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ABSTRACT

More than a decade after South Africa's transition from apartheid, the racially delineated picture of education in the country remains. Brahm Fleisch (2008) refers to the South Africa's education system as consisting effectively of two education systems: the well-performing historically white system, and the weak-performing historically black system. Significant difference in educational quality exist between these two systems. It is widely acknowledged that the role of teachers in the quality of education is vital. This paper makes use of Hierarchical Linear Modeling to investigate which teacher productive characteristics impact first of all on average student performance, and secondly, on the relationship between the socioeconomic status of students and the performance. It is found that teachers who have specialized in the subject which they teach or in the education of that subject at university, as well as teachers with between 26 and 30 years of teaching experience influence student performance positively. No teacher productive characteristics are found to weaken the relationship between students' socioeconomic status and their performance.

Keywords: Analysis of education
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INTRODUCTION

More than a decade after South Africa's transition from apartheid, the racially delineated picture of education in the country remains. Brahm Fleisch (2008) refers to the South Africa's education system as consisting effectively of two education systems, with one being predominantly white and Indian, well resourced and including a small but growing independent sector. This first system also produces the vast majority of university entrants as well as the vast majority of learners who take higher-grade mathematics and science and ensures that the learners passing through this system are equipped with numeracy and literacy skills comparable to those acquired by middle-class children anywhere in the world (Fleisch, 2008). Importantly, this first system enrolls the children of what may be considered the elite white and black middle-classes. The second school system, on the other hand, enrolls children from the working-class and poor children and therefore almost all children enrolled in this system are African. In comparison to their counterparts in the first system, children in this system acquire a somewhat restricted set of skills and knowledge and perform at a level considerably lower than children of the same age and in the same grade internationally (Fleisch, 2008).

Massive differences therefore exist in the educational outcomes of learners enrolled in the historically white school system and those enrolled in the historically black school system. As Fleisch explains, there are effectively two different education systems operating within the South African education system. Given that the historically black schooling system has a considerably lower socioeconomic status than the historically white schooling system, coupled with the fact that roughly 80% of students are enrolled in the historically black, the implications of these performance differentials for South Africa are substantial (van der Berg, 2006).

The centrality of the role of teachers in the performance of students is widely acknowledged, and it is accepted that the role of teachers in ensuring that learning takes place in the classroom becomes increasingly important as the level of classroom resources diminishes. In the case of historically black schools in South Africa, the role of the teacher is vital in the achievement of educational outcomes. This paper aims to investigate precisely which teacher characteristics impact on student performance. Hierarchical linear modeling (HLM) is used in order to investigate the nature of this relationship. Important to note is that the teacher characteristics to which the analysis refers are "productive" characteristics (i.e. education, training and experience of teachers). For this reason, the models presented below often have apparently weak explanatory power. It is therefore acknowledged that other factors impact on student performance. However, this analysis focuses only on teacher productive characteristics while controlling for the gender of the teacher and the socioeconomic status of the students being taught by a particular teacher.

Section 1 discusses the appropriateness of HLM for this investigation. Section 2 describes the analytical method used, while section 3 presents the research questions to be answered by the analysis. Section 4 describes the data set used for the analysis, and section 5 defines and describes the variables included in the analysis. Section 6 presents and discusses the empirical results, and section 7 concludes.

1. HIERARCHICAL LINEAR MODELLING: THE APPROPRIATENESS OF THE METHOD

Multilevel regression (or hierarchical linear modeling) is described as a generalization of Ordinary Least Squares (OLS) regression by Paterson (1991). It is a technique used to analyse multilevel or nested data. For the purpose of this paper, it is used to analyse data on students nested within classrooms. This section provides a brief explanation of why normal OLS regression is inappropriate for analysis of such data.

OLS examines the relationship between a dependent variable and explanatory variables at the mean, examining whether there is in fact a tendency for dependent and explanatory variables to move together in a particular relationship. In order for OLS to produce accurate estimations of the relationship between the variables under consideration, however, certain assumptions about the variance of the data are required to hold. This paper analyses students and the schools in which they are enrolled. In order for OLS to produce accurate coefficients, it would need to be assumed that the characteristics of students and the school which they attend come from a simple random sample (Arnold, 1992). However, this assumption does not hold in the case of nested data since the values for school-level characteristics will be identical for students attending the same school and so the variance in school characteristics would be misestimated if OLS regression was used to perform the analysis (Arnold, 1992). This would result in inaccurate conclusions about the effect (or lack thereof) that school characteristics may have on student performance (Arnold, 1992).

A further source of inaccuracy in the estimation of school-effects on student performance is the fact that students attending the same school are likely to be more alike than students who are randomly selected from different schools (an assumption necessary to render OLS estimates accurate). Students are therefore not from a random sample in the case of nested data (Arnold, 1992) as the variance between them is not constant but rather varies according to the school which they attend.

