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Building Mathematics-Achievement Models for Developed and Developing Countries: An Application of SAS® to Large-Scale, Secondary Data Management and Analysis

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ABSTRACT

Using TIMSS 2003, a large-scale international achievement assessment database, this study aims to demonstrate (1) how to use SAS for managing, manipulating, and analyzing complex large-scale secondary data and (2) how to apply multilevel models through SAS PROC MIXED to build models that investigate correlates of math achievement in developed and developing countries. Specifically, by constructing separate multilvel models for individual countries, this study provides strong evidence that the same statistical models worked differently across developed and developing countries. In this respect, this study highlights the importance that policy makers and educators from developing countries should not base their educational decisions and educational reform projects solely on research findings of developed countries. Rather, they need to use their country-specific findings to support their educational decisions. This study, therefore, has important practical and methodological implications. Practically, applied researchers can directly use or adapt the easy-to-follow yet innovative SAS codes provided in this paper to manage and manipulate other existing large-scale secondary data. Methodologically, this study provides a framework for investigating the effects of contextual factors on students' math achievement across countries.

INTRODUCTION

Students' mathematics achievement is often associated with future economic power of a country (Baker & LeTendre, 2005; Wobmann, 2003). Thus, the desire to build an effective educational model that can improve students' math achievement has been commonly shared among national leaders and policy makers, as well as educators around the world. In 2007, there were more than 60 countries participating in the Trends in International Mathematics and Science Study (TIMSS, 2007). It was hoped that the rich and timely data provided by the TIMSS will help participating countries to better understand their current educational status relative to those of other countries as well as to identify factors that can boost their students' math achievement.

Unfortunately, despite the fact that the TIMSS database was made publicly available by the National Center for Education Statistics (NCES) for educational research purposes, only a limited number of researchers made use of these data. Hahs-Vaughn (2005) and Moriarty et al. (1999) suggested two reasons for the under use of existing databases such as the TIMSS: (a) large-scale secondary data are often complex and (b) many researchers lack sufficient skills to be able to manage, manipulate and analyze large-scale data.

Another major issue that contributes to the ineffective use of large-scale international achievement data relates to bias in inclusion of countries in research studies of international student achievement. It has been noted that a vast majority of research studies of international student achievement tended to focus on only developed countries such as Japan, Canada, and the United States and care less about developing countries such as Chile and South Africa. As a result, research findings related to students' math achievement have been based mostly on students in developed countries. Consequently, the lack of research findings related to students' math achievement in developing countries has led many of these countries to base their policy decisions and even educational reform projects on research findings and educational models of other developed countries (Riddell, 1997). Such bases are problematic because countries differ in characteristics and a model that works in a developed country may not work in a developing country (Delaney, 2000).

Therefore, in order to address these issues and promote more effective use of large-scale international achievement databases such as the TIMSS, it is vital that researchers include a more diverse sample of countries (i.e., both developing and developed countries) in their studies and more importantly, have access to examples of how to manage, manipulate, and analyze these complex yet important data.

PURPOSE

This study has two major purposes: (1) to demonstrate how to use SAS for managing and manipulating complex large-scale secondary data. Examples of easy-to-follow yet innovative SAS codes will be provided, and (2) to apply multilevel models through SAS PROC MIXED to investigate correlates of math achievement in developed and developing countries.

METHOD
DATA SOURCE AND SAMPLE
The Trends in International Mathematics and Science Study (TIMSS) 2003 database maintained by the National Center for Education Statistics (NCES) will be used in this study. The TIMSS 2003 database comprises student achievement data in mathematics and science as well as student, teacher, school, and curricular background data for 48 countries at eighth grade (Martin, 2005). For this study, data related to eighth-grade students from five developed and five developing countries were selected from the TIMSS 2003 database. Two criteria were applied in the selection of countries. First, all the countries in the TIMSS 2003 database were stratified into two categories: developed countries and developing countries. The World Bank's (2003) official list of developing countries was used for determining country categorization (http://www.worldbank.org/).

VARIABLES
The dependent variable was O*verall Mathematics Score,* a composite variable of five sub-topic scores: *Algebra*, *Number*, *Geometry, Measurement,* and *Data.* The independent variables consisted of three student-level variables and three teacher- and school-level variables. The student-level variables were: *self confidence in mathematics, valuing mathematics*, and *time on mathematics homework.* The teacher- and school-level variables were: *mean activities in math lessons*, *class size,* and *school resources*. These were composite variables and could be precisely defined by using existing variables in the TIMSS 2003 database.

