group of countries investigated would be in the range of 0.3 to 0.4, thus underestimating the number of schools that needed to be sampled for the desired significance (Ross, Saito, Dolata, Ikeda, Zuze, Murimba, Postlethwaite and Griffin 2005: 26). *Table 1* below shows the range of this magnitude from three sets of international studies, arranged by the rho values for the reading scores in cases where both reading and mathematics were tested. The SACMEQ 2000 rho values of 0.70 for South Africa's reading scores and 0.64 for the mathematics scores confirm that inequality in performance between schools in South Africa is exceedingly high. South Africa has by far the highest recorded values, with Namibia its closest rival by this measure of the degree to which inequality applies between rather than within schools. Although the intraclass correlation for the 2003 matriculation results is considerably lower at 0.399[3], it is unlikely that this means that the

[3] This may reflect one or both of these factors:

SACMEQ data overestimated the South African rho: An unpublished Western Cape study at primary school level also found a value of 0.72 for reading, but a much lower value for mathematics (0.44), perhaps reflecting more individual variation in mathematics performance.

This high degree of inequality between schools is largely a legacy of historical educational inequality. However, it arises more from differences in educational quality than from differential attainment, since the latter has narrowed considerably in recent decades. Indeed, Lam (1999) found that South African attainment differentials between race groups had narrowed faster than in Brazil – a country with income inequality levels similar to South Africa's.

The differentials in performance between high and low SES groups, or rich and poor, far exceeded that in other SACMEQ countries in both reading and mathematics, judging by the SACMEQ indicators and their SES measure (SACMEC Indicators 2005). The differences in mean scores of rich and poor shown in *Figure 1* illustrate how far South Africa leads the field in this measure of educational inequality. Namibia (for reading) and Mauritius (for mathematics) were closest to South African differentials between rich and poor. *Figure 2* shows a similar picture, for the differential in scores between large cites and isolated rural areas. Here, South African differentials were massive: there was urban-rural gap (as here defined) of almost 180 score points for reading and almost 140 for mathematics. This is put into perspective when one considers that mean test scores have been set at 500 and the standard deviation at 100 across all SACMEQ countries, and that only Namibia had differentials more than half as large. The differentials also did not arise so much from exceptional performance of the rich or the urban populations than from relatively poor performance amongst the poor and those in isolated rural areas. This weak educational performance of large segments of the population is put into further perspective when it is considered that South Africa had a much higher per capita income than most SACMEQ countries.

- Differences in transition and drop out rates, that prevent weaker pupils from reaching matric, thus reducing variance both within and particularly between schools.
- Weaker quality differentiation in the matric examination, due to the wide subject choice allowed. However, the intraclass correlation coefficient of the Mathematics mark of those who did take this subject was only 0.389 in 2003 (the Standard Grade mark converted to Higher Grade by subtracting 10 percentage points). But this value was also reduced by self-selection: Those who were weaker at mathematics avoided the subject.

Lowess (locally weighted) regressions of the relationship between the SES derived for this study (discussed below) and test scores had very similar shapes for individuals and school averages for both reading and mathematics (Figures 3a, 3b, 4a and 4b). This relationship was quite flat over most of its range, particularly for individuals. Apparently, SES only started playing a role at a higher, threshold level of SES. At low levels of SES, individuals and indeed schools did not seem to gain much in terms of reading or mathematics score improvement from higher SES. This may indicate that most schools were not able to turn higher SES, at least up to that threshold, into educational advantage. This cannot be taken as evidence that such schools performed well in enabling poor children to perform almost as well as those from middle class backgrounds, as these scores were low in SACMEQ perspective. It was rather the case that the ineffectiveness of these schools meant that not even middle class children performed well. Many of the individuals above the SES threshold level were white and Indian pupils (slightly more than 10 per cent of national school enrolment, though because of varying school size it is uncertain what proportion of schools they constituted) who were historically clustered in schools that performed much better than average. These schools had been racially desegregated, but still largely served the highest SES groups. Based mainly on evidence for secondary schools (i.e. matriculation results), it has been argued that such schools still far outperform others (Van der Berg & Burger, 2003). The data shown here indicate that this argument also applied at primary school level.

The differentials in performance are also shown by school quintiles, where schools are arranged according to their mean SES. *Table 2* shows that mean performance per quintile remained very flat between the poorest and third poorest quintiles (for reading, it rose by only 6 per cent, with no difference in mathematics performance). From Quintiles 3 to 4, performance rose a little more, by another 10 per cent for reading and 8 per cent for mathematics. However, the richest quintile performed more than 25 per cent better than the second richest quintile in both reading and mathematics. Clearly, the richest quintile of schools far outperformed the rest. This makes s strong case for excluding them from the sample for the analysis that focuses on non-affluent schools.

The table also shows that only a few more than one third of South African pupils performed above the SACMEQ mean of 500 on each of the two tests. This proportion increased strongly across the quintiles, with the largest jump occurring when moving from the second richest to the richest quintile. The proportion of each quintile with marks below 400 (one standard deviation below the SACMEQ mean) remained very similar across the bottom three quintiles for both reading and mathematics, but dropped to a negligible share in the richest quintile.

The data

The SACMEQ II survey was conducted mainly in 2000 in 14 countries of Southern and Eastern Africa by the Southern African Consortium on Monitoring Education Quality, based on complex two-stage clustered samples. Questionnaires were administered to selected pupils, their reading and mathematics teachers, and their school principal. A chapter in the Kenya SACMEQ report by Ross *et al*. (2005) provides more detail on sampling and all stages of the process from the planning stage. In South Africa 169 schools were sampled, but because of some missing values on some of the variables (mainly interviews with principals), the actual sample in much of the analysis was reduced to 167 schools. Altogether 20 children in each school were to be tested, but again there were a few missing observations for some variables in the final data set. After allowing for these, the full sample of pupils stood at 3 163. Applying pupil weights, this sample was broadly representative of the South African Grade 6 population, and – as almost universal school attendance had been achieved up to about age 16 – was also likely to be representative also of the 12 year old age group (note that repeaters and those who started school early affected this slightly). However, SACMEQ acknowledged that the effective sample (after taking cognisance of cluster effects in sample design) was smaller for South Africa than is the norm: "In the SACMEQ II Project, two school systems, South Africa and Uganda, fell far below the required target of an effective sample size of 400 pupils. In South Africa the values were 185 and 230 for reading and mathematics, respectively …" (Ross et al., 2005). This largely resulted from the intraclass correlation being larger than allowed for in the sample design, thus too few South African schools were selected. In South Africa. "Ministry concerns about the validity of sampling and measurement" were noted with the release of the SACMEQ II data, leading to a delayed release of the data for this country (see SACMEQ, 2004).

A large number of variables were generated by SACMEQ II, as described in more detail in Ross *et al*. (2005) and elsewhere in the SACMEQ II Kenya Report (2005). These variables were largely the ones used for this study, bearing in mind that in South Africa teacher reading and mathematics skills were not tested (these skills were tested in all the other SACMEQ countries). Furthermore, an own SES variable was created, as described below.

The main variables used in the analysis can be grouped as follows:

- Pupil-level variables: Pupil age, gender, number of times a grade was repeated, whether a pupil always or sometimes spoke English at home[4], education status of pupil's parents, whether the pupil lived with his/her parents, variables relating to the existence of various household possessions, the materials the pupil's home were constructed from, the school-related items (e.g. pencils, rulers, etc) the pupil possesses, and the availability of textbooks. In addition, information was also obtained on the pupil's absence from school and the reasons for such absence.
- Teacher-level variables: For both reading and mathematics, the teacher of each pupil was interviewed to obtain information on gender, age, training, and some SES variables. As not all pupils in each school sample came from the same class, in some schools more than one teacher was interviewed in each subject.
- School variable: Information on the gender, age and training of school principals was obtained, as well as information on reported school problems relating to pupils or teachers.
- School resources: Classroom and other facilities, school building, and school equipment were all recorded.
- School location: Three types of areas were distinguished, viz. large cities, towns, and isolated rural areas.
- School processes: This included frequency of homework, frequency of correction of homework, visits by inspectors, and test frequency.

Socio-economic status of pupils is an important determinant of learning outcomes. The question in this case was how best to measure SES. The approach used by SACMEQ itself, while useful, included parent education – which was regarded as an important regressor to include separately in this study. A new SES variable was thus rather created, using the first factor in principal component analysis that included as variables possessions in and services used by the household (e.g. having a newspaper in the home, ownership of a radio, a television set, a fridge, a car, having electricity, a telephone), the type of house (judged by the wall materials) and the quantity of a list of stationery items that the pupil had in school. The SES variable constructed in this manner showed a high correlation with many of the variables one would expect it to be associated with, whilst its average value was much higher for pupils attending schools in large cities than those in towns or isolated rural areas.

[4] The test was conducted in English, one of South Africa's eleven official languages, although only 14 per cent of pupils reported always speaking English at home.

The variables used are summarized in *Table 3*, along with their mean values, standard deviations, minima and maxima.

