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Factors affecting Mathematics achievement of first-year secondary school students in Central Uganda

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This study explores the sources of variability in Mathematics achievement of Ugandan students at the student, classroom and school level. The Mathematics score and questionnaire responses of 4,819 first-year secondary school students (Grade Seven, about 14-15 years old) from 78 classrooms of 49 schools were analysed. A three-level linear model was used. The results indicate that out of the total variance in Mathematics achievement 68.8%, 14.2% and 17.0% are situated at student, classroom and school level, respectively. Of all the considered explanatory variables at the three levels, i.e. socio-economic status, gender, prior Mathematics achievement, parental support, peer influence, class mean of prior Mathematics achievement and of students' perception of good classroom assessment, school mean of class climate (class mean of attitude toward mathematics) and of parental support were significant predictors of Mathematics achievement. The relevant factors could explain 7.6%, 73.1% and 84.3%, respectively, of student-, classroom- and school-level differences. Implications of our study are considered.

Keywords: mathematics achievement, multilevel analysis, secondary school, Uganda

Introduction

Mathematics is an abstract subject, yet significant for scientific and technological development in any society. Tella (2008:16) remarked, "its usefulness in science, mathematical and technological activities as well as commerce, economics, education and even humanities is almost at par with the importance of education as a whole". In Uganda, as in most countries, Mathematics is one of the compulsory core subjects in primary and lower secondary levels of education. This is intended to improve mathematical literacy, and steer the country towards economic growth and development. Despite the wide applicability and importance of Mathematics, students consistently perform poorly in the subject, which makes Uganda lose economic advantage over other countries, because its students lag behind their counterparts in Mathematics and Science. Hence, Mathematics achievement (MA) has been a great concern for researchers, policymakers, educators, teachers, parents and students themselves. But, the desired level of MA seems to require a dynamic interplay between student, class/teacher, and school factors. The current study assessed the Mathematics performance of Ugandan students, by means of methods used in educational effectiveness research (EER).

Literature Review

Educational Effectiveness Research (EER) has focused on determining how various aspects of classes and schools are associated with differences in student outcomes. The current study has assessed academic outcome as reflected in student test scores.

While the earliest study of school effectiveness (Coleman, Campbell, Hobson, McPartland, Mood, Weinfeld & York, 1966) reported that school-level factors have little effect on achievement compared to student-level factors, subsequent studies (e.g. Creemers & Kyriakides, 2008; Ma & Klinger, 2000; Mohammadpour, 2012; Opdenakker, Van Damme, De Fraine, Van Landeghem & Onghena, 2002; Rumberger & Palardy, 2004; Scheerens & Bosker, 1997) reported that the school accounts for a sizeable proportion of variability in academic achievement.

The earliest studies could not disentangle the effects of student- and school-level factors (Mohammadpour, 2012). Indeed, Ma and Klinger (2000) have noted the inability of earlier research to accommodate the hierarchical structure of educational data. The important levels must be identified in a multilevel analysis. Researchers such as Van Landeghem, De Fraine and Van Damme (2005) argue that ignoring one or more levels in hierarchical analyses distorts and obscures the real value of the fixed coefficients, variance components and their corresponding standard errors. To avoid such negative repercussions, statistical techniques such as hierarchical linear modeling (HLM) allow researchers to analyse data with a multilevel structure, for instance students nested within classes, and classes nested within schools.

Conceptual model

Several conceptual models (e.g., Creemers, 1994; Rumberger & Palardy, 2004; Scheerens, 1990) have been used in EER. These models describe schooling as a multilevel process in which students' achievement is influenced by student characteristics (e.g., socio-economic status), classroom factors (e.g. classroom learning environment), and school factors (e.g. school resources). These models identify three major components of schooling: inputs, processes and outputs (Mohammadpour, 2012). To study educational effectiveness, Rumberger and Palardy (2004) proposed a multilevel conceptual framework, which portrays the educational process as operating at three levels: student, classroom (class/teacher) and school. Their model identifies two major factors that influence student achievement (output), namely school and classroom inputs and their processes and practices (e.g. classroom assessment). It also suggests that EER can focus on many different educational outcomes, such as MA. Educational effectiveness research (EER) seeks to investigate the extent to which schools and classes contribute to the difference in achievement. Based on a two-level analysis, which dominates most educational literature, and on a meta-analysis of 168 studies, Scheerens and Bosker (1997) found that 19% of variance lies between schools.

Longitudinal research is favoured by educational researchers who wish to study the effects of the factors at different levels upon student outcomes. However, a longitudinal three-level model is rare in developing countries, such as Uganda. There are mostly cross-sectional studies, amongst which a three-level study of Thuku and Hungi (2005) as part of the Southern Africa Consortium for Monitoring Educational Quality (SACMEQ) project. The results of this study showed that about 61.1%, 5.1% and 33.8% of the variance in Kenyan sixth-graders' Mathematics achievement was situated at student, class and school level, respectively.

Student characteristics

Research has shown that a number of individual student characteristics are associated with student outcomes. According to Rumberger and Palardy (2004), these include demographics, family characteristics, and academic background. Mohammadpour (2012) categorises them into socio-economic, personal and attitudinal factors.

Howie (2006) found that family socio-economic status (SES) affects secondary students' performance in Mathematics in South Africa. However, Heyneman and Loxley (1983) argued that in low-income countries, SES makes little difference in academic performance.

