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A Multi-level Model Approach to Investigating Factors Impacting Science Achievement for Secondary School Students – PISA Hong Kong Sample

Letao Sun[1] and Kelly D. Bradley

University of Kentucky

1. Use L. Sun as author of contact. She may be reached at sltwendysun@gmail.com

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Abstract

This study utilized data from the Programme for International Student Assessment (PISA) 2006 Hong Kong sample to investigate the factors that impact the science achievement of 15-year old students. A two- level hierarchical linear model was used to examine the factors that influence science achievement from both student and school perspectives. At the student level, the results indicated that male students, students from high SES families, and students whose parents have higher values on the importance of science are more likely to have better achievement in science. At the school level, the results showed that the variation of science achievement between schools can be explained by differences in school enrollment size and school SES composition. This finding leads to an international discussion of school size.

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Science and technology play an important role in the modern world. Science education is believed to serve as the foundation of technological development and a key factor in economic growth. Given the United States' goal of being the most scientifically advanced country in the world, the lag behind other countries in student science achievement scores is alarming (Beaton et al, 1996). International comparative studies such as International Assessment of Educational Progress (IAEP), and the Third International Mathematics and Science Study (TIMSS), have found that while students from Hong Kong, the People's Republic of China and Taiwan perform consistently higher than students from the U.S., no significant differences were found in curriculum, aptitude or expenditure per student (Wang, 2001). Other factors, such as family value system, family background, or school characteristics may play an important role in determining the academic success of the students. Studies of the academic achievement of Chinese immigrant groups (Fuligni, 1997) and Indochinese refugee families (Caplan, Choy, & Whitmore, 1992) living in the United States have demonstrated such impacts.

A distinct gender gap has been found by previous studies in science achievement scores of students at middle school and high school (Good, Woodzicka, & Wingfield, 2010; Sanchez & Wiley, 2010). Comparing scores on the National Center for Education Statistics (NAPE) across three decades, researchers found that although the gender gap in science scores has decreased since 1969, male students still outperformed female students on the assessment at middle school and high school. (Campbell, Hombo, & Mazzeo, 2001).

Family influences can be separated into several components. Coleman (1997) proposed that family influences can be divided into economic, human, and social capital components. Steinberg (1996) divided family influences into three different aspects including parenting style, established academic goals for their children, and the practices adopted to help children attain those goals. Mashile (2001) pointed out that family aspects such as parenting style, socioeconomic status (SES), parental involvement, and parental belief and attitude are particularly related to children's science achievement and academic attitude.

Parental attitudes have been show to impact students' science outcome in two ways. First, parental attitudes toward science influence the students' science attitude. Children tend to develop similar attitudes toward science as their parents. Bourdieu (1998) claimed that within social groups, parents provide experiences that result in children developing similar tastes, academic motivations and preferences. Eventually, these attributes are related to differences in academic and occupational outcomes of the students. Papanastasiou (2002) found that parents' reinforcement, like high expectation on science performance, has the second strongest direct influence on students' attitude towards science. In turn, students' attitudes have a major influence on science achievement and the pursuance of science careers. Second, parental attitude has a significant effect on parental involvement of students' science studies. This can be either direct participation in science activities or indirect improvement on home resources. George and Kaplan (1998) reported that parents with positive attitudes toward science have more interactions with schools regarding schoolwork and are more likely to take their children to libraries and science museums. In their study, the availability of home resources like computers and science books were also found to be highly correlated to parents' science attitudes.

The role of family SES in determining student academic performance has always been an area of considerable attention in educational studies. A great number of studies have established an empirical relationship between students' family SES and their academic achievement, even though the strength of the relationship varies to a great extent. Family SES, which will largely determine the location of the child's neighborhood and school, not only directly provides home resources but also indirectly provides "social capital," that is, supportive relationships among schools and individuals (i.e., parent-school collaborations) that promote the sharing of societal norms and values, which are necessary to success in school (Dika & Singh, 2002).