Regression analysis: Full sample of individuals and schools

For the regression analysis, the broad underlying model was that SES, pupil characteristics (age, gender, repeater status), access to textbooks, academic effort (as proxied by homework frequency), teacher characteristics (age, gender, training, and tertiary qualifications), school resources, school location, school processes, teacher and pupil problems experienced in the school (violence, pupil behaviour, health, etc.) and perhaps also the characteristics of the school principal may have played a role in determining learning outcomes, in addition to the unobserved ability of the individual pupil. As ability was unobserved, care should be taken in the interpretation of the models of possible ability bias that may influence results. The modelling approach taken was general to specific, initially including all variables deemed potentially relevant to the equation, but selectively dropping those found not to be significant. A few control variables usually considered to be standard explanatory variables in the education literature – including SES, pupil gender, mother's education, over age pupils, and provincial dummies (with NorthWest the reference province) – were retained irrespective of their statistical significance or sign. As the sample of individual children was clustered in schools, thus reducing heterogeneity, all regressions adjusted for sample design and weighting of individuals using Stata's survey regression cluster option. Huber-White robust standard errors were generated to deal with possible heteroskedasticity, thus ensuring stringent tests of variable significance.

The models fitted are as interesting for the variables that were retained as for those that failed to enter the regressions significantly or with an appropriate sign – see *Table 4*, regressions 1 and 2 for the full models for reading and mathematics respectively. Pupil SES was an important predictor, but the effect appeared to be non-linear. A quadratic function gave a better fit than a simple linear model for in both reading and mathematics, with SES affecting scores little at low levels of SES, but playing an increasing role at higher SES levels, as the lowess regressions had indicated may be the case. Other pupil characteristics that played a role in explaining academic performance included gender, age, home language and household structure. It is noticeable that males did worse on reading than females, but there was no significant gender difference for mathematics. The gender dummy was nevertheless retained as a control variable in all regressions. Overage children (above 12 years) performed just over 20 marks worse on both the reading and mathematics scores, whilst underage children had a disadvantage in mathematics. As the test was conducted in English, it was no surprise that speaking English at home brought strong benefits in terms of performance. It is interesting, however, that there was little difference between always speaking English at home and sometimes doing so. In this country of highly fragmented family structures, pupils who lived with their parents had a strong advantage in both reading and mathematics.

Turning to variables directly related to schooling, pupil attendance, grade repetition, parents' education and household resources appeared to be important determinants of academic success. Pupil absence from school had the expected negative impact on marks, and the effect was particularly large in the case of reading marks if such absence was due to unpaid school fees[5]. As the model already controlled for SES and fees were quite low in most schools, unpaid school fees probably partly proxied for a weaker commitment to education by less affluent and probably less well educated parents. It did not appear as if repeating grades brought pupils to the performance levels of their peers, as repeaters fared progressively worse the more years of schooling they had repeated. Although the coefficients on the repetition dummies were not all individually significant and did not show such a regular pattern for mathematics, a joint significance test showed that they did have the expected combined effect. Whilst having a mother with matric brought measurable benefits in terms of a child's reading performance, a child required his or her mother to have obtained at least a degree before the benefits of maternal education were reflected in mathematics scores. By contrast, father's education did not show significant effects. The positive impact of having more than 10 books at home was probably mainly another manifestation of home background, literacy and attitudes to knowledge.

Not having an own textbook or having to share it with more than one other pupil was associated with worse scores on reading. Interestingly, homework frequency did not lead to any significant improvement in performance when the full sample was considered.

Equipment, measured on a scale of 0-11 (a count of the presence of a first aid kit, fax machine, typewriter, duplicator, radio, tape recorder, overhead projector, TV, VCR, photocopier, and computer present in the school), played a positive role. In the case of mathematics, school buildings (measured on a scale of 0-6: a count of the presence of a school library, school hall, teacher room, office for school head, store room and cafeteria) also impacted scores positively. Teacher training or tertiary qualifications did not enter the models as significant factors. Urban schools in large cities performed much better than others, but

[5] Note that this result obtained even though schools were formally forbidden from applying sanctions against pupils whose fees were unpaid.

there was no indication that schools in towns performed better than those in isolated rural areas. Where principals reported having teacher problems, reading scores were significantly lower, although not by a large magnitude. The same result did not apply to mathematics scores.

The pupil-teacher ratio (representing class size) did not significantly enter either of the models, or entered them with the wrong sign, showing that the availability of this type of resource was not as important as often thought. This confirmed earlier work that suggested that teacher numbers play a limited role in South Africa (Crouch & Mabogoane 1998; Van der Berg & Burger 2003), particularly since apartheid era disparities in the allocation of publicly remunerated teachers between schools were eliminated. However, as in many other countries, the quality of teachers may have been more important than the quantity in which they were employed. Another relevant issue here was that, despite government's attempts at standardisation of the pupil-teacher ratio, two factors still contributed to maintaining *de facto* disparities in this measure of school quality. Firstly, schools could impose school fees to supplement public resources, and richer schools often used such funds to appoint teachers in addition to those on the public payroll. Secondly, some schools may have had difficulty filling positions – particularly schools located in deep rural areas. A factor that may have been even more decisive for education quality in poor schools was that good teachers were likely to prefer teaching in richer, urban schools. In view of the remaining differences in allocations of publicly remunerated teachers and those appointed by the school governing body, the very low correlation between mean SES of schools and pupil-teacher ratio or class size (for both, r = –=0.17) was surprising. It is not clear whether this was the result of poor reporting on pupil-teacher ratios, or whether factors other than teacher and pupil numbers (e.g. administrative and other duties that kept some teachers out of classes) conflated the relationship between class size and SES.

Regression analysis: Reduced samples

The intraclass correlation coefficient referred to earlier was substantially decreased if the sample was reduced by first dropping the richest 10 per cent of schools (numbering 17) from the sample, and then the next 10 per cent as well, as *Table 1* shows. The affluence of a school was measured by the mean SES of its pupils in the sample. The full sample reduction reduced rho from 0.70 and 0.64 for reading and mathematics, to 0.47 and 0.39 respectively. This large reduction reflected the fact that a major part of the educational performance disparity in South Africa was between rich (mainly historically white and Indian) schools and other schools. It may indicate that the superior performance of richer schools was due to both having pupils with greater private resources (evidenced by a higher SES and having more educated parents) that enhanced their schooling outcomes, and greater school efficiency in converting school and pupil inputs into performance outcomes for pupils of any given SES. Such conclusions about school efficiency in South Africa have been discussed before in Crouch & Mabogoane (1998 & 2001) and Van der Berg & Burger (2002). If such schools do operate differently, then there is a strong case for excluding white and Indian schools from the sample for the regression analysis. Two separate data generating processes may indeed have been at work, where the underlying statistical relationships would have been conflated by treating them as one. If this conception of the world was correct, then the historically white and Indian schools were best regarded as outliers which may have unduly influenced the estimated coefficients in regressions estimated for the entire schooling system.

Table 5 shows the effect of reducing the sample in terms of scores at the school level. Mean school SES scores drop quite considerably, but even more dramatic was the decline by almost half in the standard deviation across schools. Note also that the maximum values dropped precipitously.

There was no information on the former race-based department to which schools in the sample belonged. However, it was known that race and SES were still highly correlated and that historically white and Indian schools constituted a little more than 10 per cent of all schools in South Africa. To remove these schools from the data set, the sample was reduced twice in the manner described above: first the richest 10 per cent of schools were dropped, and then the next 10 per cent The same parsimonious regression was then run on the original sample as well as on the two reduced samples to see whether sample reduction strongly affected the results.

If all the data captured the same underlying relationship, then the coefficients in the three regressions should have been very similar. If on the other hand all former white and Indian schools functioned quite dissimilarly according to a different data generating process, and most were to be found in the top 10 or to 20 per cent of schools by SES, then the estimated coefficients in either or both of the reduced samples should have differed substantially from those in the original regression. This was indeed the case, as can be seen in *Table 6* for both the reading and mathematics scores: Regression equations altered fundamentally when the sample was reduced. This was best illustrated by the magnitude of the coefficient for SES, which declined for the reading scores from 9.022 in the full sample to 6.883 in the 10 per cent reduced sample and to 3.991 in the 20 per cent reduced sample. This showed that the large and significant coefficient for SES in the original sample may perhaps just have meant that richer (mainly historically white and Indian) schools performed much better, since once they were removed from the sample, the effect of SES on test scores was much smaller. For the mathematics score, the coefficient fell from 6.295 to 2.996, and finally to 0.602. At this point, the coefficient was no longer statistically significant, indicating that SES appeared to play no role in mathematics performance in historically mainly black and coloured schools. The sharp change in the coefficients with both changes in the sample may indicate that white and Indian schools were distributed across the top 20 per cent rather than only the top 10 per cent of schools by SES in the sample. Other coefficients changed with the sample reductions too, and in the case of mathematics scores even the urban dummy lost its significance as a predictor of performance when more affluent schools were dropped.

The next step was to focus on the reduced sub-sample of mainly black and coloured schools, so as to estimate the most appropriate regression models for this group of schools. Separate models were fitted again in the same manner as before for reading and mathematics scores. The results are shown in regressions 3 and 4 of *Table 4*.