HLM enables the partitioning of variance in student outcomes into the component driven by individual level characteristics and the portion driven by school level characteristics. The technique is therefore useful first of all because it enables one to model student outcomes as a function of both student and school level characteristics, and secondly because it allows one to obtain more accurate estimates of coefficients in estimating these “student” and “school” effects (because it controls for the aforementioned impact that the nesting of students within schools has on variance). This is particularly useful in the context of South Africa because of the fact that South African schools are significantly delineated along racial lines, with historically white schools outperforming historically black schools by considerable margins. Indeed, it may be said that there are effectively two separate schooling systems at work in the South African education system. Although OLS may reflect the possibility that student outcomes vary across schools, HLM is designed to control for this possibility. HLM allows for the examination of these two separate schooling systems as well as for the examination of how the factors according to which these systems differ impact on student performance.

2. ANALYTICAL METHOD

HLM is a technique that runs regressions of regressions. The analysis of multi-level data involves several separate steps occurring simultaneously. The first of these in running the within-teacher model in which the mathematics achievement of student being taught by teacher j is modeled as a function of student-level variables:

$$ZMATij = \beta_{0j} + \beta_{1j}(SES_{ij}) + \beta_{2j}(GENDER_{ij}) + \beta_{3j}(OVERAGE_{ij}) + \beta_{4j}(UNDERAGE_{ij}) + \beta_{5j}(TEST\_LANGUAGE\_HOME_{ij}) + \beta_{6j}(MOM\_2) + \beta_{7j}(MOM\_3_{ij}) + \beta_{8j}(MOM\_4_{ij}) + \beta_{9j}(MOM\_5_{ij}) + \beta_{10j}(MOM\_6_{ij}) + \beta_{11j}(MOPM\_7_{ij}) + \beta_{12j}(MOM\_8_{ij}) + \beta_{13j}(ENGLISH_{ij}) + \beta_{14j}(MINS15\text{-}30) + \beta_{15j}(MINS31\text{-}60_{ij}) + \beta_{16j}(MINS61\text{-}90_{ij}) + \beta_{17j}(MINS90plus_{ij}) + r_{ij} \quad (1)$$

This analysis focuses on how teacher level characteristics impact on overall student performance and on the relationship between student SES and student mathematics performance. It therefore investigates whether the coefficient on student SES ($ß_{1j}$) differs according to the teacher by whom students are taught. The intercept and the SES slope (β_{0j} and β_{1j} respectively) are therefore modeled as a function of level-2 (i.e. teacher) characteristics.

The combined model of student- and teacher- level characteristics therefore takes the form of

$$\mathbf{Y_{ij} = \gamma_{00} + \gamma_{01}\,(MEAN\ SES) + \gamma_{02}(MALE) + \gamma_{03}(EXP\ 6\ TO\ 10) + \gamma_{04}(EXP\ 11\ TO\ 15) + \gamma_{05}(EXP\ 16\ TO\ 20) + \gamma_{06}(EXP\ 21\ TO\ 30) + \gamma_{07}(EXP\ 31\ TO\ 26) + \gamma_{08}(MATRIC) + \gamma_{09}(POST\ MATRIC) + \gamma_{010}(DIPLOMA) + \gamma_{011}(DEGREE1) + \gamma_{012}(DEGREE2) + \gamma_{013}(TRAIN1) + \gamma_{014}(TRAIN2) + \gamma_{015}(TRAIN3) + \gamma_{016}(TRAIN4) + \gamma_{017}(TRAIN5) + \gamma_{018}(TRAIN5PLUS) + \gamma_{019}(LIC/CERT) + \gamma_{020}(STUDY\_MATH) + \gamma_{014}(MATH\_EDUC) + \gamma_{10}(X_{ij} - \bar{X}_{.j}) + \gamma_{11}\,(MEAN\ SES)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{12}(MALE)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{13}(EXP\ 6\ TO\ 10)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{14}(EXP\ 11\ TO\ 15)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{15}(EXP\ 16\ TO\ 20)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{16}(EXP\ 21\ TO\ 30)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{17}(EXP\ 31\ TO\ 26)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{18}(MATRIC)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{19}(POST\ MATRIC)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{110}(DIPLOMA)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{111}(DEGREE1)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{112}(DEGREE2)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{113}(TRAIN1)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{114}(TRAIN2)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{115}(TRAIN3)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{116}(TRAIN4)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{117}(TRAIN5)(X_{ij} - \bar{X}_{.j}) + \gamma_{118}(TRAIN5PLUS)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{119}(LIC/CERT)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{120}(STUDY\_MATH)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{114}(MATH\_EDUC)\,(X_{ij} - \bar{X}_{.j}) + \gamma_{20}(GENDER) + \gamma_{30}OVERAGE) + \gamma_{40}(UNDERAGE) + \gamma_{50}(TEST\_LANGUAGE\_HOME) + \gamma_{60}(MOM\_2) + \gamma_{70}(MOM\_3) + \gamma_{80}(MOM\_4) + \gamma_{90}(MOM\_5) + \gamma_{100}(MOM\_6) + \gamma_{110}(MOM\_7) + \gamma_{120}(MOM\_8) + \gamma_{130}(ENGLISH) + \gamma_{140}(MINS15\text{-}30) + \gamma_{150}(MINS31\text{-}60) + \gamma_{160}(MINS61\text{-}90) + \gamma_{170}(MINS90plus) + r_{ij} + u_{0j} + u_{1j}(X_{ij} - \bar{X}_{.j})} \qquad \mathbf{(2)}$$

3. RESEARCH QUESTION

The objective of this section is to investigate whether teacher characteristics (particularly human capital characteristics) impact on the performance of students in mathematics. The following research questions are posed to focus the analysis:

QUESTION 1: How does the socio-economic status (SES) of students impact on their performance in mathematics?