School factors explain student academic achievements from another perspective. OECD 2007 reported that on average of OECD countries, about one-third of all variation in student performance (33%) was between schools. In Germany and Bulgaria, the performance variation between schools was about twice the OECD average. Research on school effects plays a critical role in many on-going educational reforms. In America, the enactment of No Child Left Behind (NCLB, 2002) federal legislation requires states to develop content-based standards to assess students' academic performance annually, and to hold schools accountable for substandard student outcomes. Previous studies classified school characteristics into two types: context and climate. Context characteristics describe the physical background (e.g., school location and resources), the student body (e.g., school socioeconomic status), and the teacher body (e.g., teacher education levels and teaching experience). Climate variables referred to as evaluative variables, which describe the learning environment (e.g., instructional organization and school operation) (Ma, Ma, & Bradley, 2008).

Before 2009, the structure of the education system (a 6-5-2-3 system) in Hong Kong followed the typical British system of 6 years of primary school (G.1 to G.6), 5 years of secondary school (G.7 to G. 11 leading to a certificate examination), 2 years of pre-university study (G.12 and G.13, leading to an advanced-level examination), and 3 years of university study. The first 9 years of schooling (G.1 to G.9) are considered basic education and are compulsory for all children (typically from age 6 to 15). Beginning in 2009, the education system structure changed from 6-5-2-3 system to a 6-3-3-4 structure (6 years of primary school, 3 years of junior secondary school, 3 years of senior secondary school, and 4 years of university).

Hong Kong students have been ranked one of the highest scorers in the international assessments of student science performance since 2000: 15 year-old students ranked third in 2000 and 2003, second in 2006 in Programme for International Student Assessment (PISA); both 4th and 8th grade students ranked fourth in 2003, 4th grade students ranked third and 8th grade students ranked ninth in the 2007 in Trends in International Mathematics and Science Study (TIMSS).

The purpose of this study is to use Hierarchical Linear Model (HLM) to investigate the factors that affect Hong Kong students' science achievement. Hierarchical Linear Model or Multilevel Modeling is the most appropriate statistical technique for hierarchical structure such as students nested within schools. Using a two - level hierarchical linear model, the factors that influence science outcomes were examined from both student and school perspectives.

Method

Data Sources

Data for the present study were from the Programme for International Student Assessment (PISA) 2006 Hong Kong sample (see www.pisa.oecd.org). PISA is an internationally standardized assessment that measures students' capabilities in mathematics, reading, and science literacy. According to OECD (2001), PISA focuses on young people's ability to use their knowledge and skills to meet real-life challenges, rather than merely on the extent to which they have mastered a specific school curriculum. Beginning from 2000, PISA is administrated every three years to groups of 15-year-old students in principal industrialized countries. One of the subject or literacy areas is focused on at each administration. As the 2006 PISA study was focused on science, the 2006 PISA survey was utilized in this study. In 2006 PISA, three different questionnaires were designed for students, parents and schools respectively, and each form contained a number of scales to assess student, parent, and school effects on science achievement. The Hong Kong sample contains 4,645 7th to 11th grade students (M = 9.51, SD = .756) from 146 schools.

Variables

The dependent variable in this study is identified as student science literacy test scores. Scientific literacy was defined as "the capacity to use scientific knowledge, to identify questions and to draw evidence-based conclusions in order to understand and help make decisions about the natural world and the changes made to it through human activity" (Artlet, Baumert, Julius-McElvany, & Peschar, 2003, p. 15). PISA assessed students' science competencies over three areas:

1. Identifying scientific issues. This involves recognizing issues that are possible to investigate scientifically, identifying keywords to search for scientific information and recognizing the key features of a scientific investigation.

2. Explaining phenomena scientifically. This involves applying knowledge of science in a given situation, describing or interpreting phenomena scientifically and predicting changes and identifying appropriate descriptions, explanations and predictions.

3. Using scientific evidence. This involves interpreting scientific evidence and making and communicating conclusions, identifying the assumptions, evidence and reasoning behind conclusions, and reflecting on the societal implications of science and technological developments.