The models showed much lower coefficients on most of the regressors than in the full sample, as was already discussed for the basic parsimonious model in *Table 6*. Again, females had an advantage in reading that disappeared in mathematics, whilst the coefficients for speaking English became stronger. The reduced sample related to a group amongst whom speaking English – the language of the tests – was uncommon, and thus using the language at home was expected to give pupils an advantage in tests. Socio-economic status was significant in linear rather than non-linear form for reading, but not for mathematics. The same finding applied to urban residence, which was consequently dropped from the mathematics model. A mother with a degree represented an advantage for children's performance in both reading and mathematics, although maternal education at lower levels surprisingly did not provide any measurable benefits. Living with parents remained highly significant, but the variable relating to the presence of books at home was (surprisingly) no longer significant and consequently was dropped from both models. Absence from school remained significantly negative for both mathematics and reading, while school absence related to not paying school fees also had a significantly negative impact on reading scores. Repeating school grades remained highly negative.

Reading scores were affected by homework, although mathematics scores were not. In the model for the full sample, homework was not a significant positive determinant of performance for either reading or mathematics. Thus homework appeared to matter for explaining reading performance amongst the non-affluent schools, whilst having no textbooks negatively affected reading scores but not mathematics scores.

Overall, the model's explanatory power was much weaker than that of the model for the full sample. This is a similar result to that found by Van der Berg and Burger (2003). The lower coefficient of determination compared to its equivalent for the full sample resulted largely from the fact that all the regressors available for non-affluent schools did not appear to be able to provide as good a model of systematic relationships with performance. The greater unexplained variability in performance was probably – as has been argued before by Crouch and Mabogoane (1998) – an indication of the varying school efficiency that existed in a large part of the school system.

However, reducing the sample to only non-affluent schools did affect reading scores. This is explored further in the next section.

Regression analysis: Quantile regression

An alternative way of dealing with the different data generating processes that may be present in the sample was to use quantile regression, where the coefficient reflected the different levels or types of functioning of the underlying model for individuals performing at different levels in the overall distribution, given their characteristics and school situation. *Table 7* shows quantile regressions of the basic models for both reading and mathematics at the median (50^{th} percentile) and at the 80^{th} percentile, which may give some indication of the varying relationships in schools from different former racially based school systems. The slope and dummy coefficients were usually flatter for the median regression, reflecting both the smaller range of scores and the earlier observation that the relationship between scores and explanatory variables was much stronger in better performing schools – which were also often richer ones. This can be seen as that the returns to characteristics were much higher in richer schools. Apart from this, this analysis held no real surprises.

Regression analysis: School level

Before turning to hierarchical linear modelling, it is instructive first to model performance at the school level, since this will provide information for the HLM. *Table 8* shows two regressions each dealing with reading and mathematics performance of schools respectively. As can be seen, most of the regressors entering the final model were the school level equivalents (or averages) of the regressions for the individual models. The difference between the two models for each outcome lay in the choice of the maternal education variable, i.e. whether to use the percentage with matric or those with a degree. Both variables were significant in all the models, but they influenced the significance of the percentage of overage children in the reading model and of the percentage of male children in the mathematics model, pointing to some multi-collinearity. Interesting features of the results were the strong impact of the proportion of underage children, which came through with a much larger coefficient than that for the proportion of overage children. This was surprising in light of the result that the overage dummy played such a large role in the individual level models. The proportion of a school's pupils that were male had a strong negative consequence for marks, particularly those for reading. Whilst having an own textbook or sharing it with one other provided similar benefits in terms of reading scores, a shared textbook – even if it was shared with only one other – did not bring equivalently good results in mathematics. School equipment, but not school building, played a significant positive role in school performance. Urban location had strong positive effects. Surprisingly, mean school SES did not show a significant impact for mathematics and its impact for reading was not large either[6]. This lack of significance may have been the result of multicollinearity with mother's education, urbanization, repetition, and equipment. All of these variables were greater at the school than the individual level, possibly influencing the stability of results.

Regression analysis: Hierarchical linear modelling

Hierarchical linear models are designed to model situations such as the nesting of pupils within schools. This technique offers benefits beyond OLS since it allows researchers better to "pose hypotheses about relationships occurring at each level and across levels and also assess the amount of variation at each level" (Raudenbush & Bryk 2002: 5). In particular, by making possible the modelling of random effects, an HLM model allows modelling of outcomes in which the effects of individual schools on pupil outcomes – in terms of both the intercepts and the slopes of the estimating equations – can vary. HLM modelling permits at least a partial allowance for individual regressions for different schools with respect to some school level variables.

The hierarchical linear models used here were structured with individuals as level 1 and schools as level 2, with the dependent variable being individual scores. The level 1 model was very similar to the models employed above in the individual OLS regressions. For level 2, however, HLM allowed some of the individual effects influenced by school level factors.

[6] It should be remembered here that the SES variable had a range of only 8, which meant that scores would have differed only by about 67 marks between poorest and richest schools on account of SES alone.

For example, if one were to hypothesize that the influence of home background (as proxied by books at home) was constrained by school resources as proxied by school equipment, it would have been possible to model the effect of having books at home being influenced by school equipment, and then to test whether such a model was appropriate. Furthermore, it was also possible to allow for the effect of individual schools on this relationship to differ between schools (i.e. to have a random effect) by specifying that this sub-model should have its own error term across schools.

The model employed for explaining reading scores was the following (the model for mathematics was very similar, except that in some cases other level 1 variables were found to provide a better fit):

Level 1:

Score = β_0 + β_1*Over12 + β_2*Male + β_3*EnglishSometimes + β_4*EnglishAlways + β_5*Livedwithparents + β_6*AbsentFeesUnpaid + β_7*SES + β_8*Book11plus + β_9*Repeat1 + β_{10}*Repeat2 + β_{11}*Repeat3 + β_{12}*Homewk2 + β_{13}*Homewk3 + β_{14}*Notextbk + β_{15}*MotherMatric + β_{16}*FS + β_{17}*GAU + β_{18}*KZN + β_{19}*LIM + β_{20}*MPU + β_{21}*NC + β_{22}*EC + β_{23}*WC + R **(eq.1)**

Level 2:

All individual level regressors were assumed to be unaffected by school level factors and to have fixed effects, except for the following:

$\beta_0 = \gamma_{00} + \gamma_{01}$*(MeanSES) + U_0 **(eq.2)**

$\beta 7 = \gamma_{70} + \gamma_{71}$*(MeanSES) + U7 **(eq.3)**

This model essentially is one in which the intercept and the slope of the SES variable at level 1 were modelled as outcomes of a level 2 (school level) variable, i.e. the mean school SES. Rewriting and rearranging the above equations produced the final mixed model:

Score = γ_{00} + γ_{01}*MeanSES + β_1*Over12 + β_2*Male + β_3*EnglishSometimes + β_4*EnglishAlways + β_5*Livedwithparents + β_6*AbentFeesUnpaid + γ_{70}*SES + γ_{71}*SES*MeanSES + β_8*Book11plus + β_9*Repeat1 + β_{10}*Repeat2 + β_{11}*Repeat3 + β_{12}*Homewk2 + β_{13}*Homewk3 + β_{14}*Notextbk + β_{15}*MotherMatric + β_{16}*FS + β_{17}*GAU + β_{18}*KZN + β_{19}*LIM + β_{20}*MPU + β_{21}*NC + β_{22}*EC + β_{23}*WC + U_0 + U_7 + R **(eq.4)**

Where:

Over12 = dummy indicating pupil age was greater than 12

EnglishSometimes = dummy indicating pupils sometimes spoke English at home

EnglishAlways = dummy indicating pupil always spoke English at home

Livedwithparents = dummy indicating pupil lived with parents

AbentFeesUnpaid = dummy indicating that pupil had been absent because school fees were unpaid

SES = individual level socio-economic status indicator

MeanSES = mean socio-economic status at school level

Book11plus = home contained more than 10 books

Repeat1/Repeat2/Repeat3 = had repeated one/two/three or more times respectively

Homewk2 = pupil reported doing homework at least twice a week

Homewk3 = pupil reported doing homework's most days of the week

Notextbk = had no textbook, or shared with more than 1 other

MotherMatric = mother had matriculated

FS/GAU/KZN/LIM/MPU/NC/EC/WC = provincial dummies (NorthWest was the reference province)

U_0, U_7, R = error terms (random effects)

The models fitted are shown in *Table 9* and *Table 10*. All the variables were entered uncentered and observations were weighted at both the individual and the school level (unweighted models showed only slightly modified results, though the basic model structure remained unchanged). Where some variable values were absent for any values from a particular school, all observations for the school were dropped. This reduced the sample somewhat.

The results for the reading score model showed that most of the variables found significant at the individual level did indeed play a role, though surprisingly the frequency of homework did play a significant positive role here, unlike in the full sample OLS regressions. The main differences between the reading and mathematics models lay in homework and textbook availability not entering the mathematics model.