DATA MANAGEMENT
Once the 10 countries were selected, further managing and screening of the data will be needed in order to perform subsequent statistical analyses. Figure 1 displays a flowchart for this data management process.
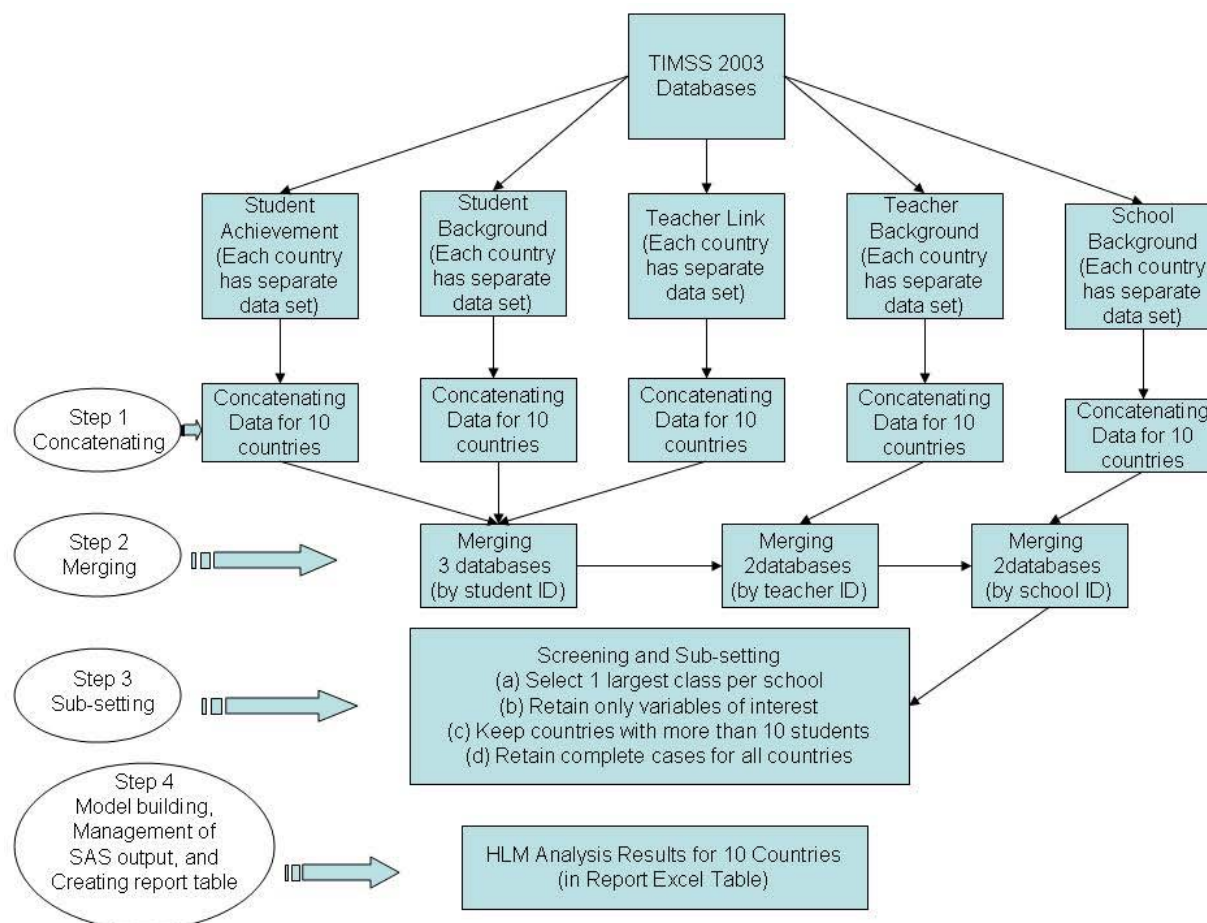

Figure 1. Flowchart for TIMSS 2003 data management

MODELS
Because the TIMSS 2003 data are reported for students nested in classes where there is one class sampled for each selected school, the analysis of the data was accomplished by the use of multilevel models through SAS PROC

MIXED, a multilevel multiple regression technique (also known as hierarchical linear modeling or HLM) useful in analyzing nested data (Littell, Milliken, Stroup, Wolfinger & Schabenberger, 2006; Raudenbush & Bryk, 2002). In order to proceed with multilevel models, the number of levels in the data needs to be specified and models need to be constructed. The TIMSS 2003 data are best described in two levels: student level (level 1), and school and teacher level (level 2). Level 1 is represented by student background variables (i.e., *self confidence in mathematics, valuing mathematics*, and *time on mathematics homework*) which are unique across students. Level 2 is represented by *instructional practices, teacher background* and *school background* variables (i.e., *mean activities in math lessons, class size,* and *school resources)* because each school has only one mathematics class sampled.

For each of the 10 countries, three models were constructed to represent level 1 and level 2 of the TIMSS 2003 data. The first model is the baseline or unconstrained model which has no level 1 or level 2 variables. The regression equation is as follows.

$$Y_{ij} = \beta_{0j} + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

where Y_{ij} is Mathematics score of student i in school j.

        β_{0j} is regression intercept of school j.

        γ_{00} is the overall average mathematics score for all schools.

        u_{0j} is the random effect of school j.

        r_{ij} is the random effect of student i in school j.

The second model is the level 1 model which includes all the student-related variables, i.e., student back ground and home resources variables.

$$Y_{ij} = \beta_{0j} + \beta_{1j}Homework_{ij} + \beta_{2j}Valuing_{ij} + \beta_{3j}Confidence_{ij} + r_{ij}$$

$$\beta_{pj} = \gamma_{p0} + u_{pj}$$

where   *p* = 0, 1, 2, 3.

        $Y_{ij}, \beta_{0j}, \gamma_{00}, u_{0j}$, and r_{ij} are as defined in the Baseline Model above.

        β_{1j} to β_{3j} refer to regression slopes of school j

        γ_{p0} refer to the level 2 fixed effects

        u_{pj} refer to the level 2 random effects.

The third model is the level 2 model which includes all the level-1 model variables plus all the level-2 variables, i.e., teacher background and school background variables. The purpose of the level-2 models is to examine the effect of the teacher and school-related factors as well as possible interactions of these variables on eighth-grade students' mathematics achievement in each country.

$$Y_{ij} = \beta_{0j} + \beta_{1j}Homework_{ij} + \beta_{2j}Valuing_{ij} + \beta_{3j}Confidence_{ij} + r_{ij}$$

$$\beta_{pj} = \gamma_{p0} + \gamma_{p1}Resources + \gamma_{p2}Activities + \gamma_{p3}ClassSize + u_{pj}$$

where   *p* = 0, 1, 2, 3.

