Fall 10-20-2010

Hierarchical Linear Modeling of Students' Mathematics Self-Efficacy and School Effects on Mathematics Achievement

Xing Liu
Eastern Connecticut State University, liux@easternct.edu

Hari P. Koirala
Eastern Connecticut State University, koiralah@easternct.edu

Hierarchical Linear Modeling of Students' Mathematics Self-Efficacy and School Effects on Mathematics Achievement

Xing Liu

Hari Koirala

Education Department

Eastern Connecticut State University

Abstract

The purpose of this study was to investigate the relationship between mathematics self-efficacy and mathematics achievement of high school sophomores across the United States, and to examine the effects of gender, ethnicities, and school characteristics on students' mathematics achievement using hierarchical linear modeling (HLM). The base-year data of the Educational Longitudinal Study (ELS): 2002 were used for analysis. Hierarchical linear models were developed from the one-way random effects ANOVA model, and the unconditional Model with mathematics self-efficacy in level 1, to the contextual models with variables in the both levels. Both fixed effects and random effects were estimated and interpreted for all the models.

Keywords: Mathematics Self-efficacy, Mathematics Achievement, School Effects, Hierarchical Linear Modeling.

Hierarchical Linear Modeling of Students' Mathematics Self-Efficacy and School Effects on Mathematics Achievement

Introduction

Self-efficacy is an important concept in social cognitive theory, which has been widely recognized as one of the most prominent theory about human learning (Ormrod, 2008). First developed by Albert Bandura (1977; 1986), self-efficacy refers to learners' beliefs about their ability to accomplish certain tasks. Many researchers, including Bandura, have demonstrated that self-efficacy affects human motivation, persistence, efforts, action, behavior, and achievement (Bandura, 1977, 2000; Zimmerman, Bandura, & Martinez-Pons, 1992). Researchers have indicated that higher self-efficacy is predictive of higher performance (Bong & Skaalvik, 2003).

Bandura (1986) defined self-efficacy as "People's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances" (p. 391). Bandura (1977) argued that self-efficacy affects an individual's choice of activities, motivation, effort and persistence. People who have a high level of self-efficacy are more likely to perform an action, while those who have low self-efficacy for accomplishing a specific task may doubt their capabilities and perform poorly (Bandura, 1977). Randhawa, Beamer and Lundberg (1993) indicated that self-efficacy is an important predictor for students' mathematics achievement.

Research on school effects on students' academic achievement has been an increasingly important topic, which mainly focuses on school climate. Previous research (Brand, Felner, Shim, Seitsinger, & Dumas, 2003; Ma, 2000, 2002; Ma & Willms, 2004) has identified that school climate played a significant role in affecting student's academic achievement. Under the No Child Left Behind (NCLB) Act, states need to develop content and achievement standards in all core subjects at every grade level, and assess the basic skills of all students in certain grade levels. In addition, individual schools and districts need to be held accountable for making adequate yearly progress on core subjects being assessed. It is common to see some schools and districts continuously outperform others in subjects, such as mathematics and reading. However, in addition to school climate, it is unknown what other school level factors contribute to the effectiveness of these outperforming schools. Therefore, it is important to identify these factors associated with students' academic achievement, which could potentially help those underperforming schools to improve.

The purpose of this study was to investigate the relationship between mathematics self-efficacy and mathematics achievement of high school sophomores across the United States, and to examine the effects of gender, ethnicities, and school characteristics on students' mathematics achievement using hierarchical linear modeling (HLM). Our research questions mainly focused on: (1) Could mathematics achievement of high school sophomores be significantly predicted by their mathematics self-efficacy? (2) Were there achievement gaps in mathematics between gender and among different ethnic groups? (3) Were school-level factors, such as number of full-time math teachers, number of students who received remedial math and school urbanicity, associated with students' mathematics achievement? (4) Were there any interaction effects between students' mathematics self-efficacy and the above school-level factors?

Methodology

Instrumentation and Data Collection

The ELS: 2002 study, conducted by the National Center for Educational Statistics (NCES), was designed to provide longitudinal data regarding the transitions of 2002 high school sophomores to postsecondary school education and their future careers. In the 2002 base year of the study, more than 15000 high school sophomores, from a national sample of 752 public and private high schools, participated in the study by taking cognitive tests and responding to surveys. These 752 schools represented the approximately 25000 public and private schools in the United States that had a 10^{th} grade in 2002; the sample students represented approximately three million 10^{th} graders in the United States attending schools in 2002. The 2002 base year sophomore cohort was followed at two-year intervals.