The interesting part of the HLM model, however, lay in the modelling of the school level effects. It was found that mean school SES affected the intercept positively, i.e. richer schools performed better, *ceteris paribus*. But, perhaps more importantly, modelling the factors contributing to the role of SES on reading scores showed that school mean SES again had a positive influence. Put differently, individual SES and school level SES interacted positively to produce improved scores. How should this finding be interpreted? A simple explanation may be that school mean SES was a proxy for peer effects that operated to produce enhanced educational outcomes. However, a superior school level predictor would then have been the average reading score in the school. This variable did not perform as well as school SES as a predictor of both the slope and the intercept. An alternative view might be that mean SES at the school level reflected the resources available to the school, but then again one would have expected school facilities potentially to be a better regressor than school mean SES. This was found not to be the case when testing this model. It cannot either be inferred that mean SES was simply a proxy for urban, which was also tested and rejected as an alternative level 2 regressor. A tentative conclusion was thus that school mean SES may be seen as proxy for all of the above.

An analysis of the random effects showed that the standard deviations were large, particularly for the mean SES model, i.e. that many schools deviate from the general pattern of relationships between the school mean SES and individual SES. If, following Raudenbush and Bryk (2002:78), the 95 per cent plausible value for the school SES slope may be considered to be the 95 per cent confidence interval of the school mean SES slope, then the latter ranged from 19.8 to –15.6: a very wide range indeed. There was thus still wide divergence between schools in how well they transformed SES into reading outcomes. The same also applied for mathematics outcomes, with a 95 per cent plausible range even much larger at 35.5 to –30.7.06. Many schools indeed even had a negative slope on SES. Reliability estimates showed that there remained large variability in slopes between schools, despite the fact that empirical Bayesian models usually shrink coefficient estimates relative to OLS estimates of the school level regressions where the latter would have fitted poorly on account of small samples and limited variation in SES values within many schools (see Raudenbusch & Bryk, 2002: 87, 88).

Variance decomposition showed that the variance of U_0 on the reading score was reduced by 74.4 per cent, whilst variance was reduced by only 13.8 per cent compared to the unconditional model for the error term R. Variance reduction thus mainly occurred through decreasing variance between schools rather than within them. This was unsurprising in view of the persistence in homogeneity in school-level SES and other characteristics – an enduring feature of South African schools even long after the demise of apartheid – and given that variance between schools was exceedingly high to start off with. A similar situation applied to mathematics scores, where variance between schools declined by 69.9 per cent while that within schools dropped by only 6.1 per cent.

Figure 5 shows the interaction between individual SES and reading scores (similar to the socio-economic gradient used by Ross and Zuze (2004)) for three types of schools: poor schools, average schools, and rich schools. Here the mean SES values used for each category were the midpoints of the range of SES scores in respectively the poorest, middle and richest quintile of schools (see footnote to *Table 2*). These lines were derived from the model in

Equation 4 and the HLM output in *Table 9*. In poor schools, not even high individual SES scores could generate a good reading score, as performance was weak throughout the spectrum. In average schools, performance varied more with individual level SES. However, in rich schools a strong benefit in terms of reading score arose for individuals with high SES. But even those few children with low SES in rich schools performed better than similar individuals in poor or average schools (although such individuals were scarce, due to barriers to entry in such schools, and the fact that the very poorest children were usually located in rural areas). At the average South African SES level of 0.00, rich schools considerably outperformed the other two groups. Attending an affluent school thus clearly yielded returns in terms of academic performance. The same broad picture also applied to mathematics scores, with the SES gradient for poor schools even being markedly negative.

Conclusion

This paper has demonstrated that socio-economic differentials in 2000 still played a major role in educational outcomes at the primary school level in South Africa. The SACMEQ data have made it possible to show – as had already been done earlier using matriculation data for the secondary school level – that the school system was not yet systematically able to overcome inherited socio-economic disadvantage, and poor schools least so. If one additionally considered that returns to education in the South African labour market appeared to be convex (i.e. that education's contribution to earnings rose strongly at higher levels of education), then differential school outcomes were likely to translate into large inequalities in labour market outcomes.

The similarity of these findings with those on matriculation data (and the even larger values of the intraclass correlation coefficient found here) suggested that policy interventions were required earlier rather than later in the education process, as this high level of between-school inequality arose before secondary school level.

The surprising finding was that, outside of the richest schools, SES had only a mild impact on test scores, which were quite low in SACMEQ context over most of the SES spectrum. A threshold effect appeared to operate, holding back even children from the middle class from performing well if they were outside schools for the rich.

As the labour market consequences of educational backlogs may persist for the productive lifetime of present pupils, and into the next generation through the impact of parent education and SES on future learning outcomes, improved functioning of poor schools is essential and urgent. This study has shown that more resources did not necessarily or without qualification improve school performance, although some resources (e.g. equipment at the school) appeared to play a role. As in much of the educational production function literature, the message from this study appeared to be not that resources did not matter, but rather that resources mattered only conditionally. There was a relatively large divergence in the ability of schools to convert resources into outcomes, as was shown in the large standard deviations on the random effects in the HLM models.

For informed policy intervention, measurement at the school level is essential to identify schools that perform below expectations. Such measurement is also essential for improving accountability of schools to the community – a particularly important goal in poor communities – and of the education system to broader society. This SACMEQ data again illustrated the importance of testing, since regular testing at various levels of the school system could play an important role in informing policy and targeting interventions.

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TABLE 1 - Intra-class correlation coefficient rho (proportion of variance at school level) from PIRLS and SACMEQ I & II studies and from South African matric data set (arranged by rho for reading scores)

Country or territory	Study	Rho for Reading	Rho for Maths
Seychelles	SACMEQ II 2002	0.08	0.08
Iceland	PIRLS 2001	0.084	..
Slovenia	PIRLS 2001	0.087	..
Sweden	PIRLS 2001	0.087	..
Norway	PIRLS 2001	0.096	..
Cyprus	PIRLS 2001	0.105	..
Turkey	PIRLS 2001	0.132	..
Germany	PIRLS 2001	0.141	..
Czech Republic	PIRLS 2001	0.157	..
France	PIRLS 2001	0.161	..
Zanzibar	SACMEQ I 1995	0.17	..
Canada (Ontario, Quebec)	PIRLS 2001	0.174	..
England	PIRLS 2001	0.179	..
Scotland	PIRLS 2001	0.179	..
Netherlands	PIRLS 2001	0.187	..
Italy	PIRLS 2001	0.198	..
Latvia	PIRLS 2001	0.213	..
Lithuania	PIRLS 2001	0.214	..
Greece	PIRLS 2001	0.221	..
Hungary	PIRLS 2001	0.222	..
Malawi	SACMEQ I 1995	0.24	..
Slovak Republic	PIRLS 2001	0.249	..
New Zealand	PIRLS 2001	0.25	..
Mauritius	SACMEQ I 1995	0.25	..
Zanzibar	SACMEQ II 2000	0.25	..
Botswana	SACMEQ II 2000	0.26	0.22
Mauritius	SACMEQ II 2001	0.26	0.25
Zambia	SACMEQ I 1995	0.27	..
Zimbabwe	SACMEQ I 1995	0.27	..
Macedonia	PIRLS 2001	0.271	..
Malawi	SACMEQ II 2002	0.29	0.15
Hong Kong	PIRLS 2001	0.295	..
Mozambique	SACMEQ II 2000	0.30	0.21
Zambia	SACMEQ II 2000	0.32	0.22
SACMEQ Total (across all countries)	SACMEQ I 1995	0.33	..
Kuwait	PIRLS 2001	0.334	..
Tanzania	SACMEQ II 2000	0.34	0.26
Bulgaria	PIRLS 2001	0.345	..
Belize	PIRLS 2001	0.348	..
Romania	PIRLS 2001	0.351	..
Swaziland	SACMEQ II 2000	0.37	0.26
SACMEQ Total (across all countries)	SACMEQ II 2000	0.37	0.32
Iran	PIRLS 2001	0.382	..
Lesotho	SACMEQ II 2000	0.39	0.30
Moldova	PIRLS 2001	0.395	..
South Africa	**2003 Matric aggregates**	**0.399**[7]	**0.389**[8]

[7] Matric aggregate for all subjects

Israel	PIRLS 2001	0.415	..
Argentina	PIRLS 2001	0.418	..
Kenya	SACMEQ I 1995	0.42	..
United States	PIRLS 2001	0.424	..
Russian Federation	PIRLS 2001	0.447	..
Kenya	SACMEQ II 2000	0.45	0.38
Colombia	PIRLS 2001	0.459	..
Morocco	PIRLS 2001	0.554	..
Uganda	SACMEQ II 2000	0.57	0.65
Singapore	PIRLS 2001	0.586	..
Namibia	SACMEQ II 2000	0.60	0.53
Namibia	SACMEQ I 1995	0.65	..
South Africa	**SACMEQ II 2000**	**0.70**	**0.64**
South Africa: Poorest 90% of schools	**SACMEQ II 2000**	**0.577**	**0.500**
South Africa: Poorest 80% of schools	**SACMEQ II 2000**	**0.466**	**0.389**

Source: Postlethwaite, 2004: Tables 3.6 and 3.7; South African matric data calculated from National Department of Education data set

[8] Mathematics mark for those who took Maths. Higher grade mark converted to standard grade equivalent by adding 10 percentage points.