To reduce the length of the test, PISA applied matrix sampling, which splits one long test booklet into several short test booklets. Therefore, each student works on one booklet only. Because students complete different tests, science achievement cannot be obtained using traditional test scores, but instead by using plausible values. Plausible values are multiple imputations of unobservable latent achievement for each student. Simply put, plausible values are some kind of student ability estimates. Instead of obtaining a point-estimate for student ability, which is a traditional test score for each student, an estimated probability distribution was derived empirically from the observed values on students' tests and their background variables. Plausible values then are drawn at random from this probability distribution for each student (Ma, Ma, & Bradley, 2008). Adams and Wu (2002) provided details about how plausible values are created and used. PISA 2006 used five plausible values to present students' science achievement.

The independent variables in this study included student level variables and school level variables. Many of the variables in these two levels were index variables from PISA surveys 2006. PISA used a number of questionnaire items to construct these indicators. Adam and Wu (2002) provided details on how those indicators were constructed.

Sex (dummy coded for female=0 and male=1), student socioeconomic status (SES), and parental values on science were selected as student level variables. At the school level, variables descriptive of school context and school climate were selected. School enrollment size, school socioeconomic composition, shortage of science teachers, and quality of education resources were selected as school context variables; school science promotion, teaching strategies, and school autonomy were used as school climate variables in this study. Table B2 in the Appendix lists how the variables were constructed.

Statistical Models and Analysis

A two-level Hierarchical Linear Model (HLM) was developed to explore the factors that affect student science literacy scores at both student and school levels. Hierarchical structure exists in a large number of educational studies. For example, students are nested within the schools, students are nested within classes, and schools are nested within districts, and so on (Hox, 2002). Because of these grouping effects, the interaction between students makes students in the same group more alike than the students in different groups. Consequently, the observation of students within group can no longer be considered statistically independent, which means the traditional statistical approaches, like regression or ANOVA, are seriously flawed and not really applicable (Goldstein, 1995; Raudenbush & Bryk, 2002). Failure to recognize the hierarchical nature of data in educational settings, or any setting for that matter, results in unreliable estimation of the effectiveness of schools and their practices, which could lead to misinformed educational policies or practices (Raudenbush & Bryk, 2002).

Hierarchical Linear Model (HLM) or Multilevel Modeling is the most appropriate statistical technique for hierarchical data. With hierarchical linear models, each of the levels in this structure is represented by its own submodel. These submodels express relationships among variables within a given level, and specify how variables at a higher level influence characteristics and processes at a lower or parallel level. Another advantage of this technique is that the software program on multilevel data analysis, Hierarchical Linear Modeling (HLM) enables the usage of plausible values. During the process of reading, the software integrates the plausible values and creates the outcome variable. (Raudenbush, Bryk, Cheong, & Congdon, 2000).

Sampling weights for students and schools were used in the analysis to correct for imperfections in the sample that might have led to bias and other departures between the sample and the reference population. In order to limit the possibility of multicollinearity, the variables at student level and school level were centered around their means. In this way, the grand mean from the multilevel model can become a meaningful average measure of science achievement of the students in Hong Kong.

A backward elimination process was used to determine whether each variable have a significant relative effect on the dependent variable when other variables are controlled, therefore, each variable was treated as fixed effect in their level. The goal is to find the least complex model to best predict the science achievement. According to Micceri (2007), "Because all social science contexts are complex, only analyses that can isolate the unique impact (unique variation) of specific factors at their various levels, such as multilevel modeling, are appropriate. Effectively, Multilevel Modeling uses Backward Elimination rather than Stepwise to model equations thereby primarily unique rather than shared variance to determine a variables contribution to a model" (p. 13).

The HLM modeling procedure in this study has three steps. At first step, the analysis produced the null model with only student level outcome variable but no independent variables at the student level or school level. This null model was similar to a random-effect ANOVA model, providing the information of the variances within and between schools for science achievement measure (Ma & Klinger, 2000). At the second step, a student level model was developed without variables at the school level. This step is to examine the effects of student characteristics on the dependent variable. School variables were added to the student model at the third step. This 'full' model was created to examine what school background characteristics influence the relationship between science achievement and student level variables. Raudenbush and Bryk (2002) provided the details about the statistical theory and methodological approach of HLM.