QUESTION 2: Are there any teacher characteristics that impact on overall student performance in mathematics or on the relationship between the SES of the students and their performance in mathematics?

If ordinary least squares (OLS) regression was used to measure the impact of both student and teacher characteristics on student outcomes, the standard errors produced would be misleadingly small and the confidence intervals produced would be "deceptively tight" (Paterson, 1991). Indeed, the fact that a group of students are taught by a common teacher adds an additional random component to the variance in question. This means that the "teacher" characteristics for students being taught by a particular teacher would not vary across those students rendering the assumption (necessary for OLS to report accurate coefficients) that the individual students are drawn from a simple random sample erroneous (Arnold, 1992). Furthermore, students being taught by a common teacher may be more alike than students being taught by another teacher, again rendering the assumption that students are drawn from a random sample inaccurate (Arnold, 1992), since the variance amongst students taught by a particular teacher varies according to the teacher.

It is important to point out at this stage that TIMSS only sampled one mathematics teacher per school. The selected teacher in the school must therefore be understood to be representative of the type of teacher likely to be found within that school.

4. DATA: TRENDS IN MATHEMATICS AND SCIENCE STUDY (2003)

The Trends in Mathematics and Science Study (TIMSS) was conducted by the International Association for the Evaluation of International Achievement (IEA). The study was conducted in three years: 1995, 1999 and 2003 in 50 countries. South Africa participated in all three TIMSS studies (Reddy, 2006). The study measures achievement in mathematics and science, as well as the attitudes of students towards these subjects. Although TIMSS was conducted at the end of Grade 4 and Grade 8, South Africa only participated in the Grade 8 study in 2003.

South African schools to participate in the TIMSS study were drawn from the School Register of Needs (SRN) database and were stratified along two dimensions, namely province and the language in which teaching and testing were conducted[2]. A three-staged stratified cluster design was used in which a sample of schools from all those eligible was selected, mathematics and science classes were randomly selected from the selected schools, and 40 learners from the sampled classes were sampled in the case of class sizes in excess of 40 (Reddy, 2006). Testing of the 8952 students in 255 schools took place in November 2002.

Important to note is that although the HLM method is useful insofar as it controls for school level factors in addition to individual level characteristics, the data being used for this study were collected from Grade 8 pupils, as mentioned above. It is generally accepted that the impact of schooling on pupil learning is cumulative, meaning that the years of schooling received by students prior to year under investigation will have a significant impact on the student outcome under investigation. In the context of South Africa, Grade 8 is the first year of secondary school and the majority of students enrolled in South African schools begin secondary school at a different school to the primary school they attended. It should therefore be highlighted that the implied similarity in "school values" for all students enrolled in the same school is less than completely accurate as students will not necessarily have attended the same primary school as the other students in their school and therefore will not have identical "school values" for previous years of schooling[3]. In addition, TIMSS does not contain pre-test data, therefore limiting the possibility of testing both the ability of students (which is known to impact significantly on the performance of students) and the amount of learning that has taken place between the pre-test and TIMSS test (which might have controlled for the differences in the impact that primary schooling has on ability in Grade 8). However, it is likely that students attending a particular secondary school would have attended largely similar primary schools, even if not the same primary school, and so the aforementioned "school values" are likely to be similar even though they are not identical for all students.

5. VARIABLES INCLUDED IN THE MODEL

The dependent variable in the study is student mathematics score. For the sake of simplicity and to aid in interpretation, the variable has been z-scored, leaving it with a mean of zero and standard deviation of one. The coefficients on independent variables are therefore interpreted as

[2] Afrikaans and English were the languages of instruction chosen by the schools in the sample selected (Reddy, 2006: x).
[3] Previous schooling is not included in the model but its impact is effectively "built in" to students and will impact substantially on their performance.

the change in standard deviations in student z-scored mathematics score. The student and teacher level variables included in the model are presented respectively in tables 1 and 2 below.

Table 1: Student Level Variables

VARIABLE
Continuous:
SES (z-scored; standardized to the South African mean within the data set.)
Dummy (1 =true for student, 0 = not true for student)
Male
Overage (born earlier than 1988)
Underage (born later than 1988)
Tested in Home Language
Mom: no schooling
Mom: primary schooling
Mom: junior secondary schooling
Mom: matric
Mom: post-matric
Mom: diploma/certificate
Mom: degree
Mom: honours or higher
Minutes on homework: 0-14
Minutes on homework: 15-30
Minutes on homework: 31-60
Minutes on homework: 61-90
Minutes on homework: more than 90
Tested in English

Table 2: Teacher Level Variables

VARIABLE
Continuous:
Average pupil SES (z-scored; standardized to South African mean within the data set)
Dummy (1 = true of teacher, 0 = not true for teacher):
Male
Experience: 1 to 5 years
Experience: 6 to 10 years
Experience: 11 to 15 years
Experience: 16 to 20 years
Experience: 21 to 25 years
Experience: 26 to 30 years
Experience: 31 to 36 years
Attained Matric
Attained Post Matric
Attained Diploma
Attained Degree
Attained Degree – honours or more
Teacher training: 0 years
Teacher training: 1 year
Teacher training: 2 years
Teacher train: 3 years
Teacher training: 4 years
Teacher training: 5 years

Teacher training: 5+ years
License/Certificate
Studied Mathematics at University
Studied Education in Mathematics at University

Descriptive statistics for these variables are presented in tables 3 and 4 below.