Data Analysis

Data were coded and analyzed using SPSS 18.0 and HLM (v. 6.06). Hierarchical linear modeling (HLM) was used to address the research questions. The HLM technique allows us to analyze multilevel data when observations at a low level are nested within observations at higher levels, for example, students are nested in schools in this study. In addition, it is a promising method of analyzing data with complex sampling design features (O'Connell & McCoach, 2008). It is a powerful tool used to model cross-level effects and partition variance and covariance components of fitted models (Hox, 2002; Raudenbush & Bryk, 2002).

The HLM analysis included a two-level hierarchical linear model of mathematics achievement. Level 1 consisted of the student-level variable, gender, ethnicity and mathematics self-efficacy. Level 2 included school-level variables such as number of full-time math teachers, number of students who received remedial math and school urbanicity. Table 1 provides the descriptive statistics of the variables in both levels. Hierarchical linear models were developed from the one-way random effects ANOVA model, and the unconditional Model with mathematics self-efficacy in level 1, to the contextual models with variables in the both levels. Both fixed effects and random effects were estimated and interpreted for all the models. Restricted maximum likelihood (REML) estimation was used in HLM (v. 6.06), since it is more advantageous than maximum likelihood (ML) in estimating variance components (McCoach, 2010). Models were compared based on the proportion reduction in variance in both levels. To make the interpretation meaningful, the predictors in the level 1 model were centered around the group mean, and predictors in the level 2 model were centered around the grand mean.

Insert Table 1 around here

The two-level conventional model (Raudenbush & Bryk, 2002) is expressed as follows:

Level 1 model: $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \beta_{2j}X_{ij} + \beta_{3j}X_{ij} + r_{ij}$, (1)

where i represents the i^{th} student and j represents j^{th} school,

Y_{ij} represents the mathematics achievement of i^{th} student in the j^{th} school,

β_{0j} is the intercept, the mean mathematics achievement in the j^{th} school,

β_{1j}, β_{2j}, and β_{3j} are the slopes for gender, ethnicity, and mathematics self-efficacy in the j^{th} school, respectively,

X_{ij} represents the values of gender, ethnicity, and mathematics self-efficacy of i^{th} student in the j^{th} school, and

r_{ij} is the random error of i^{th} student in the j^{th} school.

Level 2 model: $\beta_{qj}=\gamma_{q0} + \gamma_{q1}W_{1j} + \gamma_{q2}W_{2j} + \ldots + u_{qj}$ $(q = 0, 1, 2 \ldots)$, (2)

where $\gamma_{00}, \ldots, \gamma_{22}$ are level 2 coefficients,

W_{1j} and W_{2j} are level 2 predictors, and

u_{qj} is level 2 random effect.

Hierarchical linear models were developed from the one-way random effects ANOVA model, the unconditional Model with mathematics self-efficacy, gender and ethnicity in level 1, to the contextual model with variables in the both levels. Both fixed effects and random effects were estimated and interpreted for all the models. Models were compared based on the proportion reduction in variance in both levels. To make the interpretation meaningful, the predictors in the level 1 model will be centered around the group mean, and predictors in the level 2 model will be centered around the grand mean. HLM (v. 6.06) was used for model fitting.

Results

The results of One-way Random Effects ANOVA Model with no level-1 and level-2 variables

The one-way random effects ANOVA model can be expressed like this:

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

Table 2 presents the results of one-way random effects ANOVA model. Average school mean mathematics achievement was statistically different from zero ($\gamma_{00} = 38.91$, t = 145.62, df = 573, p = .000). For variance in school means, $\tau_{00} = 32.94$, $\chi^2 = 3233.09$, df = 573, p=.000, so there were considerable variations in the school means. ICC (intraclass correlation coefficient) = .23 (32.94/142.02= .23), indicating 23% of the variability in mathematics achievement was between schools (77% of the variability within school). The total variability was 142.02. Additional level 1 predictors (student-level) would be chosen to try to reduce the variance within schools, and additional level 2 predictors (school-level) would be added to explain between-school variance in the following models.

