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A PARTIAL SIMULATION STUDY OF PHANTOM EFFECTS IN MULTILEVEL ANALYSIS OF SCHOOL EFFECTS: THE CASE OF SCHOOL SOCIOECONOMIC COMPOSITION

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A PARTIAL SIMULATION STUDY OF PHANTOM EFFECTS IN MULTILEVEL ANALYSIS OF SCHOOL EFFECTS: THE CASE OF SCHOOL SOCIOECONOMIC COMPOSITION

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Education
at the University of Kentucky

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2019

ABSTRACT OF DISSERTATION

A PARTIAL SIMULATION STUDY OF PHANTOM EFFECTS IN MULTILEVEL ANALYSIS OF SCHOOL EFFECTS: THE CASE OF SCHOOL SOCIOECONOMIC COMPOSITION

Socioeconomic status (SES) affects students' academic achievement at different levels of an educational system. However, misspecified Hierarchical Linear Model (HLM) may bias school SES estimation. In this study, a partial simulation study was conducted to examine how misspecified HLM model bias school and student SES estimation.

The result of this study can be summarized by four important points. First, based on partial simulation procedure, phantom effects of school SES and student SES are real. Second, characteristics of phantom effects are generalized. The stronger the correlation between prior science achievement measure and present science achievement measure, the greater the decrease in both student SES effects and school SES effects. Third, the procedure of partial simulation provides a new angle to conduct theoretical studies (full simulation), which is entirely based on ideal assumption. Finally, the procedure of partial simulation offers researchers a way to create prior student academic achievement measures when they are not available for data analysis.

KEYWORDS: Partial Simulation Study, School SES Effect, Student SES Effect

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1.1 Problem Statement

Socioeconomic status (SES) affects students' academic achievement at different levels of an educational system such as students, schools, and school districts (e.g., Ma, Yuan, & Luo, 2016). Student SES is often measured through parents' education, occupation and income; school SES is often measured through the aggregation of SES among students within a school. School socioeconomic composition is, perhaps, the most popular school contextual variable and school SES has been declared to have a large and persistent effect on students' academic achievement (Perry & McConney, 2010; Willms, 2010). Also, according to a 2015 report by the Organisation for Economic Co-operation and Development (OECD), student SES and school SES have both been shown to contribute to student academic achievement among OECD countries.

In those studies, a hierarchical linear model (HLM) was typically applied to address the data hierarchy (i.e., students nested within schools). However, scholars did not include students' prior academic achievement in the HLM models, a variable that is highly related to academic achievement. The effect of school level SES on students' academic achievement might be biased by this omission (Marks, 2015; Pokropek, 2015; Televantou et al. 2015). These researchers demonstrated that in the absence of students' prior academic achievement, there are statistically significant effects of school SES on academic achievement (at the school level), but in the presence of students' prior academic achievement, the statistically significant effects of school SES on academic achievement (at the school level) tend to disappear. They coined this phenomenon as *fake compositional effects*, *statistical artifacts* or *phantom effects.*

1.2 Phantom Effects

Conceptually, phantom effects are defined as the effects of A in the absence of B, which tend to disappear in the presence of B. Although researchers cited above think about and investigate phantom effects in regard to school contextual effects, phantom effects can also occur at other levels of an educational system. For example, at the student level, in the absence of SES, the racial-ethnic background often indicates statistically significant effects on academic achievement of students; however, in the presence of SES, such significant effects often disappear, which makes the racial-ethnic effects phantom effects. With a focus on school SES, the present study investigates school contextual effects as a potential source of phantom effects in the school effectiveness research literature.

1.3 Contextual Effects

In the studies cited above, the compositional model was applied to examine the effects of school SES on student academic achievement (see Raudenbush & Bryk, 2002). With student SES at Level 1, the HLM is

$$\mathrm{ACH}_{ij} = \beta_{0j} + \beta_{1j}(\mathrm{SES}_{ij} - \overline{\mathrm{SES}}_{..}) + r_{ij},$$

where ACH_{ij} is the dependent variable (academic achievement) for person *i* in group *j*. β_{0j} is the intercept of group *j* and β_{1j} is the slope of group *j* (i.e., the effects of student SES on ACH). Finally, r_{ij} is the error term at the student level. At Level 2, β_{0j} and β_{1j} are dependent variables and can be written as

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\overline{\mathrm{SES}}_{.j} + \mu_{0j}$$

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

where γ_{00} is the overall mean for ACH. γ_{01} represents the contextual effects of school SES on ACH. γ_{10} represents the effects of student SES on ACH. μ_{0j} is the error term at the school level. Inserting Level 2 equations into Level 1 gives us the combined HLM

$$Y_{ij} = \gamma_{00} + \gamma_{10}(\mathrm{SES}_{ij} - \overline{\mathrm{SES}}_{..}) + \gamma_{01}\overline{\mathrm{SES}}_{.j} + \mu_{0j} + r_{1j}.$$

Estimation of the above HLM involves two stages centering around the variance and covariance components (see Raudenbush & Bryk, 2002). When a variable is added into the Level l model, the variance and covariance estimations change. This change is more complicated (and thus harder to control) in the two-stage estimation process. A variable highly related to ACH, such as prior academic achievement, may alter the effects of both student SES and school SES (Marks, 2015; Perry, 2018).

Prior academic performance is an important indicator of students' present academic performance. At the student level, scholars have long argued that the relationship between students' academic achievement and SES might be mediated by prior academic achievement (e.g., Marks, 2017). However, at the school level, there have been very few studies that have applied an HLM and included prior academic achievement to investigate the compositional or contextual effects of school SES on students' present academic achievement.

In one of the rare studies, Marks (2015) examines how students' prior ability influences the school SES estimation under the HLM framework. The data consisted of the (Australian) Victorian government school sector of the National Assessment Program – Literacy and Numeracy (NAPLAN) data, which included Year 3 students in 2008, Year 5 students in 2010 and Year 7 students in 2012. Each NAPLAN measurement aims to test the development of students in Year 3, 5 and 7. Each NAPLAN test was equated. Student's SES is a composite of parents' occupation and education. Parents' occupation component was named as SES_1 and parents' education component was named as SES_2. Year 3 and Year 5 students' standardized factor scores in the NAPLAN achievement tests were treated as prior academic achievement. At the level 2, school SES was the mean SES for each school. A two-level random intercept HLM was applied. The results showed that after controlling for student's prior academic achievement, school SES effect disappeared in both cases (i.e., SES_1 and SES_2). The variable, prior academic achievement, was highly related to the dependent variable (present academic achievement) and was considered the reason behind this disappearance of school SES effects. The effects of school SES were phantom effects.