Table 3: Means (and standard deviations) of Student-level Variables, by income group

VARIABLES	QUINTILE Rich (Quintile 5) (N = 1380)	Poor (Quintiles 1 -4) (N = 7572)	Total (N = 8962)
Mathematics score (z-scored)	0.919 (1.708)	-0.167 (0.684)	0 (1)
SES (z-scored)	1.338 (0.213)	-0.324 (0.831)	0 (1)
Male	0.546 (0.498)	0.476 (0.499)	0.487 (0.499)
Overage (born earlier than 1988)	0.292 (0.455)	0.529 (0.499)	0.492 (0.500)
Underage (born later than 1988)	0.181 (0.385)	0.194 (0.400)	0.192 (0.394)
Tested in home language	0.653 (0.476)	0.219 (0.414)	0.286 (0.452)
Mom: no schooling	0.028 (0.166)	0.136 (0.343)	0.119 (0.324)
Mom: primary schooling	0.057 (0.231)	0.160 (0.367)	0.144 (0.351)
Mom: junior secondary schooling	0.078 (0.268)	0.128 (0.334)	0.120 (0.325)
Mom: matric	0.222 (0.416)	0.158 (0.365)	0.168 (0.374)
Mom: post-matric	0.045 (0.207)	0.021 (0.145)	0.025 (0.156)
Mom: diploma/certificate	0.092 (0.289)	0.030 (0.169)	0.039 (0.194)
Mom: degree	0.063 (0.243)	0.015 (0.121)	0.022 (0.147)
Mom: honours or higher	0.241 (0.427)	0.184 (0.388)	0.193 (0.395)
Tested in English	0.725 (0.427)	0.931 (0.282)	0.884 (0.320)
Tested in Afrikaans	0.275 (0.447)	0.087 (0.282)	0.116 (0.320)
Minutes on homework: 0-14	0.212 (0.409)	0.239 (0.427)	0.235 (0.424)
Minutes on homework: 15-30	0.465 (0.499)	0.372 (0.482)	0.389 (0.487)
Minutes on homework: 31-60	0.162 (0.369)	0.141 (0.348)	0.144 (0.351)
Minutes on homework: 61-90	0.036 (0.185)	0.045 (0.207)	0.043 (0.204)
Minutes on homework: more than 90	0.089		0.105

	(0.285)	0.108 (0.312)	(0.307)

Note: own calculations, TIMSS 2003 (mathematics)

From table 3 it may be seen that considerable differences exist between the performance of students in the fifth quintile and student in the first, second, third and fourth quintiles. It is clear that students from more affluent backgrounds outperform their poorer counterparts at the mean with richer children on average performing close to 1 standard deviation above the South African mean and poorer students on average performing roughly 0.17 standard deviations below the South African mean. The z-scored SES value for the 2 different groups are surprisingly not very different, with the mean for richer students lying more than a standard deviation above the South African mean and for poorer student slightly more than 0.3 standard deviations below the South African mean. A slightly higher proportion of richer students is male than are poorer students, whereas a much larger proportion of poorer students is overage than are their richer counterparts. This is reflection of the higher repetition rates prevalent in the weaker performing historically black schooling system in South Africa. The proportion of underage students is largely similar across both groups. The proportion of student being tested in their home language is decidedly higher amongst richer students than it is amongst poorer students (approximately 65% versus roughly 22%), likely an indication that a large proportion of poorer South African students are African and therefore speak an African language at home. In terms of mother's education, a higher proportion of the mothers of poor students had attained only low levels of education, while the opposite is true for higher levels of mothers' education, with a higher proportion of rich students' mothers having attained higher levels of education[4]. A substantially higher number of poor students were tested in English than in Afrikaans. This is likely to be a reflection of the fact that the majority of poor students are likely African students and are therefore more likely to have been tested in English than in Afrikaans. Finally, the amount of time spent on homework does not vary substantially across the two groups of students.

[4] It is noted that irregularities may exist in the data regarding the mother's having attained at least honours degrees. These proportions are unrealistically high, given the proportions observed for the aforementioned levels of mother's education.

