ACADEMIC MOTIVATION, MATHEMATICS ACHIEVEMENT, AND THE SCHOOL CONTEXT: BUILDING ACHIEVEMENT MODELS USING TIMSS 2003

A Dissertation

presented to

the Faculty of the Graduate School

at the University of Missouri

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

---

by

ZE WANG

Dr. Steven J. Osterlind, Dissertation Supervisor

AUGUST 2008

The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

ACADEMIC MOTIVATION, MATHEMATICS
ACHIEVEMENT, AND THE SCHOOL CONTEXT:
BUILDING ACHIEVEMENT MODELS USING TIMSS 2003

presented by Ze Wang,

a candidate for the degree of doctor of philosophy,

and hereby certify that, in their opinion, it is worthy of acceptance.

____

Professor Steven J. Osterlind

____

Professor Deborah L. Carr

____

Professor Alexander C. Waigandt

____

Professor Stephen D. Whitney

____

Professor Athanasios C. Micheas

____

Professor David A. Bergin

ACKNOWLEDGEMENTS

I would like to extend my thanks to the entire department of Educational, School and Counseling Psychology for making my studies at MU an exciting and rewarding endeavor. A great thanks to my advisor, Dr. Steve Osterlind, for his invaluable academic and professional advice throughout the doctoral program and for his patience and encouragement. His assistance in every area of my research was very much appreciated. His demand for excellence in my work undoubtedly helped push me to achieve much more than was required, helping to prepare me for the challenges ahead of me as a researcher.

I am very grateful to my other committee members, Dr. Deb Carr, Dr. Alex Waigandt, Dr. Steve Whitney, Dr. Athanasios Micheas, and Dr. David Bergin for their encouragement, assistance, kindness and suggestions. I enjoyed getting to know them better and appreciate their time and willingness to help. Their support made it possible for me to complete this dissertation in time.

I would like to thank my fellow doctoral students at MU, whose friendships made the program fun. I would also like to acknowledge the financial support of the G. Ellsworth Huggins fellowship from the graduate school and the support from the College of Education and the department of Educational, School and Counseling Psychology.

Finally, I want to express my love and gratitude to my parents and siblings back in China for their trust and support. I appreciate the sacrifice you gave and your understanding that I was not always available.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

ACADEMIC MOTIVATION, MATHEMATICS
ACHIEVEMENT, AND THE SCHOOL CONTEXT:
BUILDING ACHIEVEMENT MODELS USING TIMSS 2003

Ze Wang

Dr. Steven J. Osterlind, Dissertation Supervisor

ABSTRACT

Using the TIMSS 2003 data, this study built mathematics achievement models of eighth-graders in four selected countries: the United States, the Russian Federation, Singapore and South Africa. Students' motivational beliefs, parents' education level, teachers' and principals' perceptions, and other characteristics related to the classroom and school were incorporated and used to build the achievement model in each country. Hierarchical Linear Modeling was applied to the model building process with level-1 being students and level-2 being classrooms in each country. The final achievement models suggested that student self-confidence in learning mathematics, which overlaps with self-efficacy, expectancy, and self-concept, was the most important construct among other student variables, to affect eighth-graders' mathematics achievement in all four countries. The effects of other student characteristics, along with the family, teacher, and school variables, differed across the selected countries.

CHAPTER 1

INTRODUCTION

The impact of mathematics proficiency can be viewed from varying perspectives, ranging from likelihood of a student's pursuing postsecondary education to an individual's earning capacity to a nation's ability to be competitive in the global economy (McEwan, 2000, p.2). Moses and Cobb (2001) argue that mathematical knowledge will, in the new century, figure as a path to political and cultural power, much as the capacity to read and write served in the 19th and 20th centuries. Students' mathematics achievement is often associated with the future of a country (Baker & LeTendre, 2005; Wobmann, 2003). In the United States, the report *A Nation at Risk* (National Commission on Excellence in Education [NCEE], 1983) signaled the importance of comparing the US education system to those in other countries. Ever since then, the efforts taken to understand mathematics achievement and related factors are obvious in the United States. For example, different national and international databases, with math as one of the major domains, have been established (see NAEP, TIMSS). And, nearly every state assessment program includes mathematics testing. Research on student mathematics achievement and findings will be interesting to educators, policy makers, parents and others with a stake in students' academic competency.

1.1 Statement of the Problem

Academic motivation is a very important concept in classroom learning and student performance, whether it is mathematics or other subjects. Schunk, Pintrich and Meece (2008) define motivation as “the process whereby goal-directed activity is instigated and sustained”. Motivation is an unobservable process and can be inferred from actions and verbalizations; it involves goals which may not be explicit; and it requires activity which is instigated and sustained (Schunk, Pintrich, & Meece, 2008).

One of the most influential motivational theories includes expectancy and value constructs and is from the work of Eccles, Wigfield, and their colleagues (Eccles, 1983, 1987, 1993, 2005; Eccles et al., 1989; Wigfield, 1994; Wigfield & Eccles, 1992, 2000, 2002; Wigfield, Eccles, & Rodriguez, 1998; Wigfield, Tonks, & Eccles, 2004). It has been developed from Atkinson’s (1964) concept of achievement motivation. According to this theory, the two most important predictors of achievement behaviors are expectancy and task value. Schunk, Pintrich and Meece (2008, p51) depict this theoretical model in a simplified figure. Task value addresses the question, “Why should I do this task?” (Eccles, 1983; Eccles et al., 1998) while expectancy focuses on the question, “Am I able to do this task?” (Eccles, 1983, 2005; Eccles et al., 1998; Pintrich, 1988a, 1988b; Wigfield, 1994; Wigfield & Eccles, 1992, 2002). In the task value construct, four components are identified: attainment value, intrinsic value, utility value and cost (Wigfield, Eccles & Rodriguez, 1998).

Expectancy and task value are motivational beliefs which directly influence achievement behaviors and which have precedents. They are assumed to be influenced by task-specific beliefs such as ability beliefs, the perceived difficulty of different tasks, and individuals' goals, self-schema, and affective memories. Those social cognitive variables, in turn, are influenced by individuals' perceptions of their own previous experiences and other socialization factors. Despite theoretical differences, children's and adolescents' ability beliefs and expectancies for success cannot be empirically differentiated (see Eccles et al., 1993; Eccles & Wigfield, 1995; Wigfield & Eccles, 2000).

The achievement behaviors in the expectancy-value model of achievement motivation include persistence, choice, quantity of effort, cognitive engagement and actual performance. Studies have shown that children's beliefs about their ability and expectancies for success are the strongest predictors of grades in math while children's subjective task values are the stronger predictors of children's intentions to keep taking math and actual decisions to do so (Wigfield & Eccles, 2000).

When we look at how students' motivational beliefs influence their academic achievement, we cannot ignore the effects of teachers and schools. School culture and organization can have strong effects on students' motivation and achievement (Schunk, Pintrich & Meece, 2008, p. 346). Eight dimensions are identified: Norms, values, and shared beliefs; climate; task and work structures; authority and management structures; recognition and reward structures; grouping practices; evaluation practices; and time use. For the dimension of school climate, three key aspects are considered: sense of community, warmth and civility, and feelings of safety and security. Outside the context of school, the larger picture includes external constraints/opportunities such as type of students, school size/number of students; parental/community involvement, district level constraints/opportunities, state level constraints/opportunities, etc.

The role of social relationships and perceptions within school in shaping academic outcomes has been one of the focuses in the study of student motivation in school. Students' interpersonal relationships and interactions with peers and teachers, their social goals within schools, and their perceptions of the general social climate of their classes have all been shown to be associated with a range of motivational and learning outcomes, as well as with more affective indicators of adjustment (see Anderman, 1999; Patrick, Anderman & Ryan, 2002; Urdan & Maehr, 1995; Wentzel, 1991). For example, research on teacher expectations has addressed issues such as how teachers form expectations, how they communicate them to students, and how these expectations affect student outcomes (e.g. Rosenthal, 2002).

A growing body of research has shown that students perform better academically when parents are involved with their child's schooling (see, e.g., Astone & McLanahan, 1991; Catsambis & Beveridge, 2001; Christenson, Rounds, & Gorney, 1992; Coleman, 1990b; Epstein, 1991; Fehrman, Keith, & Reimers, 1987; Feuerstein, 2000; Jeynes, 2003; Keith et al., 1993; Levine & Lezotte, 1990; Rumberger & Palardy, 2005; Sui-Chu & Willms, 1996; Thompson, 2002). In a recent study evaluating the effects of family and school capital on students' classroom achievement, Parcel and Dufur (2001) found that parental involvement in school activities had a positive impact on children's mathematics achievement. Another study found that parent involvement in academics at home is more important to a child's academic achievement than parent involvement at school (DePlanty, Coulter-Kern, & Duchane, 2007). Overall, the research has shown that parents are instrumental to their children's academic success and that parental involvement has a positive impact on student achievement. Zhao (2007), using TIMSS 1999 data, conducted a comparative study of school expectations and initiatives for parental involvement in 30 nations. Results show that students in the United States were more likely to achieve better if their schools had higher expectations for parents' direct involvement (Zhao, 2007).

Student achievement motivation can be better understood when classroom and school characteristics, as well as family characterisics are taken into consideration. However, there seems to be a lack of empirically-based studies addressing this facet of motivation. There is even less research focusing on comparison among different countries in terms of how motivational beliefs, interacting with classroom and school characteristics, influence student mathematics achievement.

In TIMSS 2003, school climate was assessed using Likert-scale items from the perceptions of students, teachers and principals. Parent involvement was measured by school principals' responses to whether their schools expected parents to be involved in some activities. Measures were also available of teachers' perceptions of school facility and safety and of limiting mathematics teaching due to student factors. Another measure, students' perception of being safe in the schools could have been added. However, the data were not available for the US sample and therefore is not included in this study. TIMSS 2003 does not have an explicit theoretical rationale for all items.

Hierarchical linear modeling (HLM) has been used to analyze data with a hierarchical structure (e.g. Ma & Don, 2000). The advantage of HLM over regression is that HLM relaxes the assumption of independence of observations and uses information from different levels of the hierarchy of data. For student mathematics achievement, information about students, their parents, teachers and schools is organized hierarchically. Statistically software is available to apply hierarchical models to study student mathematics achievement.

1.2 Purpose of the Study

The purpose of this study is to examine how student motivational beliefs relate to their mathematics achievement, within the specific classroom and school context. The student motivational beliefs of interest are student self-confidence in math, their valuing math, and their perception of school. This study uses the Trends in International Mathematics and Science Study (TIMSS) 2003 data collected by the International Association for the Evaluation of Educational Achievement (IEA). The richness of the data will allow us to examine different countries.

1.3 Research Questions

The specific questions addressed in this study include:

(1) In each country, how does mathematics achievement differ across schools or classrooms?

(2) In each country, how do student motivational beliefs relate to math achievement within the classroom and school context?

(3) In each country, is the strength of association between student characteristics and mathematics achievement similar across classrooms or schools? Are teacher and school characteristics more important factors in some classrooms and schools than in others?

(4) What are the country differences in the above measures and effects?

1.4 Significance of the Study

This study adds to the field of research on academic motivation and mathematics achievement. More importantly, this study differs from related studies in that it adds classroom and school characteristics. There is almost no cross-national empirical research on this topic. The significance of this study also lies in the scale of the analysis. TIMSS 2003 provides a very rich dataset to look into different aspects associated with mathematics and science education and achievement at the fourth and eighth grades (TIMSS 2003 User Guide). For eighth grade mathematics, data were collected from 48 countries from students, teachers, parents, school principals and national research coordinators. The differences among countries can be very informative to educators and policy makers. Bybee and Kennedy (2005) reported that,

> Comparative national data for mathematics and science in both grades reveal a near-monopoly by Asia in the top-scoring group, including Singapore, Korea, Hong Kong, Taiwan, and Japan. Several European nations cluster below that, and the United States and several other nations are in the next set. There is a considerable spread of scores among nations, with the average scaled scores from eighth-grade mathematics ranging from 605 (Singapore) to 264 (South Africa). Some of the "best performer" nations were those who ranked high on the United Nations Development Programme's Human Development Index (HDI), but students in Hungary, Malaysia, and South Korea, for example, did much better than their country's HDI. Between 1995 and 2003, scores for both fourth- and eighth-graders in both disciplines increased or held constant in most nations in the TIMSS samples, with improvement being especially noteworthy in fourth-grade mathematics scores (Science Magazine).

Bybee and Kennedy (2005) gave credit to the national standards in the United States for the improvement in this nation's achievement. On the other hand, the discrepancy between math achievement in the U.S. and in the top-scoring group (a near-monopoly by Asia) may call for some attention on effective instruction.

1.5 Description of TIMSS 2003

The Trends in International Mathematics and Science Study (TIMSS) 2003 database comprises student achievement data in mathematics and science as well as student, teacher, school, and curricular background data for the 48 countries that participated at the eighth grade and 26 countries that participated at the fourth grade.

1.5.1 Student Achievement Scores in Mathematics

The TIMSS 2003 eighth-grade mathematics assessment contains 194 items assessing five content domains (number, algebra, measurement, geometry, and data). Administering all the mathematics items, in addition to science items included in TIMSS 2003, to all students would require a lot of testing time. To address this problem, TIMSS 2003 uses a matrix-sampling technique. With this technique, the 194 mathematics items are assembled into 14 unique item blocks. Each block contains an average of 15 score points at the eighth grade. On average, there are 8-9 multiple choice items, 3-4 short-answer items and 1-2 extended-response items per block. These 14 math blocks, along with 14 science blocks, are distributed across 12 student booklets. The 12 booklets are rotated among students during test administration. (See TIMSS 2003 User Guide).

Since each student responds to only one booklet, not the entire assessment, item response theory (IRT) scaling methods are used to derive estimates for each student of the scores they would have attained had they completed the entire assessment (Gonzalez, Galia, and Li, 2004). An IRT scaling model is a latent variable model that describes the probability that a student will respond in a specific way to an item in terms of the respondent’s proficiency, which is an unobserved or latent trait, and various characteristics (called parameters) of the item. In TIMSS 2003, a three-parameter model is used with multiple-choice items, which are scored as correct or incorrect, and a two-parameter model for constructed-response items with just two response options, which also are scored as correct or incorrect. Since each of these item types has just two response categories, they are dichotomous items and fit the IRT model nicely. The IRT model for dichotomous items is:

$$p(x_i = 1 | \theta, a_i, b_i, c_i) = c_i + \frac{1 - c_i}{1 + \exp(-1.7 a_i (\theta - b_i))} = p_{i1}(\theta)$$

where

x_i is the response to item i, 1 if correct and 0 if incorrect;

θ is the proficiency of a person on a scale (a person with higher proficiency has a greater probability of responding correctly);

a_i is the slope parameter of item i, characterizing its discrimination power;

b_i is its location parameter, characterizing its difficulty;

c_i is its lower asymptote parameter, reflecting the chances of respondents of very low proficiency selecting the correct answer. When c_i is fixed at zero, it is a two-parameter model; when c_i is not constrained, it is a three-parameter model.

A partial credit model is used with polytomous constructed-response items, i.e., those with more than two score points (Martin, Mullis and Chrostowski, 2004). The IRT model for polytomous items is:

$$p(x_i = 1 | \theta, a_i, b_i, d_{i,1}, ..., d_{i,m_i-1}) = \frac{\exp(\sum_{v=0}^{l} 1.7a_i(\theta - b_i + d_{i,v}))}{\sum_{g=0}^{m_i-1} \exp(\sum_{v=0}^{g} 1.7a_i(\theta - b_i + d_{i,v}))} = p_{il}(\theta)$$

where

m_i is the number of response categories for item i;

x_i is the response to item i, possibilities ranging between 0 and $m_i - 1$;

θ is the proficiency of person on a scale;

a_i is the slope parameter of item i, characterizing its discrimination power;

b_i is its location parameter, characterizing its difficulty;

$d_{i,l}$ is category l threshold parameter.

Indeterminacy of model parameters of the polytomous model are resolved by setting $d_{i,0} = 0$ and setting $\sum_{i=1}^{m_i-1} d_{i,j} = 0$.

For student achievement scores in mathematics, IRT scaling is first performed to get estimates of each examinee's proficiency and item parameters. Those scores are then used to get overall student achievement distributions, conditional on students' background characteristics and their responses to the achievement items. Next, each student's achievement is estimated by conditioning on the student's responses and background characteristics. Because there is some error inherent in this imputation process, five such estimates were drawn for each student on each of the scales. Those estimates are plausible values. Analyses may be replicated with each of the five plausible values to assess the impact of imputation error (see Mislevy, 1991). TIMSS 2003 reports plausible values for the overall subjects as well as for the content domains. For this study, only the five plausible values for the overall mathematics subject are used.

1.5.2 Student Background Questionnaires

As part of TIMSS, additional information is gathered by questionnaires. There are four types of background questionnaires at different levels used in TIMSS 2003:

The curriculum questionnaire addresses issues of the intended national curriculum in mathematics and science. They are addressed to National Research Coordinators.

The school questionnaire asks school principals or headmasters to provide information about the school contexts for the teaching and learning of mathematics and sciences.

The teacher questionnaire collects information about the teachers' preparation and professional development, their pedagogical civilities, and the implemented curriculum. At eighth grade, there are separate versions for mathematics teachers and science teachers.

The student questionnaire seeks information about the students' home backgrounds and their experience in learning mathematics and science.

TIMSS 2003 uses a two-stage sampling design in each country. The sampling frame in the first stage includes all the schools and in the second stage classes are sampled from the selected schools. Since this two-stage sampling design does not involve sampling teachers directly, the teachers are not representative samples. Rather, they are the teachers for nationally representative samples of students. The TIMSS 2003 database has representative samples of schools.

1.5.3 Sampling Weights in TIMSS 2003 Data

The intended target populations of TIMSS 2003 are all students at their eighth and fourth years of formal schooling in the participating countries. In each country, representative samples of students are selected using a two-stage sampling design. In general, countries select at least 150 schools at the first stage using probability-proportional-to-size sampling. At the second stage, one or two classes are randomly sampled in each school. Generally, this results in a sample size of at least 4000 students per country. Due to this complex sampling design, sampling weights should be applied when conducting analyses of the data. The sampling weights reflect the probability of selection of each school and student, taking into consideration any stratification or disproportional sampling of subgroups if the country chooses to incorporate important reporting variables in their sampling design. The sampling weights also include adjustments for non-response (Joncas, 2004).

The probability of each student being selected can be calculated since the students within each country are selected using probability sampling procedures. The student sampling weight, denoted as TOTWGT in TIMSS 2003, is the inverse of the selection probability. The sum of the weights for students within a country approximates the size of the population. TOTWGT for each student is a composite of three weighting factors corresponding to the stages of the sampling design (school, class and student) and three adjustment factors for non-participation at each of these stages. The following is a description of those 6 factors as well as several other weight variables included in the student data files.

WGTFAC1 School Weighting Factor

This variable is the inverse of the probability of selection for the school where the student is enrolled.

WGTADJ1 School Non-participation Adjustment

This adjustment applies to WGTFAC1 to account for non-participating schools in the sample. Multiplying WGTFAC1 by WGTADJ1 gives the sampling weight for the school, adjusted for non-participation.

WGTFAC2 Class Weighting Factor

This is the inverse of the probability of selection of the classroom within the school.

WGTADJ2 Classroom Non-participation Adjustment

This adjustment applies to WGTFAC2 to account for non-participating classrooms or classroom where student participation is less than 50 percent. Multiplying WGTFAC2 by WGTADJ2 gives the second-stage sampling weight, adjusted for non-participation.

WGTFAC3 Student Weighting Factor

This is the inverse of the probability of selection of an individual student within a sampled classroom. In the usual TIMSS case, where entire classrooms are sampled intact, the value is set to one for all students in the classroom. In a few countries, however, students are sampled within classrooms as a third sampling stage: in these cases the value of WGTFAC3 is greater than one.

WGTADJ3 Student Weighting Adjustment

This adjustment applies to WGTFAC3 to account for non-participating students in the sampled classroom. Multiplying WGTFAC3 by WGTADJ3 gives the student-within-classroom sampling weight, adjusted for non-participation.

TOTWGT Total Student Weight

TOTWGT is obtained by multiplying the variables WGTFAC1, WGTADJ1, WGTFAC2, WGTADJ2, WGTFAC3, and WGTADJ3 for each student. The sum of these weights within a sample provides an estimate of the size of the population.

SENWGT Senate Weight

The SENWGT sampling weight is TOTWGT multiplied by 500 divided by the sum of the weights over all students in the target grade in each country. This results in a sample size of 500 in each country. SENWGT may be used in cross-country analyses in which each country should be treated equally. When SENWGT is used as the sampling weight for international estimates, the contribution of each country is the same, regardless of the size of the population.

HOUWGT House Weight

The HOUWGT sampling weight is TOTWGT multiplied by the ratio of the sample size (the number of students, n) in each country divided by the sum of the weights over all students in the target grade. HOUWGT may be used when the actual sample size is required for performing significance tests.

Besides the above weight variables included in the student data files, there is also a school weight variable in the school data files.

SCHWGT School-level Weight

The school sampling weight SCHWGT is the inverse of the probability of selection of the school, multiplied by its corresponding non-participation adjustment factor. It is the product of WGTFAC1 and WGTADJ1.

1.6 Limitation of the Study

The major limitation of this study is the formation of variables used. TIMSS 2003 does not provide an explicit rationale for the questions asked, which makes it difficult to label the derived variables used in this study. I try best to match variables with constructs from educational theories.

Another limitation is that the derived variables may mean different things in different countries. Most of the motivational constructs referred to were first established and later applied to US samples. The derived variables, supposedly to measure certain constructs, may not be conceptually comparable across countries.

Missing values in this study may not be missing at random, which might hurt the validity of the results. The sampling weights included in TIMSS 2003 adjusted for non-participation of schools, classrooms and students based on the hypothesis that non-participation is random. For those that did participate, there are some non-responses. And those non-responses may depend on different characteristics of the country, school, classroom, student and parents. This study cannot assess the extent to which the results are biased because of missing values.

1.7 Delimitation of the Study

The delimitations of this study are:

This study only focuses on the constructs which are operationalized corresponding to the derived variables. There are many other constructs which have been evidenced to influence student mathematics achievement and are not included.

Implicitly, this study assumes that student motivational beliefs, and the classroom and school context affect students' math achievement. The relationships may be reciprocal. That is, student math achievement may as well affect student motivational beliefs and the environment the student is in. While this study does not try to establish causal relationships, it does, from the standpoint of building statistical models, imply that motivational beliefs and contextual variables precede student achievement. This study does not examine other possible directions of relationships among the variables.

The analysis is conducted separately for each country. While the relationships among the variables can be compared across countries, this study does not compare the predictors themselves. Each scale only applies to that particular country.

1.8 Overview of the Subsequent Chapters

The subsequent chapters are organized as follows. Chapter 2 reviews the related literature on student self beliefs and the classroom and school environment characteristics associated with mathematics achievement. Chapter 3 describes the research design including a description of the data source, major measures of student, teacher, and school constructs, and selected statistical techniques. Chapter 4 presents the results of findings in different countries and the comparisons among them. And finally, the summary of findings, implication of the study and direction for future research are concluded in Chapter 5.

CHAPTER 2

REVIEW OF THE LITERATURE

Student academic achievement has been studied within different frameworks. Many of them have a focus on student achievement motivation. Theories with different topics such as intrinsic motivation, self-concept, attribution, goal orientation, self-efficacy, and expectations have been established during the past century. Many studies have examined the relationships among those constructs and student achievement. On the other hand, not many studies consider the context the student is in when student characteristics are examined. This chapter consists of three sections. The first section briefly reviews social theories related to student motivation, especially student self-beliefs, that involve student academic achievement. The second section compares several self-belief constructs and gives a rationale for the self-belief constructs used in this study. The third section reviews research on classroom and school characteristics that have influences on student academic achievement.

2.1 Social Theories Related to Student Achievement Motivation

Schunk, Pintrich and Meece (2008) define motivation as, “the process whereby goal-directed activity is instigated and sustained” (p. 4). Different social theories have emphases on different measures/aspects of motivation. Despite the differences, one consistent finding is that motivation is related to achievement behaviors.

2.1.1 Self-Efficacy and Social Cognitive Theory

One of the most influential motivation constructs about self-beliefs originated from Bandura (1977, 1986, 1993, 1997, 2001). “Self-efficacy” is defined as “People’s judgments of their capabilities to organize and execute courses of action required to attain designated types of performances” (Bandura, 1986, p. 391). Self-efficacy is considered to be situated within a social cognitive theory (Bandura, 1986; Pajares, 1997). Bandura (1986) describes the reciprocal interactions among personal, behavioral, and environmental factors in his framework of triadic reciprocality:

> In the social cognitive view people are neither driven by inner forces nor automatically shaped and controlled by external stimuli. Rather, human functioning is explained in terms of a model of triadic reciprocality in which behavior, cognitive and other personal factors, and environmental events all operate as interacting determinants of each other (p. 18).

Self-efficacy can be used to explain the behavioral-personal factor interaction. Research has shown that self-efficacy influences such achievement behaviors as choice of tasks, persistence, and effort (Betz & Hackett, 1981, 1983; Hackett & Betz, 1981; Schunk, 1989, 1995; Schucnk & Pajares, 2002). When self-efficacy perceptions are high, individuals will engage in tasks that foster the development of their skills and capabilities, but when self-efficacy is low, people will not engage in new tasks that might help them learn new skills (Bandura, 1997).

Research findings have demonstrated that self-efficacy is a better predicator than any other cognitive or affective processes (Schunk, 1991) and it is a valid predictor for students' motivation and performance (Hodges, 2008). On the other hand, social cognitive theory suggests that self-efficacy is not a global construct that can be measured with an omnibus instrument, but rather, it is a disposition that varies across activities and contexts (Marakas, Yi, & Johnson, 1998), i.e., self-efficacy is task-specific. Further, Bandura (1989) argued that the predictive capability of self-efficacy estimate is stronger and more accurate when using a specific measure rather than using general, global measures.

During the past three decades, the construct of self-efficacy has been used in different disciplines and settings. For instance, Paraskeva, Bouta, and Papagianni (2008) examined the relationship between general self-efficacy and computer self-efficacy of secondary education teachers and found that there was a significantly positive relationship between the two. Chan and Lam (2008) conducted a study with 71 seventh-graders in Hong Kong and found that student self-efficacy might be threatened when they are engaged in vicarious learning in a competitive classroom.

Pajares (1997) points out that self-efficacy beliefs have received increasing attention in educational research, primarily in studies of academic motivation and of self-regulation (Pintrich & Schunk, 1995). There are three major areas of research focusing on self-efficacy. The first area is the link between efficacy beliefs and college major and career choices, particularly in science and mathematics (see Lent & Hackett, 1987; Pajares, 1997). The second area is the relationship between self-efficacy beliefs of teachers and their instructional practices and various student outcomes (Ashton & Webb, 1986; Pajares, 1997). The third area is the relationships among students' self-efficacy and other motivation constructs and students' academic performances and achievement. Constructs involved in these studies include attributions, goal setting, modeling, problem solving, test and domain-specific anxiety, reward contingencies, self-regulation, social comparisons, strategy training, other self-beliefs and expectancy constructs, and varied academic performance across domains.

Graham and Weiner (1996) cited by Pajares (1997) credit the popularity of self-efficacy in motivation research to its broad application across various domains of behavior. However, the operationalization of self-efficacy is not consistent among studies. Some use measures of task-specific self-efficacy, while others use generalized, global, or multiple-scale self-efficacy measures to predict academic performances (see Multon et al., 1991). For example, Betz and Hackett (1983) created the Mathematics Self-Efficacy Scale (MSES) and used the composite scores of three subscales—individuals' judgments of their capabilities to solve math problems, perform math-related tasks, and succeed in math-related courses—as their "math self-efficacy".

Pajares (1997) points out 14 future directions in self-efficacy research:

1. Formulating Questions with an Eye to Specificity and Correspondence
2. Discovering the Generality of Self-efficacy Beliefs
3. Understanding the Implications Related to Strength and Accuracy of Self-efficacy Beliefs
4. Tracing the Sources and Effects of Self-efficacy Beliefs

5. Exploring the Causal Predominance of Self-efficacy
6. Refining the Study of Teacher Efficacy
7. Continuing Research on Self-efficacy and Career Choice
8. Closing the Confidence Gap in Mathematics
9. Developmental Perspective of Self-efficacy Beliefs
10. Distinguishing the Role of Self-efficacy as a Function of Race and Ethnicity
11. Clarifying the Influence of Social and Cultural Contexts on Self-Efficacy Beliefs
12. Investigating Collective Efficacy
13. Making the Connection from Research to Practice
14. Encouraging Intertheoretical Crosstalk and Collaboration

Two of these 14 directions (#11 and #12) call for the attention to the environment and context with research on self-efficacy beliefs.

2.1.2 Expectancy-Value Theory

Another influential motivational theory involves expectancy and value constructs and is from the work of Eccles, Wigfield, and their colleagues (Eccles, 1983, 1987, 1993, 2005; Eccles et al., 1989; Wigfield, 1994; Wigfield & Eccles, 1992, 2000; Wigfield, Eccles, & Rodriguez, 1998; Wigfield, Tonks, & Eccles, 2004). First proposed by Eccles et al. in 1983, this expectancy-value model focuses on the role of students' expectancies for academic success and their perceived value for academic tasks. According to this model, children's achievement performance, persistence, and choice of achievement tasks are most directly predicted by their expectancies for success on those tasks and the subjective task value they attach to success on those tasks (Wigfield, 1994). Children's expectancies and values are most directly determined by other achievement-related beliefs, including children's achievement goals and self-schemata, and their task-specific beliefs.

Children’s interpretations of their previous performance, and their perceptions of socializers’ attitudes and expectations influence their goals and task specific beliefs.

Expectancies for success can be defined as children’s beliefs about how well they will do on an upcoming task (Wigfield, 1994). Specifically, Wigfield and Eccles (2000) compared expectancies for success with Bandura’s (1997) definitions of efficacy expectations and outcome expectancies and argued that “we have measured individuals’ own expectations for success, rather than their outcome expectations. Thus our expectancy construct is more similar to Bandura’s efficacy expectation construct than it is to the outcome expectancy construct” (Wigfield & Eccles, 2000).

Although only interest value and utility value are included as separate constructs in Eccles, et al. (1983), Eccles and Wigfield (1995; also see Wigfield, Eccles & Rodriguez, 1998) define achievement task value in terms of four components. Attainment value is the importance of doing well on task. It denotes the extent to which task allows individuals to confirm or disconfirm salient or central aspects of their self-schema. To the extent that tasks allow more general values to be expressed, attainment value would be higher for these tasks (Wigfield & Eccles, 1992). Intrinsic value is the enjoyment people experience when doing a task, or their subjective interest in the content of a task (Wigfield & Eccles, 1992). Conceptually, it is similar to intrinsic interest in the intrinsic motivation theory of Deci and Ryan (1985), as well as the work on personal interest and flow (Csikszentmihalyi, 1975; Renninger, Hidi, & Krapp, 1992; Schiefele, 1991; Tobias, 1994). When intrinsic value is high, individuals will be more engaged in the task, persist longer, and be more intrinsically motivated to work at that task (Wigfield & Eccles, 1992). Utility value is the usefulness of the task for individuals in terms of their future goals, including career goals. It is similar to some of the extrinsic reasons for doing a task in Deci and Ryan's (1985) model. The fourth value component is cost belief and is defined as the perceived negative aspects of engaging in the task (Wigfield & Eccles, 1992). Cost includes the lost opportunity of engaging in other tasks as well as perceive amount of effort required for this particular task and the anticipated emotional states such as performance anxiety, fear of failure, etc.

Ability beliefs are assumed to be precedents of expectancies for success in the expectancy-value model because they are defined as the individual's perception of his or her current competence at a given activity while expectancies for success are future-oriented (Wigfield & Eccles, 2000). However, ability beliefs and expectancies for success cannot be empirically differentiated (see Eccles et al., 1993; Eccles & Wigfield, 1995; Wigfield & Eccles, 2000).

Eklof (2007) uses expectancy-value model to discuss the constructs of self-concept and valuing of mathematics using a Swedish sample from TIMSS 2003. Results from exploratory factor analysis indicate that the factors of mathematics self-concept and valuing math are different and could be extracted. Confirmatory factor analysis, however, shows that mathematics self-concept is a unitary construct but valuing mathematics might have different dimensions (Eklof, 2007).

The achievement behaviors in the expectancy-value model of achievement motivation include persistence, choice, quantity of effort, cognitive engagement and actual performance. Studies have shown that children's beliefs about their ability and expectancies for success are the strongest predictors of grades in math while children's subjective task values are the stronger predictors of children's intentions to keep taking math and actual decisions to do so (Wigfield & Eccles, 2000).

