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RESEARCH ARTICLE

SCHOOL-LEVEL PREDICTORS OF STUDENT ACADEMIC ACHIEVEMENT IN THE KENYA CERTIFICATE OF PRIMARY EDUCATION EXAMINATION USING A TWO-LEVEL HIERARCHICAL LINEAR MODEL

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ARTICLE INFO	ABSTRACT
Article History: Received 20 th June, 2016 Received in revised form 09 th July, 2016 Accepted 18 th August, 2016 Published online 30 th September, 2016	Available literature on the predictors of student academic scores since the 60s continues to present mixed findings and interpretation. Utilizing the education production function models, researchers have sought to test whether school or teacher-level variables explain academic achievement variance to a greater extent than do student-level variables. Within this framework, we modelled school-level predictors of academic achievement in the Kenya Certificate of Primary Education (KCPE) examination in Mumias and Kuria East Sub-Counties in Kenya. Using a two-level hierarchical linear model (with 1824 students at Level-1 nested within 61 schools at Level-2), the explained variance in
Key words:	student scores by the two levels was 64.00% with 56.64% of that explained by school-level variables.
School-level predictors, Hierarchical Linear Modelling, Kenya Certificate of Primary Education Examination, Mumias Sub-County, Kuria East Sub-County, Kenya.	At Level-2, School location in the two Sub-Counties; Boarding schools or a boarding component in a day school (often involving Class 6-8); and whether or not schools allowed their students to borrow school library textbooks and other learning materials for study and reference away from school were flagged as predictors of student academic achievement in KCPE after meeting the standardized regression coefficient cut-off of ≥ 0.10 to be flagged as such. Policy implications of these findings are discussed.

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INTRODUCTION

Since the release of the Coleman Report on the Equality of Educational Opportunity in the US (Coleman *et al.*, 1966), many scholars and researchers have designed studies aimed at understanding the drivers and predictors of student academic achievement. The Coleman Report made some landmark findings that spurred lots of research and interest in education production functions and schooling outcomes. An unexpected finding from the study which took many policy analysts by surprise suggested that variations in the level of students' achievements bore little or no relationship with school resources or programmes. That instead, out-of-school variables such as family background and neighbourhood characteristics

accounted for the observed achievement differences between students (Ejakait, Olel, Othuon, & Khasenye, 2016). Following the findings of the Coleman Report, many studies utilizing the education production function models have been designed. The studies have sought to measure whether school or teacher-level variables explained academic achievement variance to a greater extent than student-level characteristics. Three strands of findings seem to have emerged from this large body of studies since 1966: That school-level variables explain a large proportion of the variance in student academic achievement (Carbonaro & Elizabeth, 2010; Ejakait, Mutisya, Ezeh, Oketch, & Ngware, 2011; Hanushek & Rivkin, 2009; Hungi & Thuku, 2010; Southern and Eastern Africa Consortium for Measuring Education Quality, 2011); that teacher-level variables have a prominent effect on students achievement (Konstantopoulos & Chung, 2011; Neild, 2009) and that student-level variables including their socioeconomic status and other home background characteristics account for

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much of the variation in their academic achievement (Coleman et al., 1966; Legewie & DiPrete, 2012). This paper pursues the school-level effect using a two-level hierarchical linear model with 1824 students (Level-1) nested within 61 primary schools (Level-2). We test the hypothesis that school-level variables have no effect on student academic achievement in the Kenya Certificate of Primary Education (KCPE) examination involving five subject areas namely, English, Kiswahili, Mathematics, Science and Social Studies and Religious Education. Since each is scored out of a possible 100, a candidate's maximum KCPE score can stretch to 500. The KCPE examination is taken at the end of eight years of primary education which marks the end of the primary education cycle and opens way for transition into secondary school education (Ejakait et al., 2016). We now review selected literature on school-effects. A study on the effect of primary school quality on academic achievement across 29 high and low income countries in Africa, Asia, Latin America and the Middle East concluded that teacher and school quality variables were the most important in influencing student learning and academic achievement (Heyneman & Loxley, 1982, 1983). The authors argued that "...the poorer the national setting in economic terms, the more powerful this school and teacher quality effect appears to be ... " (Heyneman & Loxley, 1983, p. 1184). Their conclusion, commonly referred to as the "Heyneman-Loxley effect" or "HL effect" in educational literature was considered important because it supported the linkage between educational achievement and national economic development (Hungi & Thuku, 2010). Pupil Teacher Ratios (PTR) or class size is one of the characteristics of schools that has attracted lots of research effort. Nye, Hedges, and Konstantopoulos (1999) used a two-level HLM on data from the Tennessee class size experiment (Project STAR). They set out to address the question of the long-term effects of small classes by examining the achievement of students who were involved in Project STAR for the 5 years after the experiment ended, when these students were in Grades 4 to 8. They found that the effects of small classes in kindergarten through Grade 3 on achievement did not disappear by Grade 8. They argued that although there were positive effects of small classes on achievement, there was no compelling evidence for differentially larger effects of small classes for lower achieving students (Nye, Hedges, & Konstantopoulos, 2002). Deutsch (2003) has also found that small classes benefitted high school students through positive teacher-student interaction, increased time on instruction rather than on discipline and high teacher morale.