        $Y_{ij}, \beta_{0j}, \gamma_{00}, u_{0j}$, and r_{ij} are as defined in the Baseline model above.

        β_{1j} to β_{3j} and u_{pj} are as defined in the Level 1 models.

        γ_{p0} to γ_{p10} refer to the level 2 fixed effects.

EXAMPLES OF SAS CODE

Examples of SAS code are presented in four major steps: (1) Concatenating data, (2) Merging data, (3) Sub-setting data, and (4) Model building, management of SAS output, and creating report tables.

In Step 1 (Concatenating data), student background data from 10 countries of interest were specified. The 10 data sets then were concatenated using two sorting variables: IDCNTRY (i.e., country ID) and IDSTUD (i.e., student ID), and the macro *"doit"*. For this study, this step was repeated five times for five different databases (see Step 1, Figure 1).

For Step 2 (Merging data), the three databases (i.e., student achievement, student background, and teacher link) were merged together using the linking variable IDSTUD (i.e., student ID). This step was replicated three times (see Step 2, Figure 1), using three different linking variables (student ID, teacher ID, and school ID) in order to merge all the five databases together.

Step 1: Concatenating	Step 2: Merging
| ```
* This program joins SAS data sets of
selected countries into one SAS data set;

* Insert selected countries ;
%let cty = AUS CAN CHL EGY ENG IRN RUS SVK
USA ZAF;

* Insert the file type (BSG = student
background data);
%let type = BSG ;

* Insert the sorting variables ;
%let sortvar = IDCNTRY IDSTUD ;

* Insert the path ;
libname libdat "C:\TIMSS03
Analysis\Converted Data\Stsbackground";

%macro doit;
data &type.STSM3;
 set
  %let i = 1;
  %do %while(%length(%scan(&cty,&i)));
  %let ccode = %lowcase(%scan(&cty,&i));
    libdat.&type.&ccode.M3
  %let i = %eval(&i + 1);
  %end;

proc sort data=&type.STSM3
         out = libdat.&type.STSM3;
  by &sortvar;
run;
%mend doit;
%doit;
``` | ```
libname mysas 'C:\TIMSS03
Analysis\Converted Data\Jointdata';

* Merge 3 database (sts achievement, sts
background,& teacher link using linking
var IDSTUD. Joint file name: mysas.idstud;

data ach;
 set mysas.bsatenm3;
proc sort;
  by idcntry idstud;

data stsbk;
 set mysas.bsgstsm3;
proc sort;
  by idcntry idstud;

data link;
 set mysas.bstlinm3;
 if matwgt ne 0; *to use only students and
math teachers;

proc sort;
   by idcntry idstud;
run;

data mysas.idstud;
 merge ach stsbk link;
 by idcntry idstud;
run;
``` |

The purpose of Step 3 was to identify schools that randomly sampled more than one class per school, and the number of students in each of these classes. Next, in each school, the class with the largest number of students was retained. A new SAS data set was then created containing data of all 10 countries, with each school had one class.

Step 4 is related to HLM model building, management of SAS output, and creation of result tables in Excel using SAS macro. First, in order to reduce the file size of the data set that would be used for subsequent HLM analyses, a subset of the data obtained in Step 3 was created in the plain text format (i.e., .txt) that contained only variables of interest. Next, the macro "*hlm*" allowed for the same multilevel models to be conducted for each of the 10 countries separately. Especially, the ODS options of SAS PROC MIXED were embedded in the macro in order to output parameters of interest (i.e., covariance parameters and fixed effects parameters) for each multilevel model by country. This is a unique feature of the macro because it saves us considerable time searching for the statistics we

wanted in the many output result pages. Finally, these parameters data set were concatenated across models and countries before they were exported to excel tables for the purpose of reporting results.

In analyzing large-scale, secondary data, it is important to include sampling weights which were designed to account for complex survey design (i.e., unequal probability sampling). However, at the time this paper was written, the option of including sampling weights was not available in SAS PROC MIXED. Thus, the results of this study should be interpreted within this limitation.