2.1.3 Self-Concept

Self-concept is defined as "Individuals' belief about themselves in terms of their academic, social, athletic, and personal capabilities and characteristics" (Schunk, Pintrich & Meece, 2008, p. 379). Originally, it was treated as a general factor and the theoretical formulation of the construct was imprecise. Shavelson, Hubner, and Stanton (1976) developed a multifaceted, hierarchical structure of self-concept. In their model, self-concept had academic and nonacademic components. Academic self-concept was then divided into self-concepts in particular subject areas (e.g. mathematics, English), and nonacademic self-concept was divided into social, emotional, and physical self-concepts. Marsh (1990b) later tested the academic self-concept portion of the Shavelson et al. (1976) model and concluded that the model was supported when it was limited to self-concepts in academic core subjects such as English and mathematics.

Byrne (1984) noted that much of the interest in the relation between self-concept and achievement stemmed from the belief that academic self-concept has motivational properties such that changes in academic self-concept will lead to changes in subsequent academic achievement. Marsh (1990a) conducted a longitudinal study about the relationship between academic self-concept and academic achievement and tested two models. The self-enhancement model was based on the assumption that prior academic self-concept affects subsequent academic achievement and was used implicitly to justify many educational programs designed to enhance self-concept; and the skill development model was based on the assumption that academic self-concept merely reflected academic skills so that the best way to enhance academic self-concept is to improve academic skills (Marsh, 1990a). In reality, the relationship between academic self-concept and academic achievement is likely to be reciprocal, that is, prior academic achievement affects subsequent academic self-concept and prior academic self-concept also affects academic achievement.

2.2 All about Self and Self-beliefs

There have been different constructs proposed of student self-beliefs in academic achievement. For example, the research on students' perceptions of their competence and self-concept is similar to the research on expectancies and values (Harter, 1982, 1985, 1990, 1998; Marsh & Shavelson, 1985). Research on perceptions of competence comes from a more developmental perspective on the development of self and personal identity in contrast to the focus on motivation in expectancy-value theories (Schunk, Pintrich & Meece, 2008). Marsh and Shavelson (1985) defines self-concept broadly as “a person’s perceptions of him- or herself (p. 107).” According to their model, self-concept has six characteristics: 1) self concept is multi-faceted; 2) self-concept is arranged hierarchically; 3) global self-concept is stable, but becomes less stable as self-concept becomes more situation specific; 4) self-concept becomes more multi-faceted and distinct as a person gets older; 5) self-concept is both descriptive and evaluative; and 6) self-concept can be differentiated from other constructs such as academic achievement. Although there has been disagreement about the levels of specificity, most researchers believe that self-perceptions of competence are domain specific.

Early research on self-concept was not vey theoretically-based (see Schunck, Pintrich & Meece, 2008). Later researchers try to differentiate it from other related constructs (e.g. Bong & Skaalvik, 2003). Self-concept is generally defined as a person’s perceptions of him- or herself (Marsh & Shavelson, 1985). Self-efficacy is defined as “People’s judgments of their capabilities to organize and execute courses of action required to attain designated types of performances” (Bandura, 1986). According to Bong & Skaalvik (2003), strong self-efficacy and positive self-concept lead students to set challenging yet attainable academic goals for themselves, feel less anxious in achievement settings, enjoy their academic work more, persist longer on difficult tasks, and overall, feel better about themselves as a person and as a student. In other words, high self-efficacy and self-concept are associated with good academic outcomes. Along this line of argument, successful students usually have high self-efficacy and self-concept and the related adaptive cognitive processes. They are likely to attend to instruction, participate in tasks, rehearse information to be remembered, expand effort, persist on challenging tasks, and have proximal, specific and moderately difficult goals (and have mastery goal orientation). They also feel competent in skills and have high confidence in their ability to learn and perform on tasks. They use various cognitive and self-regulatory learning strategies. They are more likely than other students to use deeper thinking processes and practice self-observation, self-judgment and self-reaction. At the same time, they will observe their goal process. They will more likely to use self-modeling (cognitive and behavioral changes stemming from observing one's own performances). Successful students also have high motivation and enjoy the academic tasks. They are more concerned about acquiring skills and strategies rather than performing tasks. They make more adaptive attributions when they succeed or fail on a task. However, they may not always have a positive outcome expectation. They learn through their own as well as others' experiences and interpret others' feedback appropriately. They may involve in social comparison but at the same time be willing to contribute to group work. They have high self-esteem and self-worth, are optimistic but practical, agreeable and active. They are the ones teachers like and everybody wants to be.

Some researchers consider self-perceptions of competence as integral components of an individual's self-concept (Pajares 1997; see Shavelson & Bolus, 1982). Because of this, self-efficacy beliefs are often viewed as requisite judgments necessary to the creation of self-concept beliefs. Academic domain-specific self-concept has been shown to be related to academic achievement and to other motivation constructs across domains (see Hattie, 1992). However, few researchers have explored the relationships among self-efficacy, self-concept, and academic performances and the results are inconsistent (Pajares, 1997). The question still remains as which self belief has the stronger influence on achievement. Results from some studies seem to suggest that the difference between self-concept and self-efficacy is the specificity (Bandalos, Yates, & Thorndike-Christ, 1995; Skaalvik & Rankin, 1996). For example, Marsh (1990) assessed math self-concept, math achievement, performance on a math task and self-efficacy for the task and showed that achievement correlated equally strongly with domain-specific self-efficacy and self-concept. Specific performance on the math task was more strongly correlated with specifically assessed self-efficacy than domain-specific self-concept. Pajares and Miller (1995) also found that item-specific math self-efficacy beliefs were more predictive of a mathematics problem-solving than were domain-specific self-concept beliefs. These findings are consistent with Bandura’s theory (1986, p. 410).

Despite all the differences and similarity among those constructs related to self-beliefs, this current study is going to use the term “self-confidence” as the construct that how students perceive their ability in mathematics. The closest construct is, by examining definitions, is self-perception of competence which is defined as the cognitive evaluation of ability in a domain (Harter, 1998). TIMSS 2003 does not provide a theoretical rationale for including the items assessing self-beliefs. Eklof (2007) examined the items from the perspective of the expectancy-value theory. To avoid any confusion, this study uses the name of the derived index variable by TIMSS 2003, that is, “Students’ Self-Confidence in Learning Mathematics”.

2.3 Context Matters: Parents, Teachers, Classroom and School

As Wigfield, Eccles and Rodriguez (1998) mentioned, because of the emphasis on self variables by motivation researchers during the past decades, much of the research on motivation has focused on motivation as a characteristic of the individual. Recently, there has been increasing recognition of the importance of social influences on learning and motivation (Eccles et al., 1998; Marshall, 1992; McCaslin & Good, 1996; Noonan, 2004; Stewart, 2008). Researchers have found that schools vary in climate, teachers’ sense of efficacy, and general expectations regarding student potential. Variations in these dimensions influence the motivation of both teachers and students (e.g., Maehr & Midgley, 1996; Rutter et al., 1979).

School culture and organization can have strong effects on students’ motivation and achievement (Schunk, Pintrich & Meece, 2008, p. 346). Schunk, Pintrich and Meece (2008) derive a general conceptual framework of school culture and organization from the work of Lee, Bryk, and Smith (1993) and Maehr and Midgley (1991). According to this model, there are eight dimensions of school culture and organization: Norms, values, and shared beliefs; climate; task and work structures; authority and management structures; recognition and reward structures; grouping practices; evaluation practices; and time use. For the dimension of school climate, three key aspects are considered: sense of community, warmth and civility, and feelings of safety and security. Outside the context of school, the larger picture includes external constraints/opportunities such as type of students, school size/number of students; parental/community involvement, district level constraints/opportunities, state level constraints/opportunities, etc.

Stewart (2008) examines the extent to which individual-level and school structural variables are predictors of academic achievement among a sample of 10th-grade students using the National Educational Longitudinal Study database. Findings indicate that besides individual-level predictors, school climate, especially the sense of school cohesion felt by students, teachers, and administrators, is important to successful student outcomes (Stewart, 2008). Results also show that school structural characteristics have relatively small effects on student achievement when compared to individual-level characteristics.

Educational researchers have studied school characteristics—such as type of school (public or private), size, student body demographics, and teacher qualifications—and their relationship to students' academic outcomes (Carbonaro, 2005; Coleman, 1990a; Parcel & Dufur, 2001; Rumberger & Palardy, 2005). Schools exert their influence on their students' attachment, commitment, involvement, and, most important, academic achievement through their resources and climate (Freiberg, 1999).

The definition of school climate is inconsistent in studies of school characteristics. For example, Stewart (2008) examines effects of school climate on student achievement on three dimensions: school culture, school organizational structure, and school social milieu. Noonan (2004) points out that “a thorough assessment of a school’s climate can be a complex and tiresome process, consisting of a mixture of observation, surveys, interviews, and focus groups” but “there is a simpler, if less scientific, way to evaluate a school’s climate.” Seven important factors are identified to contribute to a healthy school climate (Noonan, 2004): 1) models, 2) consistency, 3) depth, 4) democracy, 5) community, 6) engagement, and 7) leadership. One of the measures of school climate is the School Level Environment Questionnaire (Burden & Fraser, 1994; Fraser & Rentoul, 1982; Johnson, Stevens & Zvoch, 2007). Using a sample of teachers, Johnson, Stevens, and Zvoch (2007) identified five constructs under the school climate: collaboration, decision making, instructional innovation, student relations and school resources. White (2005), as cited in Stevenson (2006), defines school climate indicators in elementary schools to be: the percentage of teachers and students satisfied with the learning environment, social/physical environment, and home-school relations within the schools; the percentage of students identified as gifted and talented; the percentage of students on academic plans; the portion of students on academic probation; the percentage of pupils suspended, expelled, and retained in a given year; student attendance (percent of student body in daily attendance); the percentage of teachers returning from the previous year; the portion of teachers holding advanced degrees; and teacher attendance (percent of faculty in daily attendance). Those school climate indicators are similar to those defined by Gettys (2003) in his study of middle schools.

Researchers studying classroom climate include factors such as teacher personality and warmth. They found that the effects of “climate” are dependent on other aspects of teachers’ beliefs and practices. For instance, Moos and his colleagues have shown that student satisfaction, personal growth, and achievement are maximized only when teacher warmth and supportiveness are accompanied by efficient organization, stress on academics, and provision of focused, goal-oriented lessons (Fraser & Fisher, 1982; Moos, 1979; Trickett & Moos, 1974). Furthermore, these practices are more common among teachers who believe they can influence their students’ performance and future achievement potential (Brookover, Beady, Flood, Schweitzer, & Wisenbaker, 1979; Caprara, Barbaranelli, & Steca, 2006; Rutter, Maughan, Mortimore, Ouston & Smith, 1979).

A growing body of research has shown that students perform better academically when parents are involved with their child’s schooling (see, e.g., Astone & McLanahan, 1991; Catsambis & Beveridge, 2001; Christenson, Rounds, & Gorney, 1992; Coleman, 1990b; Epstein, 1991; Fehrman, Keith, & Reimers, 1987; Feuerstein, 2000; Jeynes, 2003; Keith et al., 1993; Levine & Lezotte, 1990; Rumberger & Palardy, 2005; Sui-Chu & Willms, 1996; Thompson, 2002). In a recent study evaluating the effects of family and school capital on students’ classroom achievement, Parcel and Dufur (2001) found that parental involvement in school activities had a positive impact on children’s mathematics achievement. Another study found that parent involvement in academics at home is more important to a child's academic achievement than parent involvement at school (DePlanty, Coulter-Kern, & Duchane, 2007). Overall, the research has shown that parents are instrumental to their children's academic success and that parental involvement has a positive impact on student achievement. Zhao (2007), using TIMSS 1999 data, conducted a comparative study of school expectations and initiatives for parental involvement in 30 nations. Results show that students in the United States were more likely to achieve better if their schools had higher expectations for parents' direct involvement (Zhao, 2007).

In TIMSS 2003, school climate is assessed using Likert-scale items from the perceptions of students, teachers and principals. Parent involvement is measured by school principals' responses to whether their schools expected parents to be involved in some activities. Measures are also available of teachers' perceptions of school facility and safety and of limiting mathematics teaching due to student factors. Another measure, students' perception of being safe in the schools could have been added. However, the data were not available for the US sample and therefore are not included in this study. TIMSS 2003 does not have an explicit theoretical rationale for all items.

CHAPTER 3

METHOD

This chapter includes four sections. Section one restates the research questions of the study. Section two briefly reviews hierarchical linear modeling which is proposed as the major statistical technique utilized in this study. Section three describes the data source, procedure used to collect data and measures used in this study. Finally, in section four, statistical models are applied and analyses described.

3.1 Overview of Research Questions

The specific questions addressed in this study include:

(1) In each country, how does mathematics achievement differ across schools or classrooms?

(2) In each country, how do student motivational beliefs relate to math achievement within the classroom and school context?

(3) In each country, is the strength of association between student characteristics and mathematics achievement similar across classrooms or schools? Are teacher and school characteristics more important factors in some classrooms and schools than in others?

(4) What are the country differences in the above measures and effects?

3.2 Hierarchical Linear Modeling

Hierarchical linear modeling (HLM) has been used to analyze data with a hierarchical structure or longitudinal data in social sciences (e.g. Codding, Shiyko, Russo, Birch, Fanning & Jaspen, 2007; Ma & Klinger, 2000; Preckel, Zeidner, Goetz & Schleyer, 2008). As Qu (1997) points out, HLM are also known as random coefficient models (Rosenberg, 1973), multilevel linear models (Mason, Wong, & Entwistle, 1983) and mixed models (Goldstein, 1986). Specialists in sampling refer to HLM as multistage cluster sampling, while psychologists speak of growth curve models, and biostatisticians of repeated measure models (Qu, 1997).

In education, a lot of important information about achievement involves hierarchical data (such as students nested within schools). Classical statistical techniques such as regression cannot correctly reflect the data structure. Failure to consider the hierarchical nature of data leads to un-reliable estimation of the effectiveness of school policies and practices (see Raudenbush & Bryk, 2002; Raudenbush & Willms, 1991). Analyzing data organized into hierarchies as if they are all of the same level leads to both interpretational and statistical errors (Tabachnick & Fidell, 2007). If we disaggregate all higher order variables to the individual level, the assumption of independence of observations is no longer valid because lower-level units from the same higher level unit will have the same value on the higher-level variables. If, on the other hand, the lower-level variables are aggregated to the higher level and the analysis is done on the higher level, the within-group information is lost and interpretation is restricted to the higher level. The first alternative is called atomistic fallacy and the second ecological fallacy (Hox, 2002; Tabachnick & Fidell, 2007)

Hierarchical linear modeling relaxes the assumption of independence of observations and takes into consideration the hierarchy of data. The methodology in HLM is based on finding the optimal balance of ordinary least square and aggregation approaches (Qu, 1997). One advantage of HLM over other ways of handling hierarchical data is that predictors can be at every level of analysis. With hierarchical linear models, each of the levels is formally represented by its own submodel. As a result, usually the estimation of effects within lower-level units is improved, cross-level effects can be formulated and tested, or variance and covariance can be partitioned among levels (Raudenbush & Bryk, 2002).

Consider a two-level HLM model with one predictor as each level. Table 1 shows the submodels at each level and the denotations of the symbols.

Table 1.

Equations and Symbols in a Two-Level HLM model with One Predictor at Each Level.

Symbol	Meaning
Level-1 Equation	$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + r_{ij}$, where $r_{ij} \sim N(0, \sigma^2)$
Y_{ij}	Value on the dependent variable at Level-1 for person i in goup j
X_{ij}	Level-1 predictor
β_{0j}	Intercept for DV in group j
β_{1j}	Slope for the relationship in group j between the DV and Level-1 predictor; change in DV with 1 unit increase in Level-1 predictor in group j
r_{ij}	Random error of prediction for person i in goup j
σ^2	Variance of Level-1 random errors
Level-2 Equations	$\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j}$
	$\beta_{1j} = \gamma_{10} + \gamma_{11} W_j + u_{1j}$
	where $Var\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} = \begin{bmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{bmatrix} = \mathbf{T}$
W_j	Level-2 predictor
γ_{00}	Overall intercept; grand mean of the DV scores across all groups when all predictors equal to zero
γ_{01}	Overall regression coefficient for the relationship between a Level-2 predictor and the DV
u_{0j}	Random error for the deviation of the intercept of a group from the overall intercept; the unique effect of group j on the intercept
γ_{10}	Overall regression coefficient for the relationship between Level-1 predictor and the DV when Level-2 predictor equal to zero

γ_{11}	Change in slope for the relationship between Level-1 predictor and DV with one unit increase in Level-2 predictor
u_{1j}	Random error for the slope for relationship between Level-1 predictor and DV; unique effect of group j on slope for relationship between Level-1 predictor and DV, controlling for Level-2 predictor
τ_{00}	Variance of u_{0j}
τ_{01}, τ_{10}	Covariance between u_{0j} and u_{1j}
τ_{11}	Variance of u_{1j}
Combined Equation	$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}X_{ij} + \gamma_{11}W_jX_{ij} + u_{0j} + u_{1j}X_{ij} + r_{ij}$

One of the important issues in HLM is centering predictor variables, that is, using the deviation scores from a mean instead of the raw scores. Predictor variables can be centered so that the intercepts will be meaningful. The statistical reason to center variables is to avoid multicollinearity and singularity (Tabachnick & Fidell, 2007, p. 789). The meaning of intercept terms, however, depends on which mean is subtracted from the original scores. The two most popular centering methods are group-mean centering and grand-mean centering. For example, if the Level-1 predictor X_{ij} is centered around the group mean, the intercept β_{0j} will be the expected value of Y_{ij} for an individual whose value on X_{ij} is equal to the group mean. That is, β_{0j} would be the expected value of Y_{ij} for the average individual in the group. On the other hand, if X_{ij} is centered around the grand men, β_{0j} would be the expected value of Y_{ij} for the average individual in all the groups. The average person in a group is not necessarily to be the same as the average person in all the groups. Kreft, Leeuw, and Aiken (1995) discussed different centering methods in hierarchical linear models and concluded that which centering should be used depends on the theory and research questions asked. Although group centering seems to be favored by some researchers (Raudenbush, 1989a, 1989b), grand mean centering is more often used in studies on large-scale achievement assessment (e.g. Braun, Jenkins & Grigg, 2006). The choice is consistent with standard practice in the analysis of covariance. The intercept of the Level-1 submodel is adjusted for the linear regression of the dependent variable on the centered variable. It puts all group means on an equal footing with respect to that variable and the adjusted intercept can be described as "adjusted group means" (Braun, Jenkins & Grigg, 2006; Raudenbush & Bryk, 2002).

Another important issue in HLM is model building at each level. Raudenbush and Bryk (2002) recommend a build-up strategy for HLM analyses. First a series of standard multiple regression analyses are run, starting with the most interesting (or theoretically important) predictor and adding predictors in order of importance. Then predictors that do not enhance prediction are dropped unless they are components of cross-level interactions. Braun, Jenkins and Grigg (2006) give a complete example of using HLM to arrive at a final model.

The sampling design of TIMSS 2003 should be considered during analysis (TIMSS 2003 Technical Report, 2004). HLM is able to incorporate weight variables so that the results reflect the characteristics of the population.

When several plausible values from imputation are included, such as in the case of students' mathematics achievement in TIMSS 2003, HLM is able to produce standard errors of estimates with the variation between plausible values considered. The analysis procedure for each model is run five times, once for each set of plausible values. That is, in each run the plausible values play the role of the criterion variable at Level-1. The final estimates are the averages of the results from the five analyses. These steps are automated in the HLM program.

3.3 Data Source

As one of the largest and most complex cross-national studies of educational achievement, the Trends in International Mathematics and Science Study (TIMSS) 2003, the third data collection in the TIMSS cycle of studies, was conducted by the International Association for the Evaluation of Educational Achievement (IEA) and was administered at the eighth and fourth grades in 49 countries. Forty-eight countries participated at the eighth grade and 26 at the fourth grade.

In this study, data from 47 countries[1] at the eighth grade in the TIMSS 2003 were available. The countries included in this study are from a variety of geographic regions of the world and represent a great range of economic development levels and school systems. A total of 7221 schools, 8618 classes, 224503 students and their parents, and 9383 mathematics teachers are included (See Table 2).

[1] Argentina administered the TIMSS 2003 data collection one year late, and data were not available at release time (TIMSS 2003 User Guide).

Table 2.

Sample Size by Country in TIMSS 2003 at Eighth Grade (Mathematics).

Country	Country Code	No. of Schools	No. of Classes	No. of Students	No. of Math Teachers
Armenia	ARM	149	269	5726	246
Australia	AUS	207	207	4791	246
Bahrain	BHR	67	147	4199	153
Belgium (Flemish)	BFL	144	272	4970	272
Botswana	BWA	146	146	5150	146
Bulgaria	BGR	164	193	4117	193
Chile	CHL	195	195	6377	215
Chinese Taipei	TWN	150	150	5379	152
Cyprus	CYP	59	165	4002	165
Egypt	EGY	217	217	7095	217
England	ENG	87	130	2830	139
Estonia	EST	151	155	4040	168
Ghana	GHA	150	150	5100	153
Hong Kong, SAR	HKG	125	131	4972	147
Hungary	HUN	155	155	3302	198
Indonesia	IDN	150	150	5762	155
Iran, Islamic Rep.	IRN	181	181	4942	181
Israel	ISR	146	146	4318	353
Italy	ITA	171	216	4278	217
Japan	JPN	146	146	4856	146
Jordan	JOR	140	140	4489	140
Korea, Rep. of	KOR	149	149	5309	365
Latvia	LVA	140	179	3630	168
Lebanon	LBN	152	152	3814	152
Lithuania	LTU	143	258	4964	258
Macedonia, Rep. of	MKD	147	149	3893	149
Malaysia	MYS	150	150	5314	150
Moldova, Rep. of	MDA	149	173	4033	165
Morocco	MAR	131	131	2943	131
Netherlands	NLD	130	130	3065	130
New Zealand	NZL	169	177	3801	261
Norway	NOR	138	179	4133	179
Palestinian Nat’l	PSE	145	145	5357	145
Philippines	PHL	137	137	6917	137
Romania	ROM	148	178	4104	178
Russian Federation	RUS	214	214	4667	215
Saudi Arabia	SAU	155	172	4295	172
Scotland	SCO	128	155	3516	172
Serbia and Montene	SCG	149	176	4296	177
Singapore	SGP	164	328	6018	332
Slovak Republic	SVK	179	179	4215	179
Slovenia	SVN	174	176	3578	238
South Africa	ZAF	255	255	8952	256
Sweden	SWE	159	274	4256	300
Syrian Arab Republ	SYR	134	134	4895	166
Tunisia	TUN	150	150	4931	150
United States	USA	232	457	8912	456
Total		7221	8618	224503	9383

3.3.1 Student Variables

Student mathematics achievement was used as the outcome variable. Two motivational beliefs—self-confidence in learning math and valuing math—and the school climate from student perspective were the variables of interest whose effects on math achievement were to be tested. Three control variables were included at the student level: student's sex, parents' highest education level and student's educational expectation.

Student Mathematics Achievement. The TIMSS 2003 eighth-grade math assessment contained 194 items assessing 5 content domains (number, algebra, measurement, geometry, and data). Administering all the mathematics items, in addition to science items included in TIMSS 2003, to all students would require a lot of testing time. To address this problem, TIMSS 2003 used a matrix-sampling technique. With this technique, the 194 mathematics items were assembled into 14 unique item blocks. Each block contained an average of 15 score points at the eighth grade. On average, there were 8-9 multiple choice items, 3-4 short-answer items and 1-2 extended-response items per block. These 14 math blocks, along with 14 science blocks, were distributed across 12 student booklets. The 12 booklets were rotated among students during test administration. (See TIMSS 2003 User Guide).

Since each student responded to only one booklet, not the entire assessment, item response theory (IRT) scaling methods were used to derived estimates for each student of the scores they would have derived had they completed the entire assessment (Gonzalez, Galia, and Li, 2004). First of all, IRT scores for each student were derived. Those scores were then used to get overall student achievement distributions, conditional on students' background characteristics and their responses to the achievement items. Each student's achievement was later estimated conditional on the student's responses and background characteristics. Because there is some error inherent in this imputation process, five such estimates were drawn for each student on each of the scales. Those estimates are plausible values. TIMSS 2003 reports plausible values for the overall subjects as well as for the content domains. In this study, only the five plausible values for the overall mathematics subject are to be used and the results using those five plausible values are later integrated to account for the impact of imputation error during the stage of arriving at plausible values.

The weighted average mathematics achievement by country is in Figure 1.

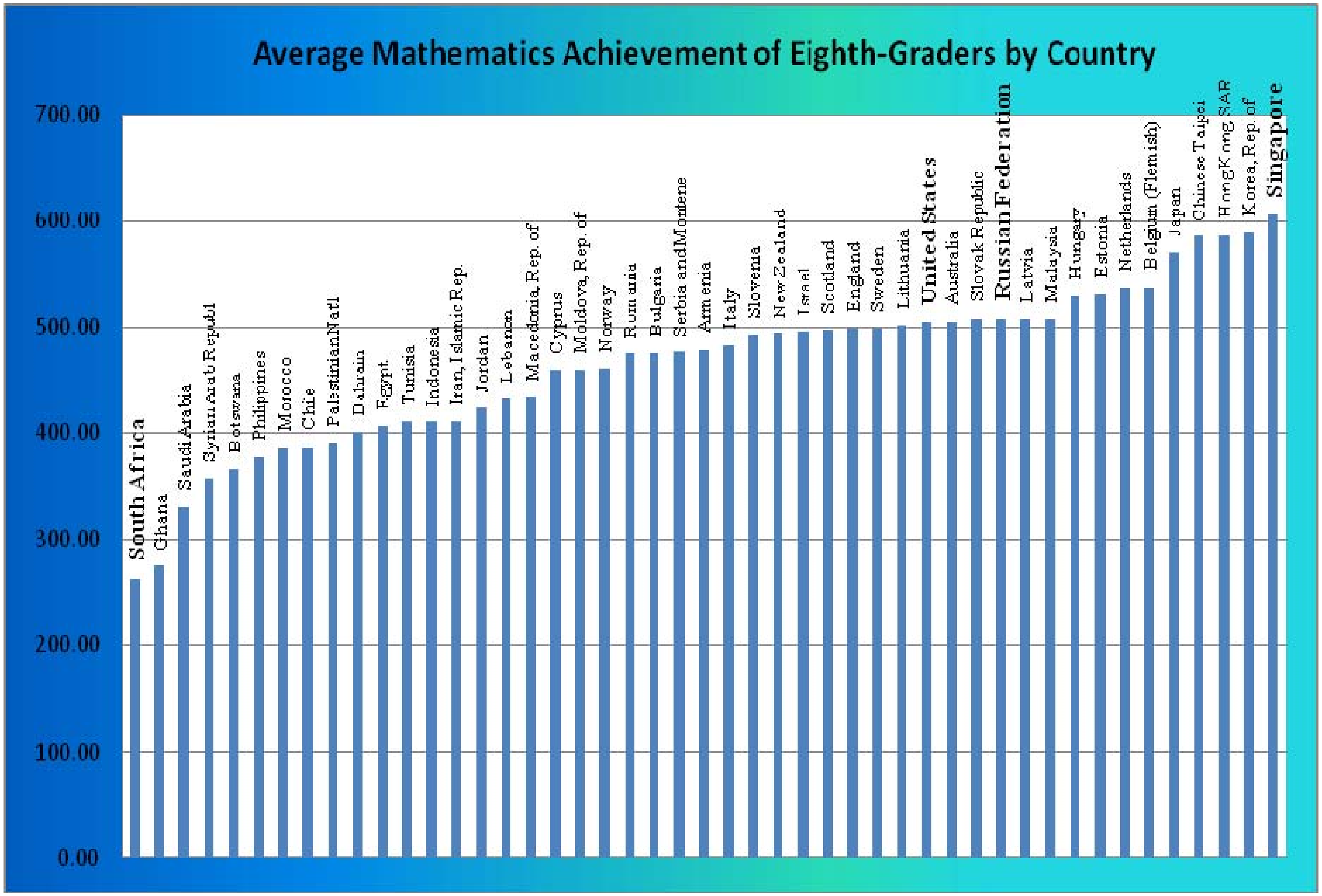

Figure 1. Weighted Average Mathematics Achievement of Eighth-graders by Country

Student Self-Confidence in Learning Mathematics. Four Likert-scale items measure student's self-confidence in learning mathematics. The response options for them were "agree a lot" (coded as 1), "agree a little" (coded as 2), "disagree a little" (coded as 3), and "disagree a lot" (coded as 4). A sample item of this measure was "I usually do well in mathematics". Responses to positive statements were reverse coded so that a higher score means more self-confidence in learning mathematics. All the items of this measure are in Appendix A. Table 3 shows the means and standard deviations of the original items. The four items were analyzed using principal components analysis (PCA) within each country. Only one factor was retained after checking the results of PCA within each country.

Table 3.

Means and Standard Deviations of Original Items for Measure of Student Self-Confidence in Learning Mathematics.

	United States	Russia	Singapore	South Africa
Usually do well in math (r)[a]	3.16 (0.83)	2.77 (0.85)	2.68 (0.90)	3.13 (0.85)
Math is difficult	2.85 (1.03)	2.75 (1.04)	2.63 (0.90)	2.35 (1.06)
Math is not a strength	2.59 (1.16)	2.76 (1.00)	2.49 (1.06)	2.36 (1.11)
Learn math quickly (r)	2.83 (0.93)	2.44 (0.92)	2.63 (0.87)	2.96 (1.01)

[a] (r) Reverse coded items.
Note. Standard deviations are in parentheses.

Student Valuing Mathematics. Seven Likert-scale items measure student's valuing mathematics. The response options for them were "agree a lot" (coded as 1), "agree a little" (coded as 2), "disagree a little" (coded as 3), and "disagree a lot" (coded as 4). A sample item of this measure was “I think learning mathematics will help me in my daily life”. A higher score on an original items means a *lower* value attached to mathematics. All the items of this measure are in Appendix A. Table 4 shows the means and standard deviations of the original items. The seven items were analyzed using principal components analysis (PCA) within each country. Only one factor was retained after checking the results of PCA within each country. Since principal component (factor) scores are standardized scores with mean equal to zero, they are subtracted from zero so that a higher score represents a *higher* value attached to mathematics on this construct.

Table 4.

Means and Standard Deviations of Original Items for Measure of Student Valuing Mathematics.

	United States	Russia	Singapore	South Africa
Math will help in daily life	1.54 (0.76)	1.58 (0.76)	1.59 (0.70)	1.41 (0.79)
Need math to learn other school subjects	1.78 (0.81)	1.63 (0.73)	1.90 (0.77)	1.70 (0.91)
Need do math well to get into university	1.41 (0.70)	1.71 (0.85)	1.41 (0.62)	1.53 (0.88)
Would like a job involving using math	2.59 (1.02)	2.58 (0.89)	2.48 (0.92)	1.75 (0.98)
Need do well in math to get job	1.88 (0.94)	1.81 (0.89)	1.93 (0.86)	1.58 (0.92)
Would like to take more math	2.54 (1.04)	2.62 (0.94)	2.12 (0.95)	1.71 (0.95)
Enjoy learning math	2.37 (1.03)	2.40 (0.90)	2.01 (0.91)	1.73 (0.98)

Note. Standard deviations are in parentheses.

Student Perception of School. Four Likert-scale items measure student’s perception of school. The response options for them were “agree a lot” (coded as 1), “agree a little” (coded as 2), “disagree a little” (coded as 3), and “disagree a lot” (coded as 4). A sample item of this measure was “I like being in school”. All the items were positive statements and a higher score indicated more *negative* perception of school. All the items of this measure are in Appendix A. Table 5 shows the means and standard deviations of the original items. The four items were analyzed using principal components analysis (PCA) within each country. Only one factor was retained after checking the results of PCA within each country. Since principal component (factor) scores are standardized scores with mean equal to zero, they are subtracted from zero so that a higher score represents a more *positive* perception of school.

Table 5.

Means and Standard Deviations of Original Items for Measure of Student Perception of School.

	United States	Russia	Singapore	South Africa
Like being in school	2.19 (0.95)	1.95 (0.81)	1.78 (0.74)	1.33 (0.72)
Students in school try their best	2.38 (0.95)	2.09 (0.83)	1.95 (0.81)	1.57 (0.81)
Teachers care about students	1.88 (0.95)	1.58 (0.70)	1.81 (0.79)	1.51 (0.83)
Teachers want students to do their best	1.50 (0.79)	1.32 (0.58)	1.40 (0.64)	1.43 (0.83)

Note. Standard deviations are in parentheses.

Parents’ Highest Education Level. This is the highest level of education of either parent and is a derived variable from students’ responses to two questions asking about the highest level of education by the mother and by the father respectively. After recoding, 1=No more than primary schooling, 2=finish lower secondary schooling, 3=finish upper secondary schooling, 4=finish post-secondary vocational/technical education but not university, and 5=finish university or equivalent or higher. Table 6 shows the mean and standard deviation of this variable.

Table 6.

Means and Standard Deviations of Parents’ Highest Education Level, Student Educational Expectation and Student Sex.