While acknowledging that the broader literature on class-size effects was inconclusive despite results from experimental studies, Milesi and Gamoran (2006) examined the effects of class size on achievement in kindergarten with data from the USA's Early Childhood Longitudinal Study involving the Kindergarten Class of 1998-99. They utilized HLM and found no evidence of class-size effects on student achievement in either reading or mathematics, and their results indicated that class size was equally insignificant for students from different race, economic, and academic backgrounds. Teacher fixed-effects analyses also yielded null findings for class size. However, instructional activities offered significant boosts to achievement, although these effects did not differ between small and large classes. Class-size is often a school-level

variable. Some researchers have found differences driven by the type of school one attended. For instance, Hanushek and Rivkin (2009) examined the change in black-white achievement gap in the US as students progressed through school and found that there was an adverse effect on achievement of attending a school with a high percentage of black students. Carbonaro and Elizabeth (2010) analyzed data from the US Education Longitudinal Study to examine sector differences in high school achievement in the era of standards based reforms. They found that students in Catholic and private secular schools enjoyed greater math gains from 10th to 12th grade compared with those in public schools and that these advantages were largely concentrated among more advanced math skills (Carbonaro & Elizabeth, 2010). Even after accounting for family background and prior achievement, students in private schools were found to have taken more academic math courses than students in public school (Carbonaro & Elizabeth, 2010). Legewie and DiPrete (2012) used a quasi-experimental research design to estimate the gender difference in the causal effect of peer socioeconomic status as an important school resource on test scores using 4372 cases from the longitudinal German ELEMENT dataset for 4th to 6th graders. They found substantial variation in the gender gap in academic performance across schools and that this variation was related to average school performance (Legewie & DiPrete, 2012). They also found that boys were more sensitive to peer-SES composition as an important dimension of school quality related to the learning environment and that on average, boys did as well or better than girls in mathematics, and the male advantage was larger on the right tail of the distribution. A policy brief from the Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ) for the third wave of data collected in 2007 involving 4,436 Standard 6 pupils in 193 primary schools in all eight provinces in Kenya (provinces were scrapped with the enactment of the Constitution of Kenya, 2010) found that one in every five pupils did not have all the three basic learning materials needed for effective participation in classroom activities. In the light of FPE which annually allocates finances for the purchase of text books, a worrying finding from the study suggested that at least four in every five pupils did not have sole use of mathematics textbooks and that most of the pupils without these mathematics textbooks were in public schools (Southern and Eastern Africa Consortium for Measuring Education Quality, 2011).

Hungi and Thuku (2010) examined important pupil, class and school-related variables that contributed to differences in mathematics and reading achievement among Grade 6 pupils in Kenya. They used SACMEQ II data with a sample of 3299 pupils, 320 classes in 185 schools in Kenya. Using a threelevel multilevel model, they found that Pupil Teacher Ratio (PTR) was an important variable in predicting student achievement. Accounting for socio-economic status and individual student characteristics, Ejakait *et al.* (2011) found that a pupil attending a public school irrespective of the residential location (Korogocho, Viwandani, Harambee or Ofafa Jerocho in Nairobi) would score up to 49.5 points less in the KCPE examination compared with what a pupil in an informal private school would score. Although studies as reviewed in this sub-section have found significant teacher effects on student academic achievement, some renowned scholars in Economics of Education such as Eric Hanushek, have reported a lack of significant positive relationship between school-level variables and student achievement. For instance, Hanushek (1986) found that estimated coefficients for teacher-based variables were statistically insignificant and that there was no strong evidence suggesting that Pupil Teacher Ratio (PTR), teacher education or teacher experience had an expected positive effect on student achievement (Ejakait et al., 2016). Similar results are reflected from Hanushek's review of 187 studies on expenditure relationships in schools (1989). From the studies, only 14 out of 152 that dealt with effects of class size reported statistically significant relationships. On teacher education, 100 out of 113 studies showed statistically insignificant coefficients. The conclusion from this review argued that there was no strong evidence that PTR, teacher education, or teacher experience had the expected positive effects on student achievement and that there was no strong or systematic relationship between school expenditures and student performance (Hanushek, 1989). In another review of close to 400 studies on student achievement, Hanushek (1997) argued that after accounting for family inputs, this large body of literature did not present compelling or consistent results that suggested a relationship between student performance and school resources (Ejakait et al., 2016).

With such mixed findings in the literature, we argue that it is prudent to choose Hierarchical Linear Modelling (HLM) over Ordinary Least Squares (OLS) for hierarchical data such as is commonly found in the modelling of academic achievement. There is abundant literature on the advantages of HLM, see for example, (Bryk & Raudenbush, 1992; Ejakait *et al.*, 2016; Goldstein, 1995; Hardin & Hilbe, 2012; Rabe-Hesketh & Skrondal, 2012; Raudenbush & Bryk, 2002; Wenglinsky, 2002). We will thus skip discussing these advantages in this paper.

The rest of this paper is organised as follows. Section 2 describes the data and methods while Sections 3 and 4 present the results and the discussion respectively. Section 5 covers our conclusion and implications for policy while section 6 is our statement of no competing interests.

Data and Methods

Sampling

The data were collected from Mumias and Kuria East Sub-Counties in Kenya. There were 280 Sub-Counties and Municipalities as extracted by the authors from the official KCPE examination results' dataset for 2012. Mumias and Kuria East were randomly sampled from Sub-Counties that had consistently been in the top and bottom 5% respectively using merit lists for 2010-2012. Stratified by Public and Private primary schools, we employed Probability Proportion to Size to sample 1824 students (Level-1) nested within 61schools (Level-2). While all Class 8 candidates in single streamed schools were included in the sample, one stream at Class 8 in multi-streamed schools was randomly sampled and all its candidates included in the sample as well. Public and private primary schools are established and maintained out of public and private funds respectively (Ejakait *et al.*, 2016).

