International Journal of Science Education
Vol. 34, No. 14, September 2012, pp. 2107–2125

A Multilevel Modelling Approach to Investigating Factors Impacting Science Achievement for Secondary School Students: PISA Hong Kong Sample

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This study utilized data from the 2006 Programme for International Student Assessment Hong Kong sample to investigate the factors that impact the science achievement of 15-year-old students. A multilevel model was used to examine the factors from both student and school perspectives. At the student level, the results indicated that male students, students from high socioeconomic status (SES) families, students with higher motivation and higher self-efficacy, and students whose parents highly value science are more likely to demonstrate achievement in science. At the school level, the results showed school science achievement differences can be explained by school enrolment size, school SES composition, and instruction time per week. Contrary to the negative influence of school size that was reported in previous studies, our findings suggested a positive relationship between school enrolment size and science achievement. This finding leads to an international discussion of school size.

Keyword: *PISA*

The past decades have witnessed a rapid economic growth and dramatic changes in everyday life due to the advances in technology and globalization. Therefore, many countries start to call for reform in science education and reinforce its fundamental

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ISSN 0950-0693 (print)/ISSN 1464-5289 (online)/12/142107–19

http://dx.doi.org/10.1080/09500693.2012.708063

role in technological development and global economic competition (Kennepohl, 2009; Liu, 2009). More and more countries and regions participate in international science assessments in recent years. Tracking their rank in international comparative science studies allows them to monitor their progress among other global competitors and detect what lies behind any differences. Beaton et al. (1996) pointed out that given the USA' goal of being the most scientifically advanced country in the world, the lag behind other countries in student science achievement scores was alarming.

Attempting to improve students' science education, a number of countries have developed relatively prescriptive curricula. However, Atkin and Black (1997) found no evidence to support the idea that a country with nationally prescribed standards resulted in higher achievement than others with no such guidelines. This finding was further supported by international comparative studies such as the International Assessment of Educational Progress, and the Third International Mathematics and Science Study (TIMSS), which revealed that while students from Hong Kong, the People's Republic of China, and Taiwan perform consistently higher than students from the USA, no significant differences were found in curriculum, aptitude, or expenditure per student (Wang, 2001, 2004). Other factors, such as family value system, family background, home environment or school characteristics are determined to play an important role in explaining the different academic success among students. Studies of the academic achievement of Chinese immigrant groups (Fuligni, 1997) and Indochinese refugee families (Caplan, Choy, & Whitmore, 1992) living in the USA have demonstrated such assertions.

The purpose of this study was to explore the factors that affect the students' science achievement in Hong Kong. We use Walberg's (1981) psychological theory of educational productivity as a theoretical framework and interpret results from a multilevel approach. Although Walberg's model has been proven to be effective and consistent across different subjects and school levels in the USA (Young, Reynolds, & Walberg, 1996), little research has been conducted concerning how predictive patterns of the latent factors may differ by gender and culture. Hong Kong students' science performance has often been compared and investigated in international comparative studies; however, fewer researches have been conducted to explore students' achievement differences within the region.

Literature Review

Walberg's Psychological Theory of Educational Productivity

Seeking to improve students' academic performance and the quality of education, many factors have been investigated for their influence on student achievement. Walberg (1981) proposed a psychological theory of educational productivity to explain student achievement differences. Walberg's model includes nine important dimensions which are categorized in three sets: student aptitude, instruction, and social–psychological environment. Student aptitude includes ability (e.g. prior achievement), development level (e.g. age), motivation or self-concept as indicated by personality tests or willingness to persevere on learning tasks. Instruction includes the quantity of the instruction (e.g. amount of time students engage in learning) and the quality of the instructional experience. The social–psychological environment factors include home, classroom or school, peer group, and mass media. These dimensions have been proven to be effective, consistent, and generalizable since they are grounded upon wide-ranging syntheses from thousands of research literature, with a particular emphasis on meta-analyses and econometric analyses of (mostly national) large-scale surveys that reveal the causes of achievement (Walberg, 1984; Wang & Staver, 2001).