1.4 Purpose of Research

The purpose of the present study is to examine the extent to which the effects of school SES on academic achievement of students are phantom effects. Data for the present study come from the 2015 Program for International Student Assessment (PISA) with students nested within schools. The PISA 2015 emphasizes science education. With measures of students' science achievement and individual background (including student SES from which school SES can be created) as well as school context and school climate, PISA data are appropriate for a research study of school effects. Specifically, to examine the potential phantom effects of school SES, the strategy is to create a prior measure of science achievement with various degrees of correlation with the measure of science achievement available in the PISA 2015 database. With HLMs fitted with and without these prior science achievement measures, the behaviors of school SES can be examined in terms of its (contextual) effects on science achievement of students. The following research questions are addressed in the present study.

1. In the absence of any prior science achievement measures, how strong are the effects of school socioeconomic composition (i.e., school SES) on science achievement of students with and without other school-level variables descriptive of school context and school climate?

2. In the presence of various prior science achievement measures, how strong are the effects of school socioeconomic composition (i.e., school SES) on science achievement of students with and without other school-level variables descriptive of school context and school climate?

The combination of empirical answers to both questions will provide evidence to address the issue of the extent to which the effects of school SES on science achievement of students are phantom effects.

1.5 Empirical Importance

The present study aims to make an important contribution to theory and practice concerning school contextual effects, in particular the effects of school socioeconomic composition.

1.5.1 Informing Policy Change

As argued earlier, many researchers have shown that school SES largely affects students' academic achievement (e.g., OECD, 2015). However, the phenomenon of phantom effects associated with school SES may threaten the credibility of claims like this. To some degree, education policymakers may have been misinformed on research evidence due to the complexity concerning school contextual effects, especially school SES. This study aims to provide empirical evidence on whether phantom effects of school SES on students' academic achievement exist and, if yes, the extent to which school SES produces phantom effects on students' academic achievement. The significance of this study is that it may promote policy change through a revisiting of educational policies and practices concerning school SES. Education policy makers may have new evidence that may help them to reconsider current educational policies and practices and develop new (and more credible) ones.

1.5.2 Promoting Pioneer Research

Overall, the research literature on the phenomenon of phantom effects (also fake compositional effects or statistical artifacts) is rather thin. Few studies have questioned whether school SES produces phantom effects on students' academic achievement. Very limited working knowledge exists in research literature on how to prevent phantom effects. A handful of researchers have begun to raise awareness on the phenomenon of phantom effects, giving rise to pioneering empirical research of great importance. This study joins this international effort to gain a better understanding of school contextual effects especially school SES on academic achievement.

1.5.3 Exploring Methodological Potential

Different from the traditional methodological approach to investigate the behaviors of certain significant variables of interest, which usually adopts simulation as the primary statistical technique, this study combines simulation data with real-world data (i.e., PISA 2015) to explore the phantom effects of school SES. Although such a strategic combination (method) is rather rare in research literature, this method has the advantage of anchoring simulation to reality. The use of the real-world data as the basis for simulation brings the empirical findings of this study closer to the real-world situation. This study purposefully aims to explore this potential as a methodological innovation.

CHAPTER 2. REVIEW OF PHANTOM EFFECTS OF SCHOOL SES

2.1 Background

School effects indicate the relationship between student learning outcomes (e.g., academic achievement) and school characteristics. School characteristics can be classified into two categories: context and climate (Ma, Ma & Bradley, 2008). Context variables include school background variables, such as location, size and SES. Climate variables include evaluative variables that are related to school policies and practices, such as teacher autonomy, principal leadership and parental involvement.

To estimate the relationship between student learning outcomes and school characteristics, many theoretical models have been proposed. Walberg (1987) proposed educational productivity theory. The author assumed that students' learning outcomes, especially academic achievement, were influenced by three main factors: student aptitude, instruction and social-psychological environment. Ecological system theory was stated by Bronfenbrenner (1979). His theory comprehensively described how peers, schools, family and other social structure influence student academic achievement. The input-process-output (IPO) model was favored by some scholars (e.g., Ma, Ma & Bradley, 2008). Input means student background (e.g., gender, race, socioeconomic status). Process refers to the frequent impact of school climate variables on student output, with control over context variables. Output refers to student output, such as academic achievement. Researchers using the IPO model carefully control student background characteristics and school context variables to examine the relationship between student outcome and school climate variables (see Ma, Ma & Bradley, 2008). The IPO model was adopted in the present study as the main theoretical framework to anchor data analysis. Since Bryk and Raudenbush (1992) developed a hierarchical linear model statistical technique, scholars have started to apply HLM to estimate the relationship between schooling outcomes and school characteristics based on different theoretical models because HLM accommodates educational hierarchy (e.g., students nested within schools). In general, scholars over the years have found critical school effects on student learning outcomes (e.g., Ho & Willms, 1996; Sammons et al., 1997; Parcel, 2001; Van Ewijk, 2010).

Among many important school characteristics, school socioeconomic status (SES)— a school background variable— plays a critical role in many educational policies and practices. In New Zealand and the United Kingdom, schools adopt a funding model that provides similar resources to all schools and provides additional funding to schools with high needs (e.g. rural school, high percentage of students from low SES, etc.) (Perry and McConney, 2010). In the United States, policymakers issued different polices aimed to adjust school SES for better distribution of educational resources, such as magnet schools and school assignment policy. The present study considers this important school characteristic.

2.2 School socioeconomic composition

Student SES is defined as a student family's economic and social position in relation to others, which is usually based on parents' education and occupation as well as family income. School SES is often defined as the average socioeconomic condition of all students within a school. Scholars showed that student SES positively significant correlated with student academic achievement (e.g., Sirin, 2005; White, 1982). Student SES is usually measured by three indictors: parental education, parental occupation and parental income (Duncan, Featherman, & Duncan, 1972). When this measurement is difficult to obtain, researchers historically use home resources to approximate SES (e.g., Organization for Economic Cooperation and Development [OECD], 2015). Home resources include household possessions, such as books, a study room, and a computer (Sirin, 2005).

At school level, school SES related with student academic achievement (e.g., Ma, 2010). School SES is often measured in two ways, either as the proportion of students enrolled in a reduced-price or free lunch program (Sirin 2005), or as aggregated from student SES. School SES equals the average score of student SES in that school. Compared with the first method, the aggregated school SES more precisely describes school SES (National Center for Education Statistics [NCES], 2012). The reason is that student level measurement includes complex indictors to measure SES, as in the case of Program for International Student Assessment (PISA). In general, School SES is dependent upon student SES.

2.3 Effects of School SES on Academic Achievement

Much evidence showed that school SES had positive effects on student academic achievement. To concisely synthesize the literature, attempts were made to use a meta-analysis to summarize the research on this topic before 2000 and then to report in detail recent individual studies after 2000 on the same topic. These studies are not intended to be comprehensive. They were selected because authors emphasized the importance of school SES on schooling outcomes. To some extent, this summary can be considered the upper limit of school SES effects.