Table 4: Means (and standard deviations) of Teacher-level Variables, by income group

	QUINTILES		
VARIABLES	**Rich (Quintile 5) (N = 50)**	**Poor (Quintiles 1 - 4) (N = 205)**	**Total (N = 255)**
Mean pupil SES (z-scored)	0.954	-0.302	-0.053
	(0.373)	(0.463)	(0.672)
Male	0.48	0.52	0.510
	(0.505)	(0.501)	(.501)
Experience: 1 to 5 years	0.22	0.16	0.17
	(0)	(0)	(0)
Experience: 6 to 10 years	0.28	0.27	0.28
	(0)	(0)	(0)
Experience: 11 to 15 years	0.18	0.26	0.24
	(0)	(0)	(0)
Experience: 16 to 20 years	0.06	0.08	0.08
	(0.)	(0)	(0)
Experience: 21 to 25 years	0.02	0.04	0.03
	(0)	(0)	(0)
Experience: 26 to 30 years	0	0.01	0.01
	(0)	(0)	(0)
Experience: 31 to 36 years	0.08	0.01	0.02
	(0)	(0)	(0)
Attained Matric	0	0.039	0.031
	(0)	(0.194)	(0.175)
Attained Post Matric	0.02	0.034	0.031
	(0.141)	(0.182)	(0.175)
Attained Diploma	0.3	0.561	0.510
	(0.463)	(0.497)	(0.501)
Attained Degree	0.22	0.190	0.196
	(0.418)	(0.393)	(0.399)
Attained Degree – honours or more	0.22	0.034	0.071
	(0.418)	(0.182)	(0.257)
Teacher training: 0 years	0.06	0.073	0.071
	(0.240)	(0.261)	(0.257)
Teacher training: 1 year	0.08	0.068	0.071
	(0.27)	(0.253)	(0.257)
Teacher training: 2 years	0.04	0.034	0.035
	(0.495)	(0.182)	(0.185)
Teacher train: 3 years	0.18	0.488	0.427
	(0.388)	(0.501)	(0.496)
Teacher training: 4 years	0.4	0.146	0.196
	(0.495)	(0.354)	(0.398)
Teacher training: 5 years	0.04	0.015	0.020
	(0.198)	(0.120)	(0.139)
Teacher training: 5+ years	0.02	0.015	0.016
	(0.141)	(0.120)	(0.125)
Studied Mathematics at University	0.54	0.566	0.561
	(0.503)	(0.497)	(0.497)
Studied Education in Mathematics at University	0.38	0.341	0.349
	(0.490)	(0.475)	(0.478)

Note: own calculations, TIMSS 2003 (mathematics)

Descriptive statistics for teacher level data are presented in table 3 above. With the exception of the category “honours degree or more”, the difference in the level of education amongst teachers teaching in rich and poor classrooms is marginal. The proportion of teachers teaching in richer schools who have obtained at least an honours degree is 22% versus just 3.4% of teachers teaching in poorer schools. A similar result is observed with regards to teacher training with the difference between the two groups of teachers being marginal and not always favoring the same group. However, in the case of teachers who have completed 4 years of teacher training, a higher proportion of teachers teaching in rich schools have completed this level of training (40%) than the proportion of teachers teaching in poorer schools who have completed this level of training (15%). Surprisingly, a higher proportion of teachers teaching in poorer schools have acquired a teaching diploma or certificate than have teachers teaching in richer school (roughly 42% versus 28%). In terms of teachers having studied mathematics at university and having studied education in mathematics at university, these proportions are largely similar across the two groups, with slightly more than 50% of teachers having studied mathematics at university and between 30% and 40% of teachers having studied education in mathematics at university.

In terms of teacher experience, the proportion of teacher having attained each level of experience is largely similar across two groups. Indeed, very little difference exists across these variables.

6. RESULTS

Before any multi-level analysis is performed, it is necessary to formally test whether variance exists at the second level (i.e. at the level of the classroom).

Partitioning the Variance in Mathematics Achievement

A fully unconditional model is run in order to partition the variance in Grade 8 mathematics performance into the part explained by student characteristics and the part explained by teacher characteristics. In order to do this, an HLM allows mean mathematics achievement at level-1 (i.e. the level of the student) to vary without adding any level-1 or leve-2 (i.e. the level of the teacher) spredictors, that is

$$\mathbf{Y_{ij} = \beta_{0j} + r_{ij}} \qquad \mathbf{(3)}$$

where $$\mathbf{\beta_{0j} = \gamma_{00} + u_{ij}} \qquad \mathbf{(4)}$$

The within-classroom component of the variance (σ^2) is estimated to be 0.562 and the between-classroom component of the variance (τ_{00}) is estimated to be 0.516. The intraclass correlation coefficient (ICC)[5] is therefore calculated to be 0.478, indicating that roughly 48% of the variation in student mathematics performance occurs at the level of the classroom (i.e. at the level of the teacher). The ICC therefore indicates that HLM is necessary to examine the variation in student mathematics performance since a substantial portion of the variance is explained by the second level of the model. The reliability of the estimate of the intercept is 0.968, indicating that a large proportion of the variance in the intercept is available to be explained by second level explanatory variables.

Within-Classroom HLM

The next step in the analysis is to model student performance based only on student level variables, in other words, to model student outcomes as a function of student level characteristics and unconditional of variables at the level of the teacher, as presented in equation 1 above. The results are presented in table 5 below.