Gender also significantly predicts MA. Gender differences in MA have been documented, with boys significantly outperforming girls (e.g. Kaahwa, 2012; Ochwo, 2013). Conversely, Namusisi (2010) has reported girls outperforming boys. However, in a meta-analysis of 100 studies, Hyde, Fennema and Lamon (1990) found no or very small gender difference in MA at the early primary level. But, some researchers (e.g. Hyde, Fennema, Ryan, Frost & Hopp, 1990; Karimi & Venkatesan, 2009; Opolot-Okurut, 2005) indicated that this trend seems to change in secondary school because girls show more Mathematics anxiety than boys.

Age has also been associated with achievement. The Uganda National Examinations Board (2013) reported that the mean scores in Mathematics of younger students in senior two (Grade Eight) were higher than those of their older counterparts within the same class. However, Ayotola and Adedeji (2009) reported that age had an insignificant negative correlation with MA of senior two students.

Studies have found that prior Mathematics achievement (PMA) is a good predictor of student's mathematical success (e.g. Hemmings, Grootenboer & Kay, 2011). Ma (1996) has pointed out that PMA is the single predictor that is statistically significant across all grades.

The consensus among researchers is that parents can exert a positive influence on their children's mathematical performance (e.g., Mji & Makgato, 2006; Wamala, Kizito & Jjemba, 2013). In Uganda, Nsubuga (2008) observed that the role of parents, particularly through Parent-Teacher Association (PTA), was instrumental to students' learning achievement.

Classroom variables

According to Rumberger and Palardy (2004), classroom inputs and processes contribute to student achievement. In EER, class composition was found to positively relate to MA of students between classes (Van Damme, De Fraine, Opdenakker, Van Landeghem & Onghena, 2000). Research has shown that high-ability students perform best when associating with other high-ability peers, while lower-ability students benefit from interaction with students in the middle of the ability distribution (Burke & Sass, 2011).

Classroom learning environment and classroom assessment were among the eight teachers' variables included in the dynamic model for measuring quality of teaching (Creemers & Kyriakides, 2008). Rajoo (2013) has shown that the quality of classroom learning environment is a significant determinant of students' MA. Formative assessment is one of the most important factors associated with effectiveness at all levels (Creemers & Kyriakides, 2008). Stears and Gopal (2010) have proposed interpretative and interactive approaches to assessment.

School variables

School inputs and school processes are important factors that have been examined in EER (Rumberger & Palardy, 2004). School resources, school size and students' SES are considered to be confounding factors that affect MA because parents with full-time jobs and steady income send their children to large schools with more resources (Mohammadpour, 2012). Kyei and Nemaorani (2014) have found school location and type to affect secondary students' Mathematics performance in South Africa, where schools closer to town perform worse, because students are distracted by entertainments, and students in private schools perform better than those in public schools. However, Yusuf and Adigun (2010) found no significant influence of school location and type on achievement.

The relationship of school size to educational outcomes remains controversial, as Slate and Jones (2005) concluded from their literature review that both very small and very large schools are negatively related to educational outcomes.

Rumberger and Palardy (2004) refer to school processes as the teaching practices and social and/or academic climate of schools among other features. In Flanders, an example of an educational system with tracking, Opdenakker and Van Damme (2001) showed that school composition and school processes jointly explain a sizeable amount of student variance in MA at the end of Seventh Grade. However, there is a gap in the international literature about the effects of the school composition and processes within an educational system without tracking, such as that of Uganda.

Research Questions

1. What proportion of the variance in Mathematics achievement in Uganda is situated at the student, classroom and school level?
2. To what extent do student intake-characteristics (SES, gender, age, PMA and parental support (PASUP)) explain the variability in Mathematics achievement?
3. To what extent do class size, class processes (learning environment, assessment, teacher support and peer influence), class climate (class mean of attitude toward mathematics (ATM)), and class composition variables (proportion of girls in the class, class mean of PMA and of PASUP) contribute to the variability in Mathematics achievement, after controlling for student intake-characteristics?
4. To what extent do school structure (type, location and size), school average of class processes and class climate, and school composition variables (school mean of PMA and PASUP) explain the net school effect?

Methodology

Study Sample

Our study used a multistage sampling design. First, four districts in Central Uganda were chosen, including Kampala and Wakiso, which are urban and populated with people from different parts of the country, and Mpigi and Mukono, which are semi-rural but reachable. Secondly, 60 schools were randomly selected from a total of 376 schools in the four districts, with 25 semi-rural and 35 urban schools. These schools followed the same curriculum, but with a variety of learning climate and teacher practices. Thirdly, four, three, two, or all classes were (randomly) selected from schools with five, four, three or less classes, respectively. The sample consisted of 4,819 first-year secondary school students (Grade Seven; about 14-15 years old). They were grouped in 78 classes of 49 schools. Table 1 describes schools and classes in the target and participating sample. Table 2 describes the categories of the participating schools. Table 3 describes the gender of participating students.

Instruments

The instruments used for this study were two Mathematics tests and a student questionnaire. Mathematics tests were administered at the beginning (23 items) and the end (40 items) of school-year 2012. The tests were in multiple-choice format. The student questionnaire was an instrument designed to collect demographic information, students' perceptions of classroom teaching of Mathematics and of teacher, peer and parental support, and attitudinal factors. Most items had to be judged on a five-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree").

Data Collection

For the data collection, schools were contacted by phoning the head teacher or dean of studies or by visiting them personally. These linked the researcher to the head of the Mathematics department. The researcher presented a letter from his supervisor at the Catholic University of Leuven (Belgium) at each school to formally introduce the research project.