Step 3: Sub-setting	Step 4: Model Building, Management of SAS Output, and Creating Report Tables

```
* Retain one largest class per school;

libname mysas 'C:\TIMSS03
Analysis\Converted Data\Jointdata';

data one;
 set mysas.tenfinal;
 if idteach=. then delete;

proc freq data=one;
tables IDCNTRY*IDSCHOOL*IDTEACH/LIST;

* Create a new variable classsnum. Then of
all the classes, select the one with
largest number of students;

proc sort data=one;
by idcntry idschool idteach;

proc means data=one noprint;
by idcntry idschool idteach;
var bsmmat;
output out=class n=classnum;
title 'Listing of students by teacher';

proc sort data=class;
by idcntry idschool classnum;

*Create SAS data set with 1 class/school;

data mysas.oneclass;
set class;
by idcntry idschool classnum;
if last.idcntry or last.idschool;

*Merging tenfinal and oneclass;

data two;
set mysas.tenfinal;
proc sort;
   by idcntry idschool idteach;

data three;
 set mysas.oneclass;
proc sort;
   by idcntry idschool idteach ;

data mysas.newtenfinal;
 merge two three;
 by idcntry idschool idteach;
run;
```

```
Options pageno = 1;

Title 'HLM Analysis';

Data one;

infile 'C:\TIMSS03 Analysis\Converted
Data\Jointdata\subten.txt';

input @1 bsmmat 6.2 @8 bsmfns 6.2 @15
bsmalg 6.2 @22 bsmmea 6.2 @29 bsmgeo 6.2
@36 bsmdap 6.2 @43 btdmtoov 5.2 @49
btdmtonu 5.2 @55 btdmtoal 5.2 @61 btdmtome
5.2 @67 btdmtoge 5.2 @73 btdmtoda 5.2 @79
btdmstud 3. @83 btdmlt 3. @87 btdmh 3. @91
bcdmst 3. @95 btdgmhy 6.2 @102 btdgmpt 5.2
@108 bsdmscl 3. @112 bsdmsv 3. @116 bsdmhw
3. @120 bsbmexto 3. @124 BSBGPS01 3. @128
BSBGPS02 3. @132 BSBGPS03 3. @136 BSBGPS04
3. @140 BSBAAML 3.2 @144 IDCNTRY 4. @149
ISOCODE $ 3. @153 IDSCHOOL 8. @162 IDCLASS
8. @171 IDTEACH 8. @180 IDLINK 8. @188
IDSTUD 8. @ 198 ITSEX 3. @202 classnum 3.;

if classnum >=10;

*Flip and recode item values so 0=low and
2=high;

BSDMHW = 3-BSDMHW;
BSDMSV = 3- BSDMSV;
bsdmscl= 3-bsdmscl;
btdmstud = 4-btdmstud;
BSBAAML = 4-BSBAAML;
bcdmst = 3-bcdmst;
```

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Step 4 (Cont. 1)	Step 4 (Cont. 2)

```
* Subsetting data two into 10 datasets,
one for each country;

Data AUS;
set one; if ISOCODE = 'AUS';
Data CAN;
set one; if ISOCODE = 'CAN';
Data CHL;
set one; if ISOCODE = 'CHL';
Data EGY;
set one; if ISOCODE = 'EGY';
Data ENG;
set one; if ISOCODE = 'ENG';
Data IRN;
set one; if ISOCODE = 'IRN';
Data RUS;
set one; if ISOCODE = 'RUS';
Data SVK;
set one; if ISOCODE = 'SVN';
Data USA;
set one; if ISOCODE = 'USA';
Data ZAF;
set one; if ISOCODE = 'ZAF';
run;

%macro hlm (data);

*ods output of proc mixed to SAS datasets:
 cov=covariance parameters, fixed=solution
for fixed effects;

proc mixed data= &data covtest noclprint;
class IDSCHOOL;
model bsmmat = / solution;
random intercept / sub = IDSCHOOL;
ODS Listing exclude solutionf;
ods output covparms=cov1_&data
solutionf=fixed1_&data;
Title2 'Model 1: Unconditional';
run;

proc mixed data= &data covtest noclprint;
class IDSCHOOL;
model bsmmat = BSDMHW BSDMSV bsdmscl /
solution;
random intercept BSDMHW BSDMSV bsdmscl/
sub=IDSCHOOL type=un;
ODS Listing exclude solutionf;
ods output covparms=cov2_&data
solutionf=fixed2_&data;
Title2 'Model 2: All Level-1 predictors -
Random slopes';
run;

proc mixed data= &data covtest noclprint;
class IDSCHOOL;
model bsmmat = bcdmst BSBAAML btdmstud
BSDMHW BSDMSV bsdmscl/ solution;
```

```
random intercept BSDMHW BSDMSV bsdmscl/
sub=IDSCHOOL type=un;
ODS Listing exclude solutionf;
ods output covparms=cov3_&data
solutionf=fixed3_&data;
Title2 'Model 3: All L-1 and L-2
predictors + Random Slopes';
run;

data cov_&data (keep = CovParm Estimate
StdErr ProbZ);
set cov1_&data cov2_&data cov3_&data;

data fixed_&data (keep = Effect Estimate
StdErr Probt);
set fixed1_&data fixed2_&data
fixed3_&data;
%mend hlm;
%hlm(data= AUS);
%hlm(data= CAN);
%hlm(data= CHL);
%hlm(data= EGY);
%hlm(data= ENG);
%hlm(data= IRN);
%hlm(data= RUS);
%hlm(data= SVK);
%hlm(data= USA);
%hlm(data= ZAF);

* Concatenating covariance parameters
obtained from 3 models for all countries
into one big covariance table. Same was
done for fixed effects;
Data covall;
set cov_aus cov_can cov_chl cov_egy
    cov_eng cov_irn cov_rus cov_svk
    cov_usa cov_zaf;
run;
Data fixedall;
set fixed_aus fixed_can fixed_chl
    fixed_egy fixed_eng fixed_irn
    fixed_rus fixed_svk fixed_usa
    fixed_zaf;
run;

proc export data= covall
dbms=excel replace
outfile
"C:\TIMSS\Results\Tables\Covall.xls";
sheet ="Covall";

proc export data= fixedall
dbms=excel replace
outfile ="C:\ TIMSS\Results\Tables
\fixedall.xls";
sheet ="fixedall";
run;
```

RESULTS
For this paper, the results produced by the examples of SAS code are presented in two parts: result tables in excel format exported from SAS Proc Mixed through ODS and results of multilevel modeling analyses across countries.