Given the demonstrated influence of educational productivity theory on achievement in academic domains, researchers have turned to an examination of how the latent factors in this theory should be measured. Along with studies in educational psychology, researchers argued that self-efficacy beliefs should be included in science education research for its profound influences on student interest, effort, and performance in science (Britner & Pajares, 2001, 2006). According to Bandura's (1986, p. 391) social cognitive theory, 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'. Self-efficacy beliefs have been shown to affect educational performance through their influence on motivation, achievement, and self-regulation. High self-efficacy beliefs are associated with stronger interests in science-related careers and with a greater likelihood of selecting science-related majors (Luzzo, Hasper, Albert, Bibby, & Martinelli, 1999; Schoon, 2001). Lent, Brown, and Larkin (1986) found that self-efficacy contributed significantly to the prediction of science grades, persistence, and range of career options even when the variance due to ability, high school achievement, and vocational interests had been removed. Pajares (1996) argued that discipline-specific assessments of self-efficacy were particularly typical in empirical studies because achievement test results are convenient and easy to obtain. Thus, researchers can utilize appropriate assessments of self-efficacy at a certain level of specificity to correspond the academic outcomes, and such correspondence will enhance the prediction of self-efficacy.

Most previous studies about the home factors that influence student science learning only considered family socioeconomic status (SES); however, more and more research findings pointed out that family dimensions such as parenting style, parental involvement, and parental attitude are significantly related to children's science achievement and academic attitude (Mashile, 2001). Parental attitudes impact student achievement in science in two ways. First, children tend to develop similar attitudes towards 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 parental reinforcement with high expectations of performance in science has the second strongest direct influence on students' attitude towards science. In turn, students' attitudes influence their science performance and their pursuit of science careers conspicuously. Also, parental attitude significantly influences parental involvement in their students' science studies. This can be either direct participation in science activities or indirect support offered at home. George and Kaplan (1998) reported that parents with positive attitudes towards science interact with schools and teachers more frequently 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. Based on the above statement, we hypothesized that parental values on the importance of science can be an effective predictor of student science learning outcomes.

In addition, recent studies on the influential role of school characteristics in explaining student achievement differences and the extent to which various school features directly impact student learning suggested examining school characteristics from two perspectives: context and climate. Context characteristics describe the physical background (e.g. school location and resources), the student body (e.g. enrolment size and student body SES), and teachers (e.g. teaching experience and teacher education levels). Climate variables, also referred to as evaluative variables, describe the learning environment (e.g. instructional organization and school autonomy) (Ma, Ma, & Bradley, 2008).

Hong Kong Education System and Hong Kong Students' Performance in International Science Assessments

Before 2009, the structure of the education system in Hong Kong followed the typical British system of six years of primary school (Grades 1–6), five years of secondary school (Grades 7–11 leading to a certificate examination), two years of pre-university study (Grades 12 and 13, leading to an advanced-level examination), and three years of university study (a 6–5–2–3 system). The first nine years of schooling (Grades 1–9) are considered basic education and are compulsory for all children (typically from age 6 to 15). Beginning in 2009, the education system changed from a 6–5–2–3 system to a 6–3–3–4 structure (six years of primary school, three years of junior secondary school, three years of senior secondary school, and four years of university). This change provides Hong Kong a better framework for setting standards/goals of science education at different school levels and comparing them with international standards.

Hong Kong students have ranked among the highest scorers in the international assessments of student science performance since 2000: 15-year-old students ranked third in 2000 and 2003, and 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 2007 in the Trends in TIMSS. Such outstanding achievement warrants further investigation to determine which specific factors affect these impressive outcomes.

Although Walberg's theory of educational productivity held up well under many rigorous tests using regression or structural model analyses (Young et al., 1996), the hierarchical nature of data in educational settings has been failed to be recognized.