At the beginning of the year, the student questionnaire was administered along with the Mathematics test. The researcher and/or his assistants administered the tests and questionnaire to the students with the help of Mathematics teacher(s) during Mathematics class time. The students were assured of confidentiality and that the data collected in the study would only be used for research purposes.

Table 1 Number of schools and sampled classes in target and participating sample

Total no. of classes per school	Target sample		Participating sample	
	No. of schools	No. of selected classes per school	No. of schools	No. of selected classes per school
5	4	4	2	4
4	8	3	6	3
3	8	2	5	2
2	7	2	6	2
1	33	1	30	1
Total	**60**	**103**	**49**	**78**

Table 2 Categories of participating schools

By category		No. of schools
By type	Government	12
	Private	37
By location	Urban	28
	Semi-urban	21
By gender	All boys	2
	All girls	2
	Co-educational	45

Table 3 Participating students' gender profile

	Overall	1st measurement point	2nd measurement point
Boys	2,170 (45%)	2,146 (45%)	1,865 (43.9%)
Girls	2,649 (55%)	2,622 (55%)	2,379 (56.1%)
Total	**4,819**	**4,768**	**4,244**

Measures

Dependent variable

The dependent variable consisted of scores on a mathematics test (α = .75) administered at the end of the year. Each test item was scored 1 if correct or 0 if wrong. The raw scores were converted into ability estimates, using Item Response Theory (IRT). The two-parameter logistic IRT model was used to estimate the item's difficulty and discrimination parameters with computer programme BILOG-MG, which uses multiple expectation-minimisation algorithms (Zimowski, Muraki, Mislevy & Bock, 1996).

Independent variables

Student-level variables

We used principal component analyses to construct SES (α = .76) as a weighted composite index of three variables: parental education (father and mother), parental occupation (father and mother) and home possessions (see Appendix A). The variables were developed from the Student Questionnaire of Programme for International Student Assessment (PISA) 2009. GENDER was a dummy variable coded 0 = boys and 1 = girls. Prior Mathematics achievement (PMA, α = .70) was measured with the Mathematics test taken at the beginning of the year. The PASUP scale (10 items, α = .79) was developed from the Fennema-Sherman Mathematics Attitudes Scale (FSMAS; Fennema & Sherman, 1976).

Classroom-level variables

First, we considered class size. Next, we constructed variables describing the class processes (classroom learning environment (CLEARN, λ = .78), classroom assessment (CLASSESS, λ = .77), mathematics-teacher support (MTSUP, λ = .83), peer influence (PEER, λ = .81) (see Appendix A). CLEARN and CLASSESS were variables modified from the student questionnaire developed and used by Kyriakides, Creemers, Panayiotou, Vanlaar, Pfeifer, Cankar and McMahon (2014) to assess the teaching of Mathematics and science in six European countries. MTSUP and PEER were variables based on FSMAS. The reliabilities of these aggregated variables were calculated using the formula given by Snijders and Bosker (1999:26).

Since ATM is regarded as a multidimensional construct (Hannula, 2002; Tapia & Marsh, 2004), we derived an attitude index from three scales, namely self-confidence and usefulness, based on FSMAS, and enjoyment, modified from the Attitudes Toward Mathematics Inventory (ATMI) (Tapia & Marsh, 2004). This composite index was aggregated to the class level to construct a class climate variable by calculating the class-mean of attitude toward Mathematics (CLATM), whose reliability at the class level was .90. Lastly, we constructed indicators of the class composition variables (proportion of girls in the class (CLGIRLS), class-means of SES (CLSES), class-means of prior Mathematics achievement (CLPMA), and class-means of parental support (CLPASUP).

School-level variables

The school type (SCHTYPE), location and size (number of classes in the school) were used to describe the school structure. The school type (SCHTYPE) was coded 0 = government and 1 = private. In Uganda, affluent parents send their children to 'high performing' rural boarding schools. Based on student questionnaire responses, we constructed a pseudo-location scale (PSELOC), coded 0 = rural-like (schools with low percentage of parents with full-time jobs), and 1 = urban-like (schools with high percentage of parents with full-time jobs). This new categorisation allows us to measure the effect of schools' location combined with school's student body on students' performance. There were 30 urban-like and 19 rural-like schools, located either in urban or rural areas.

The aggregations of the class-level variables yielded the following school variables: average of classroom learning environment (SCLEARN), classroom assessment (SCASSESS), and class climate (SCATM). We constructed the school composition variables by taking the proportion of girls in the school (SCGIRLS), school-mean of SES (SCSES), PMA (SCPMA), and parental support (SCPASUP).

Data Consideration

Missing data

Missing data is inevitably a crucial issue in social research, especially in longitudinal studies. Eleven (18%) schools did not participate in the study. In the participating schools, the percentage missing data on the first and second test were 8.7% and 6.1%, respectively, and on students' family background, perceptions about classroom teaching of Mathematics, and attitudinal variables were 7.1%, 6.6% and 7.9%, respectively.

Assuming that data were missing at random (MAR), where the missingness might depend on other variables in the model, we considered a Full Information Maximum Likelihood (FIML) estimation as an appropriate missing data method (Dong & Peng, 2013). All continuous explanatory variables from the three levels were standardised to z-scores to facilitate the interpretation of the parameter estimates.