Insert Table 2 around here

The results of unconditional model with the level-1 predictors

The unconditional model with level-1 predictors can be expressed like this:

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}Gender_{ij} + \beta_{2j}Ethn1_{ij} + \beta_{3j}Ethn2_{ij} + \beta_{4j}Ethn3_{ij} + \beta_{5j}Ethn4_{ij} + \beta_{6j}Ethn5_{ij} + \beta_{7j}Self\text{-}Efficacy_{ij} + r_{ij}$$

Level 2:

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

Table 3 shows the results of unconditional model with level-1 predictors and no level-2 predictors. After including gender, ethnicity and mathematics self-efficacy as level-1 predictors of mathematics achievement within school, within school variability was reduced by 18.73% ((109.08 – 88.65)/109.08 = 18.73%), relative to the one-way random effects ANOVA model. Overall mean mathematics achievement across schools was still significantly different from zero (γ_{00} = 40.57, t = 151.94, df = 573, p=.000). Also, there was a significant difference in Gender slope (effect of Gender on mathematics ach.) across schools (γ_{10} = .54, t = 2.58, df = 9118, p = .010). This indicated that male students performed significantly better than female students in mathematics achievement. Ethn1 to ethn5 were indicator variables with dummy coding (baseline variable was White Americans) since ethnicity had six categories. Compared to the White Americans, the native Americans performed less well in mathematics achievement (γ_{20} = -7.14, t = -5.56, df = 9118, p = .000), there was no significant difference between the Asian Americans and the White Americans (γ_{30} = .66, t = 1.54, df = 9118, p = .124); the African Americans (γ_{40} = -8.83, t = -22.46, df = 9118, p = .000), Hispanic American (γ_{50} = -6.50, t = -17.67, df = 9118, p = .000), and the multiracial Americans (γ_{60} = -2.27, t = -4.64, df = 9118, p = .000) all performed less than the White Americans in mathematics achievement.

The average effect of mathematics self-efficacy on mathematics achievement was significant (γ_{70} = 4.44, t = 35.68, df = 9118, p = .000). For each unit increase in students' mathematics self-efficacy, there were average 4.44 points increase in mathematics scores across schools. There was a statistically significant difference in remaining variance in school means

(τ_{00} = 23.30, χ^2 = 2920.50, df = 573, p = .000). This between school variance might be explained after incorporating school level (level 2) variables.

Insert Table 3 around here

The results of contextual model (1) with the level-1 and level-2 predictors

The contextual model (1) can be expressed like this:

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}Gender_{ij} + \beta_{2j}Ethn1_{ij} + \beta_{3j}Ethn2_{ij} + \beta_{4j}Ethn3_{ij} + \beta_{5j}Ethn4_{ij} + \beta_{6j}Ethn5_{ij} + \beta_{7j}Self\text{-}Efficacy_{ij} + r_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}BYURBAN_j + \gamma_{02}BYA14J_j + \gamma_{03}BYA23A_j + u_{0j}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$
$$\beta_{5j} = \gamma_{50}$$
$$\beta_{6j} = \gamma_{60}$$
$$\beta_{7j} = \gamma_{70}$$

Table 4 provides the results of the contextual model with the level-1 predictors and the level-2 predictors. At level 2, the intercept was treated as random with the school level predictors, and the remaining coefficients were specified as fixed with no predictors. Relative to the unconditional model, 10.30% of the variance in the between school difference in mean mathematics scores was accounted for by BYURBAN, BYA14J and BYA23A ((23.30-20.90)/23.30 = 10.30%). However, since τ_{00} = 20.90, p = .000, there were still considerable differences between schools that might be accounted for by other level 2 variables.

Insert Table 4 around here

Explaining the Intercepts

Overall mean mathematics achievement across schools was still significant from zero (γ_{00} = 40.44, t = 138.00, df = 570, p=.000). After controlling for BYA14J (number of remedial math students in a school) and BYA23A (number of full-time math teachers in a school), there was no significant difference in mathematics achievement between students in urban school and suburban or rural schools ($\gamma_{01} = .42$, $t = .88$, $df = 570$, $p = .379$). However, after accounting for other variables, the effect of BYA14J on mean school mathematics achievement was statistically significant ($\gamma_{02} = -.15$, $t = -6.40$, $df = 570$, $p = .000$). This result indicated that schools with larger number of school receiving remedial mathematics had a negative effect on student mathematics achievement. After accounting for other variables, the effect of BYA23A on mean school mathematics achievement was also statistically significant ($\gamma_{03} = .16$, $t = 4.27$, $df = 570$, $p = .000$), indicating that schools with more full-time mathematics teachers had a positive effect on the mean school mathematics achievement. As the average number of full-time mathematics teachers increased by one unit, the mean school mathematics achievement was increased by 0.16.