Literature was searched from January 2000 to November 2017 in the ERIC (Education Resources Information Center), SSCI (Social Science Citation Index) and PsycInfor databases. Search words were “School SES OR achievement AND Multilevel.” An “anywhere” function applied to this search, since the search terms may not be indexed as key words. The search was limited to peer-reviewed studies of relationship between academic achievement and school SES. The only studies included were those the second level units consisted of schools, and school SES were constructed by the aggregation of the first level SES. A total of seven articles were found as a result of this procedure. The review focused on these seven articles in detail.

Sirin (2005) conducted a meta-analytic review of the relationship between SES and academic performance, which included 58 published journal articles from 1990 to 2000. The author found that at the school level, the correlation between SES and academic achievement varied from 0.11 to 0.85, with a mean of .60 (SD = 0.22). The weighted effect size ranged from 0.11 to 1.25. For the fixed effect model, the average effect size was 0.67 with 95 percent confidence interval of 0.66 to 0.67.

In recent years, many studies confirmed Sirin's view. Konstantopoulos and Borman (2010) examined mathematics, reading and vocabulary subjects as outcomes. The study was a cross-sectional design with probability sampling. There were 97,660 students nested within 760 schools. Individual level variable includes gender, race, family size, family structure, reading material and SES. School level variable includes school region, school urbanization, school resources, school curriculum characteristics, faculty resources and school social context composition (include average school SES). Intra class correlation (ICC) for mathematics was 24 percent; ICC for reading was 30 percent; ICC for vocabulary was 40 percent. For all three subjects, school mean SES had statistically significant effects on academic achievement. The effect size was 0.16, 0.19 and 0.30, respectively. For each subject, 60 percent, 67 percent and 80 percent variances could be explained by school level variables for which school SES was a key member.

Willms (2010) examined science literacy scores by applying a three-level model. The study was a cross-sectional design with probability sampling. The author examined the whole 2006 PISA dataset. Individual level variable includes student SES. There were 400,000 students from 57 countries. School level variable included school SES, classroom and school contextual characteristics. There was no variable on country level. ICC was 28 percent for science literacy. School mean SES had statistically significant effects on academic achievement. The effect was 37.1 (equivalent to an effect size of 0.37). School level variable could explain 76 percent variances.

Milford, Ross, and Anderson (2010) confirmed that high school SES is associated with student science literacy scores. The authors examined 2006 American PISA dataset. The study was a cross-sectional design with probability sampling. Individual level variable included student SES. School level variable included school SES. ICC was 30 percent. The effect size for school SES was 0.71. School level variables explained 49.2 percent variance.

Sun, Bradley and Akers (2010) examined science literacy scores by applying a two-level model. The study was a cross-sectional design with probability sampling. There were 4,654 students nested with 146 schools. Individual level variable included gender, students' SES, parental values on science, motivation and science self-efficacy. School level variable included school enrolment size, school SES and quantity of instruction. ICC was 37.47 percent for science literacy. School mean SES had statistically significant effects on academic achievement. The effect was 20.36 (equivalent to an effect size of 0.20). School level variable could explain 65 percent variances. Lam and Lau (2014) applied the same data set and confirmed that school mean SES had statistically significant effects on academic achievement.

Shera (2014) examined reading literacy scores by applying a two-level model. The study was a cross-sectional design with probability sampling. There were 4,596 students nested with 181 schools. Individual level variable included student SES, gender, reading engagement, learning strategies use, classroom environment and family structure. School level variable included school SES, reading engagement, learning strategies use, classroom environment and school characteristics. ICC for reading literacy was 30 percent. School mean SES had statistically significant effects on academic achievement. The effect size was 0.71. School level variable could explain 49.2 percent variance.

Kotok (2017) examined mathematics scores by applying a two-level model. The study was a longitudinal study. There were 4,900 students in 944 schools. Individual level variables included race, student-school experience and family background (including SES). The author didn't provide any information related to ICC. School level variables included school SES, academic climate, school safety, Catholic school and private non-Catholic school and community. This study didn't report ICC and school level explained variance. School SES associated with students' mathematics score. The effect size was 0.83. (computed by the author based on the information from the article)

2.4 Multilevel Modeling Methods Estimating Effects of School SES

The vast majority of empirical studies apply multilevel modeling (MLM) as the primary statistical technique to estimate the effects of school SES. In such a model, the outcome is often a continuous measure such as student academic achievement as a linear function at both student and school levels. The data hierarchy is students nested within schools. Most models are two- level random intercept models. Most empirical studies start with the null model, which can be written in equation as

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

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

where Y_{ij} is the outcome of the ith student in the jth school, β_{0j} represents the intercept or average outcome of school j, which becomes the dependent variable at the school level and γ_{00} indicates the grand-mean outcome. Meanwhile, ϵ_{ij} is level one error term, and μ_{0j} indicates the random effect associated with unit j.

An important related estimate is ICC, which indicates the portion of the total variance that lies systematically between schools. Two level model's ICC is calculated as the following:

$$\rho = \tau_{00}/(\tau_{00} + \sigma^2)$$

where τ_{00} and σ^2 are the respective estimates of unconditional two-level model's level-1 and level 2 variances. In studies on school achievement, estimates of ICC varied considerably. When the outcome was reading, ICC was 30 percent (Konstantopoulos & Borman, 2010). When the outcome was mathematics, the ICC was 24 percent (Konstantopoulos & Borman, 2010). When the outcome was science, ICC varied between 23 percent and 37 percent (Willms, 2010; Sun et al.2012; Lam & Lau, 2014). According to Lee's (2000) suggestion, if ICC is greater than 10%, MLM need to be applied.

To estimate the effects of school SES, most models move to build the full model, which can be written in equation as

$$Y_{ij} = \beta_{0j} + \sum_{p=1}^{n} \beta_{pj} X_{pij} + \epsilon_{ij}$$

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{m} \gamma_{0q} Z_{qj} + \mu_{0j}$$

where Y_{ij} is the outcome of the ith student in the jth school, β_{0j} represents the intercept or average outcome of school j, β_{pj} $(p = 1, 2, 3 \ldots)$ are the effects of individual level variables, and ϵ_{ij} is the error term unique to each student. β_{0j} is taken into the second level as the outcome measure. γ_{00} is the adjusted grand mean of the outcome measure, γ_{0q} $(q = 2, 3, 4, \ldots)$ are the effects of school level variables, and μ_{0j} is an error term unique to each school.