Multilevel data analysis

The analyses were performed using SAS software (PROC MIXED command) with the method of FIML. The data were analysed by means of multilevel modeling techniques (Snijders & Bosker, 1999), which take into account the data's hierarchical structure: student, classroom and school. The classroom level combines the class and teacher level since the great majority of classes have a unique mathematics teacher. The multilevel analysis was performed in steps. First, an unconditional model, without explanatory variables, was fitted to estimate the variance at each of the three levels. Second, we included student intake-characteristics in the model: SES, gender, age, PMA and PASUP. Third, we added the class processes and class composition variables. Fourth, we added school structure, average of class processes and school composition variables.

Results

The analysis of the three-level unconditional model revealed that 68.8%, 14.2% and 17.0% of the variance in MA is situated at the student, classroom and school level, respectively (Table 4).

SES, gender, age, PMA and PASUP together accounted for 7.6%, 29.3% and 31.2% of the student-, classroom- and school-level variance in achievement, respectively. These intake-characteristics explained 14.7% of the total variance in MA, and about 10.0% and 11.7% of the total variance was left unexplained at the class and school level, respectively. Except age, they were significant predictors of MA. The results showed that boys significantly outperformed girls.

The exploration of bivariate correlations revealed that most classroom variables were significantly linked to MA (see Appendix B and C). When Model 2 with the class process variables was analysed, the new significant predictors were class mean of students' perceptions of PEER and good CLASSESS. When we fitted a model with the class composition variables as the only predictors at the classroom level (Model 3), a significant predictor was class-mean PMA. The individual characteristics, class processes and class composition together accounted for 68.2% and 79.6% of the classroom- and school-level variance in achievement, respectively (compare Model 4 and Model 0). The high correlations among some classroom characteristics, ranging from -0.33 to 0.65, possibly offer an explanation for having non-significant classroom-level effects in the multilevel models for factors that nevertheless correlate significantly with MA: CLEARN, class climate, MTSUP, proportion of girls in the class and class mean of PASUP. About 28.4% of the total variance was explained, and about 4.5% and 3.5% of the total variance was left unexplained at the classroom and school level, respectively.

Table 5 shows that class processes explained a higher proportion of the variance at both the class and school level than class composition did. Both of them together as well as their overlap explained a higher proportion of the variance at the school level than at the class level.

Table 4 Parameter estimates

Parameter	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	49.65***	51.33***	52.23***	52.45***	52.58***	54.63***	52.44***	52.48***	54.76***
	(1.21)	(1.04)	(0.76)	(0.87)	(0.70)	(1.75)	(0.66)	(0.69)	(1.84)
Student model									
Socioeconomic status (SES)		1.31*	1.26*	1.25*	1.22*	1.23*	1.24*	1.23*	1.23*
		(0.59)	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)
Gender		-2.01***	-1.98***	-1.94***	-1.94***	-1.94***	-1.94***	-1.94***	-1.94***
		(0.43)	(0.43)	(0.43)	(0.43)	(0.43)	(0.43)	(0.43)	(0.43)
Age		-0.40	-0.35	-0.36	-0.32	-0.34	-0.33	-0.33	-0.33
		(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
Prior math achievement (PMA)		2.13**	2.16**	2.13**	2.15**	2.14**	2.14**	2.15**	2.14**
		(0.59)	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)	(0.58)
Parental support (PASUP)		1.86***	1.80***	1.80***	1.79***	1.79***	1.78***	1.78***	1.79***
		(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
Classroom model									
Class learning environment (CLEARN)			0.36		0.09	0.24	2.24	0.11	1.99
			(0.74)		(0.67)	(0.66)	(1.36)	(0.67)	(1.36)
Class assessment (CLASSESS)			3.06**		2.23*	2.54*	1.68	2.40*	1.85
			(1.07)		(0.98)	(0.98)	(1.75)	(0.98)	(1.75)
Math teacher support (MTSUP)			0.32		0.80	0.80	0.02	0.54	0.28
			(1.21)		(1.10)	(1.08)	(1.08)	(1.11)	(1.08)
Peer support (PEER)			2.50*		1.84	1.72	2.96*	2.18*	2.35*
			(1.12)		(1.03)	(1.00)	(1.05)	(1.04)	(1.09)
Class climate (mean ATM) (CLATM)			0.60	-0.99	-1.06	-1.60	-0.65	-1.46	-0.07
			(0.71)	(0.82)	(1.09)	(1.10)	(1.11)	(1.11)	(1.35)
Proportion of girls in class (CLGIRLS)				3.26**	-0.30	0.08	-0.12	-0.20	0.12
				(0.93)	(0.70)	(0.71)	(0.66)	(0.71)	(0.71)
Class-mean PMA (CLMPA)				1.73	2.57**	3.00***	2.48**	2.58*	2.65*
				(0.90)	(0.79)	(0.80)	(0.76)	(1.20)	(1.15)
Class-mean of PASUP (CLPASUP)					1.23	2.11	2.44	3.00	1.36
					(1.28)	(1.33)	(1.31)	(1.92)	(2.10)
School model									
School type (SCHTYPE)						-0.74			-1.28
						(1.51)			(1.51)
School pseudo location						-1.44			-1.05
						(1.39)			(1.38)
School size (SCSIZE)						-1.31			-1.31
						(0.77)			(0.84)
Average of class learning environment							-2.63		-2.18
							(1.39)		(1.40)
Average of class assessment							0.78		0.89
							(1.58)		(1.62)

Parameter	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Average of class climate							-2.05		-3.67*
							(1.05)		(1.77)
School-mean PMA (SCPMS)								-0.21	0.47
								(1.38)	(1.38)
School-mean PASUP (SCPASUP)								-1.75	2.50
								(1.56)	(2.50)
Variance components									
Student variance	173.22	160.02	160.04	160.10	160.10	160.10	160.12	160.10	160.13
Class variance	35.70	25.23	14.19	15.89	11.36	11.10	9.90	11.13	9.60
School variance	42.83	29.45	12.14	17.37	8.72	7.49	7.46	8.30	6.74
Fit statistics									
-2 Log Likelihood	34157.4	33800.8	33752.6	33768.1	33737.0	33732.8	33728.2	33734.8	33724.9

Note: Standard errors are in parentheses; * significant $p < 0.05$; **significant $p < 0.01$; ***significant $p < 0.001$.