Table 5: HLM Within-Classroom Model

	Estimated fixed effects	
	Coefficients	Standard error
Intercept	0.237~	0.104
SES	0.261**	0.008
Gender	0.009	0.019
Overage (born earlier than 1988)	-0.164**	0.023
Underage (born later than 1988)	-0.029	0.028
Tested in home language	0.160**	0.028
Mom: primary schooling	0.000	0.032
Mom: junior secondary schooling	0.010	0.033
Mom: matric	0.170	0.030
Mom: post-matric	0.210*	0.062
Mom: diploma/certificate	0.065	0.051
Mom: degree	0.055	0.065
Mom: honours or higher	0.052*	0.029
Minutes on homework: 15-30	0.099**	0.023
Minutes on homework: 31-60	0.078**	0.030

[5] ICC is calculated as $\tau_{00} / (\tau_{00} + \sigma^2)$; (where τ_{00} is the variance associated with u_{0j} and σ^2 is the variance associated with r_{ij}).

Minutes on homework: 61-90	0.025		0.049
Minutes on homework: more than 90	0.084*		0.034
Tested in English	-0.288**		0.102
Estimated random effects			
	Standard deviation	**Variance**	**Chi-squared**
Intercept (Mean achievement)	0.64079	0.41062	5080.629
SES differentiation	0.08289	0.00682	311.475
Within-school	0.77751	0.60452	
Reliability of School-level random effects			
	Mean achievement	0.946	
	SES	0.410	

*Source: own calculations, TIMSS 2003 (mathematics) using HLM; ** - significant at 1% level; * - significant at 5% level; ~ - significant at 10% level.*

a. *The reference group is female students born in 1988whose mother has not attained any education, who are not tested in their home language, were tested in Afrikaans and who spend less than 15 minutes doing homework each day.*

The results indicate that the SES of students has a positive and statistically significant impact on students' achievement in mathematics. The coefficient of 0.261 indicates that at the mean, and holding all other variables constants, a 1 standard deviation increase in the SES of a student results in an improvement in their mathematics achievement of 0.261 standard deviations. The negative and statistically significant coefficient of -0.164 for the overage dummy indicates that at the mean, students born before 1988 (therefore students who are older than they should be in grade 8) perform 0.164 standard deviations below students who are the correct age. This may well result from the fact that overage students are likely either to be repeating grade 8 or to have repeated earlier grades, therefore indicating that they are academically weaker than their peers. The positive and statistically significant coefficient of 0.106 on the dummy variable controlling for whether students are tested in their home language indicates that students who are tested in their home language perform 0.16 standard deviations better than similar students who are not tested in their home language. The positive coefficients on the dummy variables controlling for whether students' mothers have completed post-matric and whether students' mothers have completed at least an honours degree, although slightly less statistically significant, both indicate that students' mothers having completed the aforementioned levels of education are associated with improvement in students' performance of respectively 0.210 and 0.052 standard deviations. In terms of time spent on homework, the coefficients on all the dummy variables (with the exception of that controlling for students spending between 61 and 90 minutes on homework every day) are positive and statistically significant, indicating that students spending between 15 and 30 minutes, 31 and 60 minutes and more than 90 minutes each day on homework each perform approximately 0.1 standard deviations better than students who spend less than 15 minutes each day completing homework. The negative and statistically significant coefficient of 0.288 on the dummy variable controlling whether students were tested in English indicates that students who were tested in English performed 0.288 standard deviations worse than the reference group at the mean. This is likely to reflect the fact that the proportion of black students comprising the group of students tested in English is higher than the proportion of black students comprising the group tested in Afrikaans and so a higher proportion of students who were tested in English is likely to be enrolled in the weak performing historically black schooling system.

After controlling for the aforementioned student-level characteristics, the variance on the intercept decreases to 0.411, indicating that once these level-1 predictors have been added to the model roughly 20% of the overall within-classroom variance has been explained away by the student level characteristics included in the model. The weak explanatory power of the model at level-1 may well result from the fact that TIMSS 2003 does not contain information on either the race groups to which students belongs or on the pre-test scores of student, both of which are known to be highly correlated with mathematics achievement (particularly in the case of South Africa). Furthermore, the variables included in the model largely reflect the home background of students rather than variables controlling for unobservable characteristics of students such as intelligence, motivation and innate ability, all of which are known to impact on student performance.

The next step in the analysis is to incorporate teacher-level characteristics in an effort to explain the relationship between student level characteristics and student performance. The coefficients from the within-classroom model are therefore modeled as a function of teacher characteristics and so the within-classroom model is no longer unconditional at the level of the teacher. It is in this sense that HLM is considered "regression of regressions" – the coefficients of the first level become the outcome of the second level.

Between-Classroom Model

The final step of the HLM analysis is therefore to model the intercept and SES slope in the within-classroom model of student performance in mathematics as a function of teacher characteristics. As mentioned earlier, the teacher characteristics of interest are those pertaining to the level of qualification and educational attainment of teachers. In this analysis, the impact of teacher characteristics on the intercept (i.e. mean mathematics achievement) and the SES slope (i.e. the relationship between the student's SES and their mathematics achievement) are modeled as functions of teacher characteristics. The results are presented in table 6 below.