The Data and Description of Variables

A description of the five KCPE academic subjects is summarised in Table 1.

Kiswahili is the first language of the Swahili people, one of the 300-600 ethnic groups in Africa who speak Bantu languages (Butt, 2006). It is a lingua franca of the African Great Lakes region and other parts of Southeast Africa, including Tanzania, Kenya, Uganda, Rwanda, Burundi, Mozambique, and the Democratic Republic of the Congo (Chiraghdin & Mnyampala, 1977). Kiswahili serves as a national language of four nations: Tanzania, Kenya, Uganda, and the Democratic Republic of the Congo and is also one of the working languages of the African Union and one of the official languages of the East African Community (Ejakait *et al.*, 2016; Massamba, 2002). For Mathematics and Science, each of the 50 items has 2 points for each of English and Kiswahili and the student's final score is calculated as given in equation (1).

$$\frac{x}{me/mk} * 100 \tag{1}$$

Where x is the student's cumulative score in English's or Kiswahili's sections A (scored out of 50) and B (scored out of 40) and *te* is the maximum score in English while *tk* is the maximum score in Kiswahili.

The same applies for Social Studies and Religious Education with the final student's score calculated as given in equation (2)

$$\frac{x}{mssre} * 100 \tag{2}$$

Where x is the student's cumulative score in the 90 items in Social Studies and Religious Education and *mssre* is the maximum score in the same examination. School and student questionnaires were fielded for data collection. Table 2 presents a description of the variables used in the two-level hierarchical linear modelling of school effects.

For ease of interpretation, the outcome variable was transformed to a standard normal score with a Mean of zero (0) and Standard Deviation and Variance of one (1) so that the residuals at each level better approximate the normality assumptions of the models. This transformation allowed the effects of the covariates in the two-level HLM to be interpreted in terms of standard deviation units of the outcome variable (Leckie, 2013; Raudenbush & Bryk, 2002). The untransformed variable ranged between 62 and 431 with mean score of 263.22 and standard deviation of 70.82.

Model Specification

In order to obtain the amounts of variance available for explanation at each level of the hierarchy, we fitted an unconditional model, also called intercept-only, null or empty model (Hungi & Thuku, 2010; Raudenbush & Bryk, 2002).

Consequently, a two-level variance components model was specified and fitted including only an intercept, school effects, and a student level residual error term. The model did not make any adjustments for predictor variables, only decomposing the total variance in the outcome variable (standardized students' total score from the five KCPE subjects) into separate school and student variance components. We followed Leckie (2013) in specifying the unconditional/null model as:

$$Y_{ii} = \beta_0 + u_{0i} + e_{ii} \tag{3}$$

Assuming that; $u_{0j} \sim N(0, \sigma_v^2)$ $e_{ij} \sim N(0, \sigma_v^2)$

Where:

 Y_{ij} is the observed KCPE total score for student *i* (*i* = 1, ..., 1824) nested within school *j* (*j* = 1, ..., 61); β_0 is the overall mean across schools; and

 u_{0j} is the effect of school *j* on student academic achievement; and

 e_{ij} is a random "student effect", that is, the deviation of student ij's score from the school mean. These effects are assumed normally distributed with a mean of 0 and a variance σ_e^2 . Table 3 presents the results of this null model.

The random intercept, β_0 , predicts that a student's z-score in the KCPE examination will be -0.02 (*SE*=0.10, *p*=.832). Since the outcome variable is approximately normalised, an estimated random intercept of zero, an estimated total variance of approximately one and a non significant intercept are all expected. The random part of the model presents the Variance Partition Coefficient (VPC) for each HLM level. Substituting the Variance Components into equation (4 and 5), the VPC available for explanation at Student (σ_e^2) and School (σ_u^2) levels is 0.3548 (35.48%) and 0.6452 (64.52%) respectively.

$$\sigma_e^2 / (\sigma_e^2 + \sigma_u^2) \tag{4}$$

$$\sigma_u^2 / (\sigma_e^2 + \sigma_u^2) \tag{5}$$

The largest variance lay between schools (64.52%) while a substantial one lay among students within school (35.48%) suggesting that most of the variation in students' scores was seen between their schools. In adding predictors from the two levels to the unconditional model in equation (3), the authors followed Leckie (Leckie, 2013) in specifying the full two-level random intercept model as:

$$\begin{aligned} Y_{ij} &= \beta_0 + \beta_1 s 21_{ij} + \beta_2 s 22 a_{ij} + \beta_3 s 23 a_{ij} + \beta_4 s 27_{ij} + \\ \beta_5 s 313 x_{ij} + \beta_6 s 36 c_{ij} + \beta_7 s 314 a_{ij} + \beta_8 s 314 b_{ij} + \\ \beta_9 s 314 e_{ij} + \beta_{10} s 314 l_{ij} + \beta_{11} s 58 x_{ij} + \beta_{12} s 61 x_{ij} + \\ \beta_{13} h 16 e_j + \beta_{14} h 24 a_j + \beta_{15} h 218 z_{ij} + \beta_{16} h 227_j + \\ \beta_{17} h 49 a_j + \beta_{18} h 432_j + \beta_{19} h 487_j + \beta_{20} h 5122_j + u_j + e_{ij} \end{aligned}$$
(6)