TABLE 2: Distribution of pupil performance across school quintiles by mean SES of schools

School SES Quintile	Mean	Std. Dev.	% with mark above 500	% with mark below 400
Pupil Reading Test Score				
Quintile 1	423.75	76.40	13.56%	37.32%
Quintile 2	422.54	67.04	10.19%	33.34%
Quintile 3	450.27	73.13	19.97%	23.21%
Quintile 4	494.59	95.36	42.15%	12.45%
Quintile 5	626.11	118.55	82.45%	2.31%
Total	**492.26**	**122.36**	**36.73%**	**20.91%**
Pupil Maths Test Score				
Quintile 1	441.49	67.01	19.94%	21.54%
Quintile 2	437.44	63.45	14.66%	25.31%
Quintile 3	441.45	61.93	15.80%	21.80%
Quintile 4	475.16	84.79	33.73%	14.90%
Quintile 5	594.18	125.52	76.36%	4.73%
Total	**486.15**	**109.06**	**35.21%**	**16.76%**

Note:

Quintile 1	*-3.8901 < School Mean SES < -1.6223*	*(34 schools)*
Quintile 2	*-1.5868 < School Mean SES < -0.5330*	*(34 schools)*
Quintile 3	*-0.5313 < School Mean SES <0.4429*	*(33 schools)*
Quintile 4	*0.4677 < School Mean SES < 1.4239*	*(34 schools)*
Quintile 5	*1.4517 < School Mean SES < 3.4141*	*(34 schools)*
Total	***-3.890110 < SchoolSES < 3.414095***	***(169 schools)***

Table 3: Description of variables used

Variable	Description	Mean.	Std Dev.	Min.	Max.
lanscore	Pupil reading test score [SACMEQ mean = 500, s.d. = 100]	484.70	117.50	5.72	1061.84
matscore	Pupil maths test score [SACMEQ mean = 500, s.d. = 100]	479.10	107.38	0.43	1065.30
PUPIL					
age	Age of pupil (in years)	12.804	1.614	10	25
gender	Gender of pupils	0.488	0.500	0	1
under12	Under 12	0.190	0.392	0	1
over12	Over 12	0.478	0.500	0	1
always	Pupil most of the time spoke English outside school	0.136	0.342	0	1
sometimes	Pupil sometimes spoke English outside school	0.624	0.484	0	1
tuition (Reading)	Extra tuition lessons outside school	0.303	0.460	0	1
tuition (Maths)	Extra tuition lessons outside school	0.315	0.464	0	1
neverrepeat	% of pupils who never repeated a grade	0.563	0.216	0.11	1
repeat1	Repeated once	0.285	0.451	0	1
repeat2	Repeated twice	0.094	0.292	0	1
repeat3	Repeated three times or more	0.058	0.234	0	1
livedwithparents	Lived with parents	0.783	0.412	0	1
absent	Number of days absent from school per month	1.604	2.804	0	26
FAMILY					
SES	Socio-economic status variable	00	2.272	-4.70	4.01
urban	School location: urban (large town)	0.281	0.450	0	1
location1	School location - small town	0.273	0.445	0	1
mothermatric	Mother had at least matric	0.309	0.462	0	1
mothertdegree	Mother had degree	0.085	0.279	0	1
fathermatric	Father had at least matric	0.316	0.199	0	0.90
fatherdegree	Father had degree	0.112	0.315	0	1
book1	1-10 books	0.466	0.499	0	1
book2	11-50 books	0.187	0.390	0	1
book3	51-100 books	0.066	0.248	0	1
book4	101-200 books	0.033	0.178	0	1
book5	201+ books	0.055	0.228	0	1
schoolfeeUnpaid	Reason for absence – school fee not paid	0.030	0.172	0	1
lightsource	Electric light at home	0.675	0.469	0	1
SCHOOL					
School resources					
ptratio	Pupil-Teacher ratio	35.466	6.614	12	57.43
pupilperclass	Number of pupils per Grade 6 class	42.230	12.039	17	98
classsize	Class Size	41.319	11.812	4	82
building	School facility – building	2.723	1.866	0	6
equipment	School facility – equipment	5.307	3.889	0	11
resource	Classroom Resources - Index	5.962	1.707	0	8
notextbook (Reading)	No textbook, or shared with two or more	0.339	0.473	0	1
notextbook (Maths)	No textbook, or shared with two or more	0.407	0.491	0	1
ownbook (Reading)	Had own textbook	0.471	0.499	0	1
ownbook (Maths)	Had own textbook	0.428	0.495	0	1
sharedwithone	Shared textbook with one pupil	0.190	0.219	0	1

(Reading)					
sharedwithone (Maths)	Shares textbook with one pupil	0.165	0.371	0	1
borrow	Library: available; can take out books	0.280	0.449	0	1
School processes					
correct (Reading)	Reading homework corrected? (1:Always, 0: Sometimes or never)	0.521	0.500	0	1
correct (Maths)	Reading homework corrected? (1:Always, 0: Sometimes or never)	0.671	0.470	0	1
homework1 (Reading)	Homework once per month	0.179	0.383	0	1
homework1 (Maths)	Homework once per month	0.102	0.303	0	1
homework2 (Reading)	Homework once per week	0.305	0.461	0	1
homework2 (Maths)	Homework once per week	0.336	0.473	0	1
homework3 (Reading)	Homework most days of the week				
homework3 (Maths)	Homework most days of the week	0.524	0.500	0	1
testfrequency (Reading)	Frequency of tests	3.996	0.922	0	5
testfrequency (Maths)	Frequency of tests	3.777	0.744	2	5
inspector	Number of visits by Inspectors in 2000	0.433	1.233	0	10
community	Community contributions	5.063	3.054	0	14
School teacher					
stage (Reading)	Teacher's age (in years)	38.55	8.128	24	64
stage (Maths)	Teacher's age (in years)	38.21	7.040	25	55
stgender (Reading)	Male teacher	0.444	0.498	0	1
stgender (Maths)	Male teacher	0.483	0.501	0	1
stteachinghours (Reading)	Teacher’s teaching hours per week	20.539	9.374	3	50
stteachinghours (Maths)	Teacher’s teaching hours per week	20.515	8.378	3	45
sttertiary (Reading)	Teacher has tertiary education	0.222	0.417	0	1
sttertiary (Maths)	Teacher has tertiary education	0.261	0.441	0	1
sttraining (Reading)	Teachers' training – Index	3.150	0.862	0	4
sttraining (Maths)	Teachers' training – Index	3.172	0.811	0	4
School principal					
shage	Principal’s age (in years)	46.186	6.471	31	61
shgender	Male principal	0.788	0.408	0	1
shteachinghours	Principal's teaching hours per week	8.307	6.806	0	35
shtertiary	Principal’s education: tertiary	0.445	0.497	0	1
shtraining	Principal's training – Index	3.351	0.788	0.50	4
School: Other					
classproblem	Classroom problems	4.385	1.717	0	8
pupilproblem	Pupils' behaviour problems	13.746	5.986	3	36
teacherproblem	Teachers' behaviour problems	4.406	3.390	0	20
PROVINCES					
EC	Eastern Cape	0.156	0.363	0	1
FS	Free State	0.088	0.283	0	1
GAU	Gauteng	0.112	0.315	0	1
KZN	KwaZulu-Natal	0.154	0.361	0	1
LIM	Limpopo	0.140	0.347	0	1
MPU	Mpumalanga	0.090	0.286	0	1
NC	Northern Cape	0.083	0.275	0	1
NW	North West	0.093	0.290	0	1
WC	Western Cape	0.085	0.279	0	1

Table 4: OLS regression models of SCAMEQ reading and mathematics test scores, for full and reduced sample

	Full sample		**Excluding richest 20% of schools**	
Dependent variable:	**Reading score**	**Mathematics score**	**Reading score**	**Mathematics score**
Underage (under 12)		-12.595		
		(2.21)*		
Overage (over 12)	-21.026	-20.641	-16.446	-9.284
	(5.46)**	(6.24)**	(4.44)**	(2.94)**
Male	-12.656	3.824	-9.818	3.273
	(4.04)**	(1.24)	(2.91)**	(1.11)
Sometimes spoke English at home	19.016	14.781	23.064	19.178
	(4.16)**	(3.13)**	(4.99)**	(3.91)**
Always spoke English at home	26.590	24.002	15.235	14.526
	(3.43)**	(3.25)**	(1.96)*	(2.23)*
Lived with parents	16.217	13.971	11.999	11.665
	(3.46)**	(2.78)**	(2.95)**	(2.99)**
Has more than 10 books at home	12.226	16.105		
	(3.11)**	(4.31)**		
No of days absent per month	-1.759	-2.832	-1.756	-2.045
	(2.29)*	(3.08)**	(2.82)**	(2.79)**
Absent because school fee not paid	-16.391		-11.251	
	(2.15)*		(1.66)	
Repeated once	-24.040	-19.691	-16.796	-12.237
	(5.81)**	(5.01)**	(3.61)**	(3.24)**
Repeated twice	-30.198	-16.094	-26.040	-12.865
	(5.36)**	(2.50)*	(4.53)**	(1.95)
Repeated three times or more	-39.833	-36.831	-28.184	-27.427
	(6.59)**	(5.79)**	(4.73)**	(4.60)**
Mother at least matric	11.394			
	(2.45)*			
Mother degree		16.082	17.616	14.115
		(2.44)*	(2.29)*	(1.79)
Homework once per month			27.653	
			(3.17)**	
Homework once per week			38.729	
			(5.08)**	
Homework most days of the week			33.363	
			(5.18)**	
SES	6.148	4.028	3.312	2.147
	(4.44)**	(2.81)**	(2.68)**	(1.42)
SES squared	1.365	2.093		
	(2.78)**	(3.70)**		
Urban	41.782	36.093	35.554	
	(3.63)**	(2.75)**	(3.09)**	
No textbook, or shared with more than 1	-13.280		-13.382	
	(2.85)**		(2.99)**	
School building	9.014	11.521		