	United States	Russia	Singapore	South Africa
Parents’ Highest Education Level	4.08 (1.16)	4.06 (0.98)	2.65 (1.21)	2.63 (1.33)
Student Educational Expectation	4.09 (1.15)	3.45 (1.07)	3.49 (1.53)	2.82 (1.64)
Student Sex	0.48 (0.50)	0.51 (0.50)	0.51 (0.50)	0.49 (0.50)

Note. Standard deviations are in parentheses.

Student Educational Expectation. Students answered the question “How far in school do you expect to go?” Their responses were recoded[2] so that 1=High school, 2= vocational/technical certificate after high school, 3 = community or junior college degree, 4 = bachelor`s degree at a college or university, and 5 = beyond Bachelor`s degree. The mean and standard deviation of this variable are in Table 6.

Sex. Student’s sex was coded as 0=girl and 1=boy. The mean and standard deviation are in Table 6.

[2] There were adaptations made by country to the international versions of this question. The expected education levels shown here are for the US sample.

3.3.2 Teacher and School Variables

There were altogether 12 teacher or school variables as the Level-2 predictors.

Mathematics Teachers' Perception of School Climate. Eight items measure mathematics teachers' perception of school climate. The response options for them were "very high" (coded as 1), "high" (coded as 2), "medium" (coded as 3), "low" (coded as 4), and "very low" (coded as 5). A sample item of this measure was "How would you characterize teachers' job satisfaction within your school?" All the items were positive statements and a higher score indicated more *negative* perception of school climate. All the items of this measure are in Appendix A. Table 7 shows the means and standard deviations of the original items. The eight items were analyzed using principal components analysis (PCA) within each country. Only one factor was retained after checking the results of PCA within each country. Since principal component (factor) scores are standardized scores with mean equal to zero, they are subtracted from zero so that a higher score represents a more *positive* perception of school climate.

Table 7.

Means and Standard Deviations of Original Items for Measure of Mathematics Teachers' Perception of School Climate.

	United States	Russia	Singapore	South Africa
Teachers' job satisfaction	2.46 (0.81)	2.93 (0.54)	2.65 (0.77)	2.77 (0.95)
Teachers' understanding of curricular goals	2.12 (0.74)	2.15 (0.45)	2.23 (0.65)	2.45 (0.89)
Teachers' implementing school curriculum	2.24 (0.72)	2.71 (0.50)	2.39 (0.68)	2.59 (0.90)
Teachers' expectation for student achievement	2.00 (0.80)	2.88 (0.44)	2.29 (0.72)	2.24 (0.94)
Parental support for student achievement	2.85 (1.00)	3.61 (0.68)	2.87 (0.80)	3.58 (1.06)
Parental involvement in school activities	2.99 (1.10)	3.49 (0.71)	3.28 (0.88)	3.73 (1.04)
Students' regard for school property	3.16 (0.91)	3.18 (0.64)	3.19 (0.87)	3.55 (1.09)
Students' desire to do well	2.94 (0.85)	3.09 (0.56)	2.72 (0.81)	3.08 (1.03)

Note. Standard deviations are in parentheses.

Principals' Perception of School Climate. Eight items were asked of the school principal about school climate. Those were the same items asked of mathematics teachers about their perception of school climate. The response options for them were "very high" (coded as 1), "high" (coded as 2), "medium" (coded as 3), "low" (coded as 4), and "very low" (coded as 5). A sample item of this measure was "How would you characterize teachers' job satisfaction within your school?" All the items were positive statements and a higher score indicated more *negative* perception of school climate. All the items of this measure are in Appendix A. Table 8 shows the means and standard deviations of the original items. The eight items were analyzed using principal components analysis (PCA) within each country. Only one factor was retained after checking the results of PCA within each country. Since principal component (factor) scores are standardized scores with mean equal to zero, they are subtracted from zero so that a higher score represents a more *positive* perception of school climate.

Table 8.

Means and Standard Deviations of Original Items for Measure of School Principals' Perception of School Climate.

	United Stated	Russia	Singapore	South Africa
Teachers' job satisfaction	2.00 (0.63)	2.78 (0.49)	2.21 (0.61)	2.79 (0.88)
Teachers' understanding of curricular goals	1.80 (0.66)	2.16 (0.47)	1.93 (0.59)	2.40 (0.76)
Teachers' implementing school curriculum	2.05 (0.69)	2.62 (0.55)	2.11 (0.66)	2.57 (0.79)
Teachers' expectation for student achievement	1.99 (0.78)	2.79 (0.44)	2.07 (0.74)	2.35 (0.87)
Parental support for student achievement	2.52 (0.97)	3.46 (0.62)	2.59 (0.76)	3.71 (1.06)
Parental involvement in school activities	2.83 (1.04)	3.32 (0.67)	3.45 (0.82)	3.81 (1.02)
Students' regard for school property	2.34 (0.78)	2.95 (0.62)	2.07 (0.69)	3.40 (1.04)
Students' desire to do well	2.41 (0.74)	2.91 (0.54)	2.11 (0.71)	2.95 (0.92)

Note. Standard deviations are in parentheses.

Mathematics Teachers' Perception of School Facility and Safety. Four Likert-scale items measured mathematics teachers' perception of school facility and safety. The response options for them were "agree a lot" (coded as 1), "agree a little" (coded as 2), "disagree a little" (coded as 3), and "disagree a lot" (coded as 4). A sample item of this measure was "Thinking about your current school, indicate the extent to which you agree or disagree that you feel safe at this school?" Responses to positive statements were reverse coded so that a higher score means more positive perception. All the items of this measure are in Appendix A. Table 9 shows the means and standard deviations of the original items. The four items were analyzed using principal components analysis (PCA) within each country. Only one factor was retained after checking the results of PCA within each country.

Table 9.

Means and Standard Deviations of Original Items for Measure of Mathematics Teachers' Perception of School Facility and Safety.

	United States	Russia	Singapore	South Africa
School facility needs significant repair	2.83 (0.86)	1.98 (0.82)	2.81 (0.82)	1.77 (0.93)
School is in a safe neighborhood (r)[a]	3.36 (0.67)	2.78 (0.67)	3.32 (0.54)	2.51 (0.94)
Feel safe at school (r)	3.48 (0.54)	3.02 (0.57)	3.34 (0.53)	2.61 (0.91)
School's security policies and practices are sufficient (r)	3.16 (0.66)	3.08 (0.55)	3.16 (0.54)	2.17 (0.90)

[a] (r) Reverse coded items.
Note. Standard deviations are in parentheses.

Expected Parent Involvement by School Principals. School principals were asked if the school expected parents to do any of the five activities: attending special events (e.g. science fair, concert, sporting events), raising funds for the school, volunteering for school projects, programs, and trips, ensuring that their child completes his/her homework, and serving on school committees (e.g. select school personnel, reviewing school finances). This variable was the sum of the activities expected of parents by school. This variable ranged from 0 to 5. Table 10 shows the means and standard deviations of the original items.

Table 10.

Means and Standard Deviations of Original Items for Measure of Expected Parent Involvement by School Principals.

	United States	Russia	Singapore	South Africa
Parents expected to attend special events	0.98 (0.14)	0.93 (0.25)	0.88 (0.33)	0.95 (0.23)
Parents expected to raise funds for school	0.61 (0.49)	0.67 (0.47)	0.63 (0.48)	0.92 (0.27)
Parents expected to volunteer for school projects, programs, and trips	0.89 (0.31)	0.87 (0.33)	0.80 (0.40)	0.91 (0.29)
Parents expected to ensure that child completes homework	0.98 (0.12)	0.84 (0.37)	0.98 (0.13)	0.94 (0.24)
Parents expected to serve on school committees	0.72 (0.45)	0.83 (0.38)	0.64 (0.48)	1.00 (0.07)

Note. Standard deviations are in parentheses.

Evaluation of Mathematics Teachers. School principals were asked if the school used any of the four procedures to evaluate the practice of eighth-grade mathematics teachers: observations by the principal or senior staff, observations by inspectors or other persons external to the school, student achievement, and teacher peer-review. This variable was the sum of procedures used by the school to evaluate mathematics teachers. It ranged from 0 to 4. Table 11 shows the means and standard deviations of the original items.

Table 11.

Means and Standard Deviations of Original Items for Measure of Evaluation of Mathematics Teachers.

	United States	Russia	Singapore	South Africa
Observations by principal or senior staff	0.99 (0.10)	0.99 (0.10)	0.99 (0.08)	0.80 (0.40)
Observations by inspectors or other persons external to school	0.28 (0.45)	0.65 (0.48)	0.04 (0.19)	0.33 (0.47)
Student achievement	0.66 (0.47)	0.98 (0.15)	0.96 (0.19)	0.86 (0.35)
Teacher peer review	0.25 (0.43)	0.95 (0.21)	0.48 (0.50)	0.48 (0.50)

Note. Standard deviations are in parentheses.

Availability of School Resources for Mathematics Instruction. This was a derived variable from ten questions asked of the school principal about whether the school's capacity to provide instruction was affected by a shortage or inadequacy of instructional resources. The response options for original items were "none" (coded as 1), "a little" (coded as 2), "some" (coded as 3), and "a lot" (coded as 4). A sample item asked whether the school's capacity to provide instruction was affected by a shortage or inadequacy of instructional materials such as textbook. All the items for this measure are in Appendix A. This variable was recoded so that: 1=low availability (average value of the first five items is greater than or equal to 3 and the average value of the last five items is greater than or equal to 3), 3=high availability (average value of the first five items is less than 2 and the average value of the last five items is less than 2), and 2=medium availability (all other combinations). All the original items of this measure are in Appendix A. Table 12 shows the mean and standard deviation of this variable.

Table 12.

Means and Standard Deviations of Availability of School Resources for Mathematics Instruction, School and Class Attendance, and Number of Mathematics Topics Taught.

	United States	Russia	Singapore	South Africa
Availability of school resources for mathematics instruction	2.50 (0.53)	1.81 (0.50)	2.88 (0.36)	1.71 (0.62)
School and class attendance	2.05 (0.55)	1.88 (0.54)	2.36 (0.57)	1.59 (0.61)
Number of mathematics topics taught	32.34 (13.90)	N/A	36.11 (6.99)	20.20 (12.08)

Note. Standard deviations are in parentheses.

School and Class Attendance. This was a derived variable from six questions asked of the school principal about students' attendance behavior. The first three questions were about the frequency of problem behaviors of students: arriving late at school, absenteeism (i.e. unjustified absences) and skipping class. The responses options were "never" (coded as 1), "rarely" (coded as 2), "monthly" (coded as 3), "weekly" (coded as 4), and "daily" (coded as 5). The next three questions were about the severity of the problems and the responses were "not a problem" (coded as 1), "minor problem" (coded as 2), and "serious problem" (coded as 3). This variable was recoded so that: 1=low level of school and class attendance (at least two serious problems, or one serious problem and two minor problems), 3=high level of school and class attendance (none of the behavior problems happened, or if any happened, it was not a problem), and 2=medium level of school and class attendance (all other combinations). The mean and standard deviation of this variable is in Table 12.

Number of Mathematics Topics Taught. Mathematics teachers were asked if topics addressed by the TIMSS 2003 mathematics test had been taught. There were altogether 45 topics related to number, algebra, measurement, geometry and data, as in Appendix A. This variable was the number of topics that had been taught before or during the year the test was administered. The range of this variable was 0 to 45. The mean and standard deviation of this variable is in Table 12.

Limiting Mathematics Instruction due to Student Factors. The mathematics teacher was asked of the extent to which six student factors might have limited how the class was taught. The responses to the six items were "not applicable" or "not at all" (coded as 0), "a little" (coded as 1), "some" (coded as 2), and "a lot" (coded as 3). A sample item of this measure was "uninterested students". A higher score meant math instruction was limited to a larger extent. All the items of this measure are in Appendix A. Table 13 shows the means and standard deviations of the original items. The six items were analyzed using principal components analysis (PCA) within each country. Only one factor was retained after checking the results of PCA within each country.

Table 13.

Means and Standard Deviations of Original Items for Measure of Limiting Mathematics Instruction due to Student Factors.

	United States	Russia	Singapore	South Africa
Students with different academic abilities limit teaching	1.60 (0.95)	2.33 (0.74)	1.96 (0.85)	1.80 (0.99)
Students from a wide range of backgrounds limit teaching	0.96 (0.94)	0.73 (0.85)	1.30 (1.02)	1.67 (1.13)
Students with special needs limit teaching	0.89 (0.96)	1.08 (1.03)	0.62 (0.89)	1.04 (1.07)
Uninterested students limit teaching	1.52 (0.96)	1.86 (0.96)	1.69 (0.94)	1.61 (0.98)
Low morale among students limit teaching	1.17 (0.93)	0.99 (1.06)	1.49 (0.96)	1.49 (0.99)
Disruptive students limit teaching	1.29 (0.91)	1.09 (1.06)	1.48 (1.02)	1.48 (1.03)

Note. Standard deviations are in parentheses.

Teacher's Gender. This variable was coded as 0=female and 1=male. The mean and standard deviation of this variable are in Table 14.

Table 14.

Means and Standard Deviations of Teacher's Gender, Number of Years as Teachers, and Teacher License or Certification.

	United States	Russia	Singapore	South Africa
Teacher's Gender	0.35 (0.48)	0.05 (0.21)	0.33 (0.47)	0.58 (0.49)
Number of Years as Teachers	14.44 (10.30)	22.49 (11.00)	12.15 (12.35)	10.92 (6.96)
Teacher License or Certification	0.07 (0.26)	0.03 (0.18)	0.03 (0.17)	0.53 (0.50)

Note. Standard deviations are in parentheses.

Number of years as teachers. The mathematics teacher was asked how many years he or she would have been taught altogether by the end of the school year during which the TIMSS was conducted. The mean and standard deviation of this variable are in Table 14.

Teacher License or Certification. This variable was coded as 0=has full license or certificate and 1=does not have full license or certificate. The mean and standard deviation of this variable are in Table 14.

A listing of the student, teacher and school variables used in this study is presented in Table 15.

Table 15.

Student, Teacher and School Variables.

Student Variables	Teacher and School Variables
Dependent Variable	Control Variables
Student Mathematics Achievement	Teacher’s Gender
	Number of years as teachers
Control Variables	Teacher License or Certification
Parents’ Highest Education Level	Number of Mathematics Topics Taught
Student Educational Expectation	School and Class Attendance
Sex	Availability of School Resources for Mathematics Instruction
Other Student Characteristics	Other Teacher and School Characteristics
Student Self-Confidence in Learning Mathematics	Mathematics Teachers’ Perception of School Climate
Student Valuing Mathematics	Principals’ Perception of School Climate
Student Perception of School	Mathematics Teachers’ Perception of School Facility and Safety
	Expected Parent Involvement by School Principals
	Evaluation of Mathematics Teachers
	Limiting Mathematics Instruction due to Student Factors

3.4 Proposed Data Analysis

To keep this study at a manageable scale, four out of the total 47 countries are selected for analysis to represent four different continents respectively and to reflect the full spectrum of mathematics achievement. Those four selected countries are: Russian Federation, Singapore, South Africa and the United States. The following section describes the statistical models used to analyze the data for each research question.

Analysis 1: In each country, how does mathematics achievement differ across schools or classrooms?

The first analysis is conducted through a one-way ANOVA model with random effects for each country. This model provides useful preliminary information about how much variation in the outcome lies within and between classrooms and about the reliability of each classroom's sample mean as an estimate of its true population mean.

This model (Model a in Table 16) can be written as:

Level-1: $Y_{ij} = \beta_{0j} + r_{ij}$

Level2: $\beta_{0j} = \gamma_{00} + u_{0j}$

Combined: $Y_{ij} = \gamma_{00} + u_{0j} + r_{ij}$

where $Var(Y_{ij}) = Var(u_{0j} + r_{ij}) = \tau_{00} + \sigma^2$ and $\rho = \tau_{00} / (\tau_{00} + \sigma^2)$

The variance in the dependent variable Y_{ij} can be decomposed into the student-level (σ^2) and the class-level (τ_{00}). A useful statistic called intraclass correlation (denoted as ρ) is an indicator of how much variance in mathematics achievement is between classrooms. Another statistic called the reliability of the sample mean tells about the reliability that the population mean can be indicated by the sample mean. For each class, this reliability is $\hat{\lambda}_j = \text{reliability}(\overline{Y}_{.j}) = \hat{\tau}_{00} / [\hat{\tau}_{00} + (\hat{\sigma}^2 / n_j)]$ and the overall measure of the reliability is $\hat{\lambda} = \sum \hat{\lambda}_j / J$.

Analysis 2: In each country, how are student self-confidence in learning mathematics, the values they attach to math, and their perception of school related to math achievement within the classroom and school context?

This analysis involves two HLM models (see Models b & c in Table 16). The first model adjusts class means for differences in the control variables of students. That is, what the class means would be if the student samples in each of the classroom had the same values on the control variables. The effects of those control variables are assumed to be random across classes. This is a random coefficient model.

The other model adjusts class means for differences in the control variables, as well as other characteristics of students. Statistically nonsignificant predictors are dropped from the model. The final set of predictor variables is determined by a sequence of exploratory analyses in which different combinations of variables are examined. This model building at Level 1 is consistent with Raudenbush and Bryk (2002).

Analysis 3: In each country, is the strength of association between student characteristics and math achievement similar across classrooms or schools? Are teacher and school characteristics more important factors in some classrooms and schools than in others?

This analysis builds on the previous analysis and also involves two models (Models d & e in Table 16). The first model adjusts class means for differences in the control variables of teachers and schools, as well as student characteristics. That is, what the class means would be, if all the samples had the same breakdown on included student variables and the same profile on included teacher and school variables. The second model adds other teacher and school characteristics. Statistically nonsignificant teacher or school predictors are dropped from the model.

Table 16.

Description of Models in Analyses.

Model	Predictors at Level 1	Predictors at Level 2
a	None	None
b	Student control variables	None
c	Student control variables + other student characteristics	None
d	Student control variables + other student characteristics	Teacher and school control variables
e	Student control variables + other student characteristics	Teacher and school control variables + other teacher and school characteristics

Analysis 4: What are the country differences in the above measures and effects?

The previous analyses are conducted separately for each country. This analysis compares the country differences in terms of adjusted class means and the effects of student, teacher and school variables.

CHAPTER 4

RESULTS

This chapter presents the findings from the analyses for the four selected countries: Russian Federation, Singapore, South Africa and the United States. First, results from principal component analyses to get measures of different constructs are described. Then, results from HLM analyses are reported. The four sets of analyses serve a model building process. The first analysis is a fully unconditional one-way ANOVA with random effects. The second set analyses builds the level-1 model of HLM. The third set of analyses builds the level-2 model of HLM. In the fourth set of analyses, based on previous ones, the final model is obtained for each country. Differences among the four countries are described in each set of analyses.

4.1 Principal Component Analyses

Three student variables and four school and teacher variables are from principal component analyses (PCAs). Each variable was based on several items. The process of combining several items into one variable was discussed by Spector (1992; see Eklof, 2007). A proper process usually includes item analysis followed by factor analysis (Eklof, 2007). The present study did not include detailed information on item analysis for each variable in each country. Exploratory factor analysis for each of the 7 variables was conducted for the USA sample and it seems that one factor could be retained for each of the 7 variables. Exploratory factor analysis was not conducted for samples from the other countries. Instead, within each country, the first component from each PCA analysis was retained and served as the proposed measure of construct. Tables 17-23 show the results for each variable formed by PCA in the four selected countries. Some of the items were reverse coded before conducting PCAs. A higher value on the derived variable (first principal component in each PCA) means more attribute on the labeled construct. A SAS macro was created to perform PCAs in each country and to create SAS datasets that later were used in HLM analyses (see Appendix B for the SAS macro).

Table 17.

Principal Component Analysis for Student Self-Confidence in Learning Mathematics.

	United States	Russia	Singapore	South Africa
Structure Coefficient				
Usually do well in math	0.838	0.822	0.850	0.755
Math is difficult	0.771	0.804	0.721	0.368
Math is not a strength	0.834	0.803	0.817	0.452
Learn math quickly	0.840	0.846	0.819	0.760
Proportion of Variance Accounted for by First Principal Component				
	0.674	0.671	0.645	0.372

In Table 18, for the construct of student valuing math, the first principal component accounts for less than 50% of the variance in all four countries although all the structure coefficients are acceptable (>.50). One reason that less than half of the variance was accounted for may be because students’ valuing math is not a unidimensional construct. The seven original items may measure three aspects of value: attainment value, utility value and intrinsic value, which is consistent with the expectancy-value model of achievement motivation (Eccles & Wigfield, 1995; Wigfield, Eccles & Rodriguez, 1998). But TIMSS 2003 does not differentiate the different aspects of value. For the purpose of this study, students' valuing math is considered as a unitary construct.

Table 18.

Principal Component Analysis for Student Valuing Mathematics.

	United States	Russia	Singapore	South Africa
Structure Coefficient				
Math will help in daily life	0.704	0.673	0.695	0.688
Need math to learn other school subjects	0.638	0.540	0.587	0.628
Need do math well to get into university	0.555	0.652	0.521	0.676
Would like a job involving using math	0.760	0.731	0.773	0.688
Need do well in math to get job	0.689	0.667	0.632	0.720
Would like to take more math	0.695	0.643	0.762	0.652
Enjoy learning math	0.705	0.672	0.765	0.654
Proportion of Variance Accounted for by First Principal Component				
	0.463	0.431	0.466	0.453

For student perception of school, in each country, more than 50% of the variance in the original items were accounted for by the first principal component with structure coefficients all greater than .60 (see Table 19).

Table 19.

Principal Component Analysis for Student Perception of School

	United States	Russia	Singapore	South Africa
Structure Coefficient				
Like being in school	0.666	0.652	0.697	0.681
Students in school try their best	0.667	0.691	0.689	0.686
Teachers care about students	0.861	0.842	0.826	0.739
Teachers want students to do their best	0.813	0.757	0.777	0.738
Proportion of Variance Accounted for by First Principal Component				
	0.573	0.546	0.562	0.506

The proportion of variance accounted for by the first principal component varies in different countries, indicating the original variables may measure different things in those four countries. For the construct of student self-confidence in learning math (see Table 17), only 37.2% of the variance in South Africa was explained by the first principal component and one of the original items ("math is more difficult for me than for many of my classmates") had a low coefficient. The construct seem to be measured well by the items in the other three countries. The discrepancy suggests that the items may have different structures or measure different things in different countries. This seems to support the conjecture that the construct is multidimensional.

Another interesting comparison is between school principals' perception of school climate and teachers' perception of school climate shown in Tables 20 and 21. Principals and math teachers responded to the same items for both measures. The results are similar for both measures in each country, indicating that principals' and math teachers' perceptions are consistent. This is indirect evidence that the responses to those items were valid. At the same time, the different structure coefficients in the two tables are suggestions of what are more important for school principals and math teachers. For example, in the USA, aspects related to teachers were thought to be more important (indicated by higher coefficients) by school principals than by math teachers. This pattern does not hold for the other three countries.

Table 20.

Principal Component Analysis for Principals' Perception of School Climate.

	United Stated	Russia	Singapore	South Africa
Structure Coefficient				
Teachers' job satisfaction	0.675	0.637	0.713	0.636
Teachers' understanding of curricular goals	0.715	0.542	0.765	0.685
Teachers' implementing school curriculum	0.782	0.615	0.826	0.696
Teachers' expectation for student achievement	0.782	0.592	0.848	0.675
Parental support for student achievement	0.762	0.701	0.770	0.791
Parental involvement in school activities	0.743	0.694	0.543	0.753
Students' regard for school property	0.677	0.504	0.719	0.624
Students' desire to do well	0.745	0.683	0.836	0.721
Proportion of Variance Accounted for by First Principal Component	0.542	0.390	0.575	0.490

Table 21.

Principal Component Analysis for Math Teachers' Perception of School Climate.

	United States	Russia	Singapore	South Africa
Structure Coefficient				
Teachers' job satisfaction	0.663	0.628	0.705	0.679
Teachers' understanding of curricular goals	0.632	0.365	0.650	0.693
Teachers' implementing school curriculum	0.669	0.568	0.588	0.689
Teachers' expectation for student achievement	0.663	0.650	0.689	0.664
Parental support for student achievement	0.836	0.672	0.783	0.734
Parental involvement in school activities	0.802	0.687	0.694	0.661
Students' regard for school property	0.742	0.587	0.730	0.703
Students' desire to do well	0.781	0.756	0.766	0.753
Proportion of Variance Accounted for by First Principal Component	0.528	0.389	0.494	0.487

Some constructs have similar structure coefficients in different countries. For example, feeling safe at school, school being in a safe neighborhood, and sufficient school security policies and practices were all important to math teachers (coefficients>.70) in all four countries (see Table 22). Uninterested students and low morale among students seemed to be annoying the math teachers the most in all four countries (see Table 23).

Table 22.

Principal Component Analysis for Math Teachers' Perception of School Facility and Safety.

	United States	Russia	Singapore	South Africa
Structure Coefficient				
School facility needs significant repair	0.522	0.155	0.468	0.450
School is in a safe neighborhood	0.811	0.720	0.891	0.823
Feel safe at school	0.855	0.859	0.900	0.883
School's security policies and practices are sufficient	0.842	0.783	0.802	0.837
Proportion of Variance Accounted for by First Principal Component				
	0.592	0.902	0.617	0.590

Table 23.

Principal Component Analysis for Limiting Mathematics Instruction due to Student Factors.

	United States	Russia	Singapore	South Africa
Structure Coefficient				
Students with different academic abilities limit teaching	0.678	0.498	0.594	0.639
Students from a wide range of backgrounds limit teaching	0.673	0.541	0.590	0.642
Students with special needs limit teaching	0.710	0.691	0.638	0.583
Uninterested students limit teaching	0.835	0.709	0.861	0.795
Low morale among students limit teaching	0.822	0.729	0.852	0.824
Disruptive students limit teaching	0.699	0.689	0.806	0.696
Proportion of Variance Accounted for by First Principal Component				
	0.547	0.421	0.537	0.493

From the proportions of variances accounted for in Tables 17-23 as well as the magnitudes of the structure coefficients, all the constructs seemed to be well measured by the original items in the United States and the first principal component could be extracted to represent the related construct. In the other three countries, all the coefficients are acceptable (>.45) except for one in Table 9 for Russia (.365) one in Table 10 for Russia (.155). In order that the later HLM model building process be consistent across countries, we assume that the first principal component of each PCA in each country represent the construct itself. The advantage of doing this is to focus on the effects of motivational beliefs on student math achievement within the school and classroom environment. The comparisons among countries would in turn be more direct.

4.2 HLM Analyses

Analysis 1: How does math achievement differ across classrooms in each country?

Each student has five plausible values representing his or her mathematics achievement. For this analysis, an ANOVA model with random effects was used and applied to each plausible value in each country. Written as a HLM model, referred to as model a in Chapter 3, it is,

Level-1: $Y_{ij} = \beta_{0j} + r_{ij}$

Level2: $\beta_{0j} = \gamma_{00} + u_{0j}$

Combined: $Y_{ij} = \gamma_{00} + u_{0j} + r_{ij}$

where $Var(Y_{ij}) = Var(u_{0j} + r_{ij}) = \tau_{00} + \sigma^2$ and $\rho = \tau_{00} / (\tau_{00} + \sigma^2)$

Estimating the one-way ANOVA model is often useful as a preliminary step in HLM. It produces a point estimate for the grand mean γ_{00}. More importantly, it provides information about the outcome variability at each of the two levels. The σ^2 parameter represents the within-group (level-1) variability and τ_{00} captures the between-group (level-2) variability. This is called a fully unconditional model in that no predictors are specified in either level 1 or 2.

In this study, the variance in student math achievement (Y_{ij}) can be decomposed into the student-level (σ^2) and the class-level (τ_{00}). A useful statistic, called intraclass correlation (ICC, denoted as ρ, see model above) is an indicator of the relative classroom differences, representing how much variance in mathematics achievement is between classrooms. ICC (ρ) ranges between 0 and 1. If ρ is very close to 0, this means all the variance in student math achievement comes from the student-level, the analysis can be performed at the student level (using regression, for example) with no class-level predictors. If ρ is very close to 1, this means that all the variance in student math achievement comes from the class-level. Data can be aggregated to the class-level (for example, using class means) and only level-2 predictors are necessary.

Another statistic about the outcome variability is the reliability of the sample mean. It tells about the reliability that the population mean can be indicated by the sample mean.

The higher this number is, the more confident that the overall achievement score in the country can be obtained from the classroom mean. For each class, this reliability is $\hat{\lambda}_j = \text{reliability}(\bar{Y}_{.j}) = \hat{\tau}_{00} / [\hat{\tau}_{00} + (\hat{\sigma}^2 / n_j)]$, where n_j is the number of students in class *j*. The overall measure of the reliability is $\hat{\lambda} = \sum \hat{\lambda}_j / J$, where *J* is the total number of classes in the sample.

The above model was run five times with a plausible value of mathematics achievement each time. The results from the five runs were later combined to reflect the error from drawing plausible values.

In addition, a student-level weight variable—HOUWGT in TIMSS 2003 indicating the relative importance of each student resulted from probability sampling (see Chapter 1)—was added to the model at level-1. The methodology used in HLM6 assumes that the weights are inversely proportional to the probability of that student being selected into the sample. HLM6 normalizes the weight to have a mean of 1 and those weights add up to the number of level-1 units included in the analysis.

Table 24.

Results from Fully Unconditional Model.

	United States	Russia	Singapore	South Africa
Grand mean, $\hat{\gamma}_{00}$	506.46	512.30	604.55	266.73
Within-classroom variance, $\hat{\sigma}^2$	2421.49	3802.99	1479.91	4167.39
Between-classroom variance, $\hat{\tau}_{00}$	3825.18	1883.83	4967.22	8316.60
Reliability estimate, $\hat{\lambda}$	0.950	0.886	0.976	0.975
ICC, $\hat{\rho}$	0.612	0.331	0.770	0.666

The estimate $\hat{\gamma}_{00}$ in Table 24 represents the estimated grand mean of mathematics achievement in each country. Those estimates are close to the results in Figure 1, when achievement scores for all students in the sample were used. The differences between $\hat{\gamma}_{00}$ and the mean achievement for each country in Figure 1 result from the fact that there are missing values on the student variables and school and teach variables. HLM 6 does not allow missing values at level-2 in a two-level model. If a missing value appears at level-2, this level-2 unit, and hence, all the level-1 units in this level-2 unit are excluded from analysis. If the missing happens at level-1, HLM6 provides two options: delete missing values when creating the MDM (multivariate data matrix) or delete missing values when doing analysis. This study deletes missing value during creating the MDM file so that all the analyses are based on the same data which only include complete observations from each country. The fact that the $\hat{\gamma}_{00}$ of each country in Table 12 is close to the country mean math achievement in Figure 1 indicates that missing values did not result in very different population estimates.

The estimate $\hat{\sigma}^2$ in Table 24 indicates the differences among students in the same classroom. A higher value represents more variability among students within the classroom. Interestingly, except for the USA, the higher the mean country achievement is, the lower the variability of math achievement among students from the same classroom. That is, students in a Singapore classroom are more homogenous than students in a South African classroom.

The estimate $\hat{\tau}_{00}$ in Table 24 represents the classroom differences. A higher value represents more variability among classrooms. South Africa has a very large classroom difference, meaning that the math achievement differs a lot across classrooms. Russia, on the other hand, has a relatively small $\hat{\tau}_{00}$, meaning that classrooms are more similar to each other.

The estimate of ICC, $\hat{\rho}$ in Table 24, suggests that only 33% of the variance of student math achievement comes from between-classrooms in Russian, while it is 61% in the US, 77% in Singapore and 67% in South Africa.

Analysis 2: In each country, how is student math achievement affected by student self-confidence in learning mathematics, the values they attach to math, and their perception of school?

For this analysis, in each country, student-level (level-1) variables were entered into HLM models. Model b includes three student-level control variables (Parents' Highest Education Level, Student Education Expectation, and Student Sex). In model c, in addition to student control variables, three variables of interest (Student Self-Confidence in Learning Math, Student Valuing Math, and Student Perception of School) are included.

Level -1 of Model b:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Parents' highest education level}) + \beta_{2j}(\text{Student Education Expectation}) + \beta_{3j}(\text{Student Sex}) + r_{ij}$$

Level -1 of Model c:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Parents' highest education level}) + \beta_{2j}(\text{Student Education Expectation}) + \beta_{3j}(\text{Student Sex}) + \\ \beta_{4j}(\text{Self-confidence in learning math}) + \beta_{5j}(\text{Valuing Math}) + \beta_{6j}(\text{Student Perception of School Climate}) + r_{ij}$$

At Level-2 of both model b and model c, all the level-1 coefficients (β 's) are specified as random. Raudenbush and Bryk (2002) suggest several empirical methods for model building at Level 1, including guidance about specifying the level-1 coefficients as random or fixed, as well as guidance about deleting variables from the model.

The above models were run five times with a plausible value of mathematics achievement each time. The results from the five runs were later combined to reflect the error from drawing plausible values. This process is automated in HLM6. Similar to Analysis 1, the student-level weight variable HOUWGT was used.

Fixed effects in each country

Table 25.

Fixed Effects in the United States from HLM Models with Predictors at Level 1.