RESULT TABLES IN EXCEL FORMAT EXPORTED FROM SAS PROC MIXED THROUGH ODS
After all the fixed effect estimates produced by SAS Proc Mixed were concatenated across models and countries (see Step 4 of examples of SAS code), they could be exported to an excel table as illustrated in Table 1. As can be seen from Table 1, the effects were presented by country and then by model as specified in the code. Three statistics were reported: estimates of fixed effects, standard error of the estimates, and the probability associated with testing that each parameter is zero in the population.

Table 1

A Snap Shot of Exported Table in Excel Format from SAS Proc Mixed for
Fixed Effect Estimates by Model across Countries

| Country | Model | Effect | Fixed Effect Estimates | | |
			Estimate	StdErr	Probt
Australia	Baseline	Intercept	495.68	4.00	0.00
	Level 1	Intercept	452.81	4.21	0.00
		bsdmhw	-4.20	1.30	0.00
		bsdmsv	0.06	1.44	0.97
		bsdmscl	36.93	1.31	0.00
	Level 2	Intercept	445.44	19.93	0.00
		bcdmst	25.49	6.84	0.00
		BSBAAML	-1.18	1.98	0.55
		btdmstud	-12.52	6.83	0.07
		bsdmhw	-5.37	1.53	0.00
		bsdmsv	0.51	1.73	0.77
		bsdmscl	37.85	1.54	0.00
Canada	Baseline	Intercept	526.81	1.99	0.00
	Level 1	Intercept	467.11	3.04	0.00
		bsdmhw	-0.43	1.11	0.70
		bsdmsv	3.10	1.09	0.00
		bsdmscl	38.60	0.95	0.00
	Level 2	Intercept	490.46	9.23	0.00
		bcdmst	7.79	3.30	0.02
		BSBAAML	-1.23	1.41	0.38
		btdmstud	-14.46	3.10	0.00
		bsdmhw	-0.23	1.18	0.85
		bsdmsv	3.62	1.16	0.00
		bsdmscl	38.51	1.01	0.00

Similarly, after all the variance/covariance estimates produced by SAS Proc Mixed were concatenated across models and countries (see Step 4 of examples of SAS code), they could be exported to an excel table as illustrated in Table 2. As can be seen from Table 2, the variances were presented by country and then by model as specified in the code. The statistics of interest in each model were variance estimates of the intercept and residual, standard error of these estimates, and the probability associated with the hypothesis test that each variance is zero in the population.

Table 2

A Snap Shot of Exported Table in Excel Format from SAS Proc Mixed for Covariance Estimates by
Model across Countries

| Country | Model | Variance | Covariance Estimates | | | |
			CovParm	Estimate	StdErr	ProbZ
Australia	Baseline	Intercept	Intercept	2921.16	312.76	0.00
		Residual	Residual	2719.96	57.37	0.00

Table 2
A Snap Shot of Exported Table in Excel Format from SAS Proc Mixed for Covariance Estimates by
Model across Countries

Country	Model	Variance	Covariance Estimates			
			CovParm	Estimate	StdErr	ProbZ
	Level 1	Intercept	UN(1,1)	2525.44	343.74	0.00
			UN(2,1)	-38.26	69.94	0.58
			UN(2,2)	54.48	27.25	0.02
			UN(3,1)	-43.66	75.82	0.56
			UN(3,2)	-4.01	20.50	0.84
			UN(3,3)	120.24	34.31	0.00
			UN(4,1)	-61.73	70.35	0.38
			UN(4,2)	-16.68	18.89	0.38
			UN(4,3)	-44.37	22.50	0.05
			UN(4,4)	105.01	26.83	0.00
		Residual	Residual	1863.40	42.57	0.00
	Level 2	Intercept	UN(1,1)	2025.22	335.01	0.00
			UN(2,1)	-23.93	75.05	0.75
			UN(2,2)	67.84	31.76	0.02
			UN(3,1)	-59.71	83.91	0.48
			UN(3,2)	-2.41	25.19	0.92
			UN(3,3)	149.72	42.33	0.00
			UN(4,1)	-67.77	78.16	0.39
			UN(4,2)	-7.26	22.74	0.75
			UN(4,3)	-54.90	28.16	0.05
			UN(4,4)	126.36	33.47	0.00
		Residual	Residual	1831.72	46.92	0.00
Canada	Baseline	Intercept	Intercept	1099.87	101.25	0.00
		Residual	Residual	2663.02	41.72	0.00
	Level 1	Intercept	UN(1,1)	1593.79	222.36	0.00
			UN(2,1)	-102.72	55.93	0.07
			UN(2,2)	81.90	24.04	0.00
			UN(3,1)	-104.76	55.43	0.06
			UN(3,2)	-12.28	16.22	0.45
			UN(3,3)	82.55	22.15	0.00
			UN(4,1)	-205.11	50.65	0.00
			UN(4,2)	25.29	14.93	0.09
			UN(4,3)	-10.24	14.50	0.48
			UN(4,4)	92.44	18.23	0.00
		Residual	Residual	1734.09	28.80	0.00
	Level 2	Intercept	UN(1,1)	1377.22	216.09	0.00
			UN(2,1)	-92.42	57.15	0.11
			UN(2,2)	83.07	25.84	0.00
			UN(3,1)	-75.93	55.59	0.17
			UN(3,2)	-15.32	17.22	0.37
			UN(3,3)	78.56	22.96	0.00
			UN(4,1)	-199.19	51.97	0.00
			UN(4,2)	32.81	16.09	0.04
			UN(4,3)	-13.38	15.40	0.38
			UN(4,4)	94.03	19.54	0.00
		Residual	Residual	1797.61	31.67	0.00