	(2.31)*	(3.05)**		
School equipment	7.704	4.377	5.640	
	(4.30)**	(2.47)*	(3.05)**	
EC	38.479	38.733	37.077	32.072
	(2.33)*	(2.47)*	(2.65)**	(2.64)**
FS	-34.160	-26.553	-11.708	30.603
	(1.90)	(1.38)	(0.70)	(2.75)**
GAU	31.589	28.782	42.270	46.056
	(1.58)	(1.49)	(2.56)*	(3.95)**
KZN	56.081	54.460	57.620	73.311
	(3.21)**	(3.06)**	(3.54)**	(3.75)**
LIM	41.946	48.061	26.913	23.322
	(2.41)*	(2.79)**	(2.00)*	(2.00)*
MPU	15.747	17.391	19.969	23.716
	(1.07)	(1.20)	(1.47)	(1.71)
NC	-10.127	-3.800	17.965	46.011
	(0.56)	(0.22)	(1.00)	(3.62)**
WC	60.113	53.055	85.427	89.258
	(2.99)**	(2.35)*	(3.77)**	(3.59)**
Constant	372.531	367.479	365.727	405.452
	(23.82)**	(25.43)**	(23.40)**	(36.19)**
Observations	3139	3113	2492	2493
R-squared	0.62	0.52	0.34	0.18

Absolute value of t statistics in parentheses, taking account of clustering effects and using Huber-White robust standard errors to deal with possible heteroskedasticity.

* significant at 5% level

** significant at 1% level

Table 5: Effect of sample reduction on scores: Observations at school levels

	Score for:	Observations (schools)	Mean	Std. Dev.	Min	Max
Full sample	Reading	169	483.3	96.9	302.8	809.0
Bottom 90% by SES	Reading	152	461.9	73.9	302.8	688.6
Bottom 80% by SES	Reading	135	447.5	57.8	302.8	626.1
Full sample	Mathematics	169	478.0	86.0	351.7	832.6
Bottom 90% by SES	Mathematics	152	457.5	58.1	351.7	719.2
Bottom 80% by SES	Mathematics	135	447.0	43.8	351.7	643.9

Table 6: Effect of sample reduction on some coefficients in basic regression models for reading and mathematics

	Reading score			Mathematics score		
	Full sample	**Excluding richest 10% of schools**	**Excluding richest 20% of schools**	**Full sample**	**Excluding richest 10% of schools**	**Excluding richest 20% of schools**
SES	9.022	6.883	3.991	6.295	2.996	0.602
	(6.91)**	(5.02)**	(3.35)**	(4.31)**	(2.22)*	(0.58)
Urban	52.002	44.325	35.866	47.272	33.969	29.672
	(3.41)**	(2.46)*	(2.41)*	(3.02)**	(1.86)	(1.39)
School equipment	9.503	8.764	5.394	6.804	5.386	1.821
	(6.82)**	(5.48)**	(4.13)**	(5.13)**	(3.81)**	(1.78)
Observations	3139	2805	2492	3113	2780	2471
R-squared	0.55	0.45	0.25	0.42	0.29	0.11

Note: Other variables included as controls were gender of pupil, overage, English spoken at home (always and sometimes separately), absence due to school fees not paid, repeated (1, 2 or more years separately), and whether the pupils lived with parents

Absolute value of t statistics in parentheses, taking account of clustering effects and using Huber-White robust standard errors to deal with possible heteroskedasticity.

* significant at 5% level

** significant at 1% level

Table 7: Quantile regressions of reading and mathematics scores at median and 80th percentile

	At median	At 80th percentile	At median	At 80th percentile
	Reading	Mathematics	Reading	Mathematics
Overage (Over 12)	-25.476	-30.298	-17.254	-17.585
	(7.44)**	(7.07)**	(5.75)**	(4.71)**
Male	-8.985	-11.478	0.996	3.806
	(3.00)**	(2.98)**	(0.38)	(1.14)
Sometimes spoke English at home	20.638	29.379	18.245	18.37
	(5.67)**	(6.36)**	(5.72)**	(4.58)**
Always spoke English at home	27.367	46.548	23.801	36.868
	(5.17)**	(7.19)**	(5.13)**	(6.53)**
Lived with parents	12.735	15.689	3.351	10.684
	(3.46)**	(3.34)**	(1.04)	(2.62)**
Repeated once	-21.186	-29.67	-17.687	-23.314
	(5.77)**	(6.46)**	(5.49)**	(5.87)**
Repeated twice	-21.466	-37.672	-18.515	-23.761
	(3.88)**	(5.44)**	(3.80)**	(3.93)**
Repeated three times or more	-19.346	-43.465	-28.809	-27.531
	(2.92)**	(5.24)**	(4.93)**	(3.70)**
SES	6.209	7.439	3.638	3.496
	(7.82)**	(7.44)**	(5.23)**	(4.11)**
Urban	51.556	64.653	36.082	48.659
	(12.04)**	(12.13)**	(9.60)**	(10.87)**
School equipment	9.168	10.696	6.979	8.702
	(15.73)**	(14.64)**	(13.61)**	(14.33)**
EC	32.628	39.475	33.793	55.108
	(5.25)**	(5.00)**	(6.19)**	(7.83)**
FS	-38.958	-45.521	-26.88	-22.359
	(5.22)**	(4.80)**	(4.11)**	(2.62)**
GAU	44.552	33.873	43.722	69.211
	(6.34)**	(3.86)**	(7.11)**	(9.24)**
KZN	56.944	67.01	62.652	89.567
	(9.21)**	(8.62)**	(11.58)**	(13.05)**
LIM	28.262	39.703	32.245	43.917
	(4.50)**	(4.90)**	(5.86)**	(6.17)**
MPU	8.224	17.208	15.762	24.345
	(1.20)	(1.98)*	(2.62)**	(3.16)**
NC	-15.473	-4.458	-7.071	-10.221
	(2.05)*	(0.47)	(1.07)	(1.21)
WC	93.318	80.023	75.014	114.838

	(11.80)**	(8.14)**	(10.84)**	(13.21)**
Constant	390.828	438.968	397.117	427.257
	(54.43)**	(46.81)**	(63.11)**	(54.85)**
Observations	3139	3139	3113	3113
Pseudo-R-squared	0.3366	0.4494	0.2186	0.3606

Absolute value of t statistics in parentheses.

* significant at 5% level

** significant at 1% level

Table 8: Regressions of school performance on reading and mathematics test

	Reading		Mathematics	
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**
% Under12	-59.116	-66.639	-124.319	-135.436
	(2.31)*	(2.63)**	(4.21)**	(4.80)**
% Over12	-47.781	-54.467	-73.033	-84.540
	(1.83)	(2.11)*	(2.72)**	(3.37)**
% Male	-95.883	-77.737	-72.106	-53.213
	(2.47)*	(1.98)*	(1.98)*	(1.41)
% Always spoke English at home	74.337	73.661	69.752	71.497
	(3.38)**	(3.34)**	(3.47)**	(3.42)**
% NeverRepeated	85.060	92.276	82.293	91.063
	(3.61)**	(3.90)**	(3.25)**	(3.65)**
SES	8.391	7.517	3.736	3.085
	(2.79)**	(2.42)*	(1.27)	(1.00)
Urban	33.241	35.575	24.862	27.619
	(2.98)**	(3.20)**	(2.28)*	(2.55)*
% Mother degree	142.092		152.819	
	(3.77)**		(4.14)**	
% Mother at least matric		59.395		51.957
		(2.86)**		(2.44)*
% Sharetxtbkwithone	39.543	38.318		
	(2.23)*	(2.11)*		
% Owntxtbook	42.628	40.354	30.441	29.218
	(3.38)**	(3.25)**	(2.34)*	(2.24)*
School equipment	5.272	5.571	3.916	4.196
	(4.83)**	(4.96)**	(3.59)**	(3.60)**
Constant	432.649	417.249	463.349	451.835
	(13.49)**	(12.42)**	(14.49)**	(13.88)**
Observations	167	167	167	167
R-squared	0.79	0.78	0.71	0.69

Absolute value of t statistics in parentheses; Huber-White robust standard errors reported to deal with possible heteroskedasticity.