A description of these predictors is presented in Table 2.Two random intercept models were fitted in steps starting with Level-1 Student variables subscripted *ij* estimated in Model-1 before fitting the Level-2 School variables subscripted *j*. These variables helped to explain the response variation allocated to the two levels as well as test the hypothesis regarding the relationship between school-level predictors and the outcome variable. The slope coefficients of these variables were assumed fixed across at Levels 2. Selection of "candidate predictors" to be included in the two-level models involved a two-step process informed by the need for parsimony in the final model. In the first step, a pair-wise correlation of all possible variables for each of the two levels was estimated. The second step involved running only those variables that were significantly correlated with the outcome variable in an exploratory Level-specific model while considering the hierarchical nature of the dataset (Hungi & Thuku, 2010; Leckie, 2010; Raudenbush & Bryk, 2002; StataCorp, 2013). For the student-level, "candidate predictors" that were correlated with the outcome variable were fitted in a studentonly model excluding school-level predictors. Only statistically significant variables at the 5% level were then preserved as the student-level predictors to be included in Model-2. This procedure was repeated at the school level. Up to 24 variables were dropped at student-level. These were: Student is Muslim (s18); Attended pre-school (s24); Student's abode during school week (s31); Mother did not go to school (s331) Mother has some primary education (s332); Mother has completed post secondary training (s336); Student's father is alive (s34); Father did not go to school (s351); Father has some primary education (s352); Father has completed post secondary training (s356); Number of sisters (s36a); Number of books (s37); Taking care of sick family members and relatives (s314c); Washing and ironing clothes (s314g); Chopping fire wood (s314i); Collecting fire wood (s314j); Taking care of livestock (s314m); Helping in a family business (s314n); Number of homework assignments in a week for all subjects (s42z); Someone at home/ school helps with homework (s43); How often teacher corrects homework: 1-5 (s46z); Number of lessons missed in a week for all subjects (s51z); Student had extra lessons in mathematics (s515c); and Student had extra lessons in social studies (s515e). Twenty one variables were dropped from the school-level-only model. These were piped water (h31e); School has a computer (h31k); Number of male teachers (h431); Number of masters degree teachers (h477); Number of untrained teachers (h481); Number of S1/Diploma teachers (h485); Approved teacher status (h486); Public primary school (h23a); School has a feeding programme (h32); Number of teachers with primary level education (h471); Number of teachers with form 6 level of education (h474); Number of teachers with a bachelor's degree (h475); Number of teachers with a P1 certificate (h484); School has store room (h31c); School age in years (h24c); Mean teacher years in current school (h410a); School has a telephone (h31g); Mean teacher age (h44a); Teacher with form 4 KCE/KCSE level of education (h473); Has been teaching subject in C8 since 2014 began (h4132); and HT's experience as HT in current school (h221a). STATA version 11.2 was used for data management and analysis with the "xtmixed" command.

RESULTS AND DISCUSSION

Descriptive Statistics of the Variables used in the Modelling

Table 4 presents the descriptive statistics for the variables used in the modeling

The focus in this paper was to assess the effect of school-level variables on student scores in the KCPE examination. The five interval or ratio school-level variables modelled had relatively small standard errors of the mean suggesting that their calculated means were not quite far away from the true population mean. There was near gender parity in candidature with 927 (50.82%) male and 897 (49.18%) female students. Using Multiple Correspondence Analysis with non-income or expenditure data as proposed by Filmer and Pritchett and as computed in the Demographic Health Surveys (Filmer & Pritchett, 2001; ORC Macro, 2016; Rutstein & Kiersten, 2004), the students' wealth index was determined from their reported home ownership of assets, such as cars motor cycles, electronics (including fridges), and bicycles among others; materials used for housing construction; source of lighting; and types of water access and sanitation facilities. This wealth index was then divided into three tertiles of 608 students each categorized as 1=High tertile (wealthiest of the three), 2=Middle tertile and 3= Low tertile (least wealthy of the three, see (Ejakait et al., 2016).

Bivariate Analysis

We ran a Pair-wise correlation between the students' total KCPE score (standardized) and the predictors as estimated in the final Model-2. The predictor with the "strongest" correlation from the student-level pool was number of siblings (r = -0.320, p < .001) although this is considered weak using Taylor's interpretation of correlation coefficients (Taylor, 1990). From the school-level pool, Sub-County and Number of female teachers had the "strongest" correlations at r = -0.574, p < .001 and r = 0.486, p < .001 respectively. Though statistically significant, the rest of the predictors under consideration had either weak or moderate correlations with the outcome variable. The results of an independent t-test with unequal variance, t(1601) = 29.79, p < .001, showed that Mumias Sub-County had 1.64 standard deviation units above the mean compared with Kuria East Sub-County's -0.68 units below the mean. The strength of the difference between the two z-score means as measured by R^2 was 0.36 which is considered a large effect (Acock, 2006). Although the achievement of males was higher (0.11 standard deviations above the mean compared with negative 0.11 for females, the strength of the difference between the two (0.22) was weak ($R^2 = 0.01$). But the strength of the difference between public and private primary schools (1.03) was quite large ($R^2 = 0.58$) with private schools scoring 0.95 standard deviation units above the mean compared with negative 0.08 for public schools. All t-test results were statistically significant (α =.05, p<001). We also ran a one-way ANOVA to determine if the total KCPE scores were different across the schools' boarding status at Class 8 where 1=Day school (n=1583, z = -.19), 2=Boarding school, (n=79, z=1.40) and 3=Day and boarding school (n=162, z=1.12). There was a statistically significant difference between the groups as determined by the one-way ANOVA, F(1821) = 268.04, p <0.001). The Bonferroni post-hoc test showed that the z-score unit difference between boarding and day schools was 1.59, p <.001, while that between Mixed day/ boarding and day schools was 1.31, p < .001. The difference between mixed day/ boarding and full boarding schools was -0.28, p <.065. The effect size, $\eta^2 = 0.22$ (measured using eta-squared), was considered large (Acock, 2006). Similarly, there were