RESULTS OF MULTILEVEL MODELING ANALYSIS ACROSS COUNTRIES
Baseline Model. The multilevel model analysis started with the baseline model where none of the level-1 or level-2 predictor was included in the model. The results of the baseline model are presented in Table 3. Across countries, the fixed effect for the intercept ranged from 268.25 (SE = 5.33, p < .05) for South Africa to 526.81 (SE = 1.99, p < .05) for Canada. This suggests considerable differences in overall average school mathematics scores across countries. Similarly, the amount of variability in math achievement seems to differ greatly across countries. Whereas the amount of within-school variability was smallest for UK (1,588.35, SE = 31.92, p < .05) and was largest for Egypt (5,278.12, SE = 90.07, p < .05), the amount of between-school variability was smallest for Canada (1,099.87, SE = 101.25, p < .05) and was largest for South Africa (6,950.35, SE = 634.39, p < .05). Likewise, the intra-class correlation (ICC) was different from one country to another, with Canada having the lowest ICC value of .29 and UK having the highest ICC value of .69. These results suggest somewhat small to moderately high level of natural clustering of students occurred between schools across countries. In other words, approximately 29% to 69% of the total variance in math scores occurred between schools.

Level-1 Model. When all the three level-1 predictors (i.e., *time on math homework, valuing math, and self-confidence)* were included in the model to predict math achievement, it appeared that this model worked the best for UK with 65% of the variance in math achievement accounted for, and less well for South Africa with only 14% of the variance in math achievement accounted for. In terms of fixed effects, *self-confidence* was statistically significant in all the countries whereas *time for home work* and *valuing math* were statistically significant in only some countries and not in the others (see Table 3).

Level-2 Model included all *level-1 variables (*i.e., *time on math homework, valuing math, and self-confidence), level-2 variables (*i.e., *mean activities in math lessons*, *class size,* and *school resources), and cross-level interaction terms.* The results of Level-2 model are presented in Table 3. As the full model, Level-2 model produced seven different types of statistically significant interactions across countries. First, the interaction between *mean activity in math lessons* and students' reported level of *self-confidence* was observed in five countries: Australia (5.65, SE = 2.74, p < .05), Canada (10.11, SE = 1.92, p < .05), Egypt (21.11, SE = 4.03, p < .05), Slovak Republic (7.72, SE = 2.86, p < .05), and South Africa (10.56, SE = 2.56, p < .05). Second, the interaction between *mean activity in math lessons* and students' reported level of *valuing math* was observed in seven countries: Canada (-10.18, SE = 2.22, p < .05), Egypt (-22.99, SE = 6.00, p < .05), Iran (-13.75, SE = 3.03, p < .05), Slovak Republic (-10.19, SE = 3.30, p < .05), South Africa (-14.81, SE = 3.34, p < .05), UK (-6.41, SE = 3.04, p < .05), and USA (-12.08, SE = 2.11, p < .05). Third, the interaction between *mean activity in math lessons* and students' reported *time spent on math homework* was observed in two countries: Iran (-9.31, SE = 2.71, p < .05) and Russia (7.86, SE = 3.96, p < .05). The following three interaction types were observed between *class size* and (a) students' reported *time spent on homework* for USA (-6.23, SE = 2.24, p <. 05), (b) students' reported level of *self-confidence* for South Africa (4.04, SE = 1.41, p <. 05), and (c) students' reported level of *valuing math* for Chile (7.86, SE = 3.96, p < .05). The final type of interaction was between *school resources* and students' reported level of *self-confidence* which occurred in only one country, Canada (-3.33, SE = 1.70, p < .05).

It can be inferred from the first interaction that the relationship between students' reported level of self-confidence and predicted math achievement was different across levels of mean activity in math lessons as well as across countries. There appeared two patterns of relationship: one for the developed countries (Australia, Canada, and Slovak Republic) and one for the developing countries (Egypt and South Africa). For the first pattern, students with higher levels of self-confidence tended to achieve higher math scores, regardless of the level of activity in math lessons. However, in the second pattern, when no activity was conducted in math lessons, students' achievement in math tended to be similarly low, regardless of their reported level of self-confidence. As the level of activity in math lessons increased, those students with higher self-confidence level performed significantly higher than their peers who reported having low level of self-confidence. Despite these major differences, the two patterns had one commonality – that is, the higher level of activity in math lessons worked best for students with high level of self-confidence.

As for the second interaction, the pattern of interaction between mean activity in math lessons and students' reported level of valuing math was also different across countries. For England and Iran, whereas having activity in almost every math lessons did not seem to have any effect on students with high level of valuing math, it substantially increased math scores of students who reported having a lower level of valuing math. In contrast, when there was no activity in math lessons, those students who reported having a high level of valuing math tended to fare significantly better in math than their peers with a lower level of valuing math. However, for the remaining countries (Canada, Egypt, Russia, USA, and South Africa), such a pattern no longer held. Surprisingly, for those students who reported having a high level of valuing math, the more frequently they have activities in math lessons, the poorer they performed in math. As for their peers who reported having a low level of valuing math, the more frequently they have activities in math lessons, the better they seemed to perform in math.