Some studies using Walberg's model argued that since nine factors are measured individually, a single-level analysis is appropriate for experimental and correlational studies. Other researchers, however, pointed out that individual performance is affected by factors at other levels. For example, students taught by the same teacher will perform more alike than those taught by different teachers. This interdependence violates the assumption of independency thus traditional single-level analysis, like regression or ANOVA, is seriously flawed and should no longer be used (Goldstein, 1995; Raudenbush & Bryk, 2002). Results from such estimations are unreliable and could mislead those who develop educational policies and practices.

The purpose of this study is to use Multilevel Modelling (MLM) to explore the factors that affect the science achievement of Hong Kong students. MLM or Hierarchical Linear Modelling is the most comprehensive statistical technique for analysing hierarchical structures such as students nested within schools. Through this approach, the factors that influence science outcomes were examined from both student and school perspectives. Determining which factors influence student science education is important to educational stakeholders, especially for educational decision-makers who can respond to new information and consider how to use these findings to guide policy and practice.

Method

This exploratory study utilized the 2006 Hong Kong PISA sample. Using MLM, various factors at the student level and the school level were explored to predict science achievement. A detailed outline of research process is presented below.

Data Sources

Data for this study were from the 2006 PISA Hong Kong sample. PISA is an internationally standardized assessment that measures students' capabilities in mathematics, reading, and science literacy. According to OECD (2001), PISA focuses on the ability of young people 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 in 2000, PISA has been administrated every three years to randomly selected groups of 15-year-old students primarily in industrialized countries. One subject or literacy areas is emphasized at each administration. As the 2006 PISA study focused on science, the 2006 PISA survey was utilized in this study. In the 2006 PISA study, three different questionnaires were designed for students, parents, and schools, and each survey 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 ($M_{\text{grade}} = 9.51$, $\text{SD}_{\text{grade}} = 0.756$) from 146 schools.

Variables

The dependent variable in this study was student science achievement which was measured by science literacy test scores in the 2006 PISA. PISA defines scientific literacy 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 from the scales of identifying scientific issues, explaining phenomena scientifically, and using scientific evidence (OECD, 2009). 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. Adams and Wu (2002) provided details about how plausible values are created and used. The 2006 PISA used five plausible values to present students' science achievement.

Based on Walberg's psychological theory of education productivity and previous research, 14 independent variables were selected to predict students' science achievement. Walberg's model recognizes the complexity of student learning but still is parsimonious in that it converges on the least number of factors that effectively and consistently predict student outcomes (Walberg, Fraser, & Welch, 1986; Wang & Staver, 2001). Since PISA is administrated only to 15-year-old students and provides no information of prior science achievement, two of Walberg's factors—age and prior achievement—were dropped from this study. Some of the independent variables were index variables from the 2006 PISA database. Adams and Wu (2002) provided details on how those indicators were constructed. Others were represented by composite indicators from the 2006 PISA survey questionnaires. Appendix 1 identifies how each predictor was constructed and coded. Previous studies of science learning consistently found that male students significantly outperformed female students in science assessments at the secondary school level (Campbell, Hombo, & Mazzeo, 2000; Good, Woodzicka, & Wingfield, 2010; Sanchez & Wiley, 2010). Therefore, sex was selected in this study as a control variable.

Since a hierarchical structure exists in the predictors of student science achievement, the independent variables in this study were classified into two groups: sex, student SES, parental values on the importance of science, motivation, science self-efficacy, science media activities, and peer environment were assigned as student factors; school enrolment size, school socioeconomic composition, shortage of science teachers, school science promotion, school educational resources, quantity of instruction, quality of instruction, and school autonomy were assigned as school factors.

Statistical Models and Analysis

A two-level multilevel model 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 classes, classes are nested within the schools, and schools are nested within districts, and so on (Hox, 2002). MLM is the most appropriate statistical technique for hierarchical data. With MLM, each of the levels in this structure is represented by its own sub model. These sub models 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 & Nonlinear Modelling (HLM 6), 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 provided by the 2006 PISA database (see, Appendix 2 for descriptive statistics of sampling weights), and they 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. To limit the possibility of multicollinearity between two levels, the variables at the student level and school level were centred on 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. Missing data were found in the 2006 Hong Kong database. However, the sample size of this study was so large (contains 4,645 students and 146 schools) that the test result will not be much different without the cases with missing data; therefore, missing data were list-wise deleted when running the analyses.