Fixed Effect	*Model b*			*Model c*		
	Coefficient	*Standard Error*	*p value*	*Coefficient*	*Standard Error*	*p value*
Grand mean, γ_{00}	507.02	3.96	.000	508.28	3.64	.000
Average effect of parents' highest education level, γ_{10}	3.39	0.87	.000	2.68	0.81	.001
Average effect of student education expectation, γ_{20}	10.62	1.31	.000	6.81	1.04	.000
Average effect of student sex, γ_{30}	7.69	1.68	.000	1.42	1.52	.351
Average effect of self-confidence in learning math, γ_{40}				24.35	1.14	.000
Average effect of valuing math, γ_{50}				-3.92	1.07	.001
Average effect of student perception of school, γ_{60}				-1.33	1.04	.203

In the United States, as shown in Table 25, those eighth-graders whose parents had a higher education level and who had a higher education expectation, had higher math achievement. The gender gap, after controlling for the effects of parents' education and student education expectation, was 7.69 on math achievement (model b). That is, boys scored higher in math than girls at eighth grade. However, when student motivational beliefs were included (model c), this gender gap in math achievement disappeared. The effects of the three student constructs (Self-Confidence in Learning Math, Valuing Math and Perception of School) can be directly compared using their coefficients because all of them were from principal component analysis and had a mean of 0 and standard deviation of 1 (before weighting). Students' self-confidence in learning math significantly affected their math achievement at eighth grade and was the largest effect among the three motivational constructs. Surprisingly, controlling for other effects, the more students valued math, the *lower* their math achievement would be. Controlling for other effects, a student at the 66 percentile on valuing math would score 3.92 points lower than a student at the 50 percentile. This effect may not be practically meaningful. Student perception of school did not seem to affect their math achievement after controlling for other variables.

Table 26.

Fixed Effects in Russia from HLM Models with Predictors at Level 1.

	Model b			*Model c*		
Fixed Effect	*Coefficient*	*Standard Error*	*p value*	*Coefficient*	*Standard Error*	*p value*
Grand mean, γ_{00}	514.37	3.83	.000	513.70	3.74	.000
Average effect of Parents' highest education level, γ_{10}	8.62	1.30	.000	4.74	1.23	.000
Average effect of student education expectation, γ_{20}	16.44	1.34	.000	8.05	1.26	.000
Average effect of student sex, γ_{30}	3.48	3.13	.271	3.14	2.70	.254
Average effect of self-confidence in learning math, γ_{40}				31.12	1.41	.000
Average effect of valuing math, γ_{50}				1.53	1.44	.291
Average effect of student perception of school, γ_{60}				-5.41	1.47	.001

In Russia, those eighth-grade students whose parents had a higher education level and who had a higher education expectation, had higher math achievement. Student sex did not affect math achievement. The effects of the three motivational constructs (Self-Confidence in Learning Math, Valuing Math and Perception of School) can be directly compared using their coefficients because all of them were from principal component analysis and had a mean of 0 and standard deviation of 1 (before weighting). Students' self-confidence in learning math significantly affected their math achievement at eighth grade and was the largest effect among the three motivational constructs. How much value the student attached to math did not affect the math achievement controlling for other effects. Surprisingly, controlling for other effects, students with more positive perception of the school climate, tended to achieve *lower* on math. Controlling for other effects, a student at the 66 percentile on perception of school would score 5.41 points lower than a student at the 50 percentile.

Table 27.

Fixed Effects in Singapore from HLM Models with Predictors at Level 1.

Fixed Effect	*Model b* *Coefficient*	*Standard Error*	*p value*	*Model c* *Coefficient*	*Standard Error*	*p value*
Grand mean, γ_{00}	604.22	4.33	.000	605.59	4.16	.000
Average effect of Parents' highest education level, γ_{10}	-0.97	0.80	.235	-1.44	0.72	.058
Average effect of student education expectation, γ_{20}	1.61	0.75	0.052	-0.17	0.73	.818
Average effect of Student Sex, γ_{30}	7.38	1.75	.000	2.80	1.61	.086
Average effect of self-confidence in learning Math, γ_{40}				16.67	1.04	.000
Average effect of valuing math, γ_{50}				3.91	0.90	.000
Average effect of Student Perception of School, γ_{60}				-1.85	1.04	.098

In Singapore, neither parents' education level nor student education expectation seemed to affect students' math achievement. There was a gender gap when motivational constructs were not entered into the model. That is, boys scored, on average, 7.38 points higher in math at eighth grade than girls. However, when the three motivational constructs (Self-Confidence in Learning Math, Valuing Math and Perception of School) were considered, the gender gap disappeared. Both student self-confidence in learning math and student valuing math positively influence the math achievement with the former had a higher effect. Student perception of school, after controlling for other effects, did not affect the math achievement.

Table 28.

Fixed Effects in South Africa from HLM Models with Predictors at Level 1.

	Model b			*Model c*		
Fixed Effect	*Coefficient*	*Standard Error*	*p value*	*Coefficient*	*Standard Error*	*p value*
Grand mean, γ_{00}	264.64	7.72	.000	265.69	7.84	.000
Average effect of parents' highest education level, γ_{10}	4.71	1.86	.032	4.02	1.78	.054
Average effect of student education expectation, γ_{20}	10.39	1.15	.000	9.16	1.05	.000
Average effect of student sex, γ_{30}	1.61	2.79	.565	0.22	2.71	.935
Average effect of self-confidence in learning math, γ_{40}				16.29	1.95	.000
Average effect of valuing math, γ_{50}				6.85	2.35	.012
Average effect of Student Perception of School, γ_{60}				1.06	1.96	.591

In South Africa, there was no gender gap in math achievement at eighth grade. Student education expectation was a significant effect but parents' education level did not seem to contribute to student math achievement substantially. Among the three motivational constructs— Self-Confidence in Learning Math, Valuing Math and Perception of School—the former two significantly affected math achievement with self-confidence in learning math having the largest effect, while there was not significant effect of student perception of school.

Variance components in each country

In HLM, besides the fixed effects, variance components provide information on how the effects vary across different units at level 2. While a fixed effect tells whether an average effect exists, random components reveal if this effect is the same across different units at level 2. If there is no evidence of an average or fixed effect, *and* the variance component associated with this effect is not significant (i.e. there is no evidence of slope heterogeneity), the variable can be deleted from the model. In other words, if both conditions satisfy, this particular level-1 predictor can be said not to belong in the model (Raudenbush & Bryk, 2002).

Another useful statistic is the reliability of level-1 coefficients. In the general sense, the reliability of a measurement is a ratio of true score variance and observed score variance. If the reliability of a level-1 coefficient is small (<.0.05 in Raudenbush & Bryk, 2002), it is likely that the true variance of a particular effect to be close to zero (the technical term is that the estimate is near the boundary of the parameter space). Low reliability may suggest that the level-1 coefficient be respecified as fixed.

Table 29.

Variance Components in the United States from HLM Models with Predictors at Level 1.

Random Effect	*Model b* *Variance*	*Model b* *p value*	*Model b* *Coefficient Reliability*	*Model c* *Variance*	*Model c* *p value*	*Model c* *Coefficient Reliability*
Mean achievement, u_{0j}	3286.14	.000	.902	2851.38	.00	.854
Parents' highest education level differentiation, u_{1j}	16.72	.118	.085	13.29	.307	.067
Student education expectation differentiation, u_{2j}	36.37	.000	.157	24.92	.268	.103
Student gender gap, u_{3j}	69.96	.341	.092	59.43	.121	.075
Self-confidence in learning math differentiation, u_{4j}				22.87	.029	.078
Valuing math differentiation, u_{5j}				31.07	.081	.089
Student perception of school differentiation, u_{6j}				35.90	.052	.119
Level-1 error, r_{ij}	2231.22			1765.79		

In the United States, the variance component for the effect of parents' highest education level on math achievement was not significant, suggesting that this (significant, see discussion on fixed effects above) effect was the same in different level-2 units (classrooms). The gender gap was also similar in different classrooms. Actually, student sex can be removed from the model when the motivational constructs are included. This is because the fixed effect of student sex was nonsignificant with the motivational constructs included (model c) and the (nonsignificant, see discussion on fixed effects above) effect applied to all the classrooms (homogenous). The (significant, see discussion on fixed effects above) effect of student education expectation was not heterogeneous when considering the effects of motivational constructs. In future analysis, the effect of student education expectation can be specified as fixed or nonrandomly varying.

Among the three motivational constructs, the (nonsignificant, see discussion on fixed effects above) effect of student perception of school applied to all the classrooms. This variable can be dropped from the model. Since the reliabilities of the coefficients for self-confidence in learning math and student valuing math is small (.078 and .089 respectively), those two (significant) effects can be modeled as nonrandom in future analysis.

Table 30.

Variance Components in Russia from HLM Models with Predictors at Level 1.

	Model b			*Model c*		
Random Effect	*Variance*	*p value*	*Coefficient Reliability*	*Variance*	*p value*	*Coefficient Reliability*
Mean achievement, u_{0j}	1598.95	.000	.802	1524.97	.000	.760
Parents' highest education level differentiation, u_{1j}	8.03	>.50	.025	16.20	.280	.053
Student education expectation differentiation, u_{2j}	27.88	.384	.097	36.68	.089	.115
Student gender gap, u_{3j}	196.08	.043	.176	80.41	.297	.083
Self-confidence in learning math differentiation, u_{4j}				27.72	.052	.084
Valuing math differentiation, u_{5j}				31.56	.343	.083
Student perception of school differentiation, u_{6j}				66.54	.047	.184
Level-1 error, r_{ij}	3365.00			2488.23		

In Russia, the variance component for the effect of parents' highest education level on math achievement was not significant, suggesting that this (significant, see discussion on fixed effects above) effect was the same in different level-2 units (classrooms). Similarly, the variance component for the effect of student education expectation on math achievement was not significant, suggesting that this (significant, see discussion on fixed effects above) effect was the same in different classrooms. The (nonsignificant) effect of student sex was also the same in different classrooms when the motivational constructs were considered. This variable can be dropped from model in future analysis.

Among the three motivational constructs, the (nonsignificant, see discussion on fixed effects above) effect of valuing math applied to all the classrooms and this variable can be dropped from the model in future analysis. The (significant, see discussion on fixed effects) effect of self-confidence in learning math did not vary much across classrooms, as evidenced by the p value (=.052) and the reliability (=.084). This effect can be modeled as nonrandom in future analysis.

The (significant, see discussion on fixed effects) effect of student perception of school on math achievement might differ across classrooms. This effect, in future analysis can be furthered modeled at Level 2.

Table 31.

Variance Components in Singapore from HLM Models with Predictors at Level 1.

Random Effect	*Model b* *Variance*	*p value*	*Coefficient Reliability*	*Model c* *Variance*	*p value*	*Coefficient Reliability*
Mean achievement, u_{0j}	4888.71	.000	.937	4494.00	.000	.892
Parents' highest education level differentiation, u_{1j}	8.68	.082	.060	7.57	.413	.050
Student education expectation differentiation, u_{2j}	3.45	.139	.043	2.31	>.50	.026
Student gender gap, u_{3j}	74.25	.027	.109	54.15	.095	.074
Self-confidence in learning math differentiation, u_{4j}				27.07	.194	.095
Valuing math differentiation, u_{5j}				20.04	.080	.065
Student perception of school differentiation, u_{6j}				23.33	.158	.099
Level-1 error, r_{ij}	1437.95			1093.98		

In Singapore, all the three variance components for the effects of the control variables (parents' highest education level, student education expectation, and student sex) are nonsigificant, when motivational constructs were included in the model. Actually, none of the three average effects was significant (see above discussion on fixed effects) in model c. In future analysis, they can be dropped from the model.

Among the three motivational constructs, the variance component for the (nonsignificant, see discussion on fixed effects above) effect of student perception of school was not significant, suggesting that this variable could be dropped for further analysis. The (significant, see discussion on fixed effects above) average effects of self-confidence in learning math and of valuing math applied to all the classrooms. Those two effects can be modeled as nonrandom in future analysis.

Table 32.

Variance Components in South Africa from HLM Models with Predictors at Level 1.

	Model b			*Model c*		
Random Effect	*Variance*	*p value*	*Coefficient Reliability*	*Variance*	*p value*	*Coefficient Reliability*
Mean achievement, u_{0j}	6637.52	.000	.948	6750.36	.000	.923
Parents' highest education level differentiation, u_{1j}	26.41	.336	.142	18.32	.264	.096
Student education expectation differentiation, u_{2j}	18.62	.215	.167	12.76	>.50	.113
Student gender gap, u_{3j}	118.91	.162	.127	113.91	.222	.115
Self-confidence in learning math differentiation, u_{4j}				36.77	.175	.095
Valuing math differentiation, u_{5j}				50.75	.113	.108
Student perception of school differentiation, u_{6j}				59.13	.162	.132
Level-1 error, r_{ij}	3811.91			3366.91		

In South Africa, none of the variance components for all the student variables were significant, suggesting that, the effects of those variables would be the same for all the level-2 units (classrooms). In other words, the average effects applied to all the classrooms.

Since each of the average effects of parents' education level, student sex, and student perception of school was nonsignificant in model c (see discussion on fixed effects above), they can be dropped from the model in future analysis. The other three (significant) effects can be modeled as nonrandom.

Analysis 3: In each country, is the strength of association between student characteristics and math achievement similar across classrooms or schools? Are teacher and school characteristics more important factors in some classrooms and schools than in others?

Based on the results from Analysis 2, teacher and school variables were entered at level 2 to model the level-1 coefficients. First, the six[3] control variables (Teacher's Gender, Number of Years as Teacher, Teacher License or Certification, Number of Math Topics Taught, School and Class Attendance, and Availability of School Resources for Math Instruction) were used as level-2 predictors. Next, another six variables (Math Teachers' Perception of School Climate, Principals' Perception of School Climate, Math Teachers' Perception of School Facility and Safety, Expected Parental Involvement by School Principals, Evaluation Methods of Math Teachers, and Limiting Math Instruction due to Student Factors) were entered at level 2.

---

[3] Data on the variable "number of math topics taught" were not available in Russia. There were only five control variables for Russia.

Models for the Selected Countries

United States:

Level-1 of both model d and model e:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Parents' highest education level}) + \beta_{2j}(\text{Student Education Expectation}) +$$
$$\beta_{3j}(\text{Self-confidence in learning math}) + \beta_{4j}(\text{Valuing Math}) + r_{ij}$$

Level -2 of model d:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Teacher's gender}) + \gamma_{02}(\text{Number of years as teacher}) + \gamma_{03}(\text{Teacher License}) + \gamma_{04}(\text{Number of math topics taught}) +$$
$$\gamma_{05}(\text{Good school and class attendance}) + \gamma_{06}(\text{Resources for math instruction}) + u_{0j}$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}(\text{Teacher's gender}) + \gamma_{q2}(\text{Number of years as teacher}) + \gamma_{q3}(\text{Teacher License}) + \gamma_{q4}(\text{Number of math topics taught}) +$$
$$\gamma_{q5}(\text{Good school and class attendance}) + \gamma_{q6}(\text{Resources for math instruction}),\ \text{q=1, 2, 3, 4}$$

Level-2 of model e:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Teacher's gender}) + \gamma_{02}(\text{Number of years as teacher}) + \gamma_{03}(\text{Teacher License}) + \gamma_{04}(\text{Number of math topics taught}) +$$
$$\gamma_{05}(\text{Good school and class attendance}) + \gamma_{06}(\text{Resources for math instruction}) + \gamma_{07}(\text{Math teacher's perception of school climate}) +$$
$$\gamma_{08}(\text{Principal's perception of school climate}) + \gamma_{09}(\text{Math teacher's percepton of school facility and safety}) +$$
$$\gamma_{0\_10}(\text{Expected parental involvement}) + \gamma_{0\_11}(\text{Evaluation of math teachers}) + \gamma_{0\_12}(\text{Limiting math instruction due to student factors}) + u_{0j}$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}(\text{Teacher's gender}) + \gamma_{q2}(\text{Number of years as teacher}) + \gamma_{q3}(\text{Teacher License}) + \gamma_{q4}(\text{Number of math topics taught}) +$$
$$\gamma_{q5}(\text{Good school and class attendance}) + \gamma_{q6}(\text{Resources for math instruction}) + \gamma_{q7}(\text{Math teacher's perception of school climate}) +$$
$$\gamma_{q8}(\text{Principal's perception of school climate}) + \gamma_{q9}(\text{Math teacher's percepton of school facility and safety})$$
$$+\gamma_{q\_10}(\text{Expected parental involvement}) + \gamma_{q\_11}(\text{Evaluation of math teachers}) + \gamma_{q\_12}(\text{Limiting math instruction due to student factors})$$
$$,\ \text{q=1, 2, 3, 4}$$

Russia:

Level-1 of both model d and model e:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Parents' highest education level}) + \beta_{2j}(\text{Student Education Expectation}) + \beta_{3j}(\text{Self-confidence in learning math}) + \beta_{4j}(\text{Student Perception of School Climate}) + r_{ij}$$

Level -2 of model d:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Teacher's gender}) + \gamma_{02}(\text{Number of years as teacher}) + \gamma_{03}(\text{Teacher License}) + \gamma_{04}(\text{Good school and class attendance}) + \gamma_{05}(\text{Resources for math instruction}) + u_{0j}$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}(\text{Teacher's gender}) + \gamma_{q2}(\text{Number of years as teacher}) + \gamma_{q3}(\text{Teacher License}) + \gamma_{q4}(\text{Good school and class attendance}) + \gamma_{q5}(\text{Resources for math instruction}),\ \text{q=1, 2, 3}$$

$$\beta_{4j} = \gamma_{40} + \gamma_{41}(\text{Teacher's gender}) + \gamma_{42}(\text{Number of years as teacher}) + \gamma_{43}(\text{Teacher License}) + \gamma_{44}(\text{Good school and class attendance}) + \gamma_{45}(\text{Resources for math instruction}) + u_{4j}$$

Level-2 of model e:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Teacher's gender}) + \gamma_{02}(\text{Number of years as teacher}) + \gamma_{03}(\text{Teacher License}) + \gamma_{04}(\text{Good school and class attendance}) + \gamma_{05}(\text{Resources for math instruction}) + \gamma_{06}(\text{Math teacher's perception of school climate}) + \gamma_{07}(\text{Principal's perception of school climate}) + \gamma_{08}(\text{Math teacher's percepton of school facility and safety}) + \gamma_{09}(\text{Expected parental involvement}) + \gamma_{0\_10}(\text{Evaluation of math teachers}) + \gamma_{0\_11}(\text{Limiting math instruction due to student factors}) + u_{0j}$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}(\text{Teacher's gender}) + \gamma_{q2}(\text{Number of years as teacher}) + +\gamma_{q3}(\text{Teacher License}) + \gamma_{q4}(\text{Good school and class attendance}) + \gamma_{q5}(\text{Resources for math instruction}) + \gamma_{q6}(\text{Math teacher's perception of school climate}) + \gamma_{q7}(\text{Principal's perception of school climate}) + \gamma_{q8}(\text{Math teacher's percepton of school facility and safety}) + \gamma_{q9}(\text{Expected parental involvement}) + \gamma_{q\_10}(\text{Evaluation of math teachers}) + \gamma_{q\_11}(\text{Limiting math instruction due to student factors})$$

Singapore:

Level-1 of both model d and model e:

$$Y_{ij} = \beta_{0j} + \beta_{1j}\text{(Self-confidence in learning math)} + \beta_{2j}\text{(Valuing Math)} + r_{ij}$$

Level -2 of model d:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\text{(Teacher's gender)} + \gamma_{02}\text{(Number of years as teacher)} + \gamma_{03}\text{(Teacher License)} + \gamma_{04}\text{(Number of math topics taught)} + \gamma_{05}\text{(Good school and class attendance)} + \gamma_{06}\text{(Resources for math instruction)} + u_{0j}$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}\text{(Teacher's gender)} + \gamma_{q2}\text{(Number of years as teacher)} + \gamma_{q3}\text{(Teacher License)} + \gamma_{q4}\text{(Number of math topics taught)} + \gamma_{q5}\text{(Good school and class attendance)} + \gamma_{q6}\text{(Resources for math instruction), q=1, 2}$$

Level-2 of model e:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\text{(Teacher's gender)} + \gamma_{02}\text{(Number of years as teacher)} + \gamma_{03}\text{(Teacher License)} + \gamma_{04}\text{(Number of math topics taught)} + \gamma_{05}\text{(Good school and class attendance)} + \gamma_{06}\text{(Resources for math instruction)} + \gamma_{07}\text{(Math teacher's perception of school climate)} + \gamma_{08}\text{(Principal's perception of school climate)} + \gamma_{09}\text{(Math teacher's percepton of school facility and safety)} + \gamma_{0\_10}\text{(Expected parental involvement)} + \gamma_{0\_11}\text{(Evaluation of math teachers)} + \gamma_{0\_12}\text{(Limiting math instruction due to student factors)} + u_{0j}$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}\text{(Teacher's gender)} + \gamma_{q2}\text{(Number of years as teacher)} + \gamma_{q3}\text{(Teacher License)} + \gamma_{q4}\text{(Number of math topics taught)} + \gamma_{q5}\text{(Good school and class attendance)} + \gamma_{q6}\text{(Resources for math instruction)} + \gamma_{q7}\text{(Math teacher's perception of school climate)} + \gamma_{q8}\text{(Principal's perception of school climate)} + \gamma_{q9}\text{(Math teacher's percepton of school facility and safety)} + \gamma_{q\_10}\text{(Expected parental involvement)} + \gamma_{q\_11}\text{(Evaluation of math teachers)} + \gamma_{q\_12}\text{(Limiting math instruction due to student factors)}\text{, q=1, 2}$$

South Africa:

Level-1 of both model d and model e:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Student Education Expectation}) + \beta_{2j}(\text{Self-confidence in learning math}) + \beta_{3j}(\text{Valuing Math}) + r_{ij}$$

Level -2 of model d:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Teacher's gender}) + \gamma_{02}(\text{Number of years as teacher}) + \gamma_{03}(\text{Teacher License}) + \gamma_{04}(\text{Number of math topics taught}) + \gamma_{05}(\text{Good school and class attendance}) + \gamma_{06}(\text{Resources for math instruction}) + u_{0j}$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}(\text{Teacher's gender}) + \gamma_{q2}(\text{Number of years as teacher}) + \gamma_{q3}(\text{Teacher License}) + \gamma_{q4}(\text{Number of math topics taught}) + \gamma_{q5}(\text{Good school and class attendance}) + \gamma_{q6}(\text{Resources for math instruction}), \text{ q=1, 2, 3}$$

Level-2 of model e:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Teacher's gender}) + \gamma_{02}(\text{Number of years as teacher}) + \gamma_{03}(\text{Teacher License}) + \gamma_{04}(\text{Number of math topics taught}) + \gamma_{05}(\text{Good school and class attendance}) + \gamma_{06}(\text{Resources for math instruction}) + \gamma_{07}(\text{Math teacher's perception of school climate}) + \gamma_{08}(\text{Principal's perception of school climate}) + \gamma_{09}(\text{Math teacher's percepton of school facility and safety}) + \gamma_{0\_10}(\text{Expected parental involvement}) + \gamma_{0\_11}(\text{Evaluation of math teachers}) + \gamma_{0\_12}(\text{Limiting math instruction due to student factors}) + u_{0j}$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1}(\text{Teacher's gender}) + \gamma_{q2}(\text{Number of years as teacher}) + \gamma_{q3}(\text{Teacher License}) + \gamma_{q4}(\text{Number of math topics taught}) + \gamma_{q5}(\text{Good school and class attendance}) + \gamma_{q6}(\text{Resources for math instruction}) + \gamma_{q7}(\text{Math teacher's perception of school climate}) + \gamma_{q8}(\text{Principal's perception of school climate}) + \gamma_{q9}(\text{Math teacher's percepton of school facility and safety}) + \gamma_{q\_10}(\text{Expected parental involvement}) + \gamma_{q\_11}(\text{Evaluation of math teachers}) + \gamma_{q\_12}(\text{Limiting math instruction due to student factors}), \text{ q=1, 2, 3}$$

Similar to Analysis 2, the fixed effects and variance components for Models d and e in each country can be examined. Since each model involves a lot of fixed effects (for example, model e for the USA has 65 fixed effects), only the estimates from model d in the USA are shown in this chapter. The actual HLM output for each model within each country, is included in Appendix C.

Table 33.

Fixed Effects in the United States from HLM Models with Predictors at Level 1 and Control Variables at Level 2.

	Model d		
Fixed Effect	*Coefficient*	*Standard Error*	*p value*
Grand mean, β_{0j}			
Intercept, γ_{00}	371.80	21.23	.000
Teacher's gender, γ_{01}	16.43	6.36	.011
Number of years as teacher, γ_{02}	0.55	0.32	.083
Teacher license, γ_{03}	22.95	13.37	.087
Number of math topics taught, γ_{04}	1.63	0.40	.000
Good attendance, γ_{05}	17.82	5.71	.002
Resources for instruction, γ_{06}	10.39	5.53	.061
Effect of Parents' highest education level, β_{1j}			
Intercept, γ_{10}	-3.16	6.64	.637
Teacher's gender, γ_{11}	-0.73	1.80	.687
Number of years as teacher, γ_{12}	0.06	0.09	.513
Teacher license, γ_{13}	2.13	2.93	.467
Number of math topics taught, γ_{14}	-0.01	0.09	.896
Good attendance, γ_{15}	-0.20	1.58	.902
Resources for instruction, γ_{16}	2.23	1.81	.231
Effect of student education expectation, β_{2j}			
Intercept, γ_{20}	7.25	6.91	.300
Teacher's gender, γ_{21}	-0.05	1.82	.977
Number of years as teacher, γ_{22}	-0.06	0.09	.500
Teacher license, γ_{23}	-0.35	3.53	.923

Number of math topics taught, γ_{24}	0.05	0.09	.563
Good attendance, γ_{25}	-1.01	1.85	.590
Resources for instruction, γ_{26}	0.17	1.87	.930
Effect of self-confidence in learning Math, β_{3j}			
Intercept, γ_{30}	26.31	6.64	.000
Teacher's gender, γ_{31}	0.32	1.88	.865
Number of years as teacher, γ_{32}	-0.04	0.13	.755
Teacher license, γ_{33}	-1.34	4.66	.775
Number of math topics taught, γ_{34}	-0.02	0.10	.807
Good attendance, γ_{35}	-1.77	1.70	.303
Resources for instruction, γ_{36}	1.30	2.12	.543
Effect of valuing math, β_{4j}			
Intercept, γ_{40}	-13.55	8.39	.110
Teacher's gender, γ_{41}	1.78	2.12	.401
Number of years as teacher, γ_{42}	-0.02	0.10	.855
Teacher license, γ_{43}	1.29	4.67	.783
Number of math topics taught, γ_{44}	0.07	0.12	.529
Good attendance, γ_{45}	1.58	2.12	.459
Resources for instruction, γ_{46}	1.20	2.03	.558

Results in the United States

Either in model d or model e, none of the school and teacher variables had a significant effect on the effect of any level-1 student variable. In other words, the slopes at level-1 (β_{qj}) did not change systematically due to changes in the teacher or school variables.

Technically, there were no cross-level interactions, although main effects of level-2 variables are still possible. The HLM representation of this is a random-intercept model. That is, the cross-level interactions can be dropped from the model in future analysis.

Results in Russia

Most of the cross-level interactions were nonsignificant in both model d and model e. However, math teachers' years of teaching experience seemed to influence the effect of student education expectation on math achievement. This cross-level interaction exhibited itself both in model d and model e and needs further analysis.

Results in Singapore

There were no cross-level interactions in model d. However, in model e, principals' perception of school climate influenced the effect of student self-confidence in learning math on math achievement; and limitation of math instruction due to student factor affected the effect of student valuing math on math achievement. Those two cross-level interactions should be retained in further models.

Results in South Africa

There was one cross-level interaction in model d. That is, math teachers' years of teaching experience seemed to influence the effect of student education expectation on math achievement. However, when more teacher and school variables were added (model e), this cross-level interaction disappeared. In further analysis, only the main effects of level-1 and level-2 variables would be considered.

Analysis 4: How do the student variables, and teacher and school variables affect student math achievement in each country?

Based on results from Analysis 3, some cross-level interactions were removed in each country and the main effects of teacher and school variables (and the cross-level interactions that should be retained from Analysis 3) on student math achievement were analyzed, in addition to the main effects of student variables from Analysis 2.

The resultant model was further reduced by removing nonsignificant main effects of teacher and school variables, and by removing cross-level interactions if they became nonsignificant. This was the final HLM model for each country.

Table 34.

Results in the United States from HLM Models with Predictors at Both Levels.

	Model based on Analysis 3			*Final Model*		
Fixed Effect	*Coefficient*	*Standard Error*	*p value*	*Coefficient*	*Standard Error*	*p value*
Grand mean, β_{0j}						
Intercept, γ_{00}	440.49	25.55	.000	439.60	14.42	.000
Teacher's gender, γ_{01}	23.11	5.57	.000	22.86	5.53	.000
Number of years as teacher, γ_{02}	0.59	.029	.040	0.63	0.29	.029
Teacher license, γ_{03}	10.23	10.77	.344	--	--	--
Number of math topics taught, γ_{04}	1.35	0.39	.001	1.36	0.38	.001
Good attendance, γ_{05}	6.21	5.07	.221	--	--	--
Resources for instruction, γ_{06}	-0.58	4.79	.904	--	--	--
Math teacher's perception of school climate, γ_{07}	4.04	3.64	.269	--	--	--
Principal's perception of school climate, γ_{08}	14.33	3.43	.000	18.73	2.77	.000
Math teacher's perception of school facility and safety, γ_{09}	1.60	3.25	.623	--	--	--
Expected parental involvement, γ_{0_10}	-0.08	2.92	.979	--	--	--
Evaluation of math teachers, γ_{0_11}	-5.73	3.19	.073	--	--	--
Limiting math instruction due to student factors, γ_{0_12}	-15.18	2.94	.000	-16.07	2.92	.000
Effect of Parents' highest education level, $\beta_{1j}\,(\gamma_{10})$	2.32	0.83	.006	2.36	0.83	.005
Effect of student education expectation, $\beta_{2j}\,(\gamma_{20})$	6.56	1.06	.000	6.54	1.05	.000
Effect of self-confidence in learning Math, $\beta_{3j}\,(\gamma_{30})$	24.42	1.14	.000	24.41	1.14	.000
Effect of valuing math, $\beta_{4j}\,(\gamma_{40})$	-4.00	1.01	.000	-4.00	1.01	.000

For the United States, there were altogether 9 significant effects on student math achievement. As parents' highest education increased by 1 level, the student's math achievement would increase by 2.36. As student education expectation increased by 1 level, his or her math achievement would increase by about 6.54. Self-confidence in learning math was the strongest indicator of math achievement. With one unit (about one standard deviation) increase in self-confidence in learning math, math achievement would increase about 24.41 points. Surprisingly, with one unit (about one standard deviation) increase in valuing math, student math achievement would *decrease* by about 4 points, although this effect may not be of practical importance.

In terms of the school context, the student was expected to obtain 22.86 points higher if the math teacher was male rather than female. As the teacher's teaching experience increased by 1, student math achievement would increase by about 0.63 points. The more the TIMSS math topics had been taught, the higher the student math achievement, with an effect of 1.36 points. Students from schools with more positive perception of school climate from the principal's perspective, would have higher math achievement. The less math instruction was limited due to student factors in a classroom, the higher achievement students in that class would obtain.

Table 35.

Results in Russia from HLM Models with Predictors at Both Levels.

Fixed Effect	*Model based on Analysis 3*			*Final Model*		
	Coefficient	*Standard Error*	*p value*	*Coefficient*	*Standard Error*	*p value*
Grand mean, β_{0j}						
Intercept, γ_{00}	504.66	29.39	.000	490.43	11.12	.000
Teacher's gender, γ_{01}	-6.04	8.74	.490	--	--	--
Number of years as teacher, γ_{02}	0.02	0.32	.939	--	--	--
Teacher license, γ_{03}	10.77	15.33	.483	--	--	--
Good attendance, γ_{04}	10.40	6.28	.099	12.39	5.69	.030
Resources for instruction, γ_{05}	-0.25	7.07	.972	--	--	--
Math teacher's perception of school climate, γ_{06}	7.42	3.11	.018	--	--	--
Principal's perception of school climate, γ_{07}	3.25	4.12	.432	--	--	--
Math teacher's perception of school facility and safety, γ_{08}	10.40	6.28	.099	7.88	2.83	.006
Expected parental involvement, γ_{09}	-3.83	3.89	.327	--	--	--
Evaluation of math teachers, γ_{0_10}	1.41	4.97	.776	--	--	--
Limiting math instruction due to student factors, γ_{0_11}	0.01	3.48	.998	--	--	--
Effect of Parents' highest education level, $\beta_{1j}\,(\gamma_{10})$	4.81	1.23	.000	4.83	1.24	.000
Effect of student education expectation, β_{2j}						
Intercept, γ_{20}	4.01	2.58	.120	8.02	1.20	.000
Number of years as teacher, γ_{21}	0.17	0.09	.082	--	--	--
Effect of self-confidence in learning Math, $\beta_{3j}\,(\gamma_{30})$	31.31	1.30	.000	31.33	1.30	.000
Effect of student perception of school, $\beta_{4j}\,(\gamma_{40})$	-5.51	1.37	.000	-5.53	1.37	.000

For Russia, the cross-level interaction between teacher's teaching experience and the effect of student education expectation on math achievement, suggested by results from Analysis 3, was removed from the final model. There were 6 main effects—4 from student variables and 2 from school and teacher variables—retained in the final model.