The coefficient of school SES, γ_{01}, estimates the effects of school SES. When the coefficient is not statistically significant, it means that school SES does not have effects on student academic achievement. When the coefficient is statistically significant, it means that school SES has effects on student academic achievement. If the coefficient is positive, school SES improves student academic achievement. If the coefficient is negative, school SES hinders student academic achievement. All studies referenced earlier showed evidence to support that students in high SES schools performed better than students in low SES schools. Some of them, however, indicated that the effects of school SES can be conditional. Lam and Lau's study (2014), after controlling school size on school's level, showed that the school SES effects disappeared. Willms (2010) showed a similar case where after controlling school contextual factors (quality of instruction, science time and school resource) at school level, the effects of school SES decreased.

2.5 Phantom effects of School SES

As mentioned in Chapter 1, phantom effects are defined as the effects of A in the absence of B, which tend to disappear in the presence of B. Although researchers investigate phantom effects along the line of school contextual effects, phantom effects can also occur at other levels of an educational system. For example, at the student level, in the absence of student SES, the effects of race-ethnicity are statistically significant on academic achievement. However, in the presence of student SES, the effects of race-ethnicity tend to disappear (Harker and Tymms, 2004). The present study is concerned with the effects of school SES. Let A = school SES and B = prior academic achievement. A = school SES often indicates statistically significant effects on academic achievement of students in the absence of B = prior academic achievement. If in the presence of B = prior academic achievement, such significant effects of A = school SES disappear, then there is a case of phantom effects of school SES (i.e., school SES effects are phantom effects.).

According to current studies, there are two ways to examine phantom effects. The first method is that MLM includes variables that highly correlated with students' present academic achievement (Harker & Tymms, 2004). The above illustration pertains to this approach. The second method applies the doubly-latent model (DL) (Lüdtke et al., 2011). Scholars argued that the DL model may reduce the bias of parameters' estimation on second level so as to make the effects of school SES disappear (Lüdtke et al., 2011; Marsh.et al., 2009; Televantou et al., 2015; Pokropek,2015). In other words, the effects of school SES are phantom effects because the model cannot adequately control for measurement errors. However, there are few empirical studies to support this view.

2.5.1 Absence of Important Variable

Marks (2015) examines students' prior ability to influence school SES estimation under the MLM framework. The data consisted of the Victorian government school sector in Australia. The National Assessment Program – Literacy and Numeracy (NAPLAN) aimed to test the development of students in Years 3, 5, 7, 9 (i.e., Grades 3, 5, 7, 9). Marks' data included Year 3 students in 2008, Year 5 students in 2010 and Year 7 students in 2012. Every student's score ranged from 0 to 1000. Each NAPLAN test was equated. Student SES was a composite of parents' occupation and education. The Year 3 and Year 5 students' standardized achievement scores in the NAPLAN achievement tests were treated as prior ability to Year 7 students' standardized achievement scores. School SES was the mean SES for each school (at the school level). A two-level random intercept HLM was applied with students nested within schools.

The author separately added Year 3 and Year 5 numeracy test achievement as student prior ability and school prior ability. For the Year 7 numeracy test, the author took Year 5 student and school numeracy test achievement as prior ability. The author found that when controlling the student prior ability, the school SES effect was much smaller than the omission of student prior ability. When controlling student and school prior ability, the school SES disappeared. Then, the author took Year 3 numeracy test achievement as student prior ability and school prior ability to estimate how school SES impacted student numeracy achievement in Year 7. The results showed the same pattern as taking Year 5 student achievement as prior ability.

2.5.2 DL Model

The original purpose of this approach is to make parameter estimates more accurate at a higher level of a multilevel model. The basic idea is that measurement error may bias the estimation of a parameter at a higher level and so needs to be corrected or adjusted. Following this line of logic, the DL model may correct the measurement error and reduce the bias of parameter's estimation on school SES. Lüdtke et al. (2008) constructed a multilevel latent model to examine phantom effects. The author tested the effect of School SES on student reading achievement after control student SES by using the German sample from 2000 PISA. The data set consisted of 4,460 students from 189 schools. The author found that after applying the

DL model, the effect of school SES was higher or stronger than the HLM approach. The author argued that the DL model might be able to correct the biased estimation of School SES, but noted that the number of schools and the number of students in each school may also bias the level 2 variables' estimation. Although not specific to the effects of school SES, Lüdtke et al. (2011) later performed two simulation studies based on multilevel latent contextual models and suggested that the DL model has some potential to provide accurate estimation for the level 2 variables aggregated from the first level.

2.5.3 Comparison of Approaches

Televantou (2015) compared the two different approaches to detect the phantom effects of school SES. The author examined how student prior ability and school prior ability (aggregated from student prior ability) influence student present academic achievement. The author considered the effect of school prior ability as a compositional effect. The data was from the Center of Evaluation and Monitoring (CEM) in Durham and the Performance Indicators at Primary School test (PIPS). The data set consisted of 19,059 students from 593 schools, which were collected for the same students in Years 1 and 4. The cohort of students entered primary school in the academic year 2004-2005. Mathematics tests were based on item-level data. Each item was given value one if it was correct; each item was given zero if it was wrong or was left blank. The dependent variable was the Year 4 mathematics score. The independent variable was Year 1 mathematics score. The author argued that both omission of important variables and measurement error might bias the variables' estimation on the second level.

2.6 Motivation of the Present Study

The literature clearly shows that relatively little scholarly attention has been given to the absence of important variable approach. There are relatively more studies similar to the DL model than what other method Both approaches have their advantages and disadvantages. To construct the DL model requires secondary datasets to provide item-level information, but many secondary datasets only report scale-level information. In addition, only a large sample size can guarantee accuracy of item-level information. Those specific requirements restricted scholars who applied the DL model. With the consistent significant improvement of all aspects of large-scale assessments, measurement errors may be reduced to a certain acceptable level. Omission of important variables, on the other hand, remains a serious source of phantom effects. Currently, few researchers have paid attention to omitted important variables in the investigation of phantom effects. Marks (2015) clearly showed that omitting student prior academic achievement biased school SES estimation. This is the motivation for this dissertation research to focus on how omitted important variables would impact school SES estimation on the second level.

CHAPTER 3. INTRODUCTION TO PARTIAL SIMULATION

3.1 PISA Background

Data for this study is from the 2015 PISA United States sample. PISA stands for the Programme for International Student Assessment, which tests three fields: reading, mathematics and science. Since 2000, PISA tests were carried out every three years. PISA has conducted seven assessments (2000 to 2018). Every three years, PISA's focus is rotated via reading literacy, scientific literacy and mathematical literacy. The 2015 PISA cycle focused on science achievement. More than half a million 15-year-old students in 72 countries and economics took 2015 PISA test (OECD, 2016). PISA contains information that comprehensively describes student, teacher and school, measured through questionnaires.