A Backward Elimination process was used to determine whether each variable had a significant relative effect on the dependent variable when other variables are controlled. Therefore, each variable was treated as a fixed effect in its 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 modelling, are appropriate. Effectively, Multilevel Modelling 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 MLM modelling procedure in this study has three steps. In the first step, the analysis produced the null model with only student-level outcome variables 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 measures (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 MLM.

Results

This study utilized the 2006 Hong Kong PISA sample to explore the factors impacting student science achievement from a MLM approach. The results of analyses are presented below.

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

Tables 2 and 3 present statistical results from the null model that was estimated based on the following Equation 1:

Level 1 Model:

$$\text{Science score}_{ij} = \beta_{0j} + r_{ij} \tag{1}$$

Level 2 Model:

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

where science score$_{ij}$ represents the dependent variable, science achievement for student i in school j, β_{0j} is the intercept representing the average science achievement for the j school, this intercept varies at the school level. r_{ij} is the error term representing a unique effect associated with student i in school j. Statistically, r_{ij} is assumed to be normally distributed with a mean of zero and a constant level-one variance of σ^2. γ_{00} is the intercept representing the grand mean of science achievement and u_{0j} is the error term representing a unique effect associated with school j. Statistically, u_{0j} measures

Table 1. Description of independent variables

Variable	*n*	*M*	SD
Student characteristics			
Sex (female = 0; male = 1)	4,611		
Student SES	4,581	−0.68	0.93
Parental values on science	4,495	0.50	2.18
Motivation	3,682	0.24	0.84
Science self-efficacy	4,595	0.07	0.95
Science media activities	4,595	0.26	0.99
Peer environment	4,611	0.72	1.43
School characteristics			
School enrolment size	145	1039.36	174.35
School SES composition	145	−0.69	0.48
Shortage of science teachers	145	1.34	0.70
Quality of instruction	145	2.26	0.13
Quantity of instruction	145	3.00	0.45
School science promotion	145	0.93	0.65
School educational resources	145	0.35	0.95
School autonomy	145	10.33	1.22

Table 2. Fixed effects in null model

	Coefficient	SE	*T*-ratio	*p*
Intercept (science achievement) γ_{00}	533.54	5.64	94.62	<0.001

the level-two random effect assumed to have a normal distribution with a mean of zero and a level-two variance τ_{00}.

Results show that the average science achievement score of Hong Kong students was 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 the student level was 5,441.34 and the variance component at the school level was 3,260.31. The result indicated a large variance of average science achievement across Hong Kong schools (χ^2 (144) $=$ 2,874.25, $p < 0.001$). Intra-class correlation of 0.3,747 indicated that about 37.47% of the total variance in science achievement was attributable to school effects.

The final full model equation of this study is shown in Equation 2.

Level 1 Model:

$$\text{Science score}_{ij} = \beta_{0j} + \beta_{1j}(\text{sex})_{ij} + \beta_{2j}(\text{student SES})_{ij} + \beta_{3j}(\text{parental values on science})_{ij} + \beta_{4j}(\text{motivation})_{ij} + \beta_{5j}(\text{science self} - \text{efficacy})_{ij} + r_{ij}.$$

Level 2 Model:

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \gamma_{01}(\text{school enrolment size})_j + \gamma_{02}(\text{school SES composition})_j \\ &\quad + \gamma_{03}(\text{quantity of instruction})_j + u_{0j}, \end{aligned} \tag{2}$$

$$\begin{aligned} \beta_{1j} &= \gamma_{10}, \\ \beta_{2j} &= \gamma_{20}, \\ &\vdots \\ \beta_{5j} &= \gamma_{50}, \end{aligned}$$

where β_{1j} is the coefficient of sex, measuring the relationship between sex and student science achievement in school *j*. γ_{01} is the coefficient of school enrolment size,