The results of contextual model (2) with the level-1 and level-2 predictors

The contextual model (2) can be expressed like this:

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}\text{Gender}_{ij} + \beta_{2j}\text{Ethn1}_{ij} + \beta_{3j}\text{Ethn2}_{ij} + \beta_{4j}\text{Ethn3}_{ij} + \beta_{5j}\text{Ethn4}_{ij} + \beta_{6j}\text{Ethn5}_{ij} + \beta_{7j}\text{Self-Efficacy}_{ij} + r_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\text{BYURBAN}_j + \gamma_{02}\text{BYA14J}_j + \gamma_{03}\text{BYA23A}_j + u_{0j}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$
$$\beta_{5j} = \gamma_{50}$$
$$\beta_{6j} = \gamma_{60}$$
$$\beta_{7j} = \gamma_{70} + \gamma_{71}\text{BYURBAN}_j + \gamma_{72}\text{BYA14J}_j + \gamma_{73}\text{BYA23A}_j + u_{7j}$$

In the final model (contextual model 2) (Table 5), the intercept and the coefficient of self-efficacy from level 1 were treated as random, and the other coefficients were fixed at level 2.

Relative to the unconditional model (Table 3), 10% of the variance in the between school difference in mean mathematics scores was accounted for by BYURBAN, BYA14J and BYA24A at level 2 ((23.30-20.97)/23.30 = 10%). $\tau_{00} = 20.97$, p = .000, indicating that there were still considerable differences between schools that might be accounted for by other level 2 variables. Because $\tau_{11} = .63$, p =.210, there was no significant variance remaining in the self-efficacy slope within schools, indicating the variability in the effect of self-efficacy on mathematics achievement was fully explained.

Insert Table 5 around here

Explaining the Intercepts

Regarding school mean mathematics achievement, the results in the final model (contextual model 2) were the same as or similar to those in the contextual model 1 (Table 4). Overall mean mathematics achievement across schools was still significant from zero (γ_{00} = 40.45, t = 138.00, df = 570, p=.000). After controlling for the number of remedial math students and the number of full-time math teachers in a school, there was no significant difference in mathematics achievement between students in urban school and suburban or rural schools (γ_{01} = .41, t = .87, df = 570, p = .387). However, after accounting for other variables, the effect of the number of remedial math students on mean school mathematics achievement was statistically significant (γ_{02} = -.15, t = -6.40, df = 570, p = .000). This result indicated that schools with a larger number of students receiving remedial mathematics had a negative effect on student mathematics achievement. After accounting for other variables, the effect of the number of full-time math teachers in a school on mean school mathematics achievement was also statistically significant (γ_{03} = .16, t = 4.26, df = 570, p = .000), indicating that schools with more full-time mathematics teachers had a positive effect on the mean school mathematics achievement.

Explaining the Gender slope

The effect of Gender on mathematics achievement in schools was statistically different from zero. $\gamma_{10} = .52$, $t = 2.47$, $df = 9112$, $p = .014$, indicating that male students performed significantly better than female students in mathematics achievement

Explaining the Ethnicity slope

Compared to the White Americans, the Native Americans performed less well in mathematics achievement ($\gamma_{20} = -6.84$, $t = -5.34$, $df = 9112$, $p = .000$). In addition, the African Americans ($\gamma_{40} = -8.85$, $t = -22.52$, $df = 9112$, $p = .000$), Hispanic American ($\gamma_{50} = -6.61$, $t = -17.92$, $df = 9112$, $p = .000$), and the multiracial Americans ($\gamma_{60} = -2.30$, $t = -4.73$, $df = 9112$, $p = .000$) all performed less than the White Americans in mathematics achievement. However, there was no significant difference between the Asian Americans and the White Americans ($\gamma_{30} = .51$, $t = 1.20$, $df = 9112$, $p = .231$);