The third interaction was between mean activity in math lessons and the students' reported time spent on math homework for two countries, Iran and Russia. It is worthy of note that these two countries had an inverse pattern of interaction. That is, in Iran, students who reported spending a high amount of time on math home work tended to score higher in math than their peers who reported spending a medium or low amount of time on math homework when there was no activity in math lessons. However, as the frequency of activity in math lessons increased (i.e., activity in almost every math lesson), students who reported spending the lowest amounts of time on homework appeared to have a highest math scores in math. Inversely, in Russia, for those who reported spending a high amount of time on math home work, their math achievement was the lowest when there was no activity in math lessons, and highest when there was activity in almost every math lessons.

The fourth interaction was between class size and students' reported time spent on homework in USA. It appears that when the class is of small size (1-24 students) students who reported spending a high amount of time on home work tended to score higher in math than their peers who reported spending a lesser amount of time on math homework. It is interesting to note, however, that as the class size increased to 41 students or more, students who reported spending a higher amount of time on math homework tended to do poorer in math than their peers who spent lesser time on doing the homework. The differences in math achievement between students seemed to be more profound when the class size was either small or large. Differences in students' math achievement were much smaller when the class size was between 25-40 students.

Similarly, the interaction between class size and students' reported level of self-confidence in South Africa suggested a substantial drop in student's math achievement scores as the class size increased from 1-24 students per class to more than 41 students per class. Of particular note, the differences in students' predicted math scores tended to be much more profound in small class rooms (1-24 students) than they were in big class rooms (41 students or more). However, regardless of class size, students who reported having a higher level of self-confidence appeared to consistently score higher in math than their peers who reported having a medium or lower level of self-confidence.

The sixth interaction suggested that, in Chile, the relationship between students' reported level of valuing math and the predicted math scores was dependent on sizes of the classroom. Specifically, students in small classes tended to perform better in math than students in larger classes (41 or more), regardless of their reported level of valuing math. However, within the small classes (1-24 students), students who reported having a low level of valuing math appeared to score higher than their peers who reported having a high level of valuing math. Such differences in math achievement seemed to be trivial as the class size increased to 41 or more students per classroom.

Finally, the seventh interaction was between school resources and students' reported level of self-confidence in Canada. Interestingly, regardless of levels of availability of school resources, it was observed that students who reported having a high level of self-confidence consistently performed higher than their peers who reported having medium or low level of self-confidence in learning math. However, the differences in students' math achievement tended to be large when the availability of school resources was low and smaller when the availability of school resources was high. In addition, across the levels of school resources, there appears a trend that more available school resources for math instruction were associated with higher math scores regardless of students' reported levels of valuing math.

In addition, the full model appeared to account for considerable amount of variance in math achievement across countries except for Egypt, Russia, and South Africa where the amount of explained variance was less than one third of the total variance (pseudo R^2 = .22, .31, and .22, respectively). Australia and Iran had the largest amount of explained variance (63% and 67%, respectively). Following were five countries (Canada, Chile, Slovak Republic, UK, and USA) with more than one third of the total variance being explained by the full model (pseudo R^2 = .33, .48, .46, .49, and .47, respectively).