Table 3. Random effects in null model

	Variance	df	χ^2	*p*
Between-school variability (intercept)	3,260.31	144	2,878.25	<0.001
Within-school variability	5,441.34			

measuring the relationship between school enrolment size and school science achievement in level 2. γ_{10} is the average effect of sex in the school. Under this model, student-level variables are treated as fixed and assumed to have the same influence across schools, resulting in $\beta_{1j} = \gamma_{10}$, $\beta_{2j} = \gamma_{20}$, ... $\beta_{5j} = \gamma_{50}$.

Tables 4 and 5 show the statistical results of the full model suggested by the HLM software program. The reliability estimate of 0.865 suggests that using the least square estimate of the coefficient (β_{0j}) to distinguish student science achievement among schools was appropriate.

When the multilevel model is fit at both student and school levels, the effects of student-level variables can be interpreted more meaningfully (Ma et al., 2008). Sex, student SES, parental values on science, motivation, and science self-efficacy at the student level impacted the student science score. The coefficient value (γ) of each independent variable was the relative effect which was adjusted for other variables in the model. For example, for every one unit increase in SES, the student science score increased 3.89 points when controlling all other variables as constant ($\gamma_{20} = 3.89$).

At the school level, school enrolment size, school SES composition, and quantity of instruction were found to be effective predictors of the average science score at each school. In this full model, the intercept of variables at the school level can be explained in this way: for every unit increase of school enrolment size, the student science achievement increased 0.13 points when all other variables were controlled ($\gamma_{01} = 0.13$).

As shown in Table 4, all the slopes (coefficients) were found to be positive. These positive coefficients suggest that: (1) on average, a male student's science literacy scores were about nine points higher than those of female students when holding other variables constant; (2) all other factors in the model positively contribute to student science achievement. In comparison with the null model, the final model explained about 21% of the variance at the student level $\left(R^2_{\text{level 1}} = 0.21\right)$ and about 65% of the variance at the school level $\left(R^2_{\text{level 2}} = 0.65\right)$.

Table 4. Fixed effects in full model

	Coefficient	*SE*	T-ratio	*p*
Intercept (science achievement) γ_{00}	549.78	3.43	160.18	<0.001
Student characteristics				
Sex (female = 0; male = 1) γ_{10}	8.75	2.92	3.00	0.004
Student SES γ_{20}	3.89	1.80	2.16	0.031
Parental views on science γ_{30}	1.86	0.61	3.03	0.003
Motivation γ_{40}	14.70	2.07	7.09	<0.001
Science self-efficacy γ_{50}	21.27	1.70	12.53	<0.001
School characteristics				
School enrolment size γ_{01}	0.13	0.02	7.56	<0.001
School SES composition γ_{02}	20.36	8.52	2.39	0.018
Quantity of instruction γ_{03}	33.26	8.42	3.95	<0.001

Table 5. Random effects in full model

	Variance	df	χ^2	p
Between-school variability (intercept)	1,153.17	141	1,027.19	<0.001
Within-school variability	4,309.76			

Discussion

The purpose of this study was to explore factors that impact student science achievement through the analysis of large hierarchical datasets. A significant gender gap was found in the Hong Kong sample: on average, a male student's science score was about nine points higher than that of a female student when holding other variables constant ($\gamma_{10} = 8.75$, $p = 0.004$). This finding is consistent with previous studies, which have indicated that male students perform better than female students in math and science. However, this study suggests an additional reason that could widen the gap between males and females in the Hong Kong sample. Chinese culture is more patriarchal and male-dominated, this culture results in more investment and higher expectations placed on males than on females (Chen, Lee, & Stevenson, 1996; Liu, 2006). The gender gap in science achievement at the secondary school level might cause the girls participation rates in science to decline after high school. The end result is that girls are less likely to pursue science/technology-related careers that attract significant earning power (Catsambis, 1995; Jacobs, 2005). This finding emphasizes the need to further investigate the reasons for performance imbalance between the genders in science study, and to develop strategies like interactive classes to encourage female student engagement in science study.