Explaining the Self-Efficacy slope

The average effect of mathematics self-efficacy on mathematics achievement was significant ($\gamma_{70} = 4.74$, $t = 30.61$, $df = 571$, $p = .000$). After controlling for the number of student receiving remedial mathematics and the number of full-time mathematics teachers, there was a significant effect of a student in an urban school on the self-efficacy slope ($\gamma_{71} = -1.07$, $t = -3.83$, $df = 570$, $p = .000$). This result indicated that the effect of mathematics self-efficacy on mean mathematics achievement was significantly different between urban school and suburban or rural schools. On average, urban schools had significantly lower self-efficacy slopes than suburban or rural schools. After controlling for the effects of the other two variables, the effect of the number of students receiving remedial mathematics in a school on the self-efficacy slope was significant, too ($\gamma_{72} = -.04$, $t = -2.41$, $df = 570$, $p = .017$). On average, schools with more students receiving remedial mathematics tended to have lower self-efficacy slopes than those with less students receiving remedial mathematics. However, there was no significant effect of the number of full-time mathematics teacher in a school on the self-efficacy slope (γ_{73} = .03, t = 1.39, df = 570, p = .165). This indicated that there was no interaction effect between the number of full-time mathematics teachers and mathematics self-efficacy on mathematics achievement.

Conclusions and Implications

In this study, multilevel (hierarchical) modeling was used to investigate the effects of mathematics self-efficacy, other student-level characteristics and school-level variables on mathematics achievement. The results of the fitted models indicated that there was substantial variance in students' mathematics achievement both across schools and within schools. Within schools variance varied more substantially than between schools variance. Both between schools variance and with schools variance were significantly accounted for after level 1 and level 2 variables were added to the HLM models.

Regarding school-level effect on student's mathematics achievement, there was no significant difference in mathematics achievement between students in urban school and suburban or rural schools. Another important finding is that schools with a larger number of students receiving remedial mathematics had a negative effect on student mathematics achievement. This finding suggests that although remedial math classes could help students who struggle in mathematics understand basic concepts and keep up with their peers, a great number of students behind the expected mathematics proficiency level in a school indicated a negative learning environment, which might have a negative effect on mathematics achievement for a particular grade. This study also found that schools with more full-time mathematics teachers had a positive effect on the mean school mathematics achievement. This finding is significant since it provides empirical evidence for recruiting full-time mathematics teachers. When school budget is tight, school administrators are more interested in hiring part-time than full-time teachers. This study suggests that a larger number of part-time mathematics teachers in a school would eventually have a negative impact on mathematics achievement.

Results also indicated that there were achievement gaps between gender and among different ethnic groups. Male students performed significantly better than female students in mathematics achievement. Compared to the White Americans, the Native Americans, the African Americans, Hispanic Americans and the multiracial Americans performed less well in mathematics achievement. No significant difference between the Asian Americans and the White Americans was identified. Our finding also identified that the average effect of mathematics self-efficacy on mathematics achievement was significant and positive.

In addition, there was an interaction effect between a school level factor and students' mathematics self-efficacy. On average, urban schools had significantly lower self-efficacy slopes than suburban or rural schools and schools with more students receiving remedial mathematics tended to have lower self-efficacy slopes than those with fewer students receiving remedial mathematics. No interaction effect between the number of full-time mathematics teachers and mathematics self-efficacy on mathematics achievement was identified.

Implications

Improving students' mathematics achievement has been a great concern for mathematics educators and educational policy makers. They are interested in whether affective factors such as attitude toward mathematics and mathematics self-efficacy have positive effect on students' mathematics learning. Further, school-level factors might also influence students' achievement. Under the No Child Left Behind Act of 2001 (NCLB), schools are required to achieve adequate yearly progress (AYP) for their students. Thus, identifying school-level attributes on students' mathematics achievement is of great interest to mathematics educators, school administrators, and policy makers.

This study was significant in three ways. First, this study would help mathematics educators, administrators, and policy makers to understand whether there was a positive relationship between mathematics self-efficacy and mathematics achievement of high school students. Our findings suggest that efforts are needed for promoting mathematics self-efficacy Second, this study might provide direction for school administrators and policy makers to take actions to close achievement gaps between gender and among ethnic groups. Finally, this study found that school factors, such as the number of students who received remedial mathematics and the number of full-time mathematics teachers had significant effects on students' mathematics achievement. This result suggests that recruiting full-time rather than part-time mathematics teachers might be more beneficial to student achievement and school districts in the long run.

References

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. (1997). *Self-efficacy: The exercise of control.* New York: W. H. Freeman & Company.

Bandura, A. (2000). Exercise of human agency through collective efficacy. Current Directions in Psychological Science, 9(3), 75-78.