As the parents' highest education increased by 1 level, student math achievement would increase by 4.83 points. As the student education expectation increased by 1 level, his or her math achievement would increase by 8.02 points. Self-confidence in learning math was the most important predictor of math achievement. With one unit increase (about one standard deviation) in this measure, the student math achievement would increase by 31.33 points. Surprisingly, a more positive perception of school by the student was related to *lower* math achievement. As the perception increased by one unit (about one standard deviation), math achievement would decrease by about 5.53 points.

Being in a class and school with good student attendance seemed helpful for math achievement. And when the math teacher had a better perception of school facility and safety, the students would be expected to have higher math achievement.

Table 36.

Results in Singapore from HLM Models with Predictors at Both Levels.

	Model based on Analysis 3			*Final Model*		
Fixed Effect	*Coefficient*	*Standard Error*	*p value*	*Coefficient*	*Standard Error*	*p value*
Grand mean, β_{0j}						
Intercept, γ_{00}	449.69	56.17	.000	436.46	42.71	.000
Teacher's gender, γ_{01}	-13.16	7.20	.068	-12.86	7.11	.071
Number of years as teacher, γ_{02}	-0.12	0.24	.617	--	--	--
Teacher license, γ_{03}	-38.01	35.28	.283	--	--	--
Number of math topics taught, γ_{04}	4.73	1.10	.000	4.67	1.13	.000
Good attendance, γ_{05}	2.30	5.86	.694	--	--	--
Resources for instruction, γ_{06}	-9.33	8.92	.297	--	--	--
Math teacher's perception of school climate, γ_{07}	0.91	4.17	.828	--	--	--
Principal's perception of school climate, γ_{08}	18.46	3.56	.000	19.77	3.08	.000
Math teacher's perception of school facility and safety, γ_{09}	10.71	3.67	.004	10.34	3.60	.005
Expected parental involvement, γ_{0_10}	-1.23	2.83	.663	--	--	--
Evaluation of math teachers, γ_{0_11}	5.25	4.86	.281	--	--	--
Limiting math instruction due to student factors, γ_{0_12}	-12.68	3.14	.000	-12.30	3.13	.000
Effect of self-confidence in learning Math, β_{1j}						
Intercept, γ_{10}	16.36	1.00	.000	16.38	1.00	.000
Principal's perception of school climate, γ_{11}	-1.66	0.75	.034	-1.66	0.75	.034
Effect of valuing math, β_{20}						
Intercept, γ_{20}	3.43	0.92	.001	3.42	0.92	.001
Limiting math instruction due to student factors, γ_{21}	1.97	0.64	.003	1.97	0.64	.003

For Singapore, in the school, the more TIMSS math topics had been taught, the higher students' math achievement would be. At the same time, principal's perception of school climate, and math teacher's perception of school facility and safety, were positively related to students' math achievement. In addition, the more limitation of math instruction due to student factors, the lower students' math achievement was. Students taught by a female math teacher were expected to have 12.86 points higher on math achievement, although this effect was only marginally significant.

Two student motivational constructs—self-confidence in learning math and student valuing math—had a positive effect on student math achievement. However, those effects were different, depending on school characteristics. The positive effect of self-confidence in learning math was *lower* in schools whose principals' had a better perception of school climate. The positive effect of valuing math was *higher* in classrooms were the math instruction was more limited due to student factors.

Table 37.

Results in South Africa from HLM Models with Predictors at Both Levels.

Fixed Effect	*Model Based on Analysis 3*			*Final Model*		
	Coefficient	*Standard Error*	*p value*	*Coefficient*	*Standard Error*	*p value*
Grand mean, β_{0j}						
Intercept, γ_{00}	322.28	44.36	.000	311.48	42.65	.000
Teacher's gender, γ_{01}	5.27	12.18	.666	--	--	--
Number of years as teacher, γ_{02}	3.60	0.87	.000	3.71	0.88	.000
Teacher license, γ_{03}	-16.85	10.63	.115	--	--	--
Number of math topics taught, γ_{04}	-0.80	0.59	.173	--	--	--
Good attendance, γ_{05}	9.35	8.56	.277	--	--	--
Resources for instruction, γ_{06}	35.67	9.06	.000	34.88	8.71	.000
Math teacher's perception of school climate, γ_{07}	-0.57	4.98	.910	20.31	5.85	.001
Principal's perception of school climate, γ_{08}	18.68	6.10	.003	22.00	6.37	.001
Math teacher's perception of school facility and safety, γ_{09}	16.97	5.83	.005	--	--	--
Expected parental involvement, γ_{0_10}	-26.39	8.19	.002	-26.01	8.26	.002
Evaluation of math teachers, γ_{0_11}	-11.04	5.53	.047	-11.70	5.56	.037
Limiting math instruction due to student factors, γ_{0_12}	-10.33	6.54	.116	--	--	--
Effect of student education expectation, β_{1j} (γ_{10})	9.69	1.02	.000	9.71	1.03	.000
Effect of self-confidence in learning Math, β_{2j} (γ_{20})	17.16	2.00	.000	17.19	2.00	.000
Effect of valuing math, β_{3j} (γ_{30})	7.61	2.12	.002	7.60	2.12	.002

For South Africa, there were 3 main effects of student variables and 6 main effects of teacher and school variables. Students with higher education expectation achieved better in math. With one unit (about one standard deviation) increase in self-confidence in learning math, the student math achievement would increase by 17.19 points. With one unit (about one standard deviation) increase in valuing math, student math achievement would increase by 7.60 points.

As the math teacher's teaching experience increased by one year, the student would achieve 3.71 points higher in math. Both the math teacher's and school principal's perception of school climate had a positive effect on student math achievement, with the latter being a little bit higher. Availability of school resources for math instruction seemed to be a very important factor in math achievement. On the other hand, the more procedures used to evaluate math teachers, the *lower* student math achievement would be. The more surprising finding is that the more parental involvement expected by the school principal, the *lower* students in the school achieved in math.

CHAPTER 5

DISCUSSION

This chapter includes three sections. Section one summarizes the findings. The results in each of the four selected countries are discussed. Section two discusses the implications of the results and compares countries. Section three gives suggestions for future research.

5.1 Summary of Findings

The findings of how student motivational beliefs, as well as the teacher and school characteristics, affect eighth-graders' mathematics achievement are summarized in the four selected countries: the United States, Russia, Singapore, and South Africa.

5.1.1 Findings in the United States

Of the six student variables (Parents' Highest Education Level, Student Education Expectation, Student Sex, Student Self-Confidence in Learning Mathematics, Student Valuing Mathematics, and Student Perception of School), four had significant effects on eighth-graders' math achievement. As parents' highest education increased by 1 level, the student's math achievement would increase by 2.36 points. As student education expectation increased by 1 level, his or her math achievement would increase by about 6.54. Self-confidence in learning math was the strongest indicator of math achievement. With one unit (about one standard deviation) increase in self-confidence in learning math, math achievement would increase about 24.41 points. Surprisingly, with one unit (about one standard deviation) increase in valuing math, student math achievement would *decrease* by about 4 points.

Of the twelve teacher and school variables (Teacher's Gender, Number of Years as Teachers, Teacher License or Certification, Number of Mathematics Topics Taught, School and Class Attendance, Availability of School Resources for Mathematics Instruction, Mathematics Teachers' Perception of School Climate, Principals' Perception of School Climate, Mathematics Teachers' Perception of School Facility and Safety, Expected Parent Involvement by School Principals, Evaluation of Mathematics Teachers, and Limiting Mathematics Instruction due to Student Factors), five had significant effects on eighth-graders' math achievement. The student was expected to obtain 22.86 points higher if the math teacher was male rather than female. As the teacher's teaching experience increased by 1, student math achievement would increase by about 0.63 points. The more the TIMSS math topics had been taught, the higher the student math achievement, with an effect of 1.36 points. Students from schools with more positive perception of school from the principal's perspective, would have higher math achievement. The less math instruction was limited due to student factors in a classroom, the higher achievement students in that class would obtain.

5.1.2 Findings in Russia

Of the six student variables (Parents' Highest Education Level, Student Education Expectation, Student Sex, Student Self-Confidence in Learning Mathematics, Student Valuing Mathematics, and Student Perception of School), four had significant effects on eighth-graders' math achievement. As the parents' highest education increased by 1 level, student math achievement would increase by 4.83 points. As the student education expectation increased by 1 level, his or her math achievement would increase by 8.02 points. Self-confidence in learning math was the most important predictor of math achievement. With one unit increase (about one standard deviation) in this measure, the student math achievement would increase by 31.33 points. Surprisingly, a more positive perception of school by the student was related to *lower* math achievement. As the perception increased by one unit (about one standard deviation), math achievement would decrease by about 5.53 points.

Only two of the eleven teacher and school variables (Teacher's Gender, Number of Years as Teachers, Teacher License or Certification, School and Class Attendance, Availability of School Resources for Mathematics Instruction, Mathematics Teachers' Perception of School Climate, Principals' Perception of School Climate, Mathematics Teachers' Perception of School Facility and Safety, Expected Parent Involvement by School Principals, Evaluation of Mathematics Teachers, and Limiting Mathematics Instruction due to Student Factors), had significant effects on eighth-graders' math achievement.

Being in a class and school with good student attendance seemed helpful for math achievement. And when the math teacher had a better perception of school facility and safety, the students would be expected to have higher math achievement.

5.1.3 Findings in Singapore

Of the twelve teacher and school variables (Teacher's Gender, Number of Years as Teachers, Teacher License or Certification, Number of Mathematics Topics Taught, School and Class Attendance, Availability of School Resources for Mathematics Instruction, Mathematics Teachers' Perception of School Climate, Principals' Perception of School Climate, Mathematics Teachers' Perception of School Facility and Safety, Expected Parent Involvement by School Principals, Evaluation of Mathematics Teachers, and Limiting Mathematics Instruction due to Student Factors), four had significant effects on eighth-graders' math achievement. In the school, the more TIMSS math topics had been taught, the higher students' math achievement would be. At the same time, principal's perception of school climate, and math teacher's perception of school facility and safety, were positively related to students' math achievement. In addition, the more limitation of math instruction due to student factors, the lower students' math achievement was. Students taught by a female math teacher were expected to have 12.86 points higher on math achievement, although this effect was only marginally significant.

Of the six student variables (Parents' Highest Education Level, Student Education Expectation, Student Sex, Student Self-Confidence in Learning Mathematics, Student Valuing Mathematics, and Student Perception of School), only two had significant effects on eighth-graders' math achievement. Student self-confidence in math and student valuing math had a positive effect on student math achievement. However, those effects were different, depending on school characteristics. The positive effect of self-confidence in learning math was *lower* in schools whose principals' had a better perception of school climate. The positive effect of valuing math was *higher* in classrooms were the math instruction was more limited due to student factors.

5.1.4 Findings in South Africa

Of the six student variables (Parents' Highest Education Level, Student Education Expectation, Student Sex, Student Self-Confidence in Learning Mathematics, Student Valuing Mathematics, and Student Perception of School), three had significant effects on eighth-graders' math achievement. Students with higher education expectation achieved better in math. With one unit (about one standard deviation) increase in self-confidence in learning math, the student math achievement would increase by 17.19 points. With one unit (about one standard deviation) increase in valuing math, student math achievement would increase by 7.60 points.

Of the twelve teacher and school variables (Teacher's Gender, Number of Years as Teachers, Teacher License or Certification, Number of Mathematics Topics Taught, School and Class Attendance, Availability of School Resources for Mathematics Instruction, Mathematics Teachers' Perception of School Climate, Principals' Perception of School Climate, Mathematics Teachers' Perception of School Facility and Safety, Expected Parent Involvement by School Principals, Evaluation of Mathematics Teachers, and Limiting Mathematics Instruction due to Student Factors), six had significant effects on eighth-graders' math achievement. As the math teacher's teaching experience increased by one year, the student would achieve 3.71 points higher in math. Both the math teacher's and school principal's perception of school climate had a positive effect on student math achievement, with the latter being a little bit higher. Availability of school resources for math instruction seemed to be a very important factor in math achievement. On the other hand, the more procedures used to evaluate math teachers, the *lower* student math achievement would be. The more surprising finding is that the more parental involvement expected by the school principal, the *lower* students in the school achieved in math.

5.2 Discussion and Implications

The findings in the four selected countries suggested that the student, teacher and school variables worked differently across countries on eighth-graders' math achievement. Table 38 summarizes the significance of the effects in the four countries.

Table 38.

Significance of Variables on Math Achievement in Each Country.

	Significant Effect?			
	United States	Russia	Singapore	South Africa
Student Variables				
Parents' Highest Education Level	Y	Y	N	N
Student Educational Expectation	Y	Y	N	Y
Sex	N	N	N	N
Student Self-Confidence in Learning Mathematics	Y	Y	Y	Y
Student Valuing Mathematics	Y	N	Y	Y
Student Perception of School	N	Y	N	N
Teacher and School Variables				
Teacher's Gender	Y	N	N	N
Number of years as teachers	Y	N	N	Y
Teacher License or Certification	N	N	N	N
Number of Mathematics Topics Taught	Y	N/A	Y	N
School and Class Attendance	N	Y	N	N
Availability of School Resources for Mathematics Instruction	N	N	N	Y
Mathematics Teachers' Perception of School Climate	N	N	N	Y
Principals' Perception of School Climate	Y	N	Y	Y
Mathematics Teachers' Perception of School Facility and Safety	N	Y	Y	N
Expected Parent Involvement by School Principals	N	N	N	Y
Evaluation of Mathematics Teachers	N	N	N	Y
Limiting Mathematics Instruction due to Student Factors	Y	N	Y	N

Influences of Student Characteristics on Math Achievement

Controlling for other variables, there was no gender gap in any of the four selected countries on math achievement at eighth-grade. This may be the result of the widespread rise in gender equality around the world and its extensive impact on academic outcomes of schooling (see Baker & LeTendre, 2005). However, during the HLM model building process to arrive at the final model for each country, there was sometimes a gender difference when other variables were not controlled. For example, during model building at Level 1 (Models b and c), there was a gender difference in the United States and Singapore when student motivational constructs were not controlled for (Model b), although the gender gap disappeared when student motivational constructs were added (Model c). This may be indicative that the gender difference exists in student motivational beliefs, which in turn affect student academic outcomes.

Student self-confidence in learning math was positively related to math achievement in all the countries. It had a much stronger effect than the other student variables, sometimes the largest effect of all the variables. This construct is similar to expectations for success and self-efficacy. The findings in all the four selected countries were consistent.

The effect of student valuing math functioned inconsistently across the four countries. While in Singapore and South Africa, there was a significant positive effect, in the United States, however, the effect was surprisingly negative. This may be because American students who achieved lowered in math were actually more likely to realize the importance of it, and it does not necessarily mean that the higher value attached to math would impede the acquiring of math knowledge.

Studies on expectancy-value theory have shown that children's subjective task values are stronger predictors of children's intentions to keep taking math and actual decisions to do so while children's beliefs about their ability and expectancies for success are the strongest predictors of grades in math (see Wigfield & Eccles, 2000). The effect of valuing math might not be a good predictor on the actual performance on math.

While the effect of student valuing math was nonsignificant, student perception of school was significant in Russia, surprisingly negative.

Student educational expectation was positively related to math achievement in the United States, Russia, and South Africa but not in Singapore. This variable was an index variable with 5 levels. It may be that all the students in Singapore had high educational expectations that there was not enough variance to model.

Influences of Family

Parents' highest education level is an index variable with 5 levels. It was a significant predictor of mathematics achievement at eighth-grade in the United States and Russia, but not in Singapore or South Africa, suggesting that, parents' educational background in generally is more influential in the United States and Russia than in the other two countries.

Expected parental involvement was not significant in the United States, Russia, or Singapore, but had a surprisingly negative effect in South Africa. It may be because in South Africa, parents were expected to be involved in school activities when the children were not doing well. Nonetheless, the findings were inconsistent with research on parental involvement (see Rumberger & Palardy, 2005).

Influences of Teachers

A major difference between the United States and the other three countries is that the teacher's gender had a significant effect on math achievement. Students might gain as much as 22.86 points if the math teacher was a male rather than a female, controlling for the other variables.

The effect of number of years of teaching experience was more obvious in South Africa (3.71) than in the United States (0.63). While this effect may not be practically important in the United States (one year increase in math teacher's teaching experience would result in an increase of 0.63 points in student math achievement), it should not be ignored in South Africa.

Interestingly, whether the math teacher was fully certified did not affect student math achievement in any of the four selected countries. If the purpose of licensing teachers is to improve academic performance only, it seemed this purpose was not fulfilled.

While teachers' perception of school climate or their perception of school facility and safety was not significant in the United States, the former was significant in South Africa and the latter was significant in Russia and Singapore.

Influences of School Structure

In Russia, being in a class and school with good student attendance seemed useful for math achievement. Russia also had the smallest intraclass correlation in the fully unconditional HLM model among the four countries, meaning that the classrooms (schools) were more similar to each other in math achievement.

The index variable of availability of school resources for math instruction was only significant in South Africa. This may be that schools were more spread on this index variable in South Africa than in the other countries.

Principal's perception of school climate, while positively significant in the other three countries, was not significant in Russia.

In South Africa, but not in the other countries, the more procedures used to evaluate math teachers, the lower student math achievement would be. The effect may be the other way around, that is, schools with lower performance on math required more procedures to evaluate teachers.

Both in the United States and Singapore, when a student was in a classroom where the math instruction was limited by student factors such as uninterested students and low morale among students, the math achievement would be lower. However, this did not happen in Russia or in South Africa.

5.3 Suggestions for Future Research

This study examined the effects of different student, teacher and school variables on eighth-graders' math achievement. It is likely that some of the effects are reciprocal. Student math achievement, for example, may influence his or her motivation, or influence teachers' and school principals' perception of school climate. It is also possible that some effects on math achievement are direct while others are indirect. Structural equation modeling techniques can be applied to compare different models related to achievement. Since the data have hierarchical structure within each country, two-level structural models are appropriate.

Three student variables and four school and teacher variables were created using principal component analyses within each country. Since principal components are scores standardized within each country, the related constructs cannot be compared across countries. An alternative is to conduct a principal component analysis for each variable with all the cases from all the countries. This will lose the comparison of the loadings across countries but make the constructs comparable in different countries. The sum or the mean of the original variables may also be used to get a measure of the construct. This will allow the researcher to see the differences in the predictors themselves across countries, in addition to the differences in student math achievement.

Several variables used in this study were index variables. Usually index variables do not have much variance to model. Continuous variables may be used in future research to represent similar constructs.

This study selected four countries for analysis. Data from 47 countries are available in TIMSS 2003. Similar studies can be conducted for other countries. This will allow the research to have a fuller spectrum of math achievement and how it is influenced by different variables.

Likewise, in the future, the study can be extended to science achievement measured in TIMSS 2003, or to the fourth-grade data, and to other similar large-scale datasets with a hierarchical feature (e.g. PISA, PIRLS).

APPENDIX A

Original Items for Measure of Student Self-Confidence in Learning Mathematics

1-Agree a lot; 2-Agree a little; 3-Disagree a little; 4-Disagree a lot
What do you think about learning math? Tell how much you agree with these statements: I usually do well in math.
What do you think about learning math? Tell how much you agree with these statements: math is more difficult for me than for many of my classmates.
What do you think about learning math? Math is not one of my strengths.
What do you think about learning math? Tell how much you agree with these statements: I learn things quickly in math.

Original Items for Measure of Student Valuing Mathematics

1-Agree a lot; 2-Agree a little; 3-Disagree a little; 4-Disagree a lot
Indicate how much you agree with these statements about math: I think learning mathematics will help me in my daily life.
Indicate how much you agree with these statements about math: I need mathematics to learn other school subjects.
Indicate how much you agree with these statements about math: I need to do well in math to get into the <university> of my choice.
Indicate how much you agree with these statements about math: I would like a job that involved using math.
Indicate how much you agree with these statements about math: I need to do well in math to get the job I want.
What do you think about learning math? Tell how much you agree with these statements: I would like to take more mathematics in school.
What do you think about learning math? Tell how much you agree with these statements: I enjoy learning math.

Original Items for Measure of Student Perception of School

1-Agree a lot; 2-Agree a little; 3-Disagree a little; 4-Disagree a lot
How much do you agree with these statements about your school? I like being in school.
How much do you agree with these statements about your school? I think that students in my school try to do their best.
How much do you agree with these statements about your school? I think that teachers in my school care about the students.
How much do you agree with these statements about your school? I think that teachers in my school want students to do their best.

Original Items for Measure of Mathematics Teachers' Perception of School Climate

1-Very high; 2-High; 3-Medium; 4-Low; 5-Very low
How would you characterize teachers' job satisfaction within your school?
How would you characterize teachers' understanding of the school's curricular goals within your school?
How would you characterize teachers' degree of success in implementing the school's curriculum within your school?
How would you characterize teachers' expectations for student achievement within your school?
How would you characterize parental support for student achievement within your school?
How would you characterize parental involvement in school activities within your school?
How would you characterize students' regard for school property within your school?
How would you characterize students' desire to do well in school within your school?

Original Items for Measure of School Principals' Perception of School Climate

1-Very high; 2-High; 3-Medium; 4-Low; 5-Very low
How would you characterize teachers' job satisfaction within your school?
How would you characterize teachers' understanding of the school's curricular goals within your school?
How would you characterize teachers' degree of success in implementing the school's curriculum within your school?
How would you characterize teachers' expectations for student achievement within your school?
How would you characterize parental support for student achievement within your school?
How would you characterize parental involvement in school activities within your school?
How would you characterize students' regard for school property within your school?
How would you characterize students' desire to do well in school within your school?

Original Items for Measure of Mathematics Teachers' Perception of School Facility and Safety

1-Agree a lot; 2-Agree a little; 3-Disagree a little; 4-Disagree a lot
Thinking about your current school, indicate the extent to which you agree or disagree that this school facility (building and grounds) is in need of significant repair?
Thinking about your current school, indicate the extent to which you agree or disagree that this school is located in a safe neighborhood?
Thinking about your current school, indicate the extent to which you agree or disagree that you feel safe at this school?
Thinking about your current school, indicate the extent to which you agree or disagree that this school's security policies and practices are sufficient?

Original Items for Measure of Availability of School Resources for Mathematics Instruction

1-None; 2-A little; 3-Some; 4-A lot
Is your school's capacity to provide instruction affected by a shortage or inadequacy of instructional materials (e.g., textbook)?
Is your school's capacity to provide instruction affected by a shortage or inadequacy of budget for supplies (e.g., paper, pencils)?
Is your school's capacity to provide instruction affected by a shortage or inadequacy of school buildings and grounds?
Is your school's capacity to provide instruction affected by a shortage or inadequacy of heating/cooling and lighting systems?
Is your school's capacity to provide instruction affected by a shortage or inadequacy of instructional space (e.g., classrooms)?
Is your school's capacity to provide instruction affected by a shortage or inadequacy of computers for mathematics instruction?
Is your school's capacity to provide instruction affected by a shortage or inadequacy of computer software for mathematics instruction?
Is your school's capacity to provide instruction affected by a shortage or inadequacy calculators for mathematics instruction?
Is your school's capacity to provide instruction affected by a shortage or inadequacy of library materials relevant to mathematics instruction?
Is your school's capacity to provide instruction affected by a shortage or inadequacy of audio-visual resources for mathematics instruction?

Main Topics Addressed by TIMSS 2003 Mathematics Test

Number
Whole numbers including place value, factorization, and the four operations
Computations, estimations, or approximations involving whole numbers
Common fractions including equivalent fractions, and ordering of fractions
Decimal fractions including place value, ordering, rounding, and converting to common fractions (and vice versa)
Representing decimals and fractions using words, numbers, or models (including number lines)
Computations with fractions
Computation with decimals
Integers including words, numbers, or models (including number lines), ordering integers, addition, subtraction, multiplication, and division with integers
Ratios (equivalence, division of a quantity by a given ratio)
Conversion of percents to fractions or decimals, and vice versa

Algebra
Numeric, algebraic, and geometric patterns or sequences (extension, missing terms, generalization of patterns)
Sums, products, and powers of expressions containing variables
Simple linear equations and inequalities, and simultaneous (two variables) equations
Equivalent representations of functions as ordered pairs, tables, graphs, words, or equations
Proportional, linear, and nonlinear relationships (travel graphs and simple piecewise functions included)
Attributes of a graph such as intercepts on axes, and intervals where the function increases, decreases, or is constant
Measurement
Standard units for measures of length, area, volume, perimeter, circumference, time, speed, density, angle, mass/weight
Relationships among units for conversions within systems of units, and for rates
Use standard tools to measure length, weight, time, speed, angle, and temperature
Estimations of length, circumference, area, volume, weight, time, angle, and speed in problem situations (e.g., circumference of a wheel, speed of a runner)
Computations with measurements in problem situations (e.g., add measures, find average speed on a trip, find population density)
Measure formulas for perimeter of a rectangle, circumference of a circle, areas of plane figures (including circles), surface area and volume of rectangular solids, and rates
Measure of irregular or compound areas (e.g., by using grids or dissecting and rearranging pieces)
Precision of measurements (e.g., upper and lower bounds of a length reported as 8 centimeters to the nearest centimeter)
Geometry
Angles – acute, right, straight, obtuse, reflex, complementary, and supplementary
Relationships for angles at a point, angles on a line, vertically opposite angles, angles associated with a transversal cutting parallel lines, and perpendicularity
Properties of angle bisectors and perpendicular bisectors of lines
Properties of geometric shapes: triangles and quadrilaterals
Properties of other polygons (regular pentagon, hexagon, octagon, decagon)
Construct or draw triangles and rectangles or given dimensions
Pythagorean theorem (not proof) to find length of a side
Congruent figures (triangles, quadrilaterals) and their corresponding measures
Similar triangles and recall their properties
Cartesian plane – ordered pairs, equations, intercepts, intersections, and gradient
Relationships between two-dimensional and three-dimensional shapes
Line and rotational symmetry for two-dimensional shapes
Translation, reflection, rotation and enlargement

Data
Organizing a set of data by one or more characteristics using a tally chart, table, or graph
Sources of error in collecting and organizing data (e.g., bias, inappropriate grouping)
Data collection methods (e.g., survey, experiment, questionnaire)
Drawing and interpreting graphs, tables, pictographs, bar graphs, pie charts, and line graphs
Characteristics of data sets including mean, median, range, and shape of distribution (in general terms)
Interpreting data sets (e.g., draw conclusions, make predictions, and estimate values between and beyond given data points)
Evaluating interpretations of data with respect to correctness and completeness of interpretation
Simple probability including using data from experiments to estimate probabilities for favorable outcomes

Original Items for Measure of Limiting Mathematics Instruction due to Student Factors

0-Not applicable or not at all; 1-A little; 2-Some; 3-A lot
In your view, to what extent do students with different academic abilities limit how you teach the TIMSS class?
In your view, to what extent do students who come from a wide range of backgrounds (e.g., economic, language) limit how you teach the TIMSS class?
In your view, to what extent do students with special needs, (e.g., hearing, vision, speech impairment, physical disabilities, mental or emotional/psychological impairment) limit how you teach the TIMSS class?
In your view, to what extent do uninterested students limit how you teach the TIMSS class?
In your view, to what extent do low morale among students limit how you teach the TIMSS class?
In your view, to what extent do disruptive students limit how you teach the TIMSS class?