Table 3
Summary of Parameter Estimates by Model across Countries

Model	Parameters	Australia Est.	SE	Canada Est.	SE	Chile Est.	SE	Egypt Est.	SE	Iran Est.	SE	Russia Est.	SE	Slovak Rep. Est.	SE	South Africa Est.	SE	UK Est.	SE	USA Est.	SE
Baseline	ICC	.52		.29		.61		.39		.39		.38		.42		.54		.69		.54	
	INT	495.68	4.00	526.81	1.99	400.80	4.93	432.10	4.24	411.94	3.39	507.24	3.37	516.14	4.36	268.25	5.33	504.91	4.26	506.45	3.74
	σ^2	2719.96	57.36	2663.02	41.72	2885.28	52.01	5278.12	90.07	1954.83	62.13	3419.17	72.82	4216.34	94.01	2760.63	41.88	1588.35	31.92	2780.07	44.36
	τ_{oo}	2921.16	312.76	1099.87	101.35	4572.58	483.27	3422.43	383.97	3031.09	220.86	2121.17	226.28	3082.02	367.02	6950.35	634.39	3576.51	372.89	3236.51	305.91
Level 1	INT	452.81	4.21	467.11	3.04	371.92	5.13	379.61	7.13	369.56	4.07	466.04	4.69	466.86	5.41	214.03	5.94	480.15	4.22	465.40	4.04
	HW	-4.20	1.30	-0.43	1.11	-4.52	1.12	-9.14	1.80	-1.11	1.29	-3.95	1.70	-3.53	2.54	-2.35	1.08	-4.04	1.54	3.88	1.54
	VM	0.06	1.44	3.10	1.09	-2.29	1.18	7.26	2.98	2.41	1.53	4.50	1.54	0.36	1.46	14.70	1.36	1.63	1.14	-1.28	1.25
	SC	36.93	1.31	38.60	0.95	32.35	1.07	36.36	1.91	34.27	1.26	36.81	1.08	45.90	1.44	26.10	1.10	18.93	1.23	29.03	0.95
	σ^2	1863.40	42.57	1734.09	28.80	2270.31	43.30	4244.97	81.46	2404.67	52.92	2365.17	55.10	2710.70	64.24	2369.38	40.64	2911.73	358.59	2136.94	35.90
	τ_{oo}	2525.44	343.74	1593.79	222.36	4235.58	541.58	5109.13	987.67	1753.52	337.26	2422.19	439.71	3174.03	580.22	7057.92	757.33	1236.80	26.40	2715.21	358.31
	R^2_1	0.31		0.35		0.21		0.20		-0.23		0.31		0.36		0.14		-0.83		0.23	
	R^2_2	0.14		-0.45		0.07		-0.49		0.42		-0.14		-0.03		-0.02		0.65		0.16	
Level 2	INT	446.07	20.87	481.83	11.50	307.57	11.92	339.79	22.09	329.69	13.83	480.58	18.55	563.08	17.68	139.63	15.66	512.69	20.99	444.94	15.47
	SR	25.45	6.84	13.20	4.33	50.21	7.51	12.93	4.98	21.66	5.72	5.73	5.9	-1.20	7.31	52.03	9.26	20.48	9.99	20.69	5.22
	MA	-1.27	4.80	-0.11	3.74	-0.96	1.55	7.14	11.32	27.22	5.76	6.13	7.85	-11.88	4.04	11.75	6.52	15.92	4.91	1.44	4.48
	CS	-12.59	6.82	-14.47	3.09	8.48	5.27	14.19	4.76	-12.17	3.80	-11.11	5.2	-32.94	6.24	16.56	6.37	-31.98	7.09	-3.09	3.67
	HW	-5.37	1.52	-0.13	1.18	-4.19	1.17	-9.22	1.86	16.48	5.14	-16.63	6.6	-3.78	2.63	-2.30	1.27	3.20	5.58	9.06	7.36
	VM	8.64	4.68	21.68	4.07	1.39	2.03	50.16	10.96	24.96	5.23	20.17	5.41	0.80	1.55	41.17	6.13	11.74	4.63	23.07	4.24
	SC	29.22	4.50	24.74	4.32	32.31	1.10	-4.28	7.90	34.41	1.33	36.99	1.09	34.09	4.78	2.40	5.28	21.27	6.44	21.68	3.84
	SR *HW	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
	SR *VM	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
	SR *SC	...	...	-3.33	1.70	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
	MA*HW	...	...	...	...	...	...	...	...	-9.31	2.71	7.86	3.96	...	...			-6.14	3.38	4.23	2.29
	MA*VM	-5.37	2.87	-10.18	2.22	...	...	-22.99	6.00	-13.75	3.03	-10.19	3.3	...	...	-14.81	3.34	-6.41	3.04	-12.08	2.11
	MA*SC	5.65	2.74	10.11	1.92	...	...	21.11	4.03	...	...	...	...	7.72	2.86	10.56	2.56	1.80	2.78	3.43	1.89
	CS*HW	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	-6.33	2.24
	CS*VM	...	...	...	...	-2.86	1.38	...	...	...	...	...	...	...	...	...	...	...	...	...	...
	CS*SC	...	...	...	...	...	...	...	...	...	...	...	...	...	...	4.04	1.41	-3.19	2.25	...	...
	σ^2	1829.26	46.87	1788.58	31.51	2250.42	44.32	4141.99	82.24	2381.05	53.95	2344.71	55.74	2708.88	65.74	2466.33	54.58	1034.37	30.17	1931.27	35.69
	τ_{oo}	2034.89	336.20	1381.16	215.96	3382.88	461.38	4524.03	938.20	991.88	252.91	2270.87	429.27	2769.39	526.07	6260.42	895.58	3067.20	502.24	2729.41	392.72
	R^2_1	0.33		0.33		0.22		0.22		-0.22		0.31		0.36		0.11		0.35		0.31	
	R^2_2	0.30		-0.26		0.26		-0.32		0.67		-0.07		0.10		0.10		0.14		0.16	

Note:
(1) Underlined Estimates (Est. in the Table) were statistically significant at .05 significance level.
(2) Abbreviated variables and parameter symbols used in the Tables are:
HW: Time on Math Homework has 3 categories Low, Medium, and High
VM: Students' Valuing Math has 3 categories Low, Medium, and High
SC: Self-confidence in learning math has 3 categories Low, Medium, and High
CS: Class size for math instruction has 4 categories 1-24, 25-32, 33-40, and 41+
MA: Mean activity in math lesson has 4 categories never, some, about half, and almost/every lesson.
SR: Availability of School Resources for Math Instruction has 3 categories Low, Medium, and High
(3) Model 1: Unconditional, Model 2: All L-1 predictors - Random slopes, and Model 3: All L-1, L-2 predictors and cross-level interactions.

σ^2: Level-1 Variance, τ_{oo}: Intercept Variance, Pseudo R^2_1: Proportion of explained level-1 variance that was accounted for by the current model

using the formula. $R^2_1 = \dfrac{\sigma^2_{Baseline} - \sigma^2_{Model}}{\sigma^2_{Baseline}}$ where Model 1 serves as the baseline model.

Pseudo R^2_2: Proportion of explained intercept variance that was accounted for the current model using the formula

$R^2_2 = \dfrac{\tau_{00\,Baseline} - \tau_{00\,Model}}{\tau_{00\,Baseline}}$ where Model 1 serves as the baseline model.

IMPORTANCE AND CONTRIBUTION
Using TIMSS 2003 database, this paper aims to provide researchers, especially educational researchers with vital data management as well as statistical analysis tools to work with complex, large-scale, secondary data. It is also hoped that through concrete and easy-to-follow examples of SAS code, researchers will increase their interest in using existing large-scale, secondary data for different research purposes. Finally, by applying advanced analytic multilevel models to investigate correlates of math achievement in each of the selected countries, this study produces country-specific research findings which can be used directly by policy makers and educators from these countries, especially developing countries to support their educational decisions.

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