PISA questionnaires include two dimensions—four levels and three types. The four levels are system level, educational institution, instructional settings level and student level. The three types are antecedents, processes and outcomes. At the educational system level, macro-economic and demographic context are reported as antecedents (e.g. Gross Domestic Product, Distribution of Wealth and percentage of immigrants). Policies and organization of education is reported as processes (e.g. organization of autonomy, program structure, teacher qualifications and training requirements, school entry-age and retention). Outcomes are reported as system level aggregates of scientific literacy. At the institution level, antecedents are descripted as characteristics of educational institution, such as the involvement of parents, social intake, source of funding, location and size. Process is institutional policies and practice. The learning outcome is institution level aggregates of scientific literacy. At the instructional setting level, the antecedents are reported as teacher qualifications and classroom size. Processes are described as learning environment. Learning outcomes are reported at class level. At the student level, the antecedents include student characteristics (e.g., grade, study program, age, gender) and family background (e.g., student SES indicators, immigration status and language spoken at home). Processes include individual learning process (e.g., engagement and attitudes about science, self-concept and self-efficacy). The outcome is scientific literacy.

The two main questionnaires are the student questionnaire and school questionnaire. In this dissertation, student characteristics (e.g., age, gender) and family background (e.g., student SES indicators, immigration status and language spoken at home) come from the student questionnaire. Some school climate variables also are obtained from the student questionnaire, such as disciplinary climate in science classes and teacher support for learning. Meanwhile, school context variables such as school size, school ownership, school location and proportion of science teacher fully certified and the school climate variable of principal leadership (defined as instructional leadership) come from the school questionnaires.

3.2 PISA Sampling

PISA sampling design is a probabilistic, stratified and cluster design. For the first strata, schools were sampled by the proportion of school sizes. Students within each selected school were sampled with equal probability. Finally, the student sample was received weight, which included school weight and within student weight. In United states, the population of schools is divided by region of the country (Northeast, Central, West, Southeast), school category (public school or private school) and whether the school includes 10th grade. Within each region, schools are stratified by grade of school, school location (city, suburb, town and rural), race (below or above 15 percent Black, Hispanic, Asian, Native Hawaiian/Pacific Islander, and American Indian/Alaska Native students), gender (> 95 percent female students; > 95 percent male students; others) and state. At the second stratum (i.e., within each school), 42 students who were age 15 were randomly selected (OECD, 2016). The U.S. sample provides data for this study with 5,712 students (15 years old) from 177 schools.

3.3 Variables

In this study, the dependent variable is student science achievement. Student science achievement was measured by the 2015 PISA science literacy test. Science literacy is defined as "the ability to understand the characteristics of science and the significance of science in our modern world, to apply scientific knowledge, identify issues, describe scientific phenomena, draw conclusions based on evidence, and the willingness to reflect on and engage with scientific ideas and subjects" (Programme for International student Assessment, 2009, p. 22). Students' scores were estimated by plausible values because students completed a subset of test items. PISA 2015 generated 10 plausible values for each student to present his or her academic achievement (OECD, 2016). The idea of plausible values was that a number of random numbers were drawn from certain established posterior distributions for each student (PISA, 2009, p.96). According to OECD (2016), plausible values contain information that included the estimation of a student's ability and the uncertainty of test estimate. Therefore, plausible values are not "real" test scores; there is a standard procedure to integrate plausible values when conducting analysis to produce a score in the traditional sense for each student (PISA, 2009). The science literacy scale varies from 0 to 1,000 (OECD, 2016).

At the student level, variables are exogenous including gender, SES, immigration status, and language at home (see Appendix A). Other important exogenous variables at the student level, including race-ethnicity, family structure, and family size, were not available in PISA 2015. Some variables used at the school level came also from information obtained at the student level, including disciplinary climate (in a science classroom), teacher support (in a science classroom) and parental support (for learning at home). Each of these variables was made from a scale of several items and is often referred to as a composite variable (PISA, 2015). They were aggregated within a school to produce school-level measures. Appendix A informs how each variable is constructed.

At the school level, variables include context variables and climate variables (Ma et al., 2008). Context variables include school size, school location, school ownership, and proportion of science teachers fully certified. The key contextual variable of school SES was aggregated from student SES within each school to describe school socioeconomic composition. According to Ma et al. (2008), four variables are essential to describe school climate including disciplinary climate, academic pressure, principal leadership, and parental involvement. In this dissertation, principle leadership is directly from school questionnaires, which is measured as principals' instructional leadership. Disciplinary climate, academic pressure and parental involvement variables are aggregated from student questionnaires. There were items measuring directly disciplinary climate, but 2015 PISA data did not directly measure academic pressure and parental involvement variable. Two proxy variables, Teacher Support in a Science Class and Parental Current Support for Learning at Home, are used as academic pressure and parental involvement. In this dissertation, overall, school climate variable was measured by instructional leadership, disciplinary climate, teacher support in a science class and parental current support for learning at home. Appendix B informs how each variable is constructed.

3.4 Models

As a preparation of the examination of phantom effects of school SES on science achievement, a null model is run with only the outcome measure (i.e., without any independent variables at any level.) The null model provides an analytical background for the current study. Essentially, the null model estimates the ICC, which represents the portion of variances is attributable to the school level. The null model can be expressed as

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

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

where Y_{ij} is science achievement for student i from school j; β_{0j} is the average science achievement for school j; ϵ_{ij} is the error term on student level; γ_{00} is the grand mean of science achievement, and μ_{0j} is the error term on the school level. The partition of variance to the student and school levels from this national sample provided the background for the examination of the phantom effects of school SES.

Ma and Hao (2018) developed a general analytical framework to examine phantom effects of school context on schooling outcomes. The current study adopted and followed their procedures. Ma and Hao (2018) essentially proposed a four-step approach to detect phantom effects. In the first step, Ma and Hao (2018) proposed what they referred to as the base model, which is also referred to by researchers in school effectiveness literature as the contextual model (see Ma, Ma, & Bradley, 2008). The purpose of this base model is to detect the phantom effects without any adjustment of other variables at either level. This base model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j} SES_{ij} + \epsilon_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01} SchSES_j + u_{0j}$$

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

where Y_{ij} is science achievement for student i from school j; β_{0j} is the average science achievement for school j with adjustment over student SES; β_{1j} is the relationship between SES and science achievement in school j; and ϵ_{ij} is the error term on student level. At the school level, γ_{00} is the grand mean of science achievement with adjustment over variables at both levels, γ_{01} is the relationship between school SES and science achievement, and μ_{0j} is the error term on the school level.