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

Brand, S., Felner, R., Shim, M., Seitsinger, A., & Dumas, T. (2003). Middle school improvement and reform: Development and validation of a school-level assessment of climate, cultural pluralism, and school safety. *Journal of Educational Psychology*, 95, 570-588.

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

Ingels, S. J., Pratt, D. J., Roger, J., Siegel, P. H., & Stutts, E. (2004). *ELS: 2002 Base Year Data File User's Manual.* Washington, DC: NCES (NCES 2004-405).

Ingels, S. J., Pratt, D. J., Roger, J., Siegel, P. H., & Stutts, E. (2005). Education Longitudinal Study: 2002/04 Public Use Base-Year to First Follow-up Data Files and Electronic Codebook System. Washington DC: NCES (NCES 2006-346).

Ma, X. (2002). Early acceleration of mathematics students and its effect on growth in self-esteem: A longitudinal study. *International Review of Education*, 48, 443-468, Ma, X., & Klinger, D. A. (2000). Hierarchical linear modeling of student and school effects on academic achievement. *Canadian Journal of Education*, 25, 41-55.

Ma, X., & Willms, J. D. (2004). School disciplinary climate: Characteristics and effects on eighth grade achievement. *Alberta Journal of Educational Research*, 50, 169-189.

McCoach, D. B. (2010). Hierarchical linear modeling. In G. R. Hancock and R. O. Muller (Eds.). *The reviewer's guide to quantitative methods in the social sciences* (pp. 123-154). New York, NY: Routledge.

O'Connell, A. A., & McCoach, D. B. (2008). Pedagogy and context for multilevel models. In A. A. O'Connell and D. B. McCoach (Eds.). *Multilevel modeling of educational data* (pp. 3-10). Charlotte, NC: Information Age Publishing.

Ormrod, J. E. (2008). *Human learning* (5th ed.). Upper Saddle River, NJ: Pearson.

Randhawa, B. S., Beamer, J. E., & Lundberg, I. (1991). Role of mathematics self-efficacy in the structural model of mathematics achievement. *Journal of Educational Psychology, 85,* 41-48.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Zimmerman, B. J., Bandura, A., & Martinez-Pons. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal-setting. *American Educational Research Journal, 29*(3), 663-676.

Table 1

Descriptive Statistics of the Variables in Both Levels

Level 1 Variables	N	Mean	SD
Mathematics Achievement	9126	39.27	11.85
Gender	9126	.48	.50
Eth1 (Native American)	9126	.01	.09
Eth2 (Asian American)	9126	.09	.29
Eth3 (African American)	9126	.10	.30
Eth4 (Hispanic American)	9126	.13	.33
Eth5 (Multiracial American)	9126	.05	.21
Eth6 (White American)	9126	.63	.48
Mathematics Self-Efficacy	9126	2.52	.85
Level 2 Variables			
BYSURBAN: suburban schools or not	574	.31	.46
BYA14J: number of students receiving remedial math in a school	574	6.05	9.81
BYA23A: number of full-time mathematics teachers in a school	574	8.85	5.95

Table 2

One-way Random Effects ANOVA Model

Fixed Effects	Coefficient (SE)	t (df)	p	Reliability
Model for mean school mathematics ach. (β_0)				
Intercept (γ_{00})	38.91 (.27)	145.62 (573)	0.000*	0.80

Random Effects	Variance	df	Chi-square
Var. in school means (τ_{00})	32.94	573	3233.09 (.000)
Var. within school (σ^2)	109.08		
	142.02		

Table 3

Unconditional Model (group-mean centering of self-efficacy)

Fixed Effects	Coefficient (SE)	t (df)	p	Reliability
Model for mean school mathematics ach. (β_0)				
Intercept (γ_{00})	40.57 (.27)	151.94 (573)	.000	0.78
Model for Gender slope (β_1)				
Intercept (γ_{10})	.54 (0.21)	2.58 (9118)	.010	
Model for Ethn1 (Native American) slope (β_2)				
Intercept (γ_{20})	-7.14 (1.29)	-5.56 (9118)	.000	
Model for Ethn2 (Asian American) slope (β_3)				
Intercept (γ_{30})	.66 (.43)	1.54 (9118)	.124	
Model for Ethn3(African American) slope (β_4)				
Intercept (γ_{40})	-8.83 (.39)	-22.46 (9118)	.000	
Model for Ethn4 (Hispanic American) slope (β_5)				
Intercept (γ_{50})	-6.50 (.37)	-17.67 (9118)	.000	
Model for Ethn5 (Multiracial American) slope (β_6)				
Intercept (γ_{60})	-2.27 (.49)	-4.64 (9118)	.000	
Model for Self-efficacy slope (β_7)				
Intercept (γ_{70})	4.44 (.12)	35.68 (9118)	.000	