statistically significant differences in achievement across the three wealth index tertiles, F(1821) = 43.59, p < 0.001).

The two-level random intercept school model

Table 5 presents the HLM results. The effect of individual student predictors remained pretty much the same, and statistically significant, across the two levels as well as through the two Models. The results are now presented and discussed under the respective sub-sections. The results of variance partitioning and variance explained are presented in the discussion under each respective sub-section.

Student-Level Predictors

Several student-level variables were flagged as predictors of student academic achievement with standardized regression coefficients of ≥0.10 (Hox, 1995; Hungi & Thuku, 2010). A female student was estimated to score up to -0.30 standard deviation units below what a male student with similar characteristics would. Students' socio-economic status had a large effect on their academic achievement with students from the low wealth index tertile performing lower than their counterparts in the high tertile (wealthiest). The same is true for the middle tertile although that result was not statistically significant. Looking after younger or older relatives for "most or some of the days" had a large negative effect on student scores of up to -0.12 and -0.10 standard deviation units respectively, below the mean compared with the scores of students who did not. Curiously, house cleaning had positive effect for students who did this chore "most of the days" (z=0.19, SE=0.05, p<.001) as well as those who did it "some of the days" (z=0.10, SE=0.05, p<.001). These are considered large effects. Gardening and/or working in vegetable gardens also had a positive effect on the scores of students who did the chore "some of the days" although the z-score coefficient did not meet the ≥ 0.10 threshold to be flagged as a predictor. Students who kept negative company (s61x) scored lower than those who did not. A one standard deviation increase in keeping negative company was associated with up to -0.23 (SE=0.03, p < .001) standard deviation units below the mean. Negative behaviour was defined as company with friends who took alcohol and/or sneaked away from home without parental permission and/or got/get into trouble with school administration or Police for something bad they did and/or engaged in sex or sexual activity and/or smoked cigarettes or used hard drugs such as bang' and/or got into fights and quarrels with other people. Positive behaviour was defined as regular attendance of church/mosque and/or desire to join secondary school, and/or working hard in academic work, and/or get good marks in academic work and/or been commended or given a gift for good work or good behaviour (Ejakait et al., 2016).

School-Level Predictors

The focus of this paper was to model the effect of school-level predictors on student scores. Three of the eight predictors modelled met the ≥ 0.10 standardized regression coefficient and were flagged as school-level predictors of student academic achievement. Schools in Kuria East Sub-County scored up to negative 0.79 (*SE*=0.08, *p*<.001) standard deviation units below what schools in Mumias Sub-County would score.

Table 1. Descri	ption of the	KCPE Examina	tion Disaggregate	d by Subject

Name of Exam		Duration (Minutes)	Number of Items	Multiple Choice?	Maximum Score
English Section A	Language	100	50	Yes	50
English Section B	Composition	40	1	No	40
Kiswahili Section A	Language	100	50	Yes	50
Kiswahili Section B	Composition	40	1	No	40
Mathematics	*	120	50	Yes	50
Science		120	50	Yes	50
Social Studies and Religious Education		135	90	Yes	90
Note. English's section A and B are comb	oined for the total	score in English. The sa	me happens for Kisv	vahili. Adapted from	"A Hierarchical Li

Modelling of Teacher Effects on Academic Achievement in the Kenya Certificate of Primary Education Examination" by E. Ejakait., M. Olel., L. Othuon., and O. Khasenye, 2016, *American Journal of Educational Research 4*(14), p. 1032.

Variable	Variable label	Variable scale	Variable values			
s17z	Student's total KCPE score (standardized)	Interval	-3.07-2.93			
s21	Female student	Nominal	0=Male; 1=Female			
s22a	Student's age in years	Interval	12.18 - 22.18			
s23a	Student's years in current school	Interval	0.56 - 10.70			
s27	Number of times student spoke English in the last 7 days	Ratio	0 - 7			
s313x	Student's Wealth Index (3 Tertiles)	Categorical	1=High tertile; 2=Middle tertile; 3=Low tertile			
s36c	Number of siblings	Ratio	0-16			
s314a	Looking after younger relatives	Categorical	1=Never; 2=Some days; 3=Most days			
s314b	Looking after elderly relatives	Categorical	1=Never; 2=Some days; 3=Most days			
s314e	House cleaning	Categorical	1=Never; 2=Some days; 3=Most days			
s314l	Gardening/working in a vegetable garden	Categorical	1=Never; 2=Some days; 3=Most days			
s58x	Number of times student has repeated classes	Ratio	0-3			
s61x	Student keeps negative company (z-score)	Interval	-0.74 - 2.65			
h16	Kuria East Sub-County	Nominal	0=Mumias; 1=Kuria East			
h24a	Boarding status at class 8	Categorical	1-3			
h218z	Mean parental contribution 0-10 scale	Interval	0-10			
h227z	Mean community school participation: 0-10 scale	Interval	0-10			
h49a	Mean teacher years since first employment	Interval	0.10-25.21			
h432	Number of female teachers	Interval	1-30			
h487	Number of graduate teachers	Interval	0-12			
h5122	Students disallowed from borrowing library books to take home	Dummy	0=Otherwise; 1=Students disallowed from			
		-	borrowing library books to take home			
Note. Stude	ent Level-1 variables are prefixed with letter "s" and School Level-2 v	with letter "h"				