Table 5 Additional variance explained by class processes and composition, plus overlap

Variables	Level	
	Class	School
Class processes	43.8%	58.8%
Class composition	37.0%	41.0%
Class processes and composition	55.0%	70.4%
Overlap	25.8%	29.4%

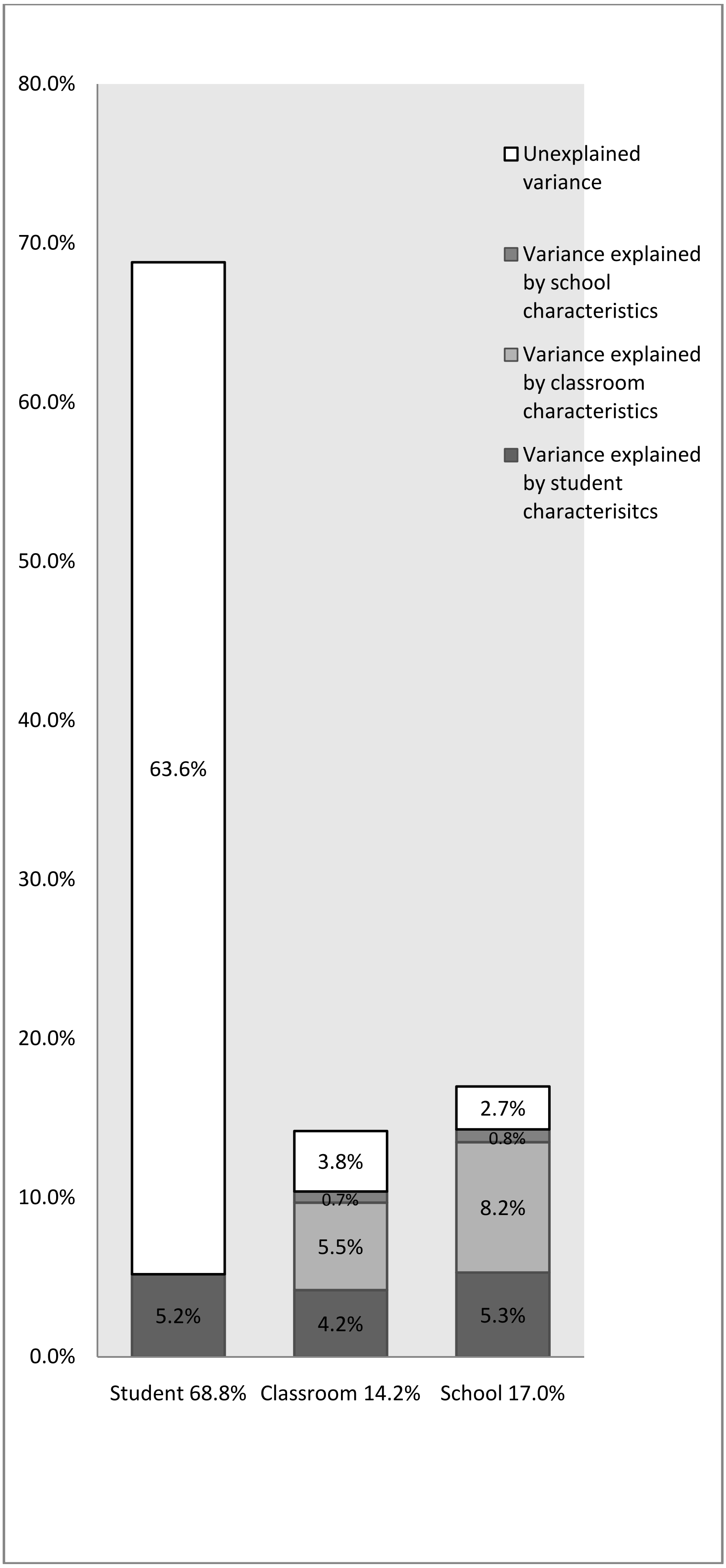

Figure 1 Variance in Math achievement explained by student, class and school characteristics

The exploration of school characteristics individually by means of bivariate correlations revealed that most of their effects were small and non-significant (see Appendix C). The school-averages of two class processes (SCLEARN and SCATM) were significant. When controlling for the student intake characteristics and classroom variables, and considering groups of school characteristics, school resources (type, location and size), school-averages of the class processes, and the school composition variables could explain 14.1%, 14.4% and 4.8% of the school-level variance, respectively (compare Model 4 and 5; Model 4 and 6, and Model 4 and 7). When considering all the variables together, SCATM was a significant predictor. All student, classroom and school variables together accounted for 73.1% and 84.3% of the classroom- and school-level variance, respectively. The school variables together could explain an extra 22.7% of the school-level variance in MA. About 29.9% of the total variance in MA was explained, and about 2.7% of the total variance was left unexplained at the school level.