APPENDIX B

SAS macro to perform Principal Component Analysis in each country and to create SAS datasets for HLM analyses

```
libname BM3 'C:\Documents and Settings\zwch6\Desktop\dissertation\BM3';
libname BM3ready 'C:\Documents and
Settings\zwch6\Desktop\dissertation\BM3readydata';

%macro MyMacro (cty);
options nodate nonumber;
/* There are 6 types of files: BCG, BSA, BSG, BST, BTM and BTS. There
are 51 files each type: 51*6=306 files in total.
48 countries participated at the 8th grade in TIMSS 2003. Data are
available for 47 countries. In addition, there are 4 regions of
benchmarking participants, 47+4=51. */

/* BCG<country>M3--School Background File
   BSA<country>M3--Student Achievement File
   BSG<country>M3--Student Background File
   BST<country>M3--Student-Teacher Linkage File
   BTM<country>M3--Teacher Background File (Mathematics)
   BTS<country>M3--Teacher Background File (Science)
   BUGMATM3--Curriculum Quationnaire File (Mathematics) (not included
in this library)
Files that are to be used in dissertation: BCG, BSG, BTM,and BST.
*/

data bcg&cty.m3;
  set bm3.bcg&cty.m3;
run;

data bsg&cty.m3;
  set bm3.bsg&cty.m3;
run;

data btm&cty.m3;
  set bm3.btm&cty.m3;
run;

data bst&cty.m3;
  set bm3.bst&cty.m3;
run;

/* The following creates a merged file of BCG<country>M3 and
BTM<country>M3.
   This file is called BTC<country>M3 and is at the teacher level.*/
```

```
proc sort data=bcg&cty.m3;
   by idcntry idschool;
run;

proc sort data=btm&cty.m3;
   by idcntry idschool;
run;

data btc&cty.m3;
  merge bcg&cty.m3 btm&cty.m3;
  by idcntry idschool;
run;



/* The following creates measures of school and math teacher
constructs. Principal-components analyses with varimax rotations are
used for scale construction. After checking the results of PCAs, only
the first principal component is retained. */


/* The first PCA creates a measure of principals' perception of school
climate using PCA. A similar index (bcdgch) was created by TIMSS.
Several  other measures are also created without using PCA.
*/

/*
proc factor data=btcusam3 rotate=varimax scree;
var BCBGCHTS BCBGCHTU BCBGCHTC BCBGCHES BCBGCHPS BCBGCHPI BCBGCHSR
BCBGCHSD;
run;
*/

proc factor data=btc&cty.m3 out=test4 scree nfactor=1;
  var BCBGCHTS BCBGCHTU BCBGCHTC BCBGCHES BCBGCHPS BCBGCHPI BCBGCHSR
BCBGCHSD;
run;


data btc&cty.m3 (drop=factor1 a001-a009);
  set test4;
  bcppsc=0-factor1;
  if bcppsc=. then bcppsc=0;
   a001=2-bcbgepse;
   a002=2-bcbgeprf;
   a003=2-bcbgepvo;
   a004=2-bcbgepch;
   a005=2-bcbgepsc;
  bcpinvol=sum(of a001-a005);
   a006=2-bcbmepos;
   a007=2-bcbmepoe;
   a008=2-bcbmepsa;
```

```
   a009=2-bcbmeptr;
  bctchev=sum (of a006-a009);
  bcdmst_r=4-bcdmst;
  bcdgsp_r=4-bcdgsp;
 label bcppsc="principals' perception of school climate"
        bcpinvol="expected parent involvement by school pincipals"
        bctchev="procedures used to evaluate math teachers"
        bcdmst_r="School Resources for Math Instruction"
        bcdgsp_r="School and Class Attendance";
run;


/* The second PCA creates a measure of math teachers' perception of
school facility and safety.

data test5;
  set btcusam3;
  btbmadsa_r=5-btbmadsa;
  btbmadme_r=5-btbmadme;
  btbmadfd_r=5-btbmadfd;
run;

proc factor data=test5 rotate=varimax scree;
  var btbmadmr btbmadsa_r btbmadhy btbmadme_r btbmaddw btbmadfd_r
btbmadrw;
run;

*/


data test6;
  set btc&cty.m3;
  btbgcusn_r=5-btbgcusn;
  btbgcusa_r=5-btbgcusa;
  btbgcuas_r=5-btbgcuas;
run;

proc factor data=test6 out=test7 scree nfactor=1;
  var btbgcure btbgcusn_r btbgcusa_r btbgcuas_r;
run;

data btc&cty.m3 (drop=factor1 btbgcusn_r btbgcusa_r btbgcuas_r);
  set test7;
  btschset=factor1;
  if btschset=. then btschset=0;
 label btschset="Teachers' perception of about school facility and
safety";
run;


/* The third PCA creates a measure of math teachers' perception of
school climate. A similar index (btdmch) was created by TIMSS. */
```

```
/*
proc factor data=btcusam3 rotate=varimax scree;
  var BTBGCHTS BTBGCHTU BTBGCHTC BTBGCHES  BTBGCHPS BTBGCHPI BTBGCHSR
BTBGCHSD;
run;
*/

proc factor data=btc&cty.m3 out=test8 scree nfactor=1;
  var BTBGCHTS BTBGCHTU BTBGCHTC BTBGCHES  BTBGCHPS BTBGCHPI BTBGCHSR
BTBGCHSD;
run;


data btc&cty.m3 (drop=factor1);
  set test8;
  btmtpsc=0-factor1;
  if btmtpsc=. then btmtpsc=0;
  label btmtpsc="Math teachers’s perception of school climate";
run;

data btc&cty.m3 (drop=i);
  set btc&cty.m3;
  array taught{45} btbmto01-btbmto45;
  bttpc=0;
 do i=1 to 45;
   if taught{i}=1 or taught{i}=2 then bttpc+1;
 end;
 label bttpc="total number of math topics taught";
run;


/* The fourth PCA creates a measure of limiting math teacher due to
student factors. */

data test10 (drop=i);
  set btc&cty.m3;
  array student{6} btbglt01-btbglt06;
  array limit{6};
  do i=1 to 6;
    if student{i}=1 or student{i}=2 then limit{i}=0;
      else if student{i}=3 then limit{i}=1;
      else if student{i}=4 then limit{i}=2;
      else if student{i}=5 then limit{i}=3;
  end;
run;

/*
proc factor data=test10 scree rotate=varimax;
var limit1-limit6;
run;
*/
```

```
proc factor data=test10 scree out=test10 nfactor=1;
var limit1-limit6;
run;

data btc&cty.m3 (drop=factor1 limit1-limit6);
  set test10;
  btlmtstu=factor1;
  if btlmtstu=. then btlmtstu=0;
  label btlmtstu="limiting math teaching due to student factors";
run;


/* The following works on the student data file BSG<country>M3. */

data test11;
  set bsg&cty.m3;
  bsdgedup_r=6-bsdgedup;
  bsbmtwel_r=5-bsbmtwel;
  bsbmtqky_r=5-bsbmtqky;
  label bsdgedup_r="Reverse code of Parents’ Highest Education Level";
run;


/* The fifth PCA creates a measure of students’ self-confidence in
learning math. TIMSS has a similar index (bsdmscl). */

/*
proc factor data=test11 scree rotate=varimax;
var BSBMTWEL_r BSBMTCLM BSBMTSTR BSBMTQKY_r;
run;
*/

proc factor data=test11 scree out=test11 nfactor=1;
var BSBMTWEL_r BSBMTCLM BSBMTSTR BSBMTQKY_r;
run;

data bsg&cty.m3 (drop=bsbmtwel_r bsbmtqky_r factor1);
   set test11;
   bsslfcm=factor1;
   if bsslfcm=. then bsslfcm=0;
   label bsslfcm="Students’ Self Confidence in Learning Math";
run;


/* The sixth PCA creates a measure of students’ valuing math. TIMSS has
a similar index (bsdmsv). */

/*
proc factor data=bsgusam3 scree rotate=varimax;
  var BSBMAHDL BSBMAOSS BSBMAUNI BSBMAJOB BSBMAGET BSBMTMOR BSBMTENJ;
run;
*/
```

```
proc factor data=bsg&cty.m3 scree out=test12 nfactor=1;
  var BSBMAHDL BSBMAOSS BSBMAUNI BSBMAJOB BSBMAGET BSBMTMOR BSBMTENJ;
run;

data bsg&cty.m3 (drop=factor1);
  set test12;
  bssvalm=0-factor1;
  if bssvalm=. then bssvalm=0;
  label bssvalm="Students’ Valuing Math";
run;


/* The seventh PCA creates a measure of students’ perception of school.
*/

/*
proc factor data=bsgusam3 scree rotate=varimax;
  var bsbgalbs bsbgattb bsbgatcs bsbgatsb;
run;
*/

proc factor data=bsg&cty.m3 scree out=test13 nfactor=1;
  var bsbgalbs bsbgattb bsbgatcs bsbgatsb;
run;

data bsg&cty.m3 (drop=factor1);
  set test13;
  bsspsc=0-factor1;
  itsex_r=itsex-1;
  bsbghfsg_r=bsbghfsg;
  if bsbghfsg_r=6 then bsbghfsg_r=.;
  if bsspsc=. then bsspsc=0;
  label bsspsc="Students’ perception of school";
run;


/* The following adds more information to dataset BTC<country>M3 so
that each class has one observation in the file. */

proc sort data=btc&cty.m3;
  by idcntry idteach idlink;
run;

proc sort data=bst&cty.m3 out=bst&cty.m3_sort;
  by idcntry idteach idlink;
run;

data test14;
 merge btc&cty.m3 bst&cty.m3_sort;
 by idcntry idteach idlink;
 if (first.idcntry or first.idteach or first.idlink) and itcourse=1;
```

```
run;

data btc&cty.m3 (drop=idstud totwgt--tchwgt);
  set test14;
  btbgsex_r=btbgsex-1;
  btdgtelc_r=btdgtelc-1;
run;

proc sort data=btc&cty.m3;
  by idcntry idclass;
run;

proc sort data=bsg&cty.m3;
 by idcntry idclass;
run;

/* The following selects variables to be used in later HLM analyses.
Variables are reordered in datasets. Missing values represented by
different symbols in SAS are changed to a period (.).

Variable names do not exceed 8 characters. Transport BSG<country>M3 and
BTC<country>M3 to .ssp files so that they can be used for HLM analyses.
*/

data BM3ready.l1&cty (keep=idcntry idschool idclass bsedup_r bsslfcm
bssvalm bsspsc itsex_r bshfsg_r houwgt bsmmat01-bsmmat05);
  length idcntry idschool idclass bsedup_r bsslfcm bssvalm bsspsc
itsex_r bshfsg_r houwgt bsmmat01-bsmmat05 8.;
  set bsg&cty.m3;
  if bsdgedup_r < -999 then bsdgedup_r=.;
  if bsslfcm < -9999 then bsslfcm=.;
  if bssvalm < -999 then bssvalm=.;
  if bsspsc < -999 then bsspsc=.;
  if itsex_r <-999 then itsex_r=.;
  if bsbghfsg_r <-999 then bsbghfsg_r=.;
  bsedup_r=bsdgedup_r;
  bshfsg_r=bsbghfsg_r;
run;

data BM3ready.l2&cty (keep=idcntry idschool idclass bcppsc bcpinvol
   bctchev bcdmst_r bcdgsp_r btschset btmtpsc bttpc btlmtstu btsex_r
btbgtaut bttelc_r);
   length idcntry idschool idclass bcppsc bcpinvol
   bctchev bcdmst_r bcdgsp_r btschset btmtpsc bttpc btlmtstu btsex_r
btbgtaut bttelc_r 8.;
   set btc&cty.m3;
  if btbgtaut <-999 then btbgtaut=.;
  btsex_r=btbgsex_r;
  bttelc_r=btdgtelc_r;
run;
```

```
libname out1 xport "C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\l1&cty..ssp";
libname out2 xport "C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\l2&cty..ssp";


proc copy in=BM3ready out=out1 memtype=data;
select l1&cty;
run;

proc copy in=BM3ready out=out2 memtype=data;
select l2&cty;
run;

%mend MyMacro;


/* The following applies the above SAS macro to four selected
countries: the United States, Russia, Singapore, and South Africa. */

%include "C:\Documents and
Settings\zwch6\Desktop\dissertation\MyMacro.sas";
%MyMacro(USA);
%MyMacro(RUS);
%MyMacro(SGP);
%MyMacro(ZAF);
```

APPENDIX C

HLM output of model d and model e in each country

Model d in the United States

```
 Program:                        HLM 6 Hierarchical Linear and Nonlinear
Modeling
 Authors:                        Stephen Raudenbush, Tony Bryk, & Richard
Congdon
 Publisher:                      Scientific Software International, Inc. (c)
2000

techsupport@ssicentral.com

www.ssicentral.com
 -------------------------------------------------------------------------------
-
 Module:      HLM2.EXE (6.04.2754.2)
 Date:        26 June 2008, Thursday
 Time:        10: 0:25
 -------------------------------------------------------------------------------
-


 SPECIFICATIONS FOR THIS HLM2 RUN


  Problem Title: no title

  The data source for this run  = USA.mdm
  The command file for this run = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\USAmodeld2.hlm
  Output file name              = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\hlm2.avg
  The maximum number of level-1 units = 4938
  The maximum number of level-2 units = 341
  The maximum number of iterations = 100
  Method of estimation: restricted maximum likelihood

  This is part of a plausible value analysis using the following variables:
    BSMMAT01
    BSMMAT02
    BSMMAT03
    BSMMAT04
    BSMMAT05


 Weighting Specification
 -----------------------
                         Weight
```

```
                        Variable
           Weighting?   Name        Normalized?
 Level 1       yes        HOUWGT        yes
 Level 2        no
 Precision      no

  The outcome variable is BSMMAT01

  The model specified for the fixed effects was:
 ----------------------------------------------------

   Level-1                  Level-2
   Coefficients             Predictors
 ----------------------   ---------------
        INTRCPT1, B0      INTRCPT2, G00
                          BCDMST_R, G01
                          BCDGSP_R, G02
                             BTTPC, G03
                           BTSEX_R, G04
                          BTBGTAUT, G05
                          BTTELC_R, G06
#% BSEDUP_R slope, B1      INTRCPT2, G10
                          BCDMST_R, G11
                          BCDGSP_R, G12
                             BTTPC, G13
                           BTSEX_R, G14
                          BTBGTAUT, G15
                          BTTELC_R, G16
#%  BSSLFCM slope, B2      INTRCPT2, G20
                          BCDMST_R, G21
                          BCDGSP_R, G22
                             BTTPC, G23
                           BTSEX_R, G24
                          BTBGTAUT, G25
                          BTTELC_R, G26
#%  BSSVALM slope, B3      INTRCPT2, G30
                          BCDMST_R, G31
                          BCDGSP_R, G32
                             BTTPC, G33
                           BTSEX_R, G34
                          BTBGTAUT, G35
                          BTTELC_R, G36
#% BSHFSG_R slope, B4      INTRCPT2, G40
                          BCDMST_R, G41
                          BCDGSP_R, G42
                             BTTPC, G43
                           BTSEX_R, G44
                          BTBGTAUT, G45
                          BTTELC_R, G46

'#' - The residual parameter variance for this level-1 coefficient has been set
      to zero.
'%' - This level-1 predictor has been centered around its grand mean.

 The model specified for the covariance components was:
 ---------------------------------------------------------

        Sigma squared (constant across level-2 units)
```

```
        Tau dimensions
              INTRCPT1


 Summary of the model specified (in equation format)
 ---------------------------------------------------

Level-1 Model

       Y = B0 + B1*(BSEDUP_R) + B2*(BSSLFCM) + B3*(BSSVALM) + B4*(BSHFSG_R) + R

Level-2 Model
       B0 = G00 + G01*(BCDMST_R) + G02*(BCDGSP_R) + G03*(BTTPC) + G04*(BTSEX_R)
         + G05*(BTBGTAUT) + G06*(BTTELC_R) + U0
       B1 = G10 + G11*(BCDMST_R) + G12*(BCDGSP_R) + G13*(BTTPC) + G14*(BTSEX_R)
         + G15*(BTBGTAUT) + G16*(BTTELC_R)
       B2 = G20 + G21*(BCDMST_R) + G22*(BCDGSP_R) + G23*(BTTPC) + G24*(BTSEX_R)
         + G25*(BTBGTAUT) + G26*(BTTELC_R)
       B3 = G30 + G31*(BCDMST_R) + G32*(BCDGSP_R) + G33*(BTTPC) + G34*(BTSEX_R)
         + G35*(BTBGTAUT) + G36*(BTTELC_R)
       B4 = G40 + G41*(BCDMST_R) + G42*(BCDGSP_R) + G43*(BTTPC) + G44*(BTSEX_R)
         + G45*(BTBGTAUT) + G46*(BTTELC_R)


THE AVERAGED RESULTS FOR THIS PLAUSIBLE VALUE RUN
 Sigma_squared =   1892.84864

 Tau
 INTRCPT1,B0   2486.78494


Tau (as correlations)
 INTRCPT1,B0  1.000

 ----------------------------------------------------
  Random level-1 coefficient   Reliability estimate
 ----------------------------------------------------
  INTRCPT1, B0                        0.941
 ----------------------------------------------------
 The outcome variables are: BSMMAT01,BSMMAT02,BSMMAT03,BSMMAT04,BSMMAT05

 Final estimation of fixed effects
 (with robust standard errors)
 ----------------------------------------------------------------------------
                                    Standard             Approx.
    Fixed Effect         Coefficient   Error      T-ratio   d.f.     P-value
 ----------------------------------------------------------------------------
 For       INTRCPT1, B0
    INTRCPT2, G00         371.797335  21.226955    17.515       334    0.000
    BCDMST_R, G01          10.386083   5.534471     1.877       334    0.061
    BCDGSP_R, G02          17.816946   5.706197     3.122       334    0.002
       BTTPC, G03           1.630509   0.400423     4.072       334    0.000
     BTSEX_R, G04          16.432497   6.364480     2.582       334    0.011
    BTBGTAUT, G05           0.551260   0.317254     1.738       334    0.083
    BTTELC_R, G06          22.951352  13.368933     1.717       334    0.087
 For BSEDUP_R slope, B1
    INTRCPT2, G10          -3.158674   6.640362    -0.476        31    0.637
```

BCDMST_R, G11	2.225032	1.813676	1.227	26	0.231
BCDGSP_R, G12	-0.195468	1.576271	-0.124	50	0.902
BTTPC, G13	-0.011678	0.088633	-0.132	68	0.896
BTSEX_R, G14	-0.728772	1.800130	-0.405	41	0.687
BTBGTAUT, G15	0.062246	0.094347	0.660	42	0.513
BTTELC_R, G16	2.130033	2.928039	0.727	1398	0.467
For BSSLFCM slope, B2					
INTRCPT2, G20	26.312730	6.641535	3.962	82	0.000
BCDMST_R, G21	1.303130	2.123105	0.614	35	0.543
BCDGSP_R, G22	-1.768705	1.703816	-1.038	83	0.303
BTTPC, G23	-0.024088	0.098120	-0.245	108	0.807
BTSEX_R, G24	0.320889	1.875947	0.171	530	0.865
BTBGTAUT, G25	-0.040115	0.126986	-0.316	22	0.755
BTTELC_R, G26	-1.341283	4.657421	-0.288	35	0.775
For BSSVALM slope, B3					
INTRCPT2, G30	-13.548463	8.387365	-1.615	71	0.110
BCDMST_R, G31	1.198763	2.032031	0.590	47	0.558
BCDGSP_R, G32	1.584483	2.115162	0.749	34	0.459
BTTPC, G33	0.074804	0.118966	0.629	2358	0.529
BTSEX_R, G34	1.784368	2.120728	0.841	181	0.401
BTBGTAUT, G35	-0.017674	0.096216	-0.184	158	0.855
BTTELC_R, G36	1.285296	4.668356	0.275	396	0.783
For BSHFSG_R slope, B4					
INTRCPT2, G40	7.253571	6.907445	1.050	46	0.300
BCDMST_R, G41	0.166035	1.874420	0.089	95	0.930
BCDGSP_R, G42	-1.009561	1.854549	-0.544	31	0.590
BTTPC, G43	0.054579	0.094434	0.578	514	0.563
BTSEX_R, G44	-0.054365	1.825310	-0.030	211	0.977
BTBGTAUT, G45	-0.060708	0.089969	-0.675	257	0.500
BTTELC_R, G46	-0.345467	3.528302	-0.098	61	0.923

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1,	U0	49.86767	2486.78494	334	6893.57264	0.000
level-1,	R	43.50688	1892.84864			

Model e in the United States

```
 Program:                       HLM 6 Hierarchical Linear and Nonlinear
Modeling
 Authors:                       Stephen Raudenbush, Tony Bryk, & Richard
Congdon
 Publisher:                     Scientific Software International, Inc. (c)
2000

techsupport@ssicentral.com

www.ssicentral.com
 -------------------------------------------------------------------------------
-
 Module:      HLM2.EXE (6.04.2754.2)
 Date:        26 June 2008, Thursday
 Time:        10: 3:38
 -------------------------------------------------------------------------------
-


 SPECIFICATIONS FOR THIS HLM2 RUN


  Problem Title: no title

  The data source for this run  = USA.mdm
  The command file for this run = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\USAmodele2.hlm
  Output file name              = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\hlm2.avg
  The maximum number of level-1 units = 4938
  The maximum number of level-2 units = 341
  The maximum number of iterations = 100
  Method of estimation: restricted maximum likelihood

  This is part of a plausible value analysis using the following variables:
    BSMMAT01
    BSMMAT02
    BSMMAT03
    BSMMAT04
    BSMMAT05


 Weighting Specification
 -----------------------
                        Weight
                        Variable
           Weighting?   Name        Normalized?
 Level 1       yes        HOUWGT        yes
 Level 2        no
 Precision      no

  The outcome variable is BSMMAT01

  The model specified for the fixed effects was:
```

```
 ----------------------------------------------------

   Level-1                  Level-2
   Coefficients             Predictors
 ----------------------   ---------------
         INTRCPT1, B0      INTRCPT2, G00
                             BCPPSC, G01
                           BCPINVOL, G02
                            BCTCHEV, G03
                           BCDMST_R, G04
                           BCDGSP_R, G05
                           BTSCHSET, G06
                            BTMTPSC, G07
                              BTTPC, G08
                           BTLMTSTU, G09
                            BTSEX_R, G010
                           BTBGTAUT, G011
                           BTTELC_R, G012
#% BSEDUP_R slope, B1      INTRCPT2, G10
                             BCPPSC, G11
                           BCPINVOL, G12
                            BCTCHEV, G13
                           BCDMST_R, G14
                           BCDGSP_R, G15
                           BTSCHSET, G16
                            BTMTPSC, G17
                              BTTPC, G18
                           BTLMTSTU, G19
                            BTSEX_R, G110
                           BTBGTAUT, G111
                           BTTELC_R, G112
#%  BSSLFCM slope, B2      INTRCPT2, G20
                             BCPPSC, G21
                           BCPINVOL, G22
                            BCTCHEV, G23
                           BCDMST_R, G24
                           BCDGSP_R, G25
                           BTSCHSET, G26
                            BTMTPSC, G27
                              BTTPC, G28
                           BTLMTSTU, G29
                            BTSEX_R, G210
                           BTBGTAUT, G211
                           BTTELC_R, G212
#%  BSSVALM slope, B3      INTRCPT2, G30
                             BCPPSC, G31
                           BCPINVOL, G32
                            BCTCHEV, G33
                           BCDMST_R, G34
                           BCDGSP_R, G35
                           BTSCHSET, G36
                            BTMTPSC, G37
                              BTTPC, G38
                           BTLMTSTU, G39
                            BTSEX_R, G310
                           BTBGTAUT, G311
                           BTTELC_R, G312
#% BSHFSG_R slope, B4      INTRCPT2, G40
```

```
                              BCPPSC, G41
                            BCPINVOL, G42
                             BCTCHEV, G43
                            BCDMST_R, G44
                            BCDGSP_R, G45
                            BTSCHSET, G46
                             BTMTPSC, G47
                               BTTPC, G48
                            BTLMTSTU, G49
                             BTSEX_R, G410
                            BTBGTAUT, G411
                            BTTELC_R, G412

'#' - The residual parameter variance for this level-1 coefficient has been set
      to zero.
'%' - This level-1 predictor has been centered around its grand mean.

 The model specified for the covariance components was:
 ---------------------------------------------------------

         Sigma squared (constant across level-2 units)

         Tau dimensions
               INTRCPT1


 Summary of the model specified (in equation format)
 ---------------------------------------------------

Level-1 Model

       Y = B0 + B1*(BSEDUP_R) + B2*(BSSLFCM) + B3*(BSSVALM) + B4*(BSHFSG_R) + R

Level-2 Model
       B0 = G00 + G01*(BCPPSC) + G02*(BCPINVOL) + G03*(BCTCHEV) + G04*(BCDMST_R)
         + G05*(BCDGSP_R) + G06*(BTSCHSET) + G07*(BTMTPSC) + G08*(BTTPC)
         + G09*(BTLMTSTU) + G010*(BTSEX_R) + G011*(BTBGTAUT) + G012*(BTTELC_R)
+ U0
       B1 = G10 + G11*(BCPPSC) + G12*(BCPINVOL) + G13*(BCTCHEV) + G14*(BCDMST_R)
         + G15*(BCDGSP_R) + G16*(BTSCHSET) + G17*(BTMTPSC) + G18*(BTTPC)
         + G19*(BTLMTSTU) + G110*(BTSEX_R) + G111*(BTBGTAUT) + G112*(BTTELC_R)
       B2 = G20 + G21*(BCPPSC) + G22*(BCPINVOL) + G23*(BCTCHEV) + G24*(BCDMST_R)
         + G25*(BCDGSP_R) + G26*(BTSCHSET) + G27*(BTMTPSC) + G28*(BTTPC)
         + G29*(BTLMTSTU) + G210*(BTSEX_R) + G211*(BTBGTAUT) + G212*(BTTELC_R)
       B3 = G30 + G31*(BCPPSC) + G32*(BCPINVOL) + G33*(BCTCHEV) + G34*(BCDMST_R)
         + G35*(BCDGSP_R) + G36*(BTSCHSET) + G37*(BTMTPSC) + G38*(BTTPC)
         + G39*(BTLMTSTU) + G310*(BTSEX_R) + G311*(BTBGTAUT) + G312*(BTTELC_R)
       B4 = G40 + G41*(BCPPSC) + G42*(BCPINVOL) + G43*(BCTCHEV) + G44*(BCDMST_R)
         + G45*(BCDGSP_R) + G46*(BTSCHSET) + G47*(BTMTPSC) + G48*(BTTPC)
         + G49*(BTLMTSTU) + G410*(BTSEX_R) + G411*(BTBGTAUT) + G412*(BTTELC_R)



THE AVERAGED RESULTS FOR THIS PLAUSIBLE VALUE RUN
 Sigma_squared =   1889.47806

 Tau
 INTRCPT1,B0   1885.76286
```

Tau (as correlations)
INTRCPT1,B0 1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1, B0	0.925

The outcome variables are: BSMMAT01,BSMMAT02,BSMMAT03,BSMMAT04,BSMMAT05

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	439.742332	25.948416	16.947	328	0.000
BCPPSC, G01	14.047392	3.463869	4.055	328	0.000
BCPINVOL, G02	0.132030	2.988647	0.044	328	0.965
BCTCHEV, G03	-6.012780	3.180761	-1.890	328	0.059
BCDMST_R, G04	-0.305409	4.744755	-0.064	328	0.949
BCDGSP_R, G05	6.347146	5.063908	1.253	328	0.211
BTSCHSET, G06	1.810079	3.256781	0.556	328	0.578
BTMTPSC, G07	4.155554	3.645263	1.140	328	0.256
BTTPC, G08	1.337747	0.387987	3.448	328	0.001
BTLMTSTU, G09	-15.350859	2.956224	-5.193	328	0.000
BTSEX_R, G010	23.000847	5.601314	4.106	328	0.000
BTBGTAUT, G011	0.572497	0.290552	1.970	328	0.049
BTTELC_R, G012	8.681635	10.546255	0.823	328	0.411
For BSEDUP_R slope, B1					
INTRCPT2, G10	-0.208644	9.556525	-0.022	17	0.983
BCPPSC, G11	0.312757	1.160609	0.269	75	0.788
BCPINVOL, G12	0.182174	0.874452	0.208	46	0.836
BCTCHEV, G13	-0.252443	0.975831	-0.259	210	0.796
BCDMST_R, G14	1.536998	1.727271	0.890	26	0.382
BCDGSP_R, G15	-0.668657	1.667932	-0.401	32	0.691
BTSCHSET, G16	0.684601	1.129442	0.606	24	0.550
BTMTPSC, G17	0.455166	1.279853	0.356	20	0.726
BTTPC, G18	-0.016992	0.085834	-0.198	76	0.844
BTLMTSTU, G19	-0.105527	0.997797	-0.106	27	0.917
BTSEX_R, G110	-0.606450	1.711231	-0.354	40	0.725
BTBGTAUT, G111	0.044205	0.090403	0.489	50	0.627
BTTELC_R, G112	1.647476	2.876797	0.573	1399	0.567
For BSSLFCM slope, B2					
INTRCPT2, G20	23.359978	9.274430	2.519	96	0.014
BCPPSC, G21	-1.178680	1.098548	-1.073	482	0.284
BCPINVOL, G22	0.243055	1.200556	0.202	31	0.841
BCTCHEV, G23	-0.053607	1.134904	-0.047	168	0.963
BCDMST_R, G24	1.625033	2.177916	0.746	31	0.461
BCDGSP_R, G25	-1.146873	1.786882	-0.642	81	0.523
BTSCHSET, G26	0.033208	1.142821	0.029	184	0.977
BTMTPSC, G27	0.457028	1.315629	0.347	223	0.728
BTTPC, G28	-0.026801	0.102893	-0.260	59	0.795
BTLMTSTU, G29	0.039050	0.958638	0.041	1374	0.968
BTSEX_R, G210	0.278209	1.860217	0.150	517	0.882

BTBGTAUT, G211	-0.041828	0.131164	-0.319	20	0.753
BTTELC_R, G212	-1.526511	4.518613	-0.338	31	0.738
For BSSVALM slope, B3					
INTRCPT2, G30	-3.200737	11.102822	-0.288	20	0.776
BCPPSC, G31	-0.868713	1.339935	-0.648	83	0.518
BCPINVOL, G32	-1.464202	1.111977	-1.317	129	0.190
BCTCHEV, G33	-0.925524	1.129610	-0.819	74	0.415
BCDMST_R, G34	0.462495	2.217280	0.209	28	0.837
BCDGSP_R, G35	1.796318	2.348039	0.765	18	0.454
BTSCHSET, G36	-0.142653	1.121080	-0.127	289	0.899
BTMTPSC, G37	1.532511	1.313283	1.167	51	0.249
BTTPC, G38	0.044906	0.117874	0.381	1562	0.703
BTLMTSTU, G39	-1.431775	1.194449	-1.199	28	0.241
BTSEX_R, G310	2.298616	2.127580	1.080	192	0.282
BTBGTAUT, G311	-0.023453	0.097687	-0.240	144	0.811
BTTELC_R, G312	0.799075	4.477508	0.178	163	0.859
For BSHFSG_R slope, B4					
INTRCPT2, G40	6.896674	7.437114	0.927	153	0.356
BCPPSC, G41	-0.461940	1.203303	-0.384	196	0.701
BCPINVOL, G42	0.826521	0.879096	0.940	232	0.348
BCTCHEV, G43	-1.143496	1.346686	-0.849	100	0.398
BCDMST_R, G44	-0.183546	1.683449	-0.109	90	0.914
BCDGSP_R, G45	-0.856548	1.736667	-0.493	36	0.624
BTSCHSET, G46	-0.121454	1.007011	-0.121	4084	0.904
BTMTPSC, G47	0.816510	1.209135	0.675	456	0.500
BTTPC, G48	0.066469	0.094798	0.701	477	0.483
BTLMTSTU, G49	-0.544153	0.988966	-0.550	401	0.582
BTSEX_R, G410	-0.078509	1.729725	-0.045	189	0.964
BTBGTAUT, G411	-0.094146	0.098164	-0.959	207	0.339
BTTELC_R, G412	-0.664148	3.456665	-0.192	57	0.849

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1,	U0	43.42537	1885.76286	328	5192.27644	0.000
level-1,	R	43.46813	1889.47806			

Model d in Russia

```
 Program:                       HLM 6 Hierarchical Linear and Nonlinear
Modeling
 Authors:                       Stephen Raudenbush, Tony Bryk, & Richard
Congdon
 Publisher:                     Scientific Software International, Inc. (c)
2000

techsupport@ssicentral.com

www.ssicentral.com
 --------------------------------------------------------------------------------
-
 Module:       HLM2.EXE (6.04.2754.2)
 Date:         26 June 2008, Thursday
 Time:         12:27: 8
 --------------------------------------------------------------------------------
-


 SPECIFICATIONS FOR THIS HLM2 RUN


  Problem Title: no title

  The data source for this run  = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\RUS.mdm
  The command file for this run = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\RUSmodeld2.hlm
  Output file name              = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\hlm2.avg
  The maximum number of level-1 units = 3325
  The maximum number of level-2 units = 196
  The maximum number of iterations = 100
  Method of estimation: restricted maximum likelihood

  This is part of a plausible value analysis using the following variables:
    BSMMAT01
    BSMMAT02
    BSMMAT03
    BSMMAT04
    BSMMAT05


 Weighting Specification
 -----------------------
                        Weight
                        Variable
           Weighting?   Name        Normalized?
 Level 1      yes         HOUWGT        yes
 Level 2       no
 Precision     no

  The outcome variable is BSMMAT01
```

```
 The model specified for the fixed effects was:
----------------------------------------------------

   Level-1                 Level-2
   Coefficients            Predictors
----------------------   ---------------
         INTRCPT1, B0      INTRCPT2, G00
                           BCDMST_R, G01
                           BCDGSP_R, G02
                            BTSEX_R, G03
                           BTBGTAUT, G04
                           BTTELC_R, G05
#% BSEDUP_R slope, B1      INTRCPT2, G10
                           BCDMST_R, G11
                           BCDGSP_R, G12
                            BTSEX_R, G13
                           BTBGTAUT, G14
                           BTTELC_R, G15
#%  BSSLFCM slope, B2      INTRCPT2, G20
                           BCDMST_R, G21
                           BCDGSP_R, G22
                            BTSEX_R, G23
                           BTBGTAUT, G24
                           BTTELC_R, G25
 %   BSSPSC slope, B3      INTRCPT2, G30
                           BCDMST_R, G31
                           BCDGSP_R, G32
                            BTSEX_R, G33
                           BTBGTAUT, G34
                           BTTELC_R, G35
#% BSHFSG_R slope, B4      INTRCPT2, G40
                           BCDMST_R, G41
                           BCDGSP_R, G42
                            BTSEX_R, G43
                           BTBGTAUT, G44
                           BTTELC_R, G45

'#' - The residual parameter variance for this level-1 coefficient has been set
      to zero.
'%' - This level-1 predictor has been centered around its grand mean.

 The model specified for the covariance components was:
---------------------------------------------------------

         Sigma squared (constant across level-2 units)

         Tau dimensions
               INTRCPT1
                 BSSPSC slope


 Summary of the model specified (in equation format)
---------------------------------------------------

Level-1 Model

       Y = B0 + B1*(BSEDUP_R) + B2*(BSSLFCM) + B3*(BSSPSC) + B4*(BSHFSG_R) + R
```

```
Level-2 Model
       B0 = G00 + G01*(BCDMST_R) + G02*(BCDGSP_R) + G03*(BTSEX_R) +
G04*(BTBGTAUT)
         + G05*(BTTELC_R) + U0
       B1 = G10 + G11*(BCDMST_R) + G12*(BCDGSP_R) + G13*(BTSEX_R) +
G14*(BTBGTAUT)
         + G15*(BTTELC_R)
       B2 = G20 + G21*(BCDMST_R) + G22*(BCDGSP_R) + G23*(BTSEX_R) +
G24*(BTBGTAUT)
         + G25*(BTTELC_R)
       B3 = G30 + G31*(BCDMST_R) + G32*(BCDGSP_R) + G33*(BTSEX_R) +
G34*(BTBGTAUT)
         + G35*(BTTELC_R) + U3
       B4 = G40 + G41*(BCDMST_R) + G42*(BCDGSP_R) + G43*(BTSEX_R) +
G44*(BTBGTAUT)
         + G45*(BTTELC_R)

THE AVERAGED RESULTS FOR THIS PLAUSIBLE VALUE RUN
 Sigma_squared =   2608.52712

 Tau
 INTRCPT1,B0   1551.66340      56.03799
   BSSPSC,B3     56.03799      67.94819


Tau (as correlations)
 INTRCPT1,B0  1.000  0.173
   BSSPSC,B3  0.173  1.000

 ----------------------------------------------------
  Random level-1 coefficient   Reliability estimate
 ----------------------------------------------------
  INTRCPT1, B0                        0.874
    BSSPSC, B3                        0.255
 ----------------------------------------------------


Note: The reliability estimates reported above are based on only 195 of 196
units that had sufficient data for computation.  Fixed effects and variance
components are based on all the data.
 The outcome variables are: BSMMAT01,BSMMAT02,BSMMAT03,BSMMAT04,BSMMAT05

 Final estimation of fixed effects
 (with robust standard errors)
 ----------------------------------------------------------------------------
                                       Standard             Approx.
    Fixed Effect         Coefficient   Error      T-ratio   d.f.     P-value
 ----------------------------------------------------------------------------
 For       INTRCPT1, B0
    INTRCPT2, G00        487.788774  15.364145    31.749       190    0.000
    BCDMST_R, G01         -1.386564   6.916889    -0.200       190    0.842
    BCDGSP_R, G02         15.299863   6.133964     2.494       190    0.014
     BTSEX_R, G03         -6.899407   7.419544    -0.930       190    0.354
    BTBGTAUT, G04         -0.002915   0.335100    -0.009       190    0.993
    BTTELC_R, G05          4.654156  16.761387     0.278       190    0.782
 For BSEDUP_R slope, B1
    INTRCPT2, G10          8.353440   6.193024     1.349        59    0.183
    BCDMST_R, G11         -0.168572   2.437907    -0.069        61    0.946
```