Table 3. Two Level Null (Empty) Model

Fixed Effect				
Variable	Variable label	Null Model		
		Est. (Std. Err.)	<i>p</i> -value	
	Intercept, β_{0i}	-0.02 (0.10)	0.832	
Random Effec	t	Variance Component		
Student (Leve	1-1), e_{ij}	0.3516 (0.01)		
School (Level	$-2), u_i$	0.6393 (0.12)		
Variance Part	tition Coefficient (VPC)			
Student (Leve	1-1), σ_{e}^{2}	0.3548		
School (Level	-2), $\sigma^2_{\rm u}$	0.6452		
Model Fit Stat	tistics			
Deviance		3509		
Akaike Inform	nation Criterion (AIC)	3515		
Bayesian Info	rmation Criterion (BIC)	3531		
Likelihood Ra	tio test vs. OLS Regression	$\chi^2(1) = 1666.71$	<.001	
Note. N= 1824	4: Est. = Estimate: Std. Err. = Sta	andard Error (in parentheses): AIC a	nd BIC statistics = smaller-is-better fit: OLS=C	rdinary Least Squares

Table 4. Descriptive Statis	tics for Variables	Used in the Anal	ysis of the Data

Variable	Variable label	Mean	Standard error (mean)	Standard deviation	Min	Max
s17z	Student's total KCPE score (standardized)	0.00	0.02	1.00	-2.84	2.37
s22a	Student's age in years	15.27	0.03	1.31	12.19	22.18
s23a	Student's years in current school	6.23	0.07	2.79	0.56	10.70
s27	Number of times student spoke English in the last 7 days	3.52	0.04	1.83	0.00	7.00
s36c	Number of siblings	5.07	0.06	2.36	0.00	16.00
s58x	Number of times student has repeated classes	0.74	0.02	0.72	0.00	3.00
s61x	Student keeps negative company (z-score)	0.00	0.01	0.49	-0.74	2.65
h218z	Mean parental contribution 0-10 scale	2.98	0.05	2.18	0.00	10.00
h227z	Mean community school participation: 0-10 scale	6.38	0.06	2.72	0.00	10.00

Continue.....

h49a	Mean teacher years since first employment	13.60	0.11	4.74	1.00	25.21
h432	Number of female teachers	6.88	0.11	4.86	1.00	30.00
h487	Number of graduate teachers	1.71	0.05	2.15	0.00	12.00
	Dummy/nominal variables	0=Male	1=Female			
s21	Female student	927 (50.82)	897 (49.18)			
		0=Mumias	1=Kuria East			
h16	Kuria East Sub-County	1,068 (58.55)	756 (41.45)			
		0=Otherwise	1=Yes			
h5122	Students disallowed from borrowing library books to take home	372 (20.39)	1,452 (79.61)			
	Categorical variables	1=High tertile	2=Middle tertile	3.Low tertile		
s313x	Student's Wealth Index (3 Tertiles)	608 (33.33)	608 (33.33)	608 (33.33)		
		1=Never	2=Some days	3=Most days		
s314a	Looking after younger relatives	458 (25.11)	1,009 (55.32)	357 (19.57)		
s314b	Looking after elderly relatives	800 (43.86)	798 (43.75)	226 (12.39)		
s314e	House cleaning	146 (8.00)	802 (43.97)	876 (48.03)		
s3141	Gardening/working in a vegetable garden	407 (22.31)	953 (52.25)	464 (25.44)		
		1=Day	2=Boarding	=Day and		
				boarding		
h24a	Boarding status at class 8	1,583 (86.79)	79 (4.33)	162 (8.88)		
Note. n= with lette	1824; Min=Minimum; Max=Maximum; percentages in er "h"	parentheses (); Stuc	lent Level-1 variables ar	e prefixed with letter	"s" and Scho	ool Level-2