The present findings are consistent with other studies which found that student SES positively contribute to students' science learning outcomes. Student family SES, which will largely determine the location of the child's neighbourhood 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 for success in school (Dika & Singh, 2002). However, the influence of SES in this study was not substantial compared to previous similar studies. The governmental intervention could be an influential component that balanced the performance differences caused by household income. Hong Kong government provides subsidized education or financial aid to support all 6–15-year-old students (Post, 2003).

Parental values on the importance of science were also found to be a statistically significant factor, and this finding supported our earlier hypothesis. The coefficient can be interpreted as with one unit increase on parental views, student science score will increase 1.86 points when controlling all other student and school variables. This finding suggested that parental views on the importance of science can be used as an effective indicator of parental or family influences on student science performance.

Similar studies using different samples are suggested for future research to generalize this effect.

Similar to other studies, student motivation and self-efficacy in science study are positively correlated with science scores and can be used as reliable predictors of science achievement. However, the function of these two variables must be interpreted with caution because previous research found that difference in self-efficacy favoured boys when girls and boys have similar performance, or even when girls received higher grades (Britner & Pajares, 2006; Schunk & Pajares, 2002). One possible explanation of this is that boys and girls interpret their grades and performance differently. For example, a girl might underestimate her competence in science because she viewed her grade of B on an exam as a poor grade that indicated her lack of science ability. A boy who received a grade of C on the same exam might report strong science ability because he viewed this grade as passing (Seymour, 1995). Student academic self-efficacy was also found to be different among cultural groups. Klassen (2004) found that students in non-Western cultures tended to have lower academic efficacy beliefs than students in the West.

More than one-half of the variance on science achievements was found to be explained by school factors in this study. Instructional quantity positively influences student learning in science. This factor was measured by the time spent per week engaged in science instruction at school. In the Hong Kong sample, the average time students spend in science classes is 2–4 h per week. In contrast to earlier findings that smaller schools are better for student learning (Cotton, 2002; Stewart, 2009), no evidence of a negative relationship between school enrolment size and student learning in science was detected. Instead, the findings suggest that the school enrolment size serves to facilitate the factor for student performance in science. In addition, no suppressor effect on school size was found in this model. A possible explanation for this finding might be that larger student body schools are more likely to have more grants or financial opportunities, and greater support from parents (a positive correlation was found between school enrolment size and school SES, $r = 0.32$, $p < 0.001$). Therefore, big schools are more likely to attract and retain qualified and talented science teachers as well as create larger peer effect as more active and bright students work together.

Present day learning reform and school reconstruction are often taking the approach of consolidating smaller schools into larger ones and breaking large schools into small learning environments. In the studies examining the effectiveness of school size on learning outcomes, many researchers have argued the negative influence of school size (Cotton, 2002; Stewart, 2009). However, this study does not support that conclusion. The findings of this study suggest a caution about reaching a foregone conclusion that disciplinary learning is always better at small schools. The impact of school size on student science achievement is associated with other factors both at student and school levels (e.g. location, race, SES, curriculum and instruction, teacher–student ratio). Similarly, some recent science and math studies had found that higher school enrolment benefits learning outcomes in high school and for high-SES students (Howley & Howley, 2004; Ma & Wilkins, 2002; 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 the large school system. Simply creating smaller schools or dividing larger schools may not produce the desired effect.

Conclusion

This study adds supplementary information to the existing body of literature on the home factors influencing student learning outcomes in science. The impact that parental values placed on the importance of science was found to be statistically significant in explaining differences in science achievement. Therefore, it is recommended that parents orient their children towards more scientific disciplines for their instrumental and pragmatic importance. This study has policy implications to promote more interaction and collaboration between schools and parents. Schools should inform parents about the importance and means through which to invest in cultural and material resources at home that support improved science learning.