BCDGSP_R, G12	-1.297745	2.409821	-0.539	48	0.592
BTSEX_R, G13	2.373675	5.416632	0.438	376	0.661
BTBGTAUT, G14	-0.043082	0.142913	-0.301	61	0.764
BTTELC_R, G15	1.031203	6.178741	0.167	1718	0.868
For BSSLFCM slope, B2					
INTRCPT2, G20	33.155544	5.106451	6.493	592	0.000
BCDMST_R, G21	-0.484590	2.522104	-0.192	98	0.848
BCDGSP_R, G22	1.392881	1.929498	0.722	921	0.470
BTSEX_R, G23	1.250201	6.337219	0.197	57	0.845
BTBGTAUT, G24	-0.147193	0.122138	-1.205	46	0.235
BTTELC_R, G25	-1.612512	7.666450	-0.210	2507	0.834
For BSSPSC slope, B3					
INTRCPT2, G30	-8.937256	7.150189	-1.250	190	0.213
BCDMST_R, G31	3.051417	3.325418	0.918	77	0.362
BCDGSP_R, G32	-1.471785	2.734316	-0.538	190	0.591
BTSEX_R, G33	-4.570933	6.706563	-0.682	190	0.496
BTBGTAUT, G34	0.035745	0.138254	0.259	190	0.796
BTTELC_R, G35	4.192741	5.509069	0.761	190	0.448
For BSHFSG_R slope, B4					
INTRCPT2, G40	0.840362	6.273917	0.134	29	0.895
BCDMST_R, G41	1.625446	2.769973	0.587	32	0.561
BCDGSP_R, G42	-1.063976	2.584986	-0.412	43	0.682
BTSEX_R, G43	1.041083	6.133038	0.170	23	0.867
BTBGTAUT, G44	0.254567	0.110496	2.304	2169	0.021
BTTELC_R, G45	7.389594	6.709044	1.101	21	0.284

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1,	U0	39.39116	1551.66340	189	1701.30928	0.000
BSSPSC slope,	U3	8.24307	67.94819	189	263.96202	0.000
level-1,	R	51.07374	2608.52712			

Note: The chi-square statistics reported above are based on only 195 of 196 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Model e in Russia

```
 Program:                       HLM 6 Hierarchical Linear and Nonlinear
Modeling
 Authors:                       Stephen Raudenbush, Tony Bryk, & Richard
Congdon
 Publisher:                     Scientific Software International, Inc. (c)
2000

techsupport@ssicentral.com

www.ssicentral.com
 -------------------------------------------------------------------------------
-
 Module:      HLM2.EXE (6.04.2754.2)
 Date:        26 June 2008, Thursday
 Time:        12:27:57
 -------------------------------------------------------------------------------
-


 SPECIFICATIONS FOR THIS HLM2 RUN


  Problem Title: no title

  The data source for this run  = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\RUS.mdm
  The command file for this run = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\RUSmodele2.hlm
  Output file name              = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\hlm2.avg
  The maximum number of level-1 units = 3325
  The maximum number of level-2 units = 196
  The maximum number of iterations = 100
  Method of estimation: restricted maximum likelihood

  This is part of a plausible value analysis using the following variables:
    BSMMAT01
    BSMMAT02
    BSMMAT03
    BSMMAT04
    BSMMAT05


 Weighting Specification
 -----------------------
                        Weight
                        Variable
           Weighting?   Name        Normalized?
 Level 1       yes        HOUWGT        yes
 Level 2        no
 Precision      no

  The outcome variable is BSMMAT01
```

```
 The model specified for the fixed effects was:
----------------------------------------------------

   Level-1                  Level-2
   Coefficients             Predictors
----------------------    ---------------
        INTRCPT1, B0      INTRCPT2, G00
                            BCPPSC, G01
                          BCPINVOL, G02
                           BCTCHEV, G03
                          BCDMST_R, G04
                          BCDGSP_R, G05
                          BTSCHSET, G06
                           BTMTPSC, G07
                          BTLMTSTU, G08
                           BTSEX_R, G09
                          BTBGTAUT, G010
                          BTTELC_R, G011
#% BSEDUP_R slope, B1     INTRCPT2, G10
                            BCPPSC, G11
                          BCPINVOL, G12
                           BCTCHEV, G13
                          BCDMST_R, G14
                          BCDGSP_R, G15
                          BTSCHSET, G16
                           BTMTPSC, G17
                          BTLMTSTU, G18
                           BTSEX_R, G19
                          BTBGTAUT, G110
                          BTTELC_R, G111
#%  BSSLFCM slope, B2     INTRCPT2, G20
                            BCPPSC, G21
                          BCPINVOL, G22
                           BCTCHEV, G23
                          BCDMST_R, G24
                          BCDGSP_R, G25
                          BTSCHSET, G26
                           BTMTPSC, G27
                          BTLMTSTU, G28
                           BTSEX_R, G29
                          BTBGTAUT, G210
                          BTTELC_R, G211
 %   BSSPSC slope, B3     INTRCPT2, G30
                            BCPPSC, G31
                          BCPINVOL, G32
                           BCTCHEV, G33
                          BCDMST_R, G34
                          BCDGSP_R, G35
                          BTSCHSET, G36
                           BTMTPSC, G37
                          BTLMTSTU, G38
                           BTSEX_R, G39
                          BTBGTAUT, G310
                          BTTELC_R, G311
#% BSHFSG_R slope, B4     INTRCPT2, G40
                            BCPPSC, G41
                          BCPINVOL, G42
                           BCTCHEV, G43
```

```
                        BCDMST_R, G44
                        BCDGSP_R, G45
                        BTSCHSET, G46
                         BTMTPSC, G47
                        BTLMTSTU, G48
                         BTSEX_R, G49
                        BTBGTAUT, G410
                        BTTELC_R, G411

'#' - The residual parameter variance for this level-1 coefficient has been set
      to zero.
'%' - This level-1 predictor has been centered around its grand mean.

 The model specified for the covariance components was:
 ---------------------------------------------------------

         Sigma squared (constant across level-2 units)

         Tau dimensions
               INTRCPT1
                 BSSPSC slope


 Summary of the model specified (in equation format)
 ---------------------------------------------------

Level-1 Model

       Y = B0 + B1*(BSEDUP_R) + B2*(BSSLFCM) + B3*(BSSPSC) + B4*(BSHFSG_R) + R

Level-2 Model
       B0 = G00 + G01*(BCPPSC) + G02*(BCPINVOL) + G03*(BCTCHEV) + G04*(BCDMST_R)
         + G05*(BCDGSP_R) + G06*(BTSCHSET) + G07*(BTMTPSC) + G08*(BTLMTSTU)
         + G09*(BTSEX_R) + G010*(BTBGTAUT) + G011*(BTTELC_R) + U0
       B1 = G10 + G11*(BCPPSC) + G12*(BCPINVOL) + G13*(BCTCHEV) + G14*(BCDMST_R)
         + G15*(BCDGSP_R) + G16*(BTSCHSET) + G17*(BTMTPSC) + G18*(BTLMTSTU)
         + G19*(BTSEX_R) + G110*(BTBGTAUT) + G111*(BTTELC_R)
       B2 = G20 + G21*(BCPPSC) + G22*(BCPINVOL) + G23*(BCTCHEV) + G24*(BCDMST_R)
         + G25*(BCDGSP_R) + G26*(BTSCHSET) + G27*(BTMTPSC) + G28*(BTLMTSTU)
         + G29*(BTSEX_R) + G210*(BTBGTAUT) + G211*(BTTELC_R)
       B3 = G30 + G31*(BCPPSC) + G32*(BCPINVOL) + G33*(BCTCHEV) + G34*(BCDMST_R)
         + G35*(BCDGSP_R) + G36*(BTSCHSET) + G37*(BTMTPSC) + G38*(BTLMTSTU)
         + G39*(BTSEX_R) + G310*(BTBGTAUT) + G311*(BTTELC_R) + U3
       B4 = G40 + G41*(BCPPSC) + G42*(BCPINVOL) + G43*(BCTCHEV) + G44*(BCDMST_R)
         + G45*(BCDGSP_R) + G46*(BTSCHSET) + G47*(BTMTPSC) + G48*(BTLMTSTU)
         + G49*(BTSEX_R) + G410*(BTBGTAUT) + G411*(BTTELC_R)
```

THE AVERAGED RESULTS FOR THIS PLAUSIBLE VALUE RUN
Sigma_squared = 2600.97072

Tau

INTRCPT1,B0	1518.58427	75.66585
BSSPSC,B3	75.66585	68.13008

Tau (as correlations)

INTRCPT1,B0	1.000	0.235
BSSPSC,B3	0.235	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1, B0	0.872
BSSPSC, B3	0.256

Note: The reliability estimates reported above are based on only 195 of 196 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The outcome variables are: BSMMAT01,BSMMAT02,BSMMAT03,BSMMAT04,BSMMAT05

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	501.612027	27.509293	18.234	184	0.000
BCPPSC, G01	3.140549	4.167693	0.754	184	0.452
BCPINVOL, G02	-3.200020	3.582097	-0.893	184	0.373
BCTCHEV, G03	2.282323	4.845218	0.471	184	0.638
BCDMST_R, G04	-1.689183	6.968201	-0.242	184	0.809
BCDGSP_R, G05	10.394579	6.245070	1.664	184	0.097
BTSCHSET, G06	0.145761	3.907794	0.037	184	0.971
BTMTPSC, G07	6.902759	3.224004	2.141	184	0.033
BTLMTSTU, G08	-0.313758	3.497733	-0.090	184	0.929
BTSEX_R, G09	-7.583599	7.518817	-1.009	184	0.315
BTBGTAUT, G010	0.035189	0.313781	0.112	184	0.911
BTTELC_R, G011	11.704480	15.251510	0.767	184	0.444
For BSEDUP_R slope, B1					
INTRCPT2, G10	14.875624	11.859766	1.254	69	0.214
BCPPSC, G11	-0.416757	1.766162	-0.236	39	0.815
BCPINVOL, G12	-1.207211	1.242321	-0.972	2017	0.332
BCTCHEV, G13	-0.718722	1.940975	-0.370	193	0.711
BCDMST_R, G14	0.126268	2.465165	0.051	83	0.960
BCDGSP_R, G15	-1.508287	2.667836	-0.565	31	0.575
BTSCHSET, G16	1.683079	1.194355	1.409	172	0.161
BTMTPSC, G17	-0.163187	1.303794	-0.125	1806	0.901
BTLMTSTU, G18	0.516328	1.584432	0.326	20	0.748
BTSEX_R, G19	2.838414	5.790206	0.490	222	0.624
BTBGTAUT, G110	-0.008833	0.138476	-0.064	81	0.950
BTTELC_R, G111	0.453608	6.789930	0.067	3265	0.947
For BSSLFCM slope, B2					

INTRCPT2, G20	17.807358	10.292687	1.730	45	0.090
BCPPSC, G21	-2.250376	1.265577	-1.778	89	0.078
BCPINVOL, G22	0.268371	1.161631	0.231	50	0.818
BCTCHEV, G23	4.014964	2.172461	1.848	60	0.069
BCDMST_R, G24	-1.817730	2.455349	-0.740	174	0.460
BCDGSP_R, G25	2.607679	2.141876	1.217	150	0.226
BTSCHSET, G26	0.081609	1.080124	0.076	1414	0.940
BTMTPSC, G27	-0.277940	1.251722	-0.222	161	0.825
BTLMTSTU, G28	-1.863328	1.040070	-1.792	635	0.073
BTSEX_R, G29	1.332826	5.942933	0.224	36	0.824
BTBGTAUT, G210	-0.116559	0.114247	-1.020	65	0.312
BTTELC_R, G211	-4.739772	7.285790	-0.651	619	0.515
For BSSPSC slope, B3					
INTRCPT2, G30	-20.106426	11.717050	-1.716	46	0.092
BCPPSC, G31	-0.260794	1.542872	-0.169	146	0.866
BCPINVOL, G32	1.974584	1.325887	1.489	164	0.138
BCTCHEV, G33	1.149727	2.134531	0.539	184	0.590
BCDMST_R, G34	1.656045	3.111270	0.532	163	0.595
BCDGSP_R, G35	0.216108	2.894765	0.075	184	0.941
BTSCHSET, G36	1.321984	1.629011	0.812	59	0.420
BTMTPSC, G37	-1.550754	1.380732	-1.123	184	0.263
BTLMTSTU, G38	0.566579	1.669532	0.339	118	0.735
BTSEX_R, G39	-5.810902	6.481488	-0.897	184	0.371
BTBGTAUT, G310	-0.024666	0.139660	-0.177	184	0.860
BTTELC_R, G311	0.980058	5.799080	0.169	184	0.866
For BSHFSG_R slope, B4					
INTRCPT2, G40	-3.032939	13.482188	-0.225	17	0.825
BCPPSC, G41	-0.765394	1.367239	-0.560	209	0.576
BCPINVOL, G42	1.006664	1.469467	0.685	190	0.494
BCTCHEV, G43	-0.409627	2.178899	-0.188	20	0.853
BCDMST_R, G44	1.202970	2.802930	0.429	31	0.670
BCDGSP_R, G45	0.261143	2.530038	0.103	62	0.919
BTSCHSET, G46	0.336627	1.227629	0.274	129	0.784
BTMTPSC, G47	-0.854697	1.217531	-0.702	278	0.483
BTLMTSTU, G48	-1.644327	1.515104	-1.085	106	0.281
BTSEX_R, G49	1.845225	6.356163	0.290	27	0.774
BTBGTAUT, G410	0.233696	0.102757	2.274	3265	0.023
BTTELC_R, G411	5.081005	6.561244	0.774	18	0.449

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1,	U0	38.96902	1518.58427	183	1619.44052	0.000
BSSPSC slope,	U3	8.25409	68.13008	183	253.96699	0.001
level-1,	R	50.99971	2600.97072			

Note: The chi-square statistics reported above are based on only 195 of 196 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Model d in Singapore

```
 Program:                       HLM 6 Hierarchical Linear and Nonlinear
Modeling
 Authors:                       Stephen Raudenbush, Tony Bryk, & Richard
Congdon
 Publisher:                     Scientific Software International, Inc. (c)
2000

techsupport@ssicentral.com

www.ssicentral.com
 -------------------------------------------------------------------------------
-
 Module:       HLM2.EXE (6.04.2754.2)
 Date:         26 June 2008, Thursday
 Time:         10:12:50
 -------------------------------------------------------------------------------
-


 SPECIFICATIONS FOR THIS HLM2 RUN


  Problem Title: no title

  The data source for this run  = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\SGP.mdm
  The command file for this run = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\SGPmodeld2.hlm
  Output file name              = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\hlm2.avg
  The maximum number of level-1 units = 3901
  The maximum number of level-2 units = 300
  The maximum number of iterations = 100
  Method of estimation: restricted maximum likelihood

  This is part of a plausible value analysis using the following variables:
    BSMMAT01
    BSMMAT02
    BSMMAT03
    BSMMAT04
    BSMMAT05


 Weighting Specification
 -----------------------
                        Weight
                        Variable
           Weighting?   Name        Normalized?
 Level 1       yes        HOUWGT        yes
 Level 2        no
 Precision      no

  The outcome variable is BSMMAT01
```

```
 The model specified for the fixed effects was:
----------------------------------------------------

  Level-1                   Level-2
  Coefficients              Predictors
----------------------    ---------------
       INTRCPT1, B0      INTRCPT2, G00
                         BCDMST_R, G01
                         BCDGSP_R, G02
                            BTTPC, G03
                          BTSEX_R, G04
                         BTBGTAUT, G05
                         BTTELC_R, G06
#%  BSSLFCM slope, B1      INTRCPT2, G10
                         BCDMST_R, G11
                         BCDGSP_R, G12
                            BTTPC, G13
                          BTSEX_R, G14
                         BTBGTAUT, G15
                         BTTELC_R, G16
#%  BSSVALM slope, B2      INTRCPT2, G20
                         BCDMST_R, G21
                         BCDGSP_R, G22
                            BTTPC, G23
                          BTSEX_R, G24
                         BTBGTAUT, G25
                         BTTELC_R, G26

'#' - The residual parameter variance for this level-1 coefficient has been set
      to zero.
'%' - This level-1 predictor has been centered around its grand mean.

 The model specified for the covariance components was:
---------------------------------------------------------

        Sigma squared (constant across level-2 units)

        Tau dimensions
              INTRCPT1


 Summary of the model specified (in equation format)
---------------------------------------------------

Level-1 Model

       Y = B0 + B1*(BSSLFCM) + B2*(BSSVALM) + R

Level-2 Model
       B0 = G00 + G01*(BCDMST_R) + G02*(BCDGSP_R) + G03*(BTTPC) + G04*(BTSEX_R)
          + G05*(BTBGTAUT) + G06*(BTTELC_R) + U0
       B1 = G10 + G11*(BCDMST_R) + G12*(BCDGSP_R) + G13*(BTTPC) + G14*(BTSEX_R)
          + G15*(BTBGTAUT) + G16*(BTTELC_R)
       B2 = G20 + G21*(BCDMST_R) + G22*(BCDGSP_R) + G23*(BTTPC) + G24*(BTSEX_R)
          + G25*(BTBGTAUT) + G26*(BTTELC_R)


THE AVERAGED RESULTS FOR THIS PLAUSIBLE VALUE RUN
```

Sigma_squared = 1169.21988

Tau
INTRCPT1,B0 3255.80812

Tau (as correlations)
INTRCPT1,B0 1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1, B0	0.972

The outcome variables are: BSMMAT01,BSMMAT02,BSMMAT03,BSMMAT04,BSMMAT05

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	362.292720	67.657949	5.355	293	0.000
BCDMST_R, G01	-5.852981	10.646136	-0.550	293	0.582
BCDGSP_R, G02	21.038500	6.017408	3.496	293	0.001
BTTPC, G03	5.924008	1.334525	4.439	293	0.000
BTSEX_R, G04	-17.529905	8.094367	-2.166	293	0.031
BTBGTAUT, G05	-0.102780	0.261781	-0.393	293	0.695
BTTELC_R, G06	-28.350503	44.214543	-0.641	293	0.522
For BSSLFCM slope, B1					
INTRCPT2, G10	15.454263	10.888183	1.419	163	0.158
BCDMST_R, G11	1.981673	2.919792	0.679	17	0.506
BCDGSP_R, G12	-1.165166	1.543430	-0.755	116	0.452
BTTPC, G13	-0.055646	0.199555	-0.279	1245	0.780
BTSEX_R, G14	0.102655	2.125513	0.048	41	0.962
BTBGTAUT, G15	-0.001701	0.078482	-0.022	48	0.983
BTTELC_R, G16	2.171850	5.717408	0.380	36	0.706
For BSSVALM slope, B2					
INTRCPT2, G20	2.820165	8.846887	0.319	18	0.753
BCDMST_R, G21	-0.510992	2.260094	-0.226	29	0.823
BCDGSP_R, G22	0.964327	1.715306	0.562	23	0.579
BTTPC, G23	-0.015052	0.148741	-0.101	31	0.921
BTSEX_R, G24	1.922156	2.051666	0.937	45	0.354
BTBGTAUT, G25	-0.032613	0.066509	-0.490	227	0.624
BTTELC_R, G26	1.281622	6.934801	0.185	35	0.855

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1,	U0	57.05969	3255.80812	293	10342.59722	0.000
level-1,	R	34.19386	1169.21988			

Model e in Singapore

```
 Program:                       HLM 6 Hierarchical Linear and Nonlinear
Modeling
 Authors:                       Stephen Raudenbush, Tony Bryk, & Richard
Congdon
 Publisher:                     Scientific Software International, Inc. (c)
2000

techsupport@ssicentral.com

www.ssicentral.com
 ----------------------------------------------------------------------------
-
 Module:       HLM2.EXE (6.04.2754.2)
 Date:         26 June 2008, Thursday
 Time:         10:14:10
 ----------------------------------------------------------------------------
-


 SPECIFICATIONS FOR THIS HLM2 RUN


  Problem Title: no title

  The data source for this run  = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\SGP.mdm
  The command file for this run = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\SGPmodele2.hlm
  Output file name              = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\hlm2.avg
  The maximum number of level-1 units = 3901
  The maximum number of level-2 units = 300
  The maximum number of iterations = 100
  Method of estimation: restricted maximum likelihood

  This is part of a plausible value analysis using the following variables:
    BSMMAT01
    BSMMAT02
    BSMMAT03
    BSMMAT04
    BSMMAT05


 Weighting Specification
 -----------------------
                        Weight
                        Variable
            Weighting?  Name        Normalized?
 Level 1       yes        HOUWGT        yes
 Level 2        no
 Precision      no

  The outcome variable is BSMMAT01
```

```
 The model specified for the fixed effects was:
----------------------------------------------------

  Level-1                  Level-2
  Coefficients             Predictors
----------------------   ---------------
        INTRCPT1, B0      INTRCPT2, G00
                            BCPPSC, G01
                          BCPINVOL, G02
                           BCTCHEV, G03
                          BCDMST_R, G04
                          BCDGSP_R, G05
                          BTSCHSET, G06
                           BTMTPSC, G07
                             BTTPC, G08
                          BTLMTSTU, G09
                           BTSEX_R, G010
                          BTBGTAUT, G011
                          BTTELC_R, G012
#%  BSSLFCM slope, B1      INTRCPT2, G10
                            BCPPSC, G11
                          BCPINVOL, G12
                           BCTCHEV, G13
                          BCDMST_R, G14
                          BCDGSP_R, G15
                          BTSCHSET, G16
                           BTMTPSC, G17
                             BTTPC, G18
                          BTLMTSTU, G19
                           BTSEX_R, G110
                          BTBGTAUT, G111
                          BTTELC_R, G112
#%  BSSVALM slope, B2      INTRCPT2, G20
                            BCPPSC, G21
                          BCPINVOL, G22
                           BCTCHEV, G23
                          BCDMST_R, G24
                          BCDGSP_R, G25
                          BTSCHSET, G26
                           BTMTPSC, G27
                             BTTPC, G28
                          BTLMTSTU, G29
                           BTSEX_R, G210
                          BTBGTAUT, G211
                          BTTELC_R, G212

'#' - The residual parameter variance for this level-1 coefficient has been set
      to zero.
'%' - This level-1 predictor has been centered around its grand mean.

 The model specified for the covariance components was:
---------------------------------------------------------

        Sigma squared (constant across level-2 units)

        Tau dimensions
              INTRCPT1
```

```
 Summary of the model specified (in equation format)
 ---------------------------------------------------

Level-1 Model

      Y = B0 + B1*(BSSLFCM) + B2*(BSSVALM) + R

Level-2 Model
      B0 = G00 + G01*(BCPPSC) + G02*(BCPINVOL) + G03*(BCTCHEV) + G04*(BCDMST_R)
        + G05*(BCDGSP_R) + G06*(BTSCHSET) + G07*(BTMTPSC) + G08*(BTTPC)
        + G09*(BTLMTSTU) + G010*(BTSEX_R) + G011*(BTBGTAUT) + G012*(BTTELC_R)
+ U0
      B1 = G10 + G11*(BCPPSC) + G12*(BCPINVOL) + G13*(BCTCHEV) + G14*(BCDMST_R)
        + G15*(BCDGSP_R) + G16*(BTSCHSET) + G17*(BTMTPSC) + G18*(BTTPC)
        + G19*(BTLMTSTU) + G110*(BTSEX_R) + G111*(BTBGTAUT) + G112*(BTTELC_R)
      B2 = G20 + G21*(BCPPSC) + G22*(BCPINVOL) + G23*(BCTCHEV) + G24*(BCDMST_R)
        + G25*(BCDGSP_R) + G26*(BTSCHSET) + G27*(BTMTPSC) + G28*(BTTPC)
        + G29*(BTLMTSTU) + G210*(BTSEX_R) + G211*(BTBGTAUT) + G212*(BTTELC_R)



THE AVERAGED RESULTS FOR THIS PLAUSIBLE VALUE RUN
 Sigma_squared =   1161.17234

 Tau
 INTRCPT1,B0   2525.83882


Tau (as correlations)
 INTRCPT1,B0  1.000

 ----------------------------------------------------
  Random level-1 coefficient   Reliability estimate
 ----------------------------------------------------
  INTRCPT1, B0                        0.964
 ----------------------------------------------------
 The outcome variables are: BSMMAT01,BSMMAT02,BSMMAT03,BSMMAT04,BSMMAT05

 Final estimation of fixed effects
 (with robust standard errors)
 ----------------------------------------------------------------------------
                                       Standard             Approx.
    Fixed Effect         Coefficient   Error      T-ratio   d.f.     P-value
 ----------------------------------------------------------------------------
 For       INTRCPT1, B0
    INTRCPT2, G00         448.939782  55.741515     8.054       287    0.000
      BCPPSC, G01          18.444478   3.559259     5.182       287    0.000
    BCPINVOL, G02          -1.225332   2.826200    -0.434       287    0.664
     BCTCHEV, G03           5.245463   4.864002     1.078       287    0.282
    BCDMST_R, G04          -9.349029   8.994418    -1.039       287    0.300
    BCDGSP_R, G05           2.398608   5.837126     0.411       287    0.681
    BTSCHSET, G06          10.689306   3.649682     2.929       287    0.004
     BTMTPSC, G07           0.914468   4.154678     0.220       287    0.826
       BTTPC, G08           4.745466   1.081637     4.387       287    0.000
    BTLMTSTU, G09         -12.740834   3.142722    -4.054       287    0.000
     BTSEX_R, G010         -13.171772   7.206600    -1.828       287    0.068
    BTBGTAUT, G011          -0.124699   0.245115    -0.509       287    0.611
```

BTTELC_R, G012	-36.649222	33.846887	-1.083	287	0.280
For BSSLFCM slope, B1					
INTRCPT2, G10	12.245942	12.457774	0.983	80	0.329
BCPPSC, G11	-2.968565	0.999672	-2.970	45	0.005
BCPINVOL, G12	-0.136683	1.040156	-0.131	20	0.897
BCTCHEV, G13	-0.724478	1.824090	-0.397	13	0.697
BCDMST_R, G14	1.452793	2.842161	0.511	21	0.614
BCDGSP_R, G15	0.692632	1.840025	0.376	40	0.708
BTSCHSET, G16	0.387461	0.885499	0.438	1860	0.661
BTMTPSC, G17	0.223088	1.062680	0.210	89	0.834
BTTPC, G18	0.026452	0.206525	0.128	299	0.899
BTLMTSTU, G19	-0.208558	0.978163	-0.213	72	0.832
BTSEX_R, G110	0.071754	2.091224	0.034	40	0.973
BTBGTAUT, G111	-0.032788	0.079311	-0.413	45	0.681
BTTELC_R, G112	2.242272	5.699753	0.393	41	0.696
For BSSVALM slope, B2					
INTRCPT2, G20	1.942843	9.993211	0.194	27	0.848
BCPPSC, G21	1.098937	1.066424	1.030	27	0.312
BCPINVOL, G22	0.054214	0.879599	0.062	118	0.951
BCTCHEV, G23	-0.471420	1.367925	-0.345	61	0.731
BCDMST_R, G24	0.325395	2.167703	0.150	29	0.882
BCDGSP_R, G25	0.644514	1.983477	0.325	17	0.749
BTSCHSET, G26	0.063783	1.074076	0.059	23	0.954
BTMTPSC, G27	1.285845	1.156272	1.112	46	0.272
BTTPC, G28	-0.011972	0.137891	-0.087	42	0.932
BTLMTSTU, G29	2.722001	0.877671	3.101	188	0.003
BTSEX_R, G210	1.318249	2.116167	0.623	25	0.539
BTBGTAUT, G211	-0.011915	0.066088	-0.180	186	0.857
BTTELC_R, G212	0.136338	7.090989	0.019	45	0.985

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1,	U0	50.25772	2525.83882	287	7876.83537	0.000
level-1,	R	34.07598	1161.17234			

Model d in South Africa

```
 Program:                       HLM 6 Hierarchical Linear and Nonlinear
Modeling
 Authors:                       Stephen Raudenbush, Tony Bryk, & Richard
Congdon
 Publisher:                     Scientific Software International, Inc. (c)
2000

techsupport@ssicentral.com

www.ssicentral.com
 -------------------------------------------------------------------------------
-
 Module:      HLM2.EXE (6.04.2754.2)
 Date:        26 June 2008, Thursday
 Time:        10:18:10
 -------------------------------------------------------------------------------
-


 SPECIFICATIONS FOR THIS HLM2 RUN


  Problem Title: no title

  The data source for this run  = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\ZAF.mdm
  The command file for this run = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\ZAFmodeld2.hlm
  Output file name              = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\hlm2.avg
  The maximum number of level-1 units = 3662
  The maximum number of level-2 units = 167
  The maximum number of iterations = 100
  Method of estimation: restricted maximum likelihood

  This is part of a plausible value analysis using the following variables:
    BSMMAT01
    BSMMAT02
    BSMMAT03
    BSMMAT04
    BSMMAT05


 Weighting Specification
 -----------------------
                        Weight
                        Variable
            Weighting?   Name        Normalized?
 Level 1       yes         HOUWGT        yes
 Level 2        no
 Precision      no

  The outcome variable is BSMMAT01
```

```
 The model specified for the fixed effects was:
----------------------------------------------------

  Level-1                  Level-2
  Coefficients             Predictors
----------------------   ---------------
        INTRCPT1, B0      INTRCPT2, G00
                          BCDMST_R, G01
                          BCDGSP_R, G02
                             BTTPC, G03
                           BTSEX_R, G04
                          BTBGTAUT, G05
                          BTTELC_R, G06
#%  BSSLFCM slope, B1     INTRCPT2, G10
                          BCDMST_R, G11
                          BCDGSP_R, G12
                             BTTPC, G13
                           BTSEX_R, G14
                          BTBGTAUT, G15
                          BTTELC_R, G16
#%  BSSVALM slope, B2     INTRCPT2, G20
                          BCDMST_R, G21
                          BCDGSP_R, G22
                             BTTPC, G23
                           BTSEX_R, G24
                          BTBGTAUT, G25
                          BTTELC_R, G26
#% BSHFSG_R slope, B3     INTRCPT2, G30
                          BCDMST_R, G31
                          BCDGSP_R, G32
                             BTTPC, G33
                           BTSEX_R, G34
                          BTBGTAUT, G35
                          BTTELC_R, G36

'#' - The residual parameter variance for this level-1 coefficient has been set
      to zero.
'%' - This level-1 predictor has been centered around its grand mean.

 The model specified for the covariance components was:
---------------------------------------------------------

        Sigma squared (constant across level-2 units)

        Tau dimensions
              INTRCPT1


 Summary of the model specified (in equation format)
---------------------------------------------------

Level-1 Model

      Y = B0 + B1*(BSSLFCM) + B2*(BSSVALM) + B3*(BSHFSG_R) + R

Level-2 Model
      B0 = G00 + G01*(BCDMST_R) + G02*(BCDGSP_R) + G03*(BTTPC) + G04*(BTSEX_R)
        + G05*(BTBGTAUT) + G06*(BTTELC_R) + U0
```

```
    B1 = G10 + G11*(BCDMST_R) + G12*(BCDGSP_R) + G13*(BTTPC) + G14*(BTSEX_R)
       + G15*(BTBGTAUT) + G16*(BTTELC_R)
    B2 = G20 + G21*(BCDMST_R) + G22*(BCDGSP_R) + G23*(BTTPC) + G24*(BTSEX_R)
       + G25*(BTBGTAUT) + G26*(BTTELC_R)
    B3 = G30 + G31*(BCDMST_R) + G32*(BCDGSP_R) + G33*(BTTPC) + G34*(BTSEX_R)
       + G35*(BTBGTAUT) + G36*(BTTELC_R)
```

```
THE AVERAGED RESULTS FOR THIS PLAUSIBLE VALUE RUN
 Sigma_squared =   3530.23253

 Tau
 INTRCPT1,B0   4641.21114


Tau (as correlations)
 INTRCPT1,B0  1.000

 ----------------------------------------------------
  Random level-1 coefficient   Reliability estimate
 ----------------------------------------------------
  INTRCPT1, B0                        0.963
 ----------------------------------------------------
 The outcome variables are: BSMMAT01,BSMMAT02,BSMMAT03,BSMMAT04,BSMMAT05

 Final estimation of fixed effects
 (with robust standard errors)
```