Table 5. Two Level Random Intercept School Model

Variable	Variable label	Model 1 (Stud	dent)	Model 2 (Sch	ool)
		Est. (Std. Err.)	p	Est. (Std. Err.)	́ p
s21	Female student	-0.30 (0.03)	<.001	-0.30 (0.03)	<.00
s22a	Student's age in years	-0.09 (0.01)	<.001	-0.09 (0.01)	<.00
s23a	Student's years in current school	-0.02 (0.005)	<.001	-0.02 (0.005)	<.00
s27	# of times student spoke English in last 7 days	0.03 (0.008)	<.001	0.03 (0.008)	<.00
s313x	Student's Wealth Index (3 Tertiles): 1=High tertile (Ref.)	· · · · ·			
	2=Middle tertile	-0.04 (0.03)	0.210	-0.03 (0.03)	0.29
	3=Low tertile	-0.13 (0.04)	<.001	-0.13 (0.04)	<.00
s36c	Number of siblings	-0.02 (0.006)	0.003	-0.02 (0.006)	0.00
s314a	Looking after younger relatives; 1=Never (Ref.)	()			
	2=Some days	-0.03 (0.03)	0.327	-0.02 (0.03)	0.58
	3=Most days	-0.13 (0.04)	0.005	-0.12 (0.04)	0.00
s314b	Looking after elderly relatives; 1=Never (Ref.)	0.15 (0.01)	0.005	0.12 (0.01)	0.00
5110	2=Some days	-0.04 (0.03)	0.149	-0.04 (0.03)	0.15
	3=Most days	-0.11 (0.05)	0.017	-0.10 (0.05)	0.02
314e	House cleaning; 1=Never (Ref.)	0.11 (0.05)	0.017	0.10 (0.05)	0.02
55170	2=Some days	0.10 (0.05)	0.051	0.10 (0.05)	0.04
	3=Most days	0.19 (0.05)	<.001	0.19 (0.05)	<.00
2141	Gardening/working in a vegetable gardens; 1=Never (Ref.)	0.19(0.03)	<.001	0.19 (0.03)	<.00
53141		0.08 (0.04)	0.039	0.08 (0.04	0.03
	2=Some days	0.08 (0.04)		· · · · · · · · · · · · · · · · · · ·	
£0	3=Most days	0.06 (0.04)	0.132	0.07 (0.04)	0.11 <.00
58x	Number of times student has repeated classes	-0.08(0.02)	<.001	-0.09(0.02)	
s61x	Student keeps negative company (z-score)	-0.23 8 (0.03)	<.001	-0.23 (0.03)	<.00
116	Kuria East Sub-County			-0.79 (0.09)	<.00
n24a	Boarding status at class 8; 1=Day (Ref.)			0.46 (0.01)	0.02
	2=Boarding			0.46 (0.21)	0.03
	3=Day and boarding			0.46 (0.17)	0.00
n218z	Mean parental contribution 0-10 scale			0.06 (0.02)	0.00
1227z	Mean community school participation: 0-10 scale			0.04 (0.02)	0.01
149a	Mean teacher years since first employment			-0.02 (0.009)	0.01
n432	Number of female teachers			0.04 (0.009)	<.00
n487	Number of graduate teachers			0.07 (0.02)	0.00
15122	Students disallowed from borrowing library books to take home			-0.14 (0.04)	0.00
	Intercept	1.63 (0.20)	<.001	1.40 (0.25)	<.00
Random Efj	fect				
		Model 1 (Stud		Model 2 (Sch	/
		Variance Compon	ient (Std.	Variance Compon	ent (Std.
		Err.)		Err.)	
Student (Le	vel-1), e_{ij}	0.2827 (0.01)		0.2812 (0.009)	
School (Lev	$(el-2), u_j$	0.5659 (0.1	1)	0.0788 (0.0	2)
	xplained (%)				
Student (Le	vel-1), σ_{e}^{2}	0.0721		0.0736	
School (Lev	$rel-2), \sigma_{u}^{2}$	0.0793		0.5664	
Model Fit S	'tatistics				
Deviance		3117		2992	
Akaike Info	rmation Criterion (AIC)	3157		3052	
Bavesian In	formation Criterion (BIC)	3267		3212	
Likelihood	Ratio test vs. OLS Regression Ratio test (Preceding vs. Current Model) 324; Est. = Estimate; Std. Err. = Standard Error (in parentheses); AIC ar	$\gamma^2(01) = 1490$	<.001	γ^2 (2) = 4815	<.00
Likelihood	Ratio test (Preceding vs. Current Model)	$\chi^2(17) = 392$	<.001	$\gamma^{2}(3) = 26$	<.00
T . NT 10	224: Eqt. = Estimate: Std. Err. = Standard Error (in parenthagon): AIC as	J DIC statistics = small	llar in hottor	fit: OIS-Ordinary Ia	

Boarding schools or day schools with a boarding component (often involving Classes 6-8) had a large positive effect of up to 0.46 standard deviation units above the mean. Schools that disallowed their students from borrowing library books and other learning materials for further reading and reference at home ended up disadvantaging those students by up to 0.14 standard deviation units.

DISCUSSION

Student-Level Predictors

The achievement difference between female and male students in Kenya seems to persist in the literature, see for example (Ejakait et al., 2011; Ejakait et al., 2016; Hungi & Thuku, 2010). There are several affirmative action programmes in Kenya targeting female students aimed at bridging this difference. For instance, within the government-funded free tuition package in primary and secondary school, sanitary pads are supplied to school girls who have commenced This is an intervention driven by research menstruation. findings showing that there was menstrual-cycle related school absenteeism among girls which was contributing to lower grades (Crichton, Okal, Kabiru, & Zulu, 2013; Jewitt & Ryley, 2014). Another affirmative action is the often lowering of cutoff points for female students joining university after secondary school. We suggest that a lot more needs to be done to reduce that achievement gap. Our results support the argument that the association between family socio-economic status and students' academic scores continues to grow (Bailey & Dynarski, 2011; Belley & Lochner, 2007; Daniel, 2009; Ejakait et al., 2011; Ejakait et al., 2016; Filmer & Pritchett, 1999; Hungi & Thuku, 2010; Jensen, 2009; Reardon & Bischoff, 2011). In our case, we argue that it appears to be a "double tragedy" that those disadvantaged in wealth are also disadvantaged in KCPE examination. Most of the students with high scores sat their examination in top of the range private schools or in boarding schools, most of which are associated with wealthier households that can afford high school fees and additional levies for improvement of the learning environment. Education in public primary schools in Kenya is subsidized by the Government through tuition fees with parents shouldering the costs of school meals (in non school meal programme schools), uniform and transport among other costs (Ejakait et al., 2016). As expected, keeping the company of negatively behaved students and friends had adverse effects on scores in KCPE. Negative behaviour distracts a student's focus on academic pursuit (Gutman & Vorhaus, 2012; Valiente, Swanson, & Eisenberg, 2012).