Results

Table 1 shows the descriptive statistics for independent variables at both student and school levels.

Table 1.

Description of independent variables.

Variable	*M*	*SD*
Student characteristics		
Sex (1=female; 2=male)		
Student SES	-.68	.93
Parental values on science	.50	2.18
School characteristics		
School enrollment size	1040.37	174.17
School SES composition	-.68	.48
Shortage of science teachers	1.34	.70
quality of education resources	.34	.96
school science promotion	.94	.65
Teaching strategies	2.26	.13
School autonomy	.33	.17

Table 2 and Table 3 present statistical results from the null model estimated based on (1):

Level 1 Model:

$$\text{Science achievement} = \beta_{0j} + \gamma_{ij} \quad (1)$$

Level 2 Model:

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

In this null model, the intercept β_{0j} represented the average science achievement for the *J* school (*j*= 1, 2, … *J*). These intercepts vary at the school level. Results show that the average science achievement of Hong Kong students is reported to be around 534 points. Given the PISA science international scale (*M* = 500, *SD* = 100), the Hong Kong students scored higher than the international average. The variance component at student level is 5441.40 and the variance component at school level is 3280.61, the result indicating a large variance of average science achievement across Hong Kong schools ($\chi^2(143)= 2874.87$, $p < 0.01$). Intra-class correlation indicates that about 37.61% of the total variance in science achievement is attributable to school effects.

Table 2.

Fixed effects of the null model

	Coefficient	*SE*	T-ratio	*p*
Intercept (science achievement) γ_{00}	533.63	5.68	94.01	<.01

Table 3.

Random effects of the null model

	Variance	*df*	Chi-square	*p*
Between-school variability (intercept)	3280.61	143	2874.87	<.01
Within-school variability	5441.40			

The final full model equation of present study is shown below. (See Equation (2)),

The intercept of the full model, β_{0j}, represent adjusted mean for each school.

Level 1 Model:

$$\text{Science achievement}_{ij} = \beta_{0j} + \beta_{1j}(\text{SEX}) + \beta_{2j}(\text{Student SES})_{ij} + \beta_{3j}(\text{Parental values on science})_{ij} + \gamma_{ij}$$

Level 2 Model: (2)

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{School enrollment size}) + \gamma_{02}(\text{School SES composition}) + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

Table 4 and Table 5 show the statistical results of the full model suggested by HLM software program. The reliability estimate of .899 suggests that it is well for us to discriminate schools using least square estimate of the coefficient (β_{0j}).

Table 4.

Fixed effects of the full model

	Coefficient	*SE*	T-ratio	*p*
Intercept (science achievement) γ_{00}	542.01	3.83	141.65	<.01
Student characteristics				
Sex (0=female; 1=male) γ_{10}	19.53	2.76	7.09	<.01
Student SES γ_{20}	8.47	1.83	4.62	<.01
Parental views on science γ_{30}	3.85	0.63	6.08	<.01
School characteristics				
School enrollment size γ_{01}	0.15	0.02	7.11	<.01
School SES composition γ_{02}	38.76	8.40	4.61	<.01

Table 5.

Random effects of the full model

	Variance	*df*	Chi-square	*p*
Between-school variability (intercept)	1482.92	141	1388.75	<.01
Within-school variability	5133.06			

When the hierarchical model is fit at both student and school levels, the effects of student level variables can be interpreted more meaningfully (Ma, Ma & Bradley, 2008). Sex, student SES, and parental values on science at student level all impact the student science achievement. Coefficient value (γ) of each independent variable is the relative effect which was adjusted /controlled for other variables in the model For example, for every one unit (*SD*) increase in students' SES, the student science score will increase 8.47 points when controlling all other variables as constant (γ_{20}=8.47).