Consistent with previous studies, sex, SES, motivation, and self-efficacy significantly influence student science achievement. These findings suggest that sex, SES, motivation and self-efficacy can be treated as reliable indicators of students' science achievement. One limitation of this study was that all the variables in the model were analyzed using unstandardized scores, which means the variables were measured on different scales; therefore, the coefficient of predictors cannot be used to compare which variable denoted the highest degree of difference in science achievement. While the 2006 Hong Kong sample shows a pattern of positive correlation between school size and science achievement, secondary schools with greater than 1,400 or less than 500 students were not sufficiently represented in the sample. Consequently, a further study of similar outcomes associated with the smallest and largest schools is recommended. In the follow-up study, attention to more functional factors like the student–teacher ratio, class size, or school location is recommended to examine their influence on student science learning.

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Appendix 1. Description of independent variables

Table A1. Variables at the student level

Variable	Questionnaire	Instrument	Resources
Sex	Are you female (1) or male (2)?	Student questionnaire for PISA 2006	Dummy coded for female = 0, and male = 1
Student SES		Student questionnaire for PISA 2006	[a]ESCS in PISA 2006 student dataset
Parental values on science		Parent questionnaire for PISA 2006	Derived from [a]QSCIMP, [a]PQGENSCI, and [a]PQPERSCI in PISA 2006 parent dataset
Motivation		Student questionnaire for PISA 2006	Derived from [a]SCIEFUT and [a]INSTSCIE PISA 2006 student dataset
Science self-efficacy		Student questionnaire for PISA 2006	[a]SCIEEFF in PISA 2006 student dataset
Science media activities		Student questionnaire for PISA 2006	[a]SCIEACT in PISA 2006 student dataset
Peer environment	From *My friends*, students learnt about each of these topics: (a) Photosynthesis (b) Formation of the continents (c) Genes and chromosomes (d) Soundproofing (e) Climate change (f) Evolution (g) Nuclear energy (h) Health and nutrition	Student Questionnaire for PISA 2006	

[a]explained in PISA 2006 technical report (OECD, 2009).

Table A2. Variables at the school level

Variable	Questionnaire	Instrument	Resources
School enrolment size	As on 1 February 2006, what was the total school enrolment (number of students)?	School questionnaire for PISA 2006	
School SES composition			Derived by averaging the ESCS within each school
Shortage of science teachers	Is your school's capacity to provide instruction hindered by any of the following? (a) A lack of qualified science teachers	School questionnaire for PISA 2006	
School educational resources		School questionnaire for PISA 2006	[a]SCMATEDU in PISA 2006 school dataset
School science promotion		School questionnaire for PISA 2006	[a]SCIPROM in PISA 2006 school dataset
Quality of instruction	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	Student questionnaire for PISA 2006	

(*Continued*)

Table A2. Continued

Variable	Questionnaire	Instrument	Resources
	(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.		
Quantity of instruction	How much time do you typically spend per week studying the following subjects? (a) Regular lessons in school science at my school	Student questionnaire for PISA 2006	
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	Student questionnaire for PISA 2006	

[a]explained in PISA 2006 Technical Report (OECD, 2009).

Appendix 2. Descriptive statistics of sampling weights

	N	*M*	SD	Minimum	Maximum
Student weight	4,645	16.18	5.21	11.29	80.21
School weight	146	3.28	2.11	2.05	24.70

International Journal of Science Education

ISSN: 0950-0693 (Print) 1464-5289 (Online) Journal homepage: https://www.tandfonline.com/loi/tsed20

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To cite this article: Letao Sun , Kelly D. Bradley & Kathryn Akers (2012) A Multilevel Modelling Approach to Investigating Factors Impacting Science Achievement for Secondary School Students: PISA Hong Kong Sample, International Journal of Science Education, 34:14, 2107-2125, DOI: 10.1080/09500693.2012.708063

To link to this article: https://doi.org/10.1080/09500693.2012.708063

Published online: 07 Aug 2012.