Ma and Hao (2018) then proposed, as the second step, to introduce any important missing variable to the base model. In the current study, it is the prior science achievement simulated to have various strength of correlation with the PISA science achievement measure (see discussion in Chapter 4). The purpose of this model is to examine the change in terms of phantom effects once a prior science achievement measure is added at the student level. This model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}SES_{ij} + \beta_{2j}PM_{ij} + \epsilon_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}SchSES_j + u_{0j}$$

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

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

where β_{2j} is the effect of simulated variable, prior science (achievement or ability), on the current PISA science outcome measure. Therefore, once a prior science achievement measure is added, a comparison with the base model would show the influence of this prior science achievement measure on the effects on the current PISA science achievement measure of both student SES (at the student level) and school SES (at the school level).

Ma and Hao (2018) referred to the two models above as the set of absolute models for phantom effects. The term absolute indicates that the influence of prior science achievement measure was examined in the absence of other variables at the student and school levels. In the last two steps, variables at the student and school levels were introduced to the set of absolute models for phantom effects. Ma and Hao (2018) referred to these models as the set of relative models for phantom effects. The term relative indicates that the influence of prior science achievement measure was examined in the presence of other variables at the student and school levels.

Specifically, in the third step, Ma and Zhou (2018) introduced variables at both the student and school levels to the base model to produce what they referred to as the full contextual model, including all student-level variables and school-level variables. These variables at the student and school levels provided adjustments to purify the effects of student SES and school SES on science achievement. This model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}SES_{ij} + \sum_{p=1}^{m} \beta_{(p+1)j} X_{pij} + \epsilon_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}SchSES_j + \sum_{q=1}^{n} r_{0(q+1)} Z_{qj} + u_{0j}$$

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

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

In the final (fourth) step, Ma and Zhou (2018) introduced variables at both student and school levels to the model fitted in the second step so that these variables at the student and school levels could provide adjustments to purify the influence of prior science achievement measure. This model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}SES_{ij} + \beta_{2j}PM_{ij} + \sum_{p=1}^{m} \beta_{(p+2)j} X_{pij} + \epsilon_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}SchSES_j + \sum_{q=1}^{n} r_{0(q+1)} Z_{qj} + u_{0j}$$

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

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

3.5 Partial Simulation

PISA data does not include variables that measure prior academic achievement. For the current study, prior measures of science achievement needed to be generated. Simulated data would then work with actual data to address a statistical issue, thus named partial simulation. The partial simulation procedure can generate a random variable with a defined correlation to an existing variable. In other words, the partial simulation procedure in the current study is to generate a random variable with a defined correlation to a dependent variable. The conditions manipulated were the correlation between the dependent variable and the created variables. Ten conditions or correlations were considered (0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, and 0.95). Once these prior measures of science achievement were generated, a separate multilevel analysis was performed with models that were discussed in the previous section. As a result, 10 sets of multilevel analyses were conducted for each of the ten correlation conditions. The following tables synthesize results from these sets of multilevel analyses.

3.6 Working with Plausible Values in Partial Simulation

According to PISA (2009), there were four steps to cope with plausible values. The 2015 PISA data has 10 plausible values. Each plausible value is treated as a dependent variable in a specified regression model, and regression coefficients are computed with the final weights and the 80 replicate weights, running a total of 81 regression analyses. Overall, in the first step, 810 regression coefficients are computed. Table 3.1 shows the procedure to estimate 810 coefficients. $\hat{\beta}_1$ to $\hat{\beta}_{10}$ denotes 10 separate estimation with final weights. $\hat{\beta}_{1\_1}, \hat{\beta}_{1\_2}, \hat{\beta}_{1\_3} \ldots \hat{\beta}_{1\_80}$ denote 80 separate estimations each with a replicate weight. $\sigma^2{}_{\widehat{\beta_1}}\ to\ \sigma^2{}_{\widehat{\beta_{10}}}$ are sampling variance (e.g., $\sigma^2{}_{\widehat{\beta_1}}$ is the variance of $\hat{\beta}_{1\_1}, \hat{\beta}_{1\_2}, \hat{\beta}_{1\_3} \ldots \hat{\beta}_{1\_80}$) (OECD, Chapter 7, p.104).

The second step is to take the average value of the 10 values for each parameter with final weights and sampling variance such as

$$\hat{\beta} = \frac{\hat{\beta}_1 + \hat{\beta}_2 + \cdots + \hat{\beta}_{10}}{10}$$

$$\sigma^2{}_{\hat{\beta}} = \frac{1}{10} * (\sigma^2{}_{\widehat{\beta_1}} + \sigma^2{}_{\widehat{\beta_2}} + \cdots + \sigma^2{}_{\widehat{\beta_{10}}})$$

where $\hat{\beta}$ is the final estimate parameter, $\sigma^2{}_{\hat{\beta}}$ is final estimate of the sampling error.

The third step is to calculate the imputation variance

$$\sigma^2{}_{*} = \frac{1}{NP - 1} * \sum_{i=1}^{10} (\hat{\beta}_i - \hat{\beta})^2$$

where $\sigma^2{}_*$ is the imputation variance, $\hat{\beta}_i$ is estimated with the final weights based on statistical model. The final step is to calculate the final standard error

$$\mathrm{SE} = \sqrt{\sigma^2{}_{\hat{\beta}} + (1 + \frac{1}{NP}) * \sigma^2{}_*}$$

where SE is standard error.

What makes the partial simulation procedure far more complicated in this dissertation is the fact that there are 10 plausible values in PISA 2015. To work with plausible values in partial simulation, there are three steps. The first step is to pick a correlation. The second step is to generate a prior measure with the first PL and run 81 times with final weight and replicate weights. The third step is to replicate the above two steps for other plausible values. There are 810 regression coefficients computed for each level parameter. Table 3.2 shows the procedure to generate these coefficients. For example, if 0.05 correlation is picked, the second step is generating a prior measure with the first PL and running 81 times with final weights and replicate weights. There are 81 regression coefficients computed for each level parameter. The third step is to replicate the two steps for other plausible values. The final standard errors of the interested variables at different levels are based on the 810 coefficients (see earlier discussion).