Our results show that when all the relevant variables at the three levels are included in the model, about 10.4% and 14.3% of the total variance is explained at the classroom and school level, respectively (Figure 1). Also, at least in this study, between-school differences are explained mainly by classroom characteristics.

Discussion and Conclusion

In this study, we explored the variability in MA of secondary school students in Central Uganda as a function of student-, classroom- and school-level factors. The use of the model of Rumberger and Palardy (2004) helps to see the decomposition of the variances at the three levels. The results show that the variation in MA was mostly between students (68.8%). This is partly due to intake differences. Considering the selection of schools from urban and semi-urban regions, and that there is neither tracking nor ability grouping in Grade Seven in Uganda, 14.2% and 17.0% of the classroom- and school-level variance, respectively, indicate a relative heterogeneity of schools and, in cases with more than one class per school, also between classes within schools in Central Uganda.

Similar to the findings of Howie (2006), students from higher SES families in Central Uganda tend to achieve significantly better at Mathematics than those from lower SES families. Literate and well-to-do Ugandan parents generally provide increased resources and educational support. These parents are able to settle their school fees on time. Students from poor families may not find fees easily, resulting in higher absenteeism and, consequently, poorer performance amongst these students (Heyneman & Loxley, 1983; Ochwo, 2013).

As for gender, the results concur with one Ugandan study that showed that in Mathematics, boys perform better than girls (Ochwo, 2013). However, they are inconsistent with the observation of Namusisi (2010) that girls outperform boys in primary schools, and that nevertheless teachers themselves are surprised if a girl performs excellently in the subject, because traditionally the girls have been taken to be poor in Mathematics. A possible explanation for the gender difference in MA is included in research by Ochwo (2013), who contends that gender-based tasks hamper academic achievement. For instance, girls especially in day schools in rural areas are given domestic duties, unlike boys. Such duties include fetching water from the well, collecting firewood, cooking, cleaning dishes, taking care of the younger siblings and elderly family members. Consequently, they have less time to do their homework, or to revise class notes. And they may even be forced to miss days of school in order to attend to these home duties. Generally, boys have less domestic tasks and thus more time to focus on their academic work. For Opolot-Okurut (2005), boys perform better than girls mathematically as a result of their higher and positive attitude scores. According to Kaahwa (2012), the factors that may contribute to the underperformance of girls include corporal punishment, sexual harassment, no teacher support, the abstract nature of Mathematics, Mathematics being considered as a male domain and lack of female role models.

Consistent with Hemmings et al. (2011) and many other studies (e.g. Ma, 1996), previous MA is important in paving the way for future achievement. Students who have high MA in primary schools will mostly perform well in secondary-level Mathematics. Primary school teachers have the mandate to provide quality Mathematics instruction so that students can attain a high level of proficiency in primary and secondary schools.

The results show that parental support is associated positively with students' performance in Mathematics. This can be realized through payment for extra tuition, buying textbooks, encouragement to work hard, involvement in activities such as attending Parent-Teacher Association meetings, helping with homework, and counseling. The findings of Wamala et al. (2013) reveal that the difference in the father and mother's education levels explains the difference in each one's support for their children's achievement. Although parental support is important for students' achievement, it is still generally low, especially in the rural areas. As observed by Mji and Makgato (2006), students' MA will improve if parents allocate time for homework and monitor it. But, illiteracy and poverty need to be overcome so as to have parents involved in children's education.

We found that the addition of class composition variables to the model with class processes caused a decline in the effect of class processes. This is because a percentage of explained variance at classroom level is a result of the joint effect of characteristics of class processes and class composition. A significant contribution to the international research literature is that both class processes and composition are important in explaining the variance in MA at the classroom, but also at the school level, and that the net effect of class processes is larger than that of class composition. The classroom characteristics explain an important part of the school-level variance. In EER, it has indeed been shown that class-level characteristics have greater impact on students' achievement than school-level variables (Teddlie & Reynolds, 2000).

We observe students' aggregated perceptions of classroom formative assessment (FA) to be a significant part of the teaching/learning process and its effects. Students appreciate the positive and constructive feedback from their teachers. As FA occurs concurrently with instruction, it provides teachers feedback to modify their teaching strategies and students to actively be involved in their own learning. Like influential coaches, the best mathematics teachers recognise the importance of ongoing feedback from assessments as the means for students to improve their performance in Mathematics. However, feedback will only enhance learning if it is provided early and often. Formative Assessment (FA) should help teachers diagnose and monitor students' academic needs and offer timely feedback so as to gain a holistic understanding of learning that occurs in classrooms (Stears & Gopal, 2010).

In agreement with Burke and Sass (2011), students perform better when they are positively influenced by their classmates and/or schoolmates. Kaahwa (2012) found peer support to manifest in form of study groups, discussion, advice and encouragement. Girls especially want co-operative and discovery modes of learning. In other words, they prefer constructivist methods, which encourage group work. Mathematics teachers need to create a classroom culture where students positively support each other for their improvement in mathematics performance.

As shown by Yusuf and Adigun (2010), school type and location are not significantly related to achievement after controlling for student-level characteristics. This indicates that it makes no difference whether a student goes to aprivate or government, and urban-like or rural-like school.