At the school level, school enrollment size and school SES composition were found to be the predictors of the average science achievement at each school. In this full model, the intercept of variables at school level can be explained like: for every unit (*SD*) increase of school enrollment size, the student science achievement will increase 0.15 points when all other variables were controlled (γ_{01}=0.15). All the slops (coefficients) we found to be positive, which suggests that: (1) on average, a male student's science literacy scores will be 19.53 points higher than female students; (2) students from higher SES families are more likely to have better achievement in science; (3) students whose parents have higher values on the importance of science are more likely to have higher science scores; (4) students from schools with bigger enrollment size are more likely to have science achievement; and (5) students from the higher average SES schools are more likely to have science achievement. In comparison with the null model, the final student model explained about 6% of the variance at student level and about 55% of the variance at the school level.

Discussion

There was a relatively large gap found between male and female scores in the present study (γ_{10}= 19.53). This is consistent with previous studies, which have indicated that male students perform better than female students in math and science. However, the present study points out an additional reason that could widen the gap between males and females in the Hong Kong sample. This factor is related to the Chinese culture that is more patriarchal and male-dominated, which results in more investment and higher expectations placed on males than on females (Chen, Lee, & Stevenson, 1996; Liu, 2006). Still, there is a common trend in current research to demonstrate a decline in male/female differences in science performance, yet female representation in science-related fields is still low (Jacobs, 2005).

The present findings seem to be consistent with other studies which found that students' SES performs as a statistically significant positive contributor to students' science learning outcomes; however, this effect here was not very substantial compares to previous similar studies. The governmental intervention could be an influential component in education; Hong Kong government provides subsidized education or financial aid to support all 6 to 15-year-old students (Post, 2003).

Parental values on the importance of science was also found to be a statistically significant factor. The results suggest that the with one unit increase of parental views, student science achievement will increase 3.85 points when controlling all other variables. This factor was ranged from -8.65 to 5.76 with a mean score of 2.18 and *SD* of .5, these findings suggest that on average, Hong Kong parents have a higher value on the importance of science.

More than half of the variances on science achievements were found to be explained by school factors in this study. In contrast to earlier findings that smaller schools is better for student learning (Cotton, 2002; Steward, 2009), however, no evidence of negative relationship between school enrollment size and student science learning outcomes was detected. Instead, the findings indicate that the school enrollment size acts as a facilitating factor for students' science performance. In addition, a bivariate correlation test between school size and school average science score suggests a positive linear relationship and no suppressor effect in this model. A possible explanation for this might be that larger student body schools are more likely to have more grants or financial opportunities, and greater support from parents (There is a positive correlation between school enrollment size and school SES, $r = .363$, $p < .001$), therefore, they are more likely to attract and retain qualified and talented teachers, as well as create larger peer effect as more active and bright students work together.

Significance

The current study adds supplementary information to the existing body of literature on the parental factors influencing the students' learning outcomes. The impact of parental values on the importance of science was found to be statistically significant in explaining differences in academic achievement. Therefore, it is recommended that parents orient their children toward more scientific disciplines for their instrumental and pragmatic importance. This study has policy implications by generating more interaction/cooperation between schools and parents. Schools should expend more effort in informing parents about how to better invest cultural resources than material resources at home, so that the latter becomes more informed about the significance of scientific studies and therefore influence their children's preference and academic choices.

Also, it is suggested by TIMSS study (Kifer & Robitaille, 1989), indicators of home support was found to have positive effects on students' math achievements in some countries but have negative effects in other countries. Such contradictory findings suggest similar studies on parental values on science in other countries and regions in order to generalize the findings of this research at the international level.

The present effective learning reform of school reconstruction is taking the trends of both consolidating smaller schools into larger schools and breaking large schools into small learning environments. The findings of present study suggest a reconsideration of criticizing larger schools. The impact of school size on student achievement is associated with other factors both at student level and school level (e.g., SES, teacher-student ratio, race, location, curriculum and instruction). Some recent studies had found that bigger school size is benefit for learning outcomes in high school and for high SES students (Howley & Howley, 2004; McMillen, 2004; Weiss, Carolan, & Baker-Smith, 2010). Therefore, public policy makers should not be in a hurry to conclude that "smaller is better" before accurately assessing the downside of large school system. Simply creating smaller schools or dividing larger schools may not produce the desired effect. Because of the sample limits, even though the Hong Kong 2006 sample shows a pattern of positive correlation between school size and science achievement, the influence of schools which size is bigger than 1400 or less than 500 had not been explored. Also, researchers are suggested to use more functional factors like the student-teacher ratio, class size to replace school size or to explore what is the best unit size for student learning in future studies.