Table 6: Final HLM Model 1 (N = 8952, J = 255)

Estimated fixed effects		
	Coefficients (only controlling for average school SES)	**Coefficients**
Intercept		
Intercept	-0.034 (0.097)	0.059 (0.128)
Mean student SES	0.339** (0.043)	0.301** (0.041)
Gender (1=male)		-0.051 (0.052)
Experience: 6 to 10 years		-0.019 (0.015)
Experience: 11 to 15 years		-0.065 (0.066)
Experience: 16 to 20 years		0.049 (0.159)
Experience: 21 to 25 years		-0.153 (0.132)
Experience: 26 to 30 years		0.756** (0.326)
Experience: 31 to 36 years		0.442 (0.278)
Attained Post Matric		-0.000 (0.170)
Attained Diploma		-0.170 (0.104)
Attained Degree		0.131 (0.128)
Attained Degree – honours or more		0.198 (0.191)
Teacher training: 1 year		0.133 (0.188)
Teacher training: 2 years		-0.158 (0.148)
Teacher train: 3 years		-0.098 (0.094)
Teacher training: 4 years		-0.049 (0.119)
Teacher training: 5 years		-0.056 (0.381)
Teacher training: 5+ years		0.109 (0.407)
License/Certificate		0.042 (0.056)
Studied Mathematics at University		0.209** (0.071)
Studied Education in Mathematics at University		0.161** (0.065)

SES		
Intercept	0.027** (0.007)	-0.027 (0.023)
Mean student SES	0.037** (0.008)	0.028 (0.008)
Gender (1=male)		0.021 (0.013)
Experience: 6 to 10 years		0.003 (0.004)
Experience: 11 to 15 years		-0.021 (0.017)
Experience: 16 to 20 years		0.021 (0.032)
Experience: 21 to 25 years		-0.045 (0.039)
Experience: 26 to 30 years		0.299 (0.188)
Experience: 31 to 36 years		-0.012 (0.067)
Attained Post Matric		0.077 (0.045)
Attained Diploma		-0.012 (0.027)
Attained Degree		0.022 (0.028)
Attained Degree – honours or more		0.029 (0.035)
Teacher training: 1 year		0.032 (0.033)
Teacher training: 2 years		-0.005 (0.040)
Teacher train: 3 years		0.009 (0.022)
Teacher training: 4 years		-0.000 (0.025)
Teacher training: 5 years		0.106 (0.089)
Teacher training: 5+ years		0.052 (0.070)
License/Certificate		0.038 (0.012)
Studied Mathematics at University		0.006 (0.016)
Studied Education in Mathematics at University		0.017 (0.014)
Gender	0.009 (0.018)	0.008 (0.018)
Overage (born earlier than 1988)	-01.55** (0.022)	-0.157** (0.022)
Underage (born later than 1988)	-0.030 (0.028)	-0.032 (0.029)
Tested in home language	0.144** (0.030)	0.146** (0.030)
Mom: primary schooling	0.008 (0.030)	0.009 (0.030)
Mom: junior secondary schooling	0.010 (0.033)	0.012 (0.033)

Mom: matric	0.008 (0.030)	0.009 (0.030)
Mom: post-matric	0.200** (0.085)	0.196* (0.085)
Mom: diploma/certificate	0.060 (0.078)	0.057 (0.078)
Mom: degree	0.050 (0.086)	0.046 (0.088)
Mom: honours or higher	0.048 (0.031)	0.050 (0.031)
Minutes on homework: 15-30	0.096** (0.021)	0.096** (0.021)
Minutes on homework: 31-60	0.075** (0.029)	0.077** (0.029)
Minutes on homework: 61-90	0.029 (0.045)	0.036 (0.044)
Minutes on homework: more than 90	0.083* (0.033)	0.086* (0.033)
Tested in English	-0.020 (0.103)	-0.023 (0.093)

Estimated random effects

	Standard deviation	Variance	Chi-squared
Intercept (Mean achievement)	0.42120	0.17741	2190.42
SES differentiation	0.06114	0.00374	282.94
Within-school	0.77666	0.60321	

Reliability of School-level random effects

Intercept	0.884
SES slope	0.283

*Source: own calculations, TIMSS 2003 (math) using HLM; ** - significant at 1% level; * - significant at 5% level; ~ - significant at 10% level. Standard errors are reported in parentheses.*

a. *The reference group in terms of teachers is female teachers with between 1 and 5 years of teaching experience, no teacher training, no license/certificate to teacher, who studied neither mathematics nor education in mathematics at university and whose highest level of educational attainment is matric.*
b. *The reference group in terms of students is female students born in 1988whose mother has not attained any education, who are not tested in their home language, were tested in Afrikaans and who spend less than 15 minutes doing homework each day.*

The between-classroom model is initially run controlling only for the average SES of students being taught by a particular teacher. That is, the intercept and SES slope are modeled only as a function of average student SES. The positive and statistically significant coefficient on average student SES on the intercept indicates that a 1 standard deviation increase in average student SES from mean average student SES of all classrooms increases average mathematics achievement by 0.339 standard deviations. The positive and significant coefficient on average student SES on the intercept indicates that a 1 standard deviation increase of SES from the average SES of students being taught by a particular teacher will increase mean mathematics achievement by 0.037 standard deviations, implying that the relationship between student SES and mathematics achievement is stronger in classrooms (or at least among student being taught by a particular teachers) when the average student SES is higher. The benefit of being a more affluent classroom therefore increases disproportionately with student SES (van der Berg and Louw, 2007: 11). Controlling for classroom SES reduces the variation in the SES slope from 0.00682 to 0.00471, implying that approximately 31% of the variance in the SES slope is accounted for by differences in the average classroom SES. In other words, differences in the average SES in classrooms "explain away" approximately 31% of the variance in the relationship between student SES and student performance.