This study had some limitations. Though student ratings provide valuable information to measure quality of Mathematics teaching, this could potentially be a source of inaccuracy and/or bias. Data from teachers or from observers about the teaching-learning process could also be informative. Secondly, measured variables at the class and especially at the school level might have been insufficient to explain school and classroom effectiveness.

Nevertheless, our study has some strengths, including: longitudinal data was used, and school categories by type, location and size were considered. In applying Rumberger and Palardy's (2004) model as a three-level analysis approach, the effects of the predictors of MA of secondary school students were analysed at student, classroom and school level.

Future research is needed to assess the performance of boys and girls in the different areas of Mathematics, so as to squarely address the mathematics gender-gap. Also, a structural equation modeling path analytic approach can be adopted to assess the direct or indirect impact of variables on MA and to develop a fuller understanding of the nature and quality of Mathematics teaching and learning in the Ugandan secondary education context.

The large percentage of variance left unexplained at the student level implies that there are important factors that influence students' MA, which were not considered in this study. Hence, future research should include other student-level factors (e.g., time spent on homework, textbook ownership). This is also the case for other levels: several classroom processes (e.g., teaching practices; Rumberger & Palardy, 2004) and school processes (e.g., educational leadership and orderly atmosphere; Scheerens & Bosker, 1997) were lacking in our study.

Reasons behind the demonstrated gender-gap need to be explored by policy makers, school heads, Mathematics teachers and parents, so as to diminish gender-based achievement differences. Hence, these stakeholders must employ strategies/interventions to promote gender parity in education in support of educational, social and economic growth and development of the country.

Our study has demonstrated that student intake-characteristics play a role in students' MA in Uganda. Though these characteristics are generally outside government control, the results still warrant government's consideration. The Ministry of Education and Sports should sensitise parents about the value of children's education and their role of involvement, especially in attending Parent-Teacher meetings. School administrators should provide incentives for teachers to attend seminars, workshops, conferences and in-service training to acquire effective formative assessment skills, especially of providing high quality feedback on student work.

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Appendices

Appendix A: Scales and Items

Section about family background

Note: Questions for the mother were the same as for the father.

What is your mother (female guardian) currently doing? (*Please tick only one.*)
Working full-time for .... _ 4
Working part-time for .... _ 3
Not working, but looking for a job .... _ 2
Other (e.g. home duties, retired) .... _ 1

If your mother (female guardian) is working, what is her main job? (*Please tick only one.*)
House wife .... _ 1 Farmer/peasant .... _ 2 Business .... _ 3 Professional .... _ 4

Which of the following did your mother (female guardian) complete at school? (*Please tick as many as apply.*)
Primary .... _ Institute .... _ University .... _
Senior secondary .... _ College .... _ None .... _

Does your mother (female guardian) or father (male guardian) have any of the following qualifications? (*Please tick as many as apply for any of the persons.*)

	Mother (female guardian)	Father (male guardian)
Certificate (Primary)	--	--
Certificate (Secondary)	--	--
Diploma	--	--
Bachelor's degree	--	--
Master's degree	--	--
Doctorate	--	--
None	--	--
I don't know	--	--

Which of these do you have at your home? (*Please tick as many as apply.*)
Phone .... … _ Television .... _ Computer .... _ Motorcar .... _

In the following sections, two representative items of each scale used are given:

Section about the teaching of mathematics

Please indicate your opinion about the teaching of mathematics in your classroom. Response format: 5-point Likert scale:
1 = Never 2 = Rarely 3 = Sometimes 4 = Often 5 = Almost always

Classroom as a learning environment: high score = good and low score = poor
1. Our teacher encourages us to work together with our classmates during lessons.
2. Our teacher makes us feel that we can ask him/her for help or advice if we need it.

Classroom assessment: high score = good & low score = poor
1. A few days before the test, my teacher gives us similar exercises to those that will be in the test.
2. When we go over our homework, our teacher finds what we had problems with and helps us to overcome these difficulties.

Section about teacher, peer and parents support

Items marked with the symbol '(-)' were inverted. Response format: 5-point Likert scale
1 = Strongly disagree 2 = Disagree 3 = Undecided 4 = Agree 5 = Strongly agree

How do you agree with the following statements about your math teacher?
1. My math teacher has made me feel I have the ability to go on in math.
2. Getting a math teacher to talk to me about math has usually been a problem. (-)

How much do you agree with the statements about your peer?
1. My classmates have encouraged me to take math at all levels.
2. My friends think taking math is a waste of time. (-)

How much do you agree with the statements about your parents?
1. My father has strongly encouraged me to do well in math.
2. My mother has shown no interest in whether I take more math courses. (-)

Section about student's attitude toward math used to construct class climate
How much do you agree with the statement describing your confidence in math?
1. I have a lot of self-confidence when it comes to math.
2. Math does not scare me at all.

How do you agree with the following statements about the usefulness of math?
1. I study math because I know how useful it is.
2. Math will not be important to me in my life's work. (-)

How much do you agree with the following statements describing your enjoyment of math?
1. Math is enjoyable and stimulating to me.
2. I find hard to solve mathematical problems. (-)

Appendix B: Means, Standard Deviations and Inter-correlations among Predictors and Dependent Variable

Table B1 Student-level predictors and mathematics achievement for total sample (N = 4,768)

	SES	GENDER	AGE	PMA	PASUP	MA
SES	1					
GENDER	-.079**	1				
AGE	-.123**	-.195**	1			
PMA	.077**	-.086**	-.100**	1		
PASUP	.159**	.069**	-.165**	.141**	1	
MA	.380**	-.129**	-.107**	.372**	.227**	1
MEAN	47.80	-	14.18	50.00	83.25	51.21
SD	21.53	-	1.27	10.00	14.89	16.24

Note: ** = significant $p < 0.01$; *SD* = standard deviation.