* significant at 5% level

** significant at 1% level

Table 9: Hierarchical linear model for reading scores

		Coefficient	**Standard error**	**t-value**	**Degrees of freedom**	**Significance**
Model for intercept						
Intercept	γ_{00}	446.870	13.309	33.58	153	0.000
Mean SES	γ_{01}	21.893	4.087	5.36	153	0.000
Model for SES slope:						
Intercept	γ_{70}	5.174	1.221	4.24	153	0.000
Mean SES	γ_{71}	2.191	0.855	2.56	153	0.012
Other fixed effects:						
Over12	β_1	-18.924	3.361	-5.63	2886	0.000
Male	β_2	-11.171	2.772	-4.03	2886	0.000
EnglishSometimes	β_3	14.456	3.200	4.52	2886	0.000
EnglishAlways	β_4	17.326	4.777	3.63	2886	0.001
Livedwithparents	β_5	7.998	3.193	2.51	2886	0.013
AbsentFeesUnpaid	β_6	-19.532	6.989	-2.80	2886	0.006
Boooks11plus	β_8	8.980	3.398	2.64	2886	0.009
Repeat Once	β_9	-15.214	3.402	-4.47	2886	0.000
Repeat Twice	β_{10}	-24.692	5.073	-4.87	2886	0.000
Repeat 3+ times	β_{11}	-26.592	5.185	-5.13	2886	0.000
Homew2	β_{12}	9.785	4.819	2.03	2886	0.042
Homew3	β_{13}	8.004	4.333	1.85	2886	0.064
Notextbook	β_{14}	-10.785	3.789	-2.85	2886	0.005
MotherMatric	β_{15}	7.538	3.930	1.92	2886	0.055
FS	β_{16}	-5.678	13.892	-0.41	2886	0.682
GAU	β_{17}	68.793	19.994	3.44	2886	0.001
KZN	β_{18}	48.384	13.977	3.46	2886	0.001
LIM	β_{19}	19.966	14.203	1.41	2886	0.160
MPU	β_{20}	12.055	14.647	0.82	2886	0.411
NC	β_{21}	25.874	15.873	1.63	2886	0.103
EC	β_{22}	19.594	14.806	1.32	2886	0.186
WC	β_{23}	86.619	18.565	4.67	2886	0.000
Random effects		**Standard deviation**	**Variance**	**Chi-square**	**Degrees of freedom**	**P-value**
Intercept	U_0	52.283	2733.513	1163.697	153	0.000
Mean-SES	U_7	9.126	83.276	297.412	153	0.000
Level 1	R	61.181	3743.171			

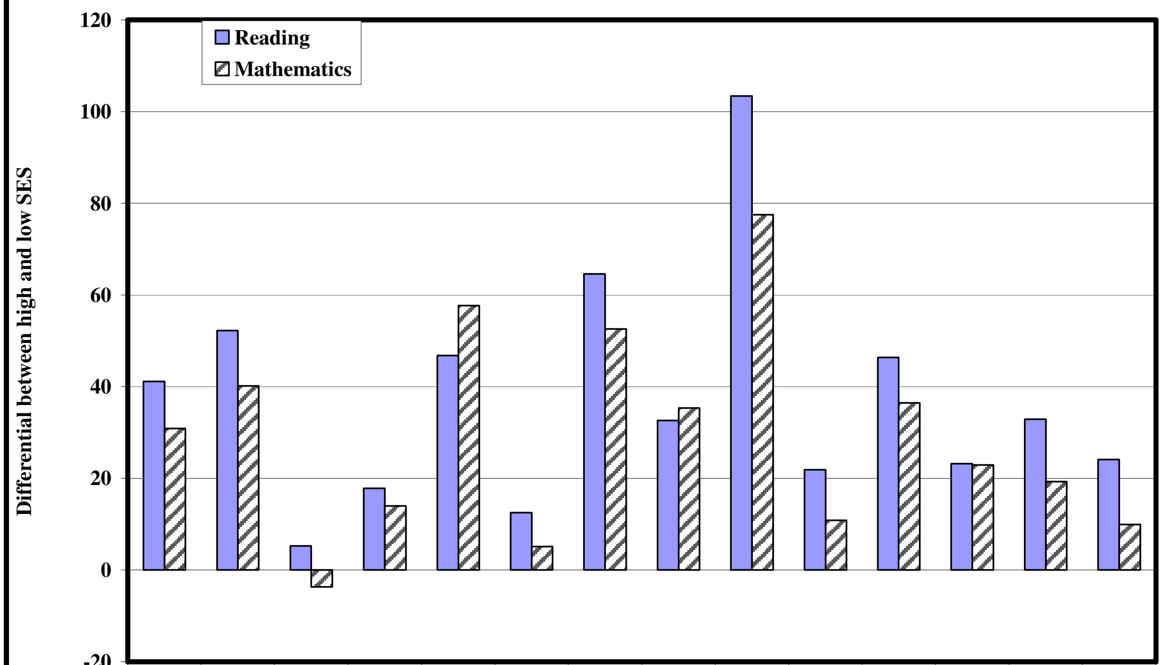
Note: Robust standard errors reported.

Table 10: Hierarchical linear model for mathematic score

		Coefficient	Standard error	t-value	Degrees of freedom	Significance
Model for intercept:						
Intercept	γ_{00}	420.752	12.817	32.83	153	0.000
Mean SES	γ_{01}	14.979	3.679	4.07	153	0.000
Model for SES slope:						
Intercept	γ_{70}	4.095	1.031	3.97	153	0.000
Mean SES	γ_{71}	2.380	0.715	3.33	153	0.001
Other fixed effects:						
Over12	β_1	-11.989	2.565	-4.67	2863	0.000
Male	β_2	1.916	2.571	0.75	2863	0.456
EnglishSometimes	β_3	12.316	3.793	3.25	2863	0.002
EnglishAlways	β_4	17.671	4.961	3.56	2863	0.001
Livedwithparents	β_5	10.644	3.162	3.37	2863	0.001
AbsentFeesUnpaid	β_6	-12.518	5.994	-2.09	2863	0.037
Boooks11plus	β_8	7.904	3.332	2.37	2863	0.018
Repeat Once	β_9	-11.279	3.025	-3.73	2863	0.000
Repeat Twice	β_{10}	-12.626	4.687	-2.69	2863	0.008
Repeat 3+ times	β_{11}	-20.574	4.862	-4.23	2863	0.000
Absentfromschool	β_{12}	-1.422	0.581	-2.45	2863	0.015
MotherMatric	β_{13}	6.252	3.266	1.91	2863	0.055
FS	β_{14}	11.133	13.241	0.84	2863	0.401
GAU	β_{15}	69.453	17.362	4.00	2863	0.000
KZN	β_{16}	67.251	16.423	4.10	2863	0.000
LIM	β_{17}	34.922	14.851	2.35	2863	0.019
MPU	β_{18}	21.661	13.772	1.57	2863	0.116
NC	β_{19}	38.639	13.887	2.78	2863	0.006
EC	β_{20}	36.618	13.782	2.66	2863	0.008
WC	β_{21}	90.146	19.868	4.54	2863	0.000
Random effects		**Standard deviation**	**Variance**	**Chi-square**	**Degrees of freedom**	**P-value**
Intercept	U_0	48.499	2352.126	828.542	153	0.0000
Mean-SES	U_7	6.765	45.769	208.530	153	0.0020
Level 1	R	62.257	3875.956			

Note: Robust standard errors reported.

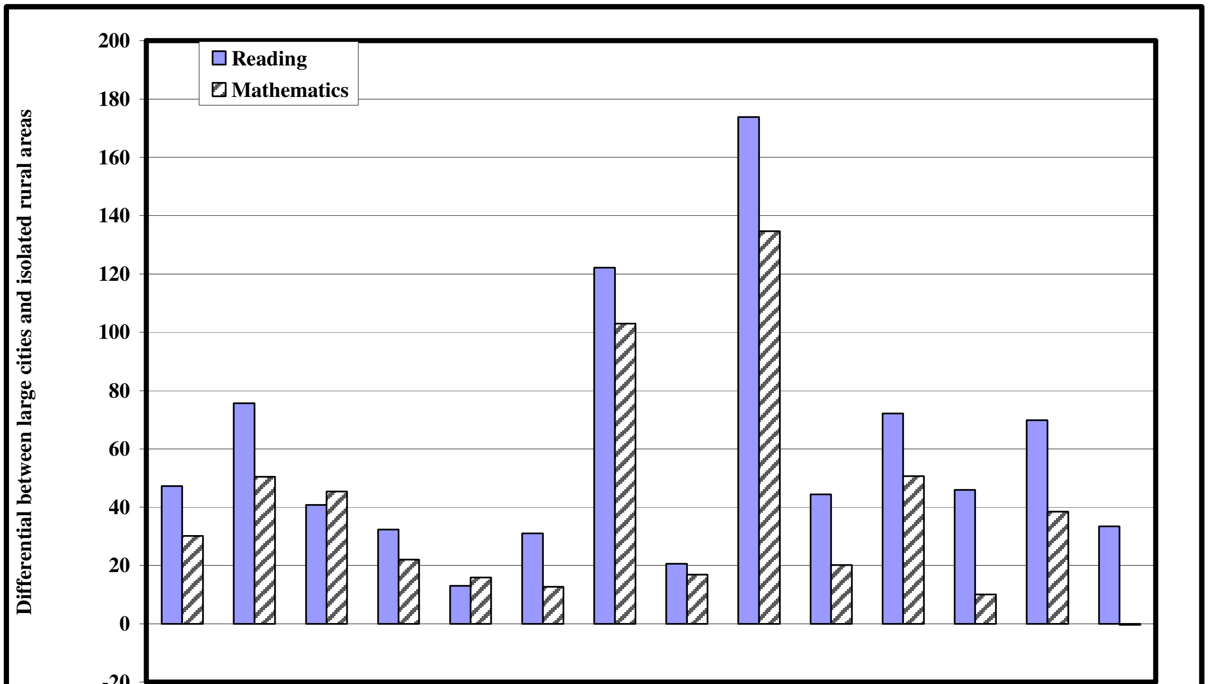
Figure 1: Differential in reading and mathematics performance between high and low socio-economic status group by country: SACMEQ II