The final between-classroom model is constructed in order to investigate which teacher characteristics impact on overall student performance in mathematics and which teacher characteristics impact on the relationship between student SES and student performance in mathematics after controlling for the impact of classroom SES. Teacher-level factors on which the intercept (i.e. mean mathematics achievement) is modeled represent factors that either increase or decrease the overall performance of students being taught by a particular teacher. Table 6 indicates that mean mathematics achievement amongst pupils being taught by teachers with between 26 and 30 years of teaching experience is roughly 0.756 standard deviations above the mean mathematics achievement of students being taught by teachers with between 1 and 5 years of teaching experience. This indicates that students being taught by teachers with considerable teaching experience perform better – a finding that contradicts the literature on the impact of teaching experience on student performance. As mentioned in section 3 of the paper, teacher experience beyond roughly 4 to 5 years has not been found to impact significantly on student performance, although admittedly, this evidence was reported for the USA – an education system that is likely to function very differently to that of South Africa.

None of the other teaching experience variables enter the model significantly. Interestingly, none of the variables controlling for the educational attainment of teachers have a statistically significant impact on mean student achievement. Similarly, teacher training appears to be insignificant in explaining overall achievement in mathematics amongst students. The positive and statistically significant coefficient on the dummy variable taking a value of 1 if teachers studies mathematics at university indicates that the mean mathematics performance amongst students being taught by teachers for whom this variable takes a value of 1 is 0.209 of a standard deviations higher than that of students being taught by teachers who did not study mathematics at university. Similarly, the positive and statistically significant coefficient on the variable controlling for whether the teacher studies education in mathematics at university indicates that the mean mathematics achievement of students being taught by teachers who did study education in mathematics at university is 0.160 standard deviations above that of students being taught by teachers who did not study the aforementioned material at university.

In terms of the impact that teacher characteristics have on the relationship between the student's SES and their performance in mathematics, only two variables enter the model significantly. The coefficient on the dummy variable taking a value of 1 for teachers who have attained post-matric indicates that the benefit of a 1 standard deviation increase in SES is 0.077 standard deviations higher for students being taught by teachers who have attained post-matric. This means that the advantage of having higher SES is greater for students being taught by a teacher who has attained post-matric. The implication of this is that the attainment of post-matric by teachers increases the level of inequality in the classroom since the positive coefficient on this teacher-level variable effectively makes the impact of student SES on student performance in mathematics stronger. However, it must be noted that this coefficient is only statistically significant at a 10% level. The second teacher characteristic to enter the model significantly is whether teacher have a certificate or license to teach. The coefficient on the dummy variable taking a value of 1 if teachers have attained the aforementioned certificate or license indicates that the benefit associated with a 1 standard deviation increase in SES amongst students is 0.038 standard deviations higher if the student is taught by a teacher who has attained a certificate or license to teach, again implying that the effect of student SES on mathematics performance is stronger for students being taught by teachers with this level of qualification and implying a higher degree of inequality in the student outcomes. Both teacher characteristics therefore enhance the impact of student SES on their performance in mathematics, therefore also enhancing the inequality of an already grossly unequal schooling system.

The variance on the SES slope decreases again from 0.00471 in the within-teacher model in which just the mean SES of the students being taught by a particular teacher was controlled for, to 0.00374 in the final between-teacher model, indicating that 21% of the variance in the SES slope is explained by the factors included in the between-teacher model.

The overall objective of the analysis is to highlight the teacher characteristics that both enhance the overall performance of students as well as diminish the impact that SES has on student performance (i.e. diminish the level of inequality in the schooling system). From the analysis, it is clear that no teacher characteristic achieves both of these objectives. However, it was found that students being taught by teachers with between 26 and 30 years of teaching experience, teachers with between 31 and 36 years of teaching experience and who have studied either mathematics or education in mathematics at university perform better than students being taught by teachers in the reference group.

7. CONCLUSION

Teachers with a considerable amount of teaching experience and who have specialized in some way in the subject in which they teach contribute most substantially to the overall performance of students. It may therefore prove worthwhile to investigate the possibilities of transforming the teaching profession into a more attractive one (financially) to these individuals with measures designed either to encourage very experienced teachers to remain in the teaching force or to attract individuals specializing in particular subjects or in the education of those subjects to join the teaching force. Indeed, the need to encourage and convince these teachers to teach in weak performing historically black school is considerable.

8. REFERENCES

Arnold, CL. 1992. “Methods, Plainly Speaking: An Introduction to Hierarchical Linear Models”. *Measurement and Evaluation in Counseling and Development*. Volume 25. 58-90.

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

Patterson, L. 1992. “An introduction to multilevel modeling” in Raudenbush, SW and Willms, JD (eds). *Schools, Classrooms and Pupils.* San Diego: Academic Press. 13-24.

Van der Berg, S. 2008. “How effective are poor schools? Poverty and educational outcomes in South Africa”. *Studies in Educational Evaluation.* 34 (3). 145-154.