Table B2 Classroom-level predictors and mathematics achievement for the class sample (N = 78)

	1	2	3	4	5	6	7	8	9	10	11
1. CLEARN	1										
2. CLASSESS	.566**	1									
3. MTSUP	.233**	.547**	1								
4. PEER	.336**	.488**	.536**	1							
5. CLIMA	.249**	.501**	.654**	.638**	1						
6. CLSIZE	.083**	.260**	.318**	.507**	.303**	1					
7. CLGIRLS	.037*	-.074**	.041**	.053**	.047**	-.123**	1				
8. CLSES	.273	.426**	.470**	.437**	.382**	.313**	-.029**	1			
9. CLPMA	.347**	.557**	.442**	.541**	.359**	.477**	-.328**	.542**	1		
10 CLPASUP	.376**	.612**	.185**	.383**	.303**	.252**	-.323**	.315**	.504**	1	
11. MA	.243**	.386**	.240**	.275**	.213**	.195**	-.221**	.263**	.484**	.412**	1
MEAN	77.53	73.79	73.07	71.71	78.34	66.52	55.81	65.60	50.03	83.37	51.21
SD	3.96	4.62	4.90	4.93	4.33	16.48	18.04	8.10	3.70	5.44	16.24

Note: ** = significant $p < 0.01$; * = significant $p < 0.05$; CLIMA= class climate; CLSIZE = class size; CLPASUP = class-mean parental support.

Table B3 School-level predictors and mathematics achievement for the total school sample (N = 49)

	1	2	3	4	5	6	7	8	9	10	11
1. SCHTYPE	1										
2. SCPER	-.207**	1									
3. SCSIZE	-.065	.321**	1								
4. SCLEARN	.056	.126**	.487**	1							
5. SCASSESS	-.006*	.264**	.041**	.070**	1						
6. SCLIMA	-.218	.304**	.406**	.367**	.186**	1					
7. SGIRLS	.141**	-.012**	.355**	.153**	.054**	.084**	1				
8. SCSES	-.111**	.288**	.131**	-.077**	-.108**	.219**	-.456**	1			
9. SCPMA	.000	.350**	.432**	.288**	.226**	.325**	-.314**	.530**	1		
10. SCPASUP	-.128	.488**	.580**	.373**	.410**	.601*	.107**	.297**	.560**	1	
11. MA	-.055**	.136**	.177**	.080**	.088**	.213**	-.202**	.402**	.438**	.288**	1
MEAN	-	-	2.18	77.54	73.77	78.27	54.00	47.83	50.02	83.36	51.21
SD	-	-	1.55	3.64	4.10	3.54	17.78	7.69	3.30	4.98	16.24

Note: ** = significant $p < 0.01$; * = significant $p < 0.05$; SCPER = percentage of parents with full-time job; SCSIZE = school size; SCLIMA = average of class climate; SGIRLS = proportion of girls in the school.

Appendix C: Parameter Estimates of Models with Individual Variables

Parameter	Model 1a .... f	Model 2 a .... j	Model 3 a i
Student model			
Socio-economic status (SES)	1a) 3.50*** (0.22)	SES	SES
Gender	1b) -1.82*** (0.44)	Gender	Gender
Age	1c) -0.51* (0.22)	Age	Age
Prior math achievement (PMA)	1d) 3.52*** (0.22)	PMA	PMA
Parental support (PASUP)	1e) 2.05*** (0.22)	PASUP	PASUP
Class model			
Class size (CLSIZE)		2a) 1.24 (1.24)	------------------------------
Class learning environment (CLEARN)		2b) 2.82** (0.77)	CLEARN
Class assessment (CLASSESS)		2c) 4.56*** (0.66)	CLASSESS
Math teacher support (MTSUP)		2d) 4.27*** (0.70)	MTSUP
Peer influence (PEER)		2e) 4.53*** (0.88)	PEER
Class climate (class mean of ATM) (CLATM)		2f) 2.59** (0.80)	CLATM
Proportion of girls in the class (CLGIRLS)		2g) -1.87 (0.99)	CLGIRLS
Class-mean SES (CLSES)		2h) 0.98 (0.93)	------------------------------
Class-mean PMA (CLPMA)		2i) 4.48*** (0.77)	CLPMA
Clean-mean parental support (CLPASUP)		2j) 3.66*** (0.83)	CLPASUP
School model			
School type (SCHTYPE)			3a) 0.07 (1.66)
School pseudo-location (PSELOC)			3b) -1.57* (1.51)
School size (SCSIZE)			3c) -1.38 (0.83)
Average class learning environment			3d) -2.47* (1.18)
Average class assessment			3e) -1.88 (1.27)
Average class climate			3f) -2.16* (1.07)
Proportion of girls in the school (SGIRLS)			3g) 3.84 (2.37)
School-mean PMA (SCPMA)			3h) -1.12 (1.23)
School-mean parental support (SCPASUP)			3i) -1.89 (1.38)

Notes:
1. Standard errors in parentheses; *significant $p < 0.05$; **significant $p < 0.01$; ***significant $p < 0.001$.
2. Significance levels of classroom variables are estimated after controlling for student intake characteristics.
3. Significance levels of school variables are estimated after controlling for student intake characteristics and classroom variables.