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	130.173861	32.275246	4.033	160	0.000
BCDMST_R, G01	41.173855	11.092010	3.712	160	0.000
BCDGSP_R, G02	22.262916	10.044408	2.216	160	0.028
BTTPC, G03	-0.500268	0.642092	-0.779	160	0.437
BTSEX_R, G04	3.508161	13.638090	0.257	160	0.797
BTBGTAUT, G05	4.498982	0.997972	4.508	160	0.000
BTTELC_R, G06	-24.044591	12.105426	-1.986	160	0.048
For BSSLFCM slope, B1					
INTRCPT2, G10	15.387523	7.904957	1.947	33	0.060
BCDMST_R, G11	0.407334	2.449115	0.166	311	0.868
BCDGSP_R, G12	0.594027	2.299787	0.258	1041	0.796
BTTPC, G13	-0.092438	0.214772	-0.430	24	0.670
BTSEX_R, G14	3.415792	4.044067	0.845	19	0.409
BTBGTAUT, G15	0.078435	0.212067	0.370	49	0.713
BTTELC_R, G16	-1.242445	4.294258	-0.289	11	0.778
For BSSVALM slope, B2					
INTRCPT2, G20	11.162044	9.536645	1.170	15	0.260
BCDMST_R, G21	0.005915	3.422196	0.002	64	0.999
BCDGSP_R, G22	-0.060799	3.073093	-0.020	220	0.984
BTTPC, G23	-0.014721	0.179197	-0.082	107	0.935
BTSEX_R, G24	-1.296437	4.024935	-0.322	19	0.751
BTBGTAUT, G25	-0.348363	0.225902	-1.542	62	0.128
BTTELC_R, G26	2.405833	4.753229	0.506	10	0.623
For BSHFSG_R slope, B3					
INTRCPT2, G30	9.101205	4.872489	1.868	16	0.080

BCDMST_R, G31	-0.175680	1.798071	-0.098	36	0.923
BCDGSP_R, G32	0.461456	1.679378	0.275	19	0.786
BTTPC, G33	-0.072737	0.097045	-0.750	73	0.456
BTSEX_R, G34	-1.051590	1.774521	-0.593	221	0.554
BTBGTAUT, G35	0.214121	0.098060	2.184	151	0.030
BTTELC_R, G36	0.068331	1.884015	0.036	46	0.972

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1,	U0	68.12643	4641.21114	160	4594.51837	0.000
level-1,	R	59.41576	3530.23253			

Model e in South Africa

```
 Program:                       HLM 6 Hierarchical Linear and Nonlinear
Modeling
 Authors:                       Stephen Raudenbush, Tony Bryk, & Richard
Congdon
 Publisher:                     Scientific Software International, Inc. (c)
2000

techsupport@ssicentral.com

www.ssicentral.com
 ------------------------------------------------------------------------------
-
 Module:       HLM2.EXE (6.04.2754.2)
 Date:         26 June 2008, Thursday
 Time:         10:19:56
 ------------------------------------------------------------------------------
-


 SPECIFICATIONS FOR THIS HLM2 RUN


  Problem Title: no title

  The data source for this run  = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\ZAF.mdm
  The command file for this run = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\ZAFmodele2.hlm
  Output file name              = C:\Documents and
Settings\zwch6\Desktop\dissertation\HLM\hlm2.avg
  The maximum number of level-1 units = 3662
  The maximum number of level-2 units = 167
  The maximum number of iterations = 100
  Method of estimation: restricted maximum likelihood

  This is part of a plausible value analysis using the following variables:
    BSMMAT01
    BSMMAT02
    BSMMAT03
    BSMMAT04
    BSMMAT05


 Weighting Specification
 -----------------------
                        Weight
                        Variable
           Weighting?   Name        Normalized?
 Level 1       yes        HOUWGT        yes
 Level 2        no
 Precision      no

  The outcome variable is BSMMAT01
```

```
  The model specified for the fixed effects was:
 ----------------------------------------------------

   Level-1                  Level-2
   Coefficients             Predictors
 ----------------------   ---------------
        INTRCPT1, B0      INTRCPT2, G00
                            BCPPSC, G01
                          BCPINVOL, G02
                           BCTCHEV, G03
                          BCDMST_R, G04
                          BCDGSP_R, G05
                          BTSCHSET, G06
                           BTMTPSC, G07
                             BTTPC, G08
                          BTLMTSTU, G09
                           BTSEX_R, G010
                          BTBGTAUT, G011
                          BTTELC_R, G012
#%  BSSLFCM slope, B1      INTRCPT2, G10
                            BCPPSC, G11
                          BCPINVOL, G12
                           BCTCHEV, G13
                          BCDMST_R, G14
                          BCDGSP_R, G15
                          BTSCHSET, G16
                           BTMTPSC, G17
                             BTTPC, G18
                          BTLMTSTU, G19
                           BTSEX_R, G110
                          BTBGTAUT, G111
                          BTTELC_R, G112
#%  BSSVALM slope, B2      INTRCPT2, G20
                            BCPPSC, G21
                          BCPINVOL, G22
                           BCTCHEV, G23
                          BCDMST_R, G24
                          BCDGSP_R, G25
                          BTSCHSET, G26
                           BTMTPSC, G27
                             BTTPC, G28
                          BTLMTSTU, G29
                           BTSEX_R, G210
                          BTBGTAUT, G211
                          BTTELC_R, G212
#% BSHFSG_R slope, B3      INTRCPT2, G30
                            BCPPSC, G31
                          BCPINVOL, G32
                           BCTCHEV, G33
                          BCDMST_R, G34
                          BCDGSP_R, G35
                          BTSCHSET, G36
                           BTMTPSC, G37
                             BTTPC, G38
                          BTLMTSTU, G39
                           BTSEX_R, G310
                          BTBGTAUT, G311
                          BTTELC_R, G312
```

```
'#' - The residual parameter variance for this level-1 coefficient has been set
      to zero.
'%' - This level-1 predictor has been centered around its grand mean.

 The model specified for the covariance components was:
 ---------------------------------------------------------

         Sigma squared (constant across level-2 units)

         Tau dimensions
               INTRCPT1


 Summary of the model specified (in equation format)
 ---------------------------------------------------

Level-1 Model

       Y = B0 + B1*(BSSLFCM) + B2*(BSSVALM) + B3*(BSHFSG_R) + R

Level-2 Model
       B0 = G00 + G01*(BCPPSC) + G02*(BCPINVOL) + G03*(BCTCHEV) + G04*(BCDMST_R)
         + G05*(BCDGSP_R) + G06*(BTSCHSET) + G07*(BTMTPSC) + G08*(BTTPC)
         + G09*(BTLMTSTU) + G010*(BTSEX_R) + G011*(BTBGTAUT) + G012*(BTTELC_R)
+ U0
       B1 = G10 + G11*(BCPPSC) + G12*(BCPINVOL) + G13*(BCTCHEV) + G14*(BCDMST_R)
         + G15*(BCDGSP_R) + G16*(BTSCHSET) + G17*(BTMTPSC) + G18*(BTTPC)
         + G19*(BTLMTSTU) + G110*(BTSEX_R) + G111*(BTBGTAUT) + G112*(BTTELC_R)
       B2 = G20 + G21*(BCPPSC) + G22*(BCPINVOL) + G23*(BCTCHEV) + G24*(BCDMST_R)
         + G25*(BCDGSP_R) + G26*(BTSCHSET) + G27*(BTMTPSC) + G28*(BTTPC)
         + G29*(BTLMTSTU) + G210*(BTSEX_R) + G211*(BTBGTAUT) + G212*(BTTELC_R)
       B3 = G30 + G31*(BCPPSC) + G32*(BCPINVOL) + G33*(BCTCHEV) + G34*(BCDMST_R)
         + G35*(BCDGSP_R) + G36*(BTSCHSET) + G37*(BTMTPSC) + G38*(BTTPC)
         + G39*(BTLMTSTU) + G310*(BTSEX_R) + G311*(BTBGTAUT) + G312*(BTTELC_R)



THE AVERAGED RESULTS FOR THIS PLAUSIBLE VALUE RUN
 Sigma_squared =   3526.03385

 Tau
 INTRCPT1,B0   3584.79775


Tau (as correlations)
 INTRCPT1,B0  1.000

 ----------------------------------------------------
  Random level-1 coefficient   Reliability estimate
 ----------------------------------------------------
  INTRCPT1, B0                        0.953
 ----------------------------------------------------
 The outcome variables are: BSMMAT01,BSMMAT02,BSMMAT03,BSMMAT04,BSMMAT05

 Final estimation of fixed effects
 (with robust standard errors)
 ----------------------------------------------------------------------------
```

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0					
INTRCPT2, G00	319.436409	43.181923	7.397	154	0.000
BCPPSC, G01	18.980899	6.041460	3.142	154	0.002
BCPINVOL, G02	-25.262893	7.840476	-3.222	154	0.002
BCTCHEV, G03	-11.474672	5.465822	-2.099	154	0.037
BCDMST_R, G04	35.143780	8.836245	3.977	154	0.000
BCDGSP_R, G05	8.966720	8.479445	1.057	154	0.292
BTSCHSET, G06	16.180778	5.739886	2.819	154	0.006
BTMTPSC, G07	-0.549931	4.963882	-0.111	154	0.912
BTTPC, G08	-0.830168	0.584353	-1.421	154	0.157
BTLMTSTU, G09	-10.112855	6.475410	-1.562	154	0.120
BTSEX_R, G010	5.711018	11.963302	0.477	154	0.633
BTBGTAUT, G011	3.562306	0.880793	4.044	154	0.000
BTTELC_R, G012	-16.126763	10.585404	-1.523	154	0.129
For BSSLFCM slope, B1					
INTRCPT2, G10	12.513954	13.978753	0.895	28	0.379
BCPPSC, G11	0.064313	2.551246	0.025	11	0.981
BCPINVOL, G12	1.260027	2.459554	0.512	37	0.611
BCTCHEV, G13	-1.693117	1.959383	-0.864	10	0.408
BCDMST_R, G14	0.345579	2.362522	0.146	162	0.884
BCDGSP_R, G15	0.871326	2.280095	0.382	1585	0.702
BTSCHSET, G16	-0.720548	2.368064	-0.304	13	0.766
BTMTPSC, G17	0.787090	1.693334	0.465	41	0.644
BTTPC, G18	-0.083908	0.218320	-0.384	27	0.703
BTLMTSTU, G19	0.167453	1.904950	0.088	36	0.931
BTSEX_R, G110	2.641972	4.082190	0.647	18	0.525
BTBGTAUT, G111	0.148657	0.257865	0.576	20	0.570
BTTELC_R, G112	-1.120569	3.713617	-0.302	16	0.767
For BSSVALM slope, B2					
INTRCPT2, G20	2.128947	16.339009	0.130	44	0.897
BCPPSC, G21	-3.370724	2.166665	-1.556	33	0.129
BCPINVOL, G22	0.543241	2.536861	0.214	3610	0.831
BCTCHEV, G23	0.901980	1.803024	0.500	20	0.622
BCDMST_R, G24	0.388429	3.158689	0.123	28	0.903
BCDGSP_R, G25	1.479103	3.083772	0.480	56	0.633
BTSCHSET, G26	-0.814412	1.766319	-0.461	157	0.645
BTMTPSC, G27	-0.663723	2.082143	-0.319	40	0.751
BTTPC, G28	0.018147	0.197192	0.092	69	0.927
BTLMTSTU, G29	0.809444	1.825175	0.443	98	0.658
BTSEX_R, G210	-0.322457	3.954612	-0.082	27	0.936
BTBGTAUT, G211	-0.274040	0.256721	-1.067	44	0.292
BTTELC_R, G212	1.222296	4.322708	0.283	12	0.782
For BSHFSG_R slope, B3					
INTRCPT2, G30	12.933638	8.040298	1.609	46	0.114
BCPPSC, G31	0.422323	1.264435	0.334	87	0.739
BCPINVOL, G32	-0.782295	1.475454	-0.530	27	0.600
BCTCHEV, G33	0.410339	0.863029	0.475	89	0.635
BCDMST_R, G34	-0.128874	1.796044	-0.072	24	0.944
BCDGSP_R, G35	-0.013375	1.678885	-0.008	21	0.994
BTSCHSET, G36	0.537144	1.003040	0.536	78	0.593
BTMTPSC, G37	0.034262	1.030408	0.033	56	0.974
BTTPC, G38	-0.084387	0.097175	-0.868	200	0.386
BTLMTSTU, G39	-0.022562	1.540168	-0.015	8	0.989
BTSEX_R, G310	-0.939570	1.720944	-0.546	382	0.585
BTBGTAUT, G311	0.173096	0.116162	1.490	49	0.142

BTTELC_R, G312	0.509357	1.796363	0.284	54	0.778

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1,	U0	59.87318	3584.79775	154	3576.05531	0.000
level-1,	R	59.38042	3526.03385			

REFERENCES

Anderman, E. (2002). School effects on psychological outcomes during adolescence. *Journal of Educational Psychology*, *94*(4), 795-809.

Anderman, L. H. (1999). Expanding the disccusion of social perceptions and academic outcomes: Mechanisms and contextural influences. In T. Urdan (Ed.), *Advances in motivation and achievement* (Vol. 11, pp. 303-336). Greenwich, CT: JAI Press.

Ashton, P. T., & Webb, R. B. (1986). *Making a difference: Teachers' sense of efficacy and student achievement*. New York: Longman.

Astone, N. M., & McLanahan, S. S. (1991). Family structure, parental practices and high school completion. *American Sociological Review, 56*, 309-320.

Atkinson, J. W. (1964). *An introduction to motivation*. Princeton, NJ: Van Nostrand.

Baker, D. P., & LeTendre, G. K. (2005). *National differences, global similarities: World culture and the future of schooling*. Stanford, CA: Stanford University Press.

Bandura, A. (1977). Self-Efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review, 84*, 191-215.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (1989). Social cognitive theory. In R. Vasta (Ed.), *Annals of child development* (Vol. 6, pp. 1-60). Greenwich, CT: JAI Press.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist, 28*, 117-148.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York: Freeman.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology, 52*, 1-26.

Berndt, T. J., & Keefe, K. (1996). Friends' influence on school adjustment: A motivational analysis. In J. Juvonen & K. R. Wentzel (Eds.), *Social motivation: Understanding children's school adjustment* (pp. 248-278). New York: Cambridge University Press.

Betz, N. (1983). The relationship of mathematics self-efficacy expectations to the selection of science-based college majors. *Journal of Vocational Behavior, 23*(3), 329-345.

Betz, N., & Hackett, G. (1981). The relationship of career-related self-efficacy expectations to perceived career options in college women and men. *Journal of Counseling Psychlogy, 28*, 399-410.

Betz, N., & Hackett, G. (1983). The relationship of mathematics self-efficacy expectations to the selection of science-based college majors. *Journal of Vocational Behavior, 23*, 329-345.

Bong, M., & Skaalvik, E. M. (2003). Academic self-concept and self-efficacy: How different are they really? *Educational Psychology Review, 15*, 1-40.

Braun, H., Jenkins, F., & Grigg, W. (2006). *A Closer Look at Charter Schools Using Hierarchical Linear Modeling. NCES 2006-460*.

Brigman, G. A., Webb, L. D., & Campbell, C. (2007). Building skills for school success: improving the academic and social competence of students. *Professional School Counseling, 10*(3), 279-288.

Brookover, W., Beady, C., Flood, P., Schweitzer, J., & Wisenbaker, J. (1979). *School social systems and student achievement: Schools can make a difference*. New York: Praeger.

Bryne, B. M. (1984). The general/academic self-concept nomological network: A review of construct validation research. *Review of Educational Research, 54,* 427-456.

Burden, R., & Fraser, B. (1994). Examining teachers' perceptions of their working environments: Introducing the School Level Environment Questionnaire. *Educational Psychology in Practice, 10*, 67-71.

Bybee, R. W., & Kennedy, D. (2005). Math and science achievement. *Science,* pp. 481-481,

Caprara, G. V., Barbaranelli, C., Steca, P., & Malone, P. S. (2006). Teachers' self-efficacy beliefs as determinants of job satisfaction and students' academic achievement: A study at the school level. *Journal of School Psychology, 44*(6), 473-490.

Carbonaro, W. (2005). Tracking, students' effort, and academic achievement. *Sociology of Education, 78*, 27-49.

Chan, J. C. Y., & Lam, S.-f. (2008). Effects of competition on students' self-efficacy in vicarious learning. *British Journal of Educational Psychology, 78*(1), 95-108.

Chen, P., & Zimmerman, B. (2007). A cross-national comparison study on the accuracy of self-efficacy beliefs of middle-school mathematics students. *Journal of Experimental Education, 75*(3), 221-244.

Coleman, J. S. (1990a). *Equality and achievement in education*. San Francisco: Westview Press.

Coleman, J. S. (1990b). *Foundations of ocial theory*. Cambridge, MA: Harvard University Press.

Csikszentmihalyi, M. (1975). *Beyond boredom and anxiety*. San Francisco: Jossey-Bass.

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. New York: Plenum.

DePlanty, J., Coulter-Kern, R., & Duchane, K. A. (2007). Perceptions of parent involvement in academic achievement. *Journal of Educational Research, 100*(6), 361-368.

Eccles, J., S. (1983). Expectancies, values and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives* (pp. 75-146). San Francisco: Freeman.

Eccles, J., S. (1987). Gender roles and women's achievement-related decisions. *Psychology of Women Quarterly, 11*, 135-172.

Eccles, J., S. (1993). School and family effects on the ontogeny of children's interests, self-perceptions, and activity choice. In J. Jacobs (Ed.), *Nebraska symposium on motivation: Developmental perspectives on motivation* (pp. 145-208). Lincoln, NE: University of Nebraska Press.

Eccles, J., S. (2005). Subjective task value and the Eccles et al. model of achievement-related choice. In A. J. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 105-121). New York: Guilford Press.

Eccles, J., S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*, 215-225.

Eccles, J., S., Wigfield, A., Flanagan, C., Miller, C., Reuman, D., & Yee, D. (1989). Self-concepts, domain values, and self-esteem: Relations and changes at early adolescence. *Journal of Personality, 57*, 283-310.

Eccles, J., S., Wigfield, A., Harold, R., & Blumenfeld, P. (1993). Age and gender differences in children's self-and task perceptions during elementary school. *Child Development, 64*, 830-847.

Eccles, J., S., Wigfield, A., & Schiefele, U. (1998). Motivation to succeed. In N. Eisenberg (Ed.), *Social, emotional, and personality development* (5th ed., Vol. 3, pp. 1017-1095). New York: Wiley.

Eklof, H. (2007). Self-concept and valuing of mathematics in TIMSS 2003: Scale structure and relation to performance in a Swedish setting. *Scandinavian Journal of Educational Research, 51*(3), 297-313.

Feuerstein, A. (2000). School characteristics and parent involvement: influences on participation in children's schools. *The Journal of Educational Research, 94*(1), 29-39.

Ford, M. (1992). *Motivating humans: Goals, emotions, and personal agency beliefs*. Newbury Park, CA: Sage.

Fraser, B. J., & Rentoul, A. J. (1982). Relationships between school-level and classroom-level environment. *Alberta Journal of Educational Research, 28*, 212-225.

Freiberg, H. J. (Ed.). (1999). *School climate: Measuring, improving, and sustaining healthy learning environments*. Philadelphia: Falmer Press.

Gettys, J. M. (2003). The effect of school size on school climate variables in middle schools of South Carolina. University of South Carolina.

Goldstein, H. I. (1986). Multilevel mixed linear model analysis using iterative generalized least squares. *Biometrika, 73*, 43-56.

Gonzalez, E. J., Galia, J., & Li, I. (2004). Scaling methods and procedures for the TIMSS 2003 mathematics and science scales. In M. O. Martin, I. V. S. Mullis & S. J. Chrostowski (Eds.), *TIMSS 2003 Technical Report*. Chestnut Hill, MA: Boston College.

Gottfried, A. E. (1990). Academic intrinsic motivation in young elementary school children. *Journal of Educational Psychology, 82*(3), 525-538.

Gottfried, A. E., Fleming, J. S., & Gottfried, A. W. (1994). Role of parental motivational practices in children's academic intrinsic motivation and achievement. *Journal of Educational Psychology, 86*(1), 104-113.

Gottfried, A. E., Fleming, J. S., & Gottfried, A. W. (2001). Continuity of academic intrinsic motivation from childhool through late adolescence: a longitudinal study. *Journal of Educational Psychology, 93*(1), 3-13.

Graham, S., & Weiner, B. (1996). Theories and principles of motivation. In D. C. Berliner & R. C. Calfee (Eds.), *Handbook of educational psychology* (pp. 63-84). New York: Simon & Schuster Macmillan.

Guillet, E., Sarrazin, P., Fontayne, P., & Brustad, R. J. (2006). Understanding female sport attrition in a stereotypical male sport within the framework of Eccles's expectancy-value model. *Psychology of Women Quarterly, 30*(4), 358-368.

Hackett, G., & Betz, N. (1981). A self-efficacy approach to the career development of women. *Journal of Vocational Behavior, 18*, 326-339.

Harter, S. (1982). The perceived competence scale for children. *Child Development, 53*, 87-97.

Harter, S. (1985). Competence as a dimension of self-evaluation: toward a comprehensive model of self-worth. In R. Leahy (Ed.), *The development of the self* (pp. 55-121). New York: Academic Press.

Harter, S. (1990). Causes, correlates, and the functinal role of self-worth: A life-span perspective. In R. J. Sternberg & J. Kolligian (Eds.), *Competence considered* (pp. 67-97). New Haven, CT: Yale University Press.

Harter, S. (1998). The development of self-representations. In N. Eisenberg (Ed.), *Social, emotional, and personality development* (5th ed., Vol. 3, pp. 553-617). New York: Wiley.

Hodges, C. B., Stackpole-Hodges, C. L., & M., C. K. (2008). Self-Efficacy, Self-Regulation, and Cognitive Style as Predictors of Achievement with Podcast Instruction. *Journal of Educational Computing Research, 38*(2), 139-153.

Hox, J. J. (2002). *Multilevel analysis*. Mahwah, NJ: Lawrence Erlbaum Associates.

Johnson, B., Stevens, J. J., & Keith, Z. (2007). Teachers' perceptions of school climate: A validity study of scores from teh revised School Level Environment Questionnaire. *Educational and Psychological Measurement, 67*, 833-844.

Joncas, M. (2004). TIMSS 2003 sampling weights and participation rates. In M. O. Martin, I. V. S. Mullis & S. J. Chrostowski (Eds.), *TIMSS 2003 Technical Report*. Chestnut Hill, MA: Boston College.

Kreft, I. G. G., Leeuw, J. d., & Aiken, L., S. (1995). The effects of different forms of centering in hierarchical linear models. *Multivariate Behavioral Research, 30*(1), 1-21.

Lee, V. E., Bryk, A. S., & Smith, J. B. (1993). *The organization of effective secondary schools.* (Vol. 19). Washington, DC: American Educational Research Association.

Lent, R. W., & Hackett, G. (1987). Career self-efficcy: Empirical status and future directions. *Journal of Vocational Behavior, 30*, 347-382.

Lepper, M., R., Corpus, J. H., & Iyengar, S. S. (2005). Intrinsic and Extrinsic Motivational Orientations in the Classroom: Age Differences and Academic Correlates. *Journal of Educational Psychology, 97*(2), 184-196.

Ma, X., & Don, A. K. (2000). Hierarchical linear modelling of student and school effects on academic achievement. *Canadian Journal of Education, 25*(1), 41-55.

Maehr, M. L., & A., K. D. (Eds.). (1987). *Advances in motivation and achievement* (Vol. 5). Greenwich, Connecticut: JAI.

Maehr, M. L., & Midgley, C. (1991). Enhancing student motivation: A schoolwide approach. *Educational Psychologist, 26*, 399-427.

Maehr, M. L., & Midgley, C. (1996). *Transforming school cultures*. Boulder, CO: Westview Press.

Marakas, G. M., Yi, M. Y., & Johnson, R. D. (1998). The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. *Information Systems Research, 9*(2), 126-163.

Marsh, H. W. (1990a). Causal ordering of academic self-concept and academic achievement: A multivariate, longitudinal panel analysis. *Journal of Educational Psychology, 82*, 646-656.

Marsh, H. W. (1990b). The structure of academic self-concept: The Marsh/Shavelson model. *Journal of Educational Psychology, 82*(4), 623-636.

Marsh, H. W., & Shavelson, R. (1985). Self-concept: Its multifaceted hierarchical structure. *Educational Psychologist, 20*, 107-123.

Martin, M. O. (Ed.). (2005). *TIMSS 2003 User Guide for the International Database*. Chestnut Hill, MA: Boston College.

Martin, M. O., Mullis, I. V. S., & Chrostowski, S. J. (Eds.). (2004). *TIMSS 2003*

Technical Report. Chestnut Hill, MA: Boston College.

Mason, W. M., Wong, G. M., & Entwistle, B. (1983). Contextual analysis through the multilevel linear models. In S. Leinhardt (Ed.), *Sociological Methodology* (pp. 72-103). San Francisco: Jossey-Bass.

McEwan, E. K. (2000). *The principal's guide to raising math achievement*. Thousand Oaks, California: Corwin Press, Inc.

Mislevy, R. J. (1991). Randomisation based inference about latent variables from complex samples. *Psychometrika, 56*, 177-196.

Moses, R., & Cobb, C. (2001). *Radical equations: Math literacy and civil rights*. Boston: Beacon Press.

Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analytic investigation. *Journal of Counseling Psychology, 38*, 30-38.

National Commission on Excellence in Education (NCEE). (1983). *A Nation at Risk.* Washington, DC: U.S. Government Printing Office.

Noonan, J. (2004). School climate and the safe school: Seven contributing factors. *Educational Horizons, 80*(1), 61-65.

Otis, N., Grouzet, F., M. E., & Pelletier, L. G. (2005). Latent motivational change in an academic setting: A 3-year longitudinal study. *Journal of Educational Psychology, 97*(2), 170-183.

Pajares, F. (1997). Current directions in self-efficacy research. In M. Maehr & P. R. Pintrich (Eds.), *Advances in motivation and achievement* (Vol. 10, pp. 1-49). Greenwich, CT: JAI Press.

Pajares, F., & Miller, M. D. (1995). Mathematics self-efficacy and mathematics performances: The need for specificity of assessment. *Journal of Counseling Psychology, 42*, 190-198.

Paraskeva, F., Bouta, H., & Papagianni, A. (2008). Individual characteristics and computer self-efficacy in secondary education teachers to integrate technology in educational practice. *Computers & Education, 50*(3), 1084-1091.

Parcel, T. L., & Dufur, M. J. (2001). Capital at home and at school: Effects on student achievement. *Social Forces, 79*(3), 881-991.

Patrick, H., Anderman, L. H., & Ryan, A. M. (2002). Social motivation and the classroom social environment. In C. Midgley (Ed.), *Goals, goal structures, and patterns of adaptive learning* (pp. 85-104). Hillsdale, NJ: Lawrence Erlbaum.

Pintrich, P. R. (1988a). A process-oriented view of student motivation and cognition. In J. Stark & L. Mets (Eds.), *Improving teaching and learning through research: New directions for institutional research* (Vol. 57, pp. 65-79). San Francisco: Jossey-Bass.

Pintrich, P. R. (1988b). Student learning and college teaching. In R. Young & K. Eble (Eds.), *College teaching and learning :Preparing for new commitments: new directionsl for teaching and learning* (Vol. 33, pp. 71-86). San Francisco: Jossey-Bass.

Pintrich, P. R., & Maehr, M. L. (Eds.). (2004). *Advances in motivation and achievement* (Vol. 13). Amsterdam; Boston: JAI.

Pintrich, P. R., & Maehr, M. L. (Eds.). (2004). *Motivating students, improving school: The legacy of Carol Midgley* (Vol. 13): Elsevier.

Pintrich, P. R., & Schunk, D. H. (1995). *Motivation in education: Theory, research and applications*. Englewood Cliffs, NJ: Prentice Hall.

Preckel, F., Zeidner, M., Goetz, T., & Schleyer, E. J. (2008). Female ‘big fish’ swimming against the tide: The ‘big-fish-little-pond effect’ and gender-ratio in special gifted classes. *Contemporary Educational Psychology, 33*(1), 78-96.

Raudenbush, S. W. (1989a). “Centering” predictors in multilevel analysis: Choices in consequences. *Multilevel Modeling Newsletter, 1*(2), 10-12.

Raudenbush, S. W. (1989b). A response to Longford and Plewis. *Multilevel Modeling Newsletter, 1*(3), 8-10.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical Linear Models* (2nd ed.). Newbury Park, CA: Sage.

Renninger, K. A., Hidi, S., & Krapp, A. (1992). *The role of interest in learning and development*. Hillsdale, NJ: Erlbaum.

Rosenberg, B. (1973). Linear regression with randomly dispersed parameters. *Biometrika, 60*, 61-75.

Rosenthal, & Rosenthal, R. (2002). Covert communication in classrooms, clinics, courtrooms, and cubicles. *American Psychologist, 57*(11), 839-849.

Rumberger, R. W., & Palardy, G. J. (2005). Test scores, dropout rates, and transfer rates as alternative indicators of high school performance. *American Educational Research Journal*, *42*(1), 3-42.

Rutter, M., Maughan, B., Mortimore, P., Ouston, J., & Smith, A. (1979). *Fifteen thousand hours: Secondary schools and their effects on children*. Cambridge, MA: Harvard University Press.

Schiefele, U. (1991). Interest, learning, and motivation. *Educational Psychologist, 26*, 299-323.

Schunk, D. H. (1989). Self-efficay and cognitive skill learning. In C. Ames & R. Ames (Eds.), *Research on motivation in education* (Vol. 3, pp. 13-44). San Diego, CA: Academic Press.

Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational Psychologist, 26*, 207-231.

Schunk, D. H. (1995). Self-efficacy and education and instruction. In J. E. Maddux (Ed.), *Self-efficacy, adaptation, and adjustment: Theory, research and application* (pp. 281-303). New York: Plnum Press.

Schunk, D. H., & Pajares, F. (2002). The development of academic self-efficacy. In A. Wigfield & J. S. Eccles (Eds.), *Development of achievement motivation* (pp. 15-31). San Diego: Academic Press.

Schunk, D. H., Pintrich, P. R., & Meece, J. L. (2008). *Motivation in education: Theory, research, and applications* (3th ed.). Upper Saddle River, New Jersey: Pearson/Merrill Prentice Hall.

Shavelson, R., & Bolus, R. (1982). Self concept: the interplay of theory and methods. *Journal of Educational Psychology*, *74*, 3-17.

Shavelson, R. J., Hubner, J. J., & Stanton, G. C. (1976). Validation of construct interpretations. *Review of Educational Research, 46*, 407-441.

Spector, P. (1992). *Summated rating scale construction: An introduction*. Newbury Park, CA: Sage.

Stevenson, K. (2006). *School size and its relationship to student outcomes and school climate: A review and analysis of eight South Carolina state-wide studies*: National Clearinghouse for Educational Facilities.

Stewart, E. B. (2008). Individual and school structural effects on African American high school students' academic achievement. *High School Journal, 91*(2), 16-34.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Boston: Allyn & Bacon.

Tienken, C. (2008). Rankings of international achievement test performance and economic strength: Correlation or Conjecture? [Electronic Version]. *International Journal of Educational Policy and Leadership, 3,* from http://www.ijepl.org

Tobias, S. (1994). Interest, prior knowledge, and learning. *Review of Educational Research, 64*, 37-54.

Urdan, T. C., & Maehr, M. L. (1995). Beyond a two-goal theory of motivation and achievement: A case for social goals. *Review of Educational Research, 56,* 760-770.

Wang, J. (1999). Reasons for Hierarchical Linear Modeling: A reminder. *Journal of Experimental Education, 68*(1), 89.

Wentzel, K. R. (1991). Social competence at school: Relation between social responsibility and academic achievement. *Review of Educational Research, 61*, 1-24.

Wentzel, K. R., Barry, C. M., & Caldwell, K. A. (2004). Friendships in middle school: Influences on motivation and school adjustment. *Journal of Educational Psychology, 96*, 195-203.

White, S. M. T. (2005). The relationship of school size and school climate in public elementary schools in South Carolina. Unpublished Doctoral Dissertation. University of South Carolina.

Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review, 6*, 49-78.

Wigfield, A., & Eccles, J., S. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review, 12*, 265-310.

Wigfield, A., & Eccles, J., S. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology, 25*, 68-81.

Wigfield, A., & Eccles, J., S. (2002). The development of competence beliefs, expectancies for success, and achievement values from childhood through adolescence. In A. Wigfield & J. S. Eccles (Eds.), *Development of achievement motivation* (pp. 91-120). San Diego: Academic Press.

Wigfield, A., Eccles, J., S., & Rodriguez, D. (1998). The development of children's motivation in school context. *Review of Research in Education, 23,* 73-118.

Wigfield, A., Tonks, S., & Eccles, J., S. (2004). Expectancy-value theory in cross-cultural perspective. In D. M. McInerney & S. Van Etten (Eds.), *Big theories revisited* (pp. 165-198). Greenwich, CT: Information Age Publishing.

Zhao, H. (2007). School expectations and initiatives for parental involvement in 30 nations: A comparative study using TIMSS 1999 Data. Unpublished Doctoral Dissertation. University of Missouri-Columbia.

VITA

Ze Wang was born November 30, 1979, in Suizhou, China. She received a B. S. in English and Science and a B. E. in Electronic Information and Engineering with high honors from the University of Science and Technology of China (2002). She also received her M. A. in Educational Psychology from the University of Missouri-Columbia (2005). She will become an Assistant Professor at the Department of Educational, School and Counseling Psychology in the University of Missouri.