	Botswana	Kenya	Lesotho	Malawi	Mauritius	Mozambique	Namibia	Seychelles	South Africa	Swaziland	Tanzania	Uganda	Zambia	Zanzibar
Reading	41.1	52.2	5.3	17.8	46.8	12.5	64.6	32.6	103.4	21.9	46.4	23.2	32.9	24.1
Mathematics	30.9	40.2	-3.7	14	57.7	5.1	52.6	35.4	77.5	10.9	36.5	22.9	19.3	9.9

Source: Derived from indicators on SACMEQ website. Available online at: http://www.sacmeq.org/indicate.htm

Figure 2: Differential in reading and mathematics performance between large cities and isolated rural areas by country: SACMEQ II



	Botswana	Kenya	Lesotho	Malawi	Mauritius	Mozambique	Namibia	Seychelles	South Africa	Swaziland	Tanzania	Uganda	Zambia	Zanzibar
Reading	47.2	75.6	40.8	32.3	13	31	122.1	20.6	173.8	44.4	72.1	45.9	69.9	33.5
Mathematics	30.1	50.5	45.4	22.1	15.9	12.7	102.9	16.9	134.7	20.2	50.7	10.1	38.4	-0.3

Source: Derived from indicators on SACMEQ website. Available online at**:** http://www.sacmeq.org/indicate.htm

Figure 3a & 3b: Lowess regression: Individual reading score vs. SES and Average Reading Score vs. mean school SES

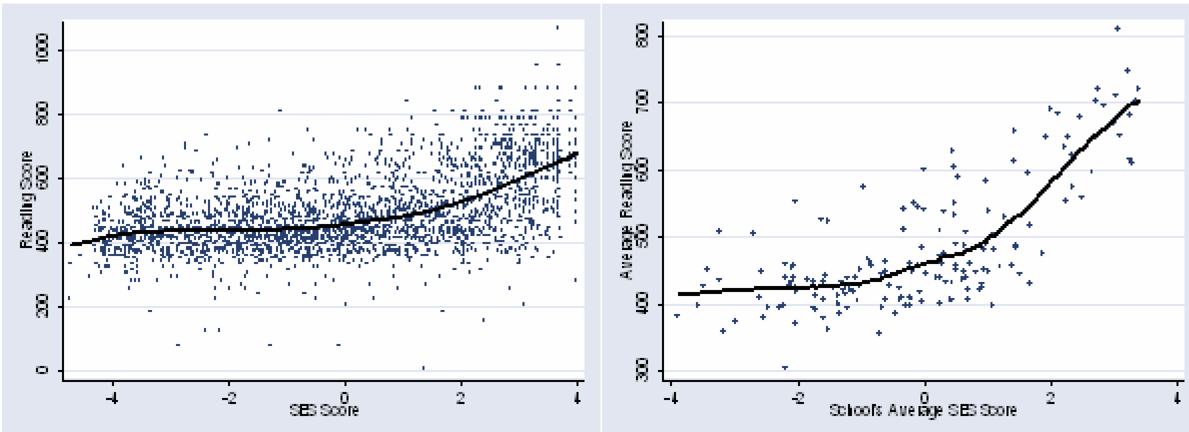


Figure 4a & 4b: Lowess regression: Individual mathematics score vs. SES and Average Mathematics Score vs. mean school SES

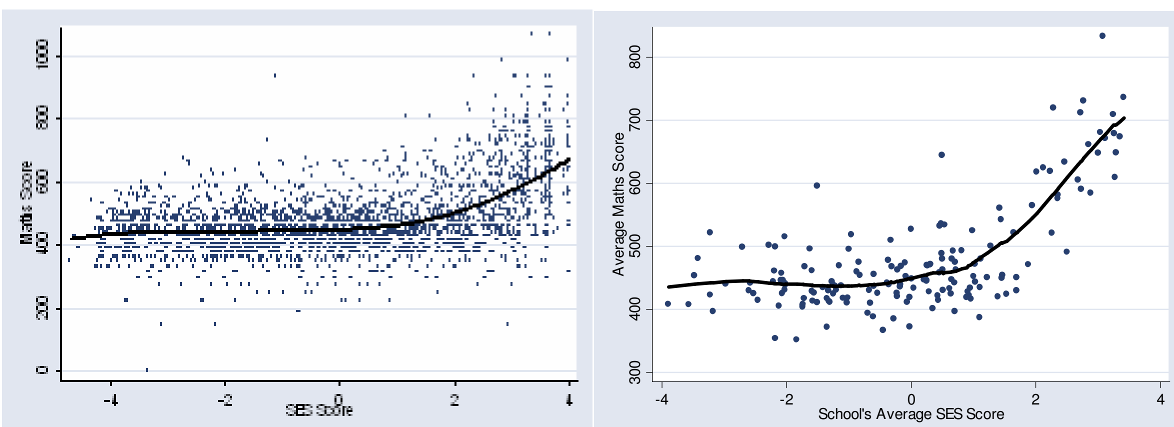
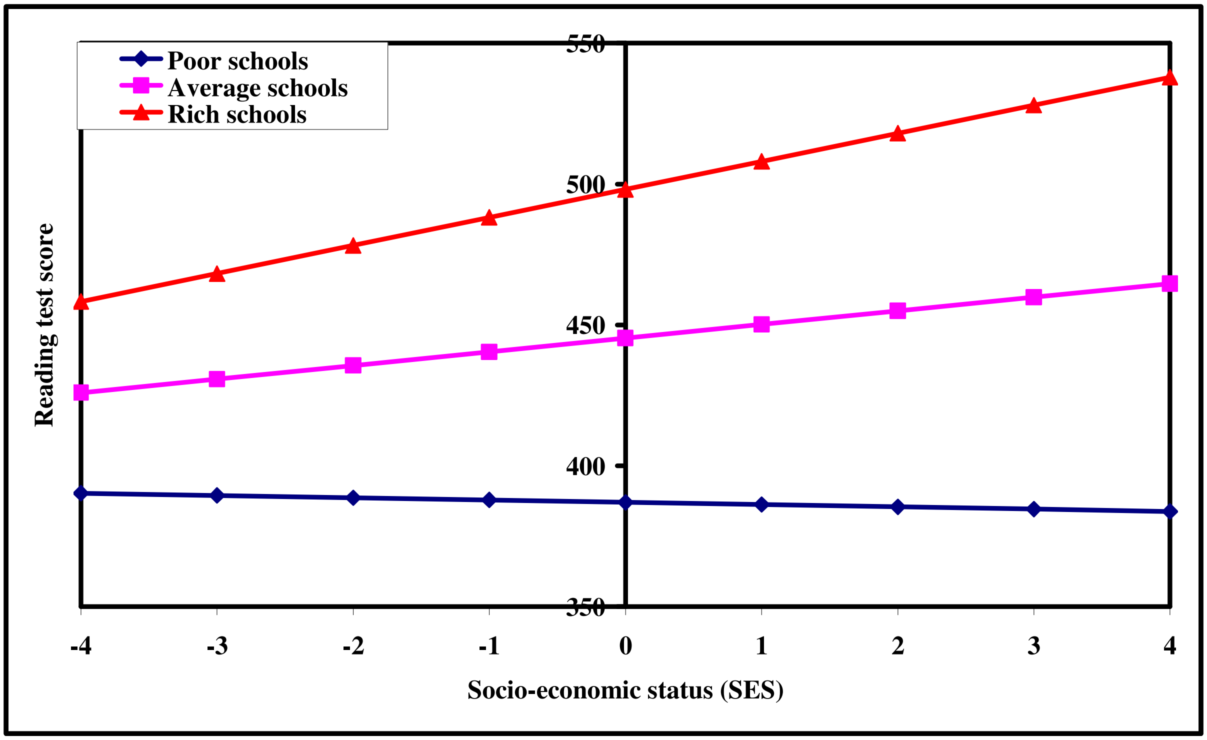


Figure 5: Effect of individual socio-economic status on reading test scores as derived from HLM model for poor, average and rich schools (for reference person)



Note: From the model in Equation 4, the regression lines for the reference person reduced to:

$$Score = \gamma 00 + \gamma 01*MeanSES + \gamma 70*SES + \gamma 71*SES*MeanSES$$

This was applied above to each of the three SES school types.