Table 3.1 The 810 Regression coefficient estimates

Weight	PV1	PV2	PV3	PV4	PV5	PV6	PV7	PV8	PV9	PV10
Final	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$	$\hat{\beta}_6$	$\hat{\beta}_7$	$\hat{\beta}_8$	$\hat{\beta}_9$	$\hat{\beta}_{10}$
Replicate 1	$\hat{\beta}_{1\_1}$	$\hat{\beta}_{2\_1}$	$\hat{\beta}_{3\_1}$	$\hat{\beta}_{4\_1}$	$\hat{\beta}_{5\_1}$	$\hat{\beta}_{6\_1}$	$\hat{\beta}_{7\_1}$	$\hat{\beta}_{8\_1}$	$\hat{\beta}_{9\_1}$	$\hat{\beta}_{10\_1}$
Replicate 2	$\hat{\beta}_{1\_2}$	$\hat{\beta}_{2\_2}$	$\hat{\beta}_{3\_2}$	$\hat{\beta}_{4\_2}$	$\hat{\beta}_{5\_2}$	$\hat{\beta}_{6\_2}$	$\hat{\beta}_{7\_2}$	$\hat{\beta}_{8\_2}$	$\hat{\beta}_{9\_2}$	$\hat{\beta}_{10\_2}$
Replicate 3	$\hat{\beta}_{1\_3}$	$\hat{\beta}_{2\_3}$	$\hat{\beta}_{3\_3}$	$\hat{\beta}_{4\_3}$	$\hat{\beta}_{5\_3}$	$\hat{\beta}_{6\_3}$	$\hat{\beta}_{7\_3}$	$\hat{\beta}_{8\_3}$	$\hat{\beta}_{9\_3}$	$\hat{\beta}_{10\_3}$
……	……	……	……	……	……	……	……	……	……	……
Replicate 80	$\hat{\beta}_{1\_80}$	$\hat{\beta}_{2\_80}$	$\hat{\beta}_{3\_80}$	$\hat{\beta}_{4\_80}$	$\hat{\beta}_{5\_80}$	$\hat{\beta}_{6\_80}$	$\hat{\beta}_{7\_80}$	$\hat{\beta}_{8\_80}$	$\hat{\beta}_{9\_80}$	$\hat{\beta}_{10\_80}$
Sampling variance	$\sigma^2_{\hat{\beta}_1}$	$\sigma^2_{\hat{\beta}_2}$	$\sigma^2_{\hat{\beta}_3}$	$\sigma^2_{\hat{\beta}_4}$	$\sigma^2_{\hat{\beta}_5}$	$\sigma^2_{\hat{\beta}_6}$	$\sigma^2_{\hat{\beta}_7}$	$\sigma^2_{\hat{\beta}_8}$	$\sigma^2_{\hat{\beta}_9}$	$\sigma^2_{\hat{\beta}_{10}}$

Table 3.2 The 810 regression coefficient estimates for 2 level HLM

Weight	PV1		PV2		PV3		……	PV10	
Final	$\hat{\beta}_{1j\_1}$	$\hat{\gamma}_{01\_1}$	$\hat{\beta}_{1j\_2}$	$\hat{\gamma}_{01\_2}$	$\hat{\beta}_{1j\_3}$	$\hat{\gamma}_{01\_3}$	……	$\hat{\beta}_{1j\_10}$	$\hat{\gamma}_{01\_10}$
Replicate 1	$\hat{\beta}_{1j\_1\_1}$	$\hat{\gamma}_{01\_1\_1}$	$\hat{\beta}_{1j\_2\_1}$	$\hat{\gamma}_{01\_2\_1}$	$\hat{\beta}_{1j\_3\_1}$	$\hat{\gamma}_{01\_3\_1}$	……	$\hat{\beta}_{1j\_10\_1}$	$\hat{\gamma}_{01\_10\_1}$
Replicate 2	$\hat{\beta}_{1j\_1\_2}$	$\hat{\gamma}_{01\_1\_2}$	$\hat{\beta}_{1j\_2\_2}$	$\hat{\gamma}_{01\_2\_2}$	$\hat{\beta}_{1j\_3\_2}$	$\hat{\gamma}_{01\_3\_2}$	……	$\hat{\beta}_{1j\_10\_2}$	$\hat{\gamma}_{01\_10\_2}$
Replicate 3	$\hat{\beta}_{1j\_1\_3}$	$\hat{\gamma}_{01\_1\_3}$	$\hat{\beta}_{1j\_2\_3}$	$\hat{\gamma}_{01\_2\_3}$	$\hat{\beta}_{1j\_3\_3}$	$\hat{\gamma}_{01\_3\_3}$	……	$\hat{\beta}_{1j\_10\_3}$	$\hat{\gamma}_{01\_10\_3}$
……	……	……	……	……	……	……	……	……	……
Replicate 80	$\hat{\beta}_{1j\_1\_8}$	$\hat{\gamma}_{01\_1\_8}$	$\hat{\beta}_{1j\_2\_8}$	$\hat{\gamma}_{01\_2\_8}$	$\hat{\beta}_{1j\_3\_8}$	$\hat{\gamma}_{01\_3\_8}$	……	$\hat{\beta}_{1j\_10\_8}$	$\hat{\gamma}_{01\_10\_8}$
Sampling variance	$\sigma^2_{\hat{\beta}_{1j\_1}}$	$\sigma^2_{\hat{\gamma}_{01\_1}}$	$\sigma^2_{\hat{\beta}_{1j\_2}}$	$\sigma^2_{\hat{\gamma}_{01\_2}}$	$\sigma^2_{\hat{\beta}_{1j\_3}}$	$\sigma^2_{\hat{\gamma}_{01\_3}}$	……	$\sigma^2_{\hat{\beta}_{1j\_10}}$	$\sigma^2_{\hat{\gamma}_{01\_10}}$

Note: $\hat{\beta}_{1j\_1}$ to $\hat{\beta}_{1j\_10}$ is the coefficient of student SES from the 10 separate estimations with final weights at the student level. $\hat{\gamma}_{01\_1}$ to $\hat{\gamma}_{01\_10}$ is the coefficient of school SES from the 10 separate estimations with final weights at the school level. $\sigma^2_{\hat{\beta}_{1j\_1}}$ to $\sigma^2_{\hat{\beta}_{1j\_10}}$ is the sampling variance associated with student SES (e.g., $\sigma^2_{\hat{\beta}_{1j\_1}}$ is the variance of $\hat{\beta}_{1j\_1}$ to $\hat{\beta}_{1j\_1\_80}$). $\sigma^2_{\hat{\gamma}_{01\_1}}$ to $\sigma^2_{\hat{\gamma}_{01\_10}}$ is the sampling variance associated with school SES (e.g., $\sigma^2_{\hat{\gamma}_{01\_1}}$ is the variance of $\hat{\gamma}_{01\_1}$ to $\hat{\gamma}_{01\_10}$)

CHAPTER 4. RESULTS

Several multilevel models were run to explore phantom effects in multilevel modeling of school effects. Final weights and replicate weights are applied to all these models. Final weights and replicate weights for the student level are scaled by:

$$w_{ij}{}^{*} = w_{ij} * \left(\frac{\sum_i w_{ij}}{\sum_i w^2{}_{ij}}\right)$$

where w_{ij} indicates each student's weights in each school (Rabe-Hesketh et al., 2002). To cope with missing data in 2015 PISA, the *PISA Data Analysis Manual* (2009) suggested a single imputation. For continuous variables, missing values are replaced by the weighted school mean. If the weighted school mean cannot be calculated, the missing value is replaced by the weighted country mean. The final weight was applied for each weighted mean. For a dichotomous missing variable, the missing value is replaced by 0. The categorical variable was replaced by the baseline value. All the following multilevel analyses were based on the above treatments.