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APPENDIX

Table A1: *Description of weights.*

	N	Mean	*SD*	Min	Max
Student Weight	4645	16.18	5.21	11.29	80.21
School Weight	146	3.28	2.11	2.05	24.70

Table B1: Variables at the student level.

Variable	Questionnaire
Sex	*Are you female (1) or male (2)?
Student socioeconomic status (SES) ([a] ESCS in PISA 2006 dataset)	
Parental values on science (derived from □ PQSCIMP, □ PQGENSCI, and □ PQPERSCI in PISA 2006 dataset)	

Note: * indicates items from the Student Questionnaire.
[a] ESCS is explained in PISA 2006 Technical Report (OECD, 2009, p. 346), measures economic, social and cultural status.
□ PQSCIMP is explained in PISA 2006 Technical Report (OECD, 2009, p. 343), measures parent's views on importance of science.
□ PQGENSCI is explained in PISA 2006 Technical Report (OECD, 2009, p. 344), measures parents' view on general value of science.
□ PQPERSCI is explained in PISA 2006 Technical Report (OECD, 2009, p. 344), measures parents' view on personal value of science.

Table B2: Variables at school level.

Variable	Questionnaire
School enrollment size	***As at <February 1, 2006>, What was the total school enrolment (number of students)?
School socioeconomic composition (created by averaging the SES of students within each school)	
Shortage of teachers	***Is your school's capacity to provide instruction hindered by any of the following? a) A lack of qualified science teachers

Table B2: Variables at school level (continued)

Quality of education resources ([a] SCMATEDU in PISA 2006 dataset)	
School science promotion (□ SCIPROM in PISA 2006 dataset)	
Teaching strategies	*When learning <school science> topics at school, how often do the following activities occur? a) Students are given opportunities to explain their ideas b) Students spend time in the laboratory doing practical experiments c) Students are required to design how a school science question could be investigated in the laboratory d) The students are asked to apply a school science concept to everyday problems e) The lessons involve students' opinions about the topics f) Students are asked to draw conclusions from an experiment they have concluded g) The teacher explains how a school science idea can be applied to a number of different phenomena (e.g. the movement of objects, substances with similar properties) h) Students are allowed to design their own experiments i) There is a class debate or discussion j) Experiments are done by the teacher as demonstrations k) Students are given the chance to choose their own investigations l) The teacher uses school science to help students understand the world outside school m) Students have discussions about the topics n) Students do experiments by following the instructions of the teacher o) The teacher clearly explains the relevance of broad science concepts to our lives p) Students are asked to do an investigation to test out their own ideas q) The teacher uses examples of technological

	application to show how school science is relevant to society.
School autonomy	***Regarding your school, who has a considerable responsibility for the following tasks? a) Selecting teachers for hire b) Firing teachers c) Establishing teachers' starting salaries d) Determining teachers' salaries increases e) Formulating the school budget f) Deciding on budget allocations within the school g) Establishing student disciplinary policies h) Establish student assessment policies i) Approving students for admission to the school j) Choosing which textbooks are used k) Determining course content l) Deciding which courses are offered.

Note: * indicates items from the Student Questionnaire; ***indicates item from the School Questionnaire.
Categories relate to Shortage of teachers and Shortage of instructional resources were “not at all”, “very little”, “to some extent” and “a lot”.
Categories relate to Science promotion program were “yes” and “no”.
Categories relate to Teaching strategies were “in all lessons”, “in most lessons”, “in some lessons”, and “never or hardly ever”.
Categories relate to School autonomy were “principal or teachers”, “school governing board”, “regional or local education authority”, and “national education authority”.
[a] SCMATEDU is explained in PISA 2006 Technical Report (OECD, 2009, p. 340), measures of quality of educational resources.
 SCIPROM is explained in PISA 2006 Technical Report (OECD, 2009, p. 341), measures of school activities to promote the learning of science.