Random Effects	Variance	df	Chi-square
Var. in school means(τ_{00})	23.30	573	2920.50 (.000)
Var. within school (σ^2)	88.65		
	111.95		

Table 4
Contextual Model (1) with BYSUB, BYRURAL, BYA14J and BYA23A in the Level-1 Random Intercept

Fixed Effects	Coefficient (SE)	t (df)	p	Reliability
Model for mean school mathematics ach. (β_0)				
Intercept (γ_{00})	40.44 (.29)	137.997 (570)	.000	0.76
BYSURBAN (γ_{01})	.42 (.48)	.88 (570)	.379	
BYA14J (γ_{02})	-.15 (.02)	-6.40 (570)	.000	
BYA23A (γ_{03})	.16 (.04)	4.27 (570)	.000	
Model for Gender slope (β_1)				
Intercept (γ_{10})	.55 (0.21)	2.60 (9115)	.010	
Model for Ethn1 (Native American) slope (β_2)				
Intercept (γ_{20})	-6.79 (1.28)	-5.30 (9115)	.000	
Model for Ethn2 (Asian American) slope (β_3)				
Intercept (γ_{30})	.50 (.43)	1.17 (9115)	.242	
Model for Ethn3(African American) slope (β_4)				
Intercept (γ_{40})	-8.91 (.39)	-22.65 (9115)	.000	
Model for Ethn4 (Hispanic American) slope (β_5)				
Intercept (γ_{50})	-6.63 (.37)	-17.95 (9115)	.000	
Model for Ethn5 (Multiracial American) slope (β_6)				
Intercept (γ_{60})	-2.33 (.49)	-4.76 (9115)	.000	
Model for Self-efficacy slope (β_7)				
Intercept (γ_{70})	4.44 (.12)	35.69 (9115)	.000	

Random Effects	Variance	df	Chi-square
Var. in school means(τ_{00})	20.90	570	2689.04 (.000)
Var. within school (σ^2)	88.62		

Table 5

Contextual Model (2) with BYSUB, BYRURAL, BYA14J and BYA23A in the Level-1 Random Intercept and the Self-Efficacy Slope

Fixed Effects	Coefficient (SE)	t (df)	p	Reliability
Model for mean school mathematics ach. (β_0)				
Intercept (γ_{00})	40.45 (.29)	138.00 (570)	.000	0.77
BYURBAN (γ_{01})	.41 (.48)	.87 (570)	.387	
BYA14J (γ_{02})	-.15 (.02)	-6.40 (570)	.000	
BYA23A (γ_{03})	.16 (.04)	4.26 (570)	.000	
Model for Gender slope (β_1)				
Intercept (γ_{10})	.52 (0.21)	2.47 (9112)	.014	
Model for Ethn1 (Native American) slope (β_2)				
Intercept (γ_{20})	-6.84 (1.28)	-5.34 (9112)	.000	
Model for Ethn2 (Asian American) slope (β_3)				
Intercept (γ_{30})	.51 (.43)	1.20 (9112)	.231	
Model for Ethn3(African American) slope (β_4)				
Intercept (γ_{40})	-8.85 (.39)	-22.52 (9112)	.000	
Model for Ethn4 (Hispanic American) slope (β_5)				
Intercept (γ_{50})	-6.61 (.37)	-17.92 (9112)	.000	
Model for Ethn5 (Multiracial American) slope (β_6)				
Intercept (γ_{60})	-2.30 (.49)	-4.73 (9112)	.000	
Model for Self-efficacy slope (β_7)				
Intercept (γ_{70})	4.74 (.16)	30.61 (570)	.000	
BYURBAN (γ_{71})	-1.06 (.28)	-3.83 (570)	.000	
BYA14J (γ_{72})	-.04 (.01)	-2.41 (570)	.017	
BYA23A (γ_{73})	.03 (.02)	1.39 (570)	.165	

Random Effects	Variance	df	Chi-square
Var. in school means (τ_{00})	20.97	568	2668.50 (.000)
Var. in Self-Efficacy slope (τ_{11})	.63	568	593.94 (.210)
Var. within school (σ^2)	88.00		
	109.60		