The explainable variance at student-level in Table 4 was 0.3548 (35.48%). Student-level variables explained 0.1514 (15.14%) of the variation in student scores in Model-1 across the two levels (Level-1, 7.21% and Level-2, 7.93%). Focussing only at Level-1 while adjusting for the school-level covariates (Level-2) in Model-2, student-level variables explained 0.0736 (7.36%) of the 0.3548 (35.48%) variance available for explanation in the unconditional model in Table 4 leaving up to 0.2812 (28.12%) of the variation unexplained. Future research on student-level variables probably needs to consider other variables beyond those considered in these models.

School-Level Predictors

Our results confirmed Kuria East's low ranking on the merit list for the period 2010-2012 compared with Mumias Sub-County which was ranked in the top 5% percent Sub-Counties for the same period. We argue that a 'culture' of low academic achievement seems to have established itself in Kuria East. The teachers in Kuria East are in many ways similar to those found in Mumias because they attended and trained in similar teacher training colleges and are in similar employment grades. If Free Primary Education (FPE) has helped remove differences in resources and learning materials in schools, and the teachers are largely the same, why would schools in Kuria East post lower student scores compared with those in Mumias? Boarding schools or those with a boarding component within a day school had a positive effect on student scores compared with day schools. Boarding schools certainly have an advantage of "more time for students" over day schools whose students often have to attend to home chores after school. This may eat into their time for private study and completion of homework. There is a move in Kenya towards establishing more day schools at secondary school level because they are cheaper to run compared with boarding schools which are also prone to indiscipline. For instance, within second term (May-August 2016), more than 100 boarding secondary schools in Kenya had reported fire incidences with dormitories or other infrastructure being torched by students for a myriad of reasons that are still under investigation (Ejakait et al., 2016). Schools opened for the last term of the year on 29th August 2016 and already two cases of torched dormitories were reported at Keringet and St. Joseph Kirandich Secondary Schools in Nakuru County on Friday 09 September 2016 (Openda, 2016). Although no boarding primary school had reported any such cases in second or third term, these fire incidences are an indication of the "soft underbelly" that boarding schools are. As already discussed, one of the provisions to schools under FPE is learning materials including text books. In a bid to avoid losses and probable tear and ware, most schools lock up these textbooks and other learning materials which limits student contact with the same. Our results suggest that schools that disallowed borrowing of textbooks and other materials by students for further reading at home ended up disadvantaging their students. Adjusting for covariates at Level-1, school-level predictors explained 0.5664 (56.64%) of the 0.6452 (64.52%) variance available for explanation at that level in the unconditional model in Table 4. Since the two levels and two models explained 64.00% of the variation in student scores, school-level variables (56.64%) can be said to have accounted for a large proportion of the variation seen in student academic achievement in the KCPE examination. This is beyond the range found by other studies using three level models since some of that variation is taken up by teacher or class-levels in such three level models (Hungi & Thuku, 2010). For instance, in Latin American countries, the variance between schools in mathematics achievement among Grades 3 and 5 pupils ranged from 19.5% to 41.2% (Willms & Somers, 2001).

Conclusion and Implications for Policy

With much of the variation in student scores in the KCPE examination explained at the school-level, the predictors of

academic achievement at that level were the County of where the school was located (h16); Boarding status at Class 8 (h24a); and whether or not schools allowed their students to borrow school library books and other learning materials for further study and reference away from school (h5122). At student-level, the predictors were: The sex of the student (s21); Students' Wealth Index (s313x); Students taking up home chores such as looking after younger (s314la) or elderly relatives (s314la), and house cleaning (s314le); and the type of company the student kept (s61x). With differences in achievement between female and male students, we propose strong girl-centred mentorship programmes involving female role models who have succeeded in academic-driven fields to help boost academic performance among female students. Similar programmes have worked in performing arts and music in Kenya and could probably help narrow the gap in education as well. Lifting the lowest wealth tertile out of their current status is a long term undertaking often involving actions at local and macro level. But the fact that there is a persistent association in the literature between socioeconomic status and academic scores demands that short term measures be considered. These could include identifying students in the lowest wealth tertile and making practical interventions aimed at boosting their academic scores. These actions can be at household level, school level, community level and could be escalated all the way to national level. We suggest a resultsoriented stakeholder forum for Kuria East to discuss why the Sub-County has consistently been ranked in the bottom 5% whereas all other variables in the education production function remain much similar with those of Sub-Counties in the top 5%. The forum should suggest radical solutions to reverse this trend. We also suggest that schools should make textbooks and other learning materials a lot more accessible to students as this will encourage further reading and study among them instead of locking this away in safe school cabinets and lockers, only to be used during class time.

Statement of Competing Interests

The authors have no competing interests

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