A short discussion on the variables employed at the student level and at the school level is in order before the modeling activities. Table 4.1 shows that at the student level, 50 percent of the students are male. The average age of the students is 15.81 years with a standard deviation of 0.28 years. SES is an index, and the average SES of students is 0.08 with a standard deviation of 1. In addition, 26percent of the students are native, and 81 percent of the students speak English at home. At the school level, the average school size is 1,251 students with a standard deviation of 887 students Meanwhile, 38 percent of the schools are located in city areas, 49 percent of the schools are located in town areas, and 13 percent of the schools are located in rural areas. Also, 94 percent of the schools are public. The average school SES is .07 with a standard deviation of .54. Disciplinary climate is an index, and the average disciplinary climate is 0.28 with a standard deviation of 0.38. The average proportion of science teachers fully certified is .93. Teacher support is an index, and the average teacher support is .35 with a standard deviation of .30. Finally, principle instructional leadership is an index, and the average principle instructional leadership is .97 with a standard deviation of .82.

4.1 The Null Model

The null model (see Chapter 3) provides the background for all the subsequent analyses. The results of the null model show that the average science achievement of U.S. students is 494 points. Therefore, according to the PISA science scale (*M* = 500, *SD* = 100), U.S. students scored a little lower than the international average. The variance in science achievement at the student level is 7727.50, and variance in science achievement at the school level is 1876.65. Intra-class correlation is approximately 0.20, which indicates that 20 percent of the total variance in science achievement is due to the school level.

4.2 The Absolute Effects Models

As discussed in Chapter 3, the absolute effects models examine student SES effects and school SES effects in the absence of student and school background variables (at student and school levels). Table 4.2 shows the results of the base model and the absolute effects models after the addition of prior (science achievement) measures. Within this table, the panel labeled as "no prior" indicates the base model. For the base model, the results show that both student SES and school SES have positive and quite strong effects on student science achievement. At the student level, for one unit increase in student SES, student science achievement increases by 22.84 points. At the school level, for one unit increase in school SES, student science achievement increases by 35.78 points. Because the PISA science scale has a *SD* = 100, an effect size as the proportion of one *SD* can be easily calculated. At the student level, the model shows that with every increase of one standard deviation in student SES, the student science achievement rises by .23 *SD*. At the school level, the model shows that with every increase of one standard deviation in school SES, student science achievement rises by .36 *SD*.

The rest of the models in Table 4.2 all have the addition of the prior measures in various correlations with the present (PISA) measure. These prior measures are arranged in terms of the magnitude of the correlation with the present (PISA) measure from weak (small) to strong (large). With the correlation increasing from .15 to .95, the positive effects of student SES on student science achievement decrease from 22.45 to 2.61 and meanwhile the positive effects of school SES on student science achievement decrease from 35.78 to 3.52.

Some examples are provided. When a prior measure is added to the model with a correlation of .15 with the present measure, at the student level, for one unit increase in student SES, student science achievement increases by 22.45 points. At school level, for one unit increase in school SES, student science achievement increases by 35.78 points. When a prior measure is added to the model with a correlation of .95 with the present measure, at the student level, for one unit increase in student SES, student science achievement increases by 2.61 points. At school level, for one unit increase in school SES, student science achievement increases by 3.52 points.

In terms of effect size, these results correspond to the effects of student SES at about .22 *SD* at the school level and the effects of school SES at about .35 *SD* when correlation of the prior measure is .15 with the current measure. Meanwhile, the above results correspond to the effects of student SES at about .03 *SD* at the student level, and the effects of School SES at about .04 *SD* when correlation of the prior measure is .95 with the current measure.

These results clearly show that the presence of a prior science achievement measure dramatically decreases both student SES effects and school SES effects in student science achievement. The stronger the correlation between the prior science achievement measure and the present science achievement measure, the greater the decrease in both student SES effects and school SES effects.

It is important to emphasize that, although all effects are statistically significant at the alpha level of .05 in Table 4.2, some effects have rather small effect sizes. If 25 percent of a *SD* can be considered practically important (e.g., Cohen, 1988), then phantom effects of school SES appear when a prior measure has a correlation of .65 (even .55) with the present measure. For example, compared with the base model, student SES effects and school SES effects in the model with .75 correlation between prior and present measures are decreased by 51 percent and 53 percent respectively.

4.3 The Relative Effects Models

As discussed in Chapter 3, the relative effects models examine student SES effects and school SES effects in the presence of student and school background variables (at student and school levels). Table 4.3 shows the results of the full model and the relative effects models after the addition of prior (science achievement) measures. The focus of this table, in general, is on the effects of student SES and school SES on science achievement. As a result, this table has omitted other statistical information pertaining to student and school characteristics at student and school levels in order to highlight potential phantom effects of school SES. Within this table, the panel labeled as "no prior" indicates the full model. For the full model, the results show that, even after control over student and school characteristics, both student SES and school SES have positive and quite strong effects on student science achievement. At the student level, after statistical control over other variables at student and school levels, for one unit increase in student SES, student science achievement increases by 20.95 points. At the school level, after statistical control over other variables at student and school levels, for one unit increase in school SES, student science achievement increases 27.16 points. At the student level, after statistical control over other variables at student and school levels, for one standard deviation increase in student SES, student science achievement rises by .21 *SD*. At the school level, after statistical control over other variables at student and school levels, for one standard deviation increase in school SES, student science achievement rises by .27 *SD*.

The rest of the models in Table 4.3 all have the addition of the prior measures in various correlations with the present (PISA) measure. As in Table 4.2, these prior measures are arranged in terms of the magnitude of the correlation with the present (PISA) measure from weak (small) to strong (large). With the correlation increasing from .15 to .95, the positive effects of student SES on student science achievement decrease from 20.67 to 2.66 while the positive effects of school SES on student science achievement decrease from 27.16 to 3.73.

Some examples are provided. When a prior measure is added to the model with a correlation of .15 with the present measure, after statistical control over other variables at student and school levels, at the student level, for one unit increase in student SES, student science achievement increases by 20.67 points. At school level, for one unit increase in school SES, student science achievement increases by 26.92 points. When a prior measure is added to the model with a correlation of .95 with the present measure, at the student level, for one unit increase in student SES, student science achievement increases by 2.66 points. At school level, for one unit increase in school SES, student science achievement increases by 3.73 points.

In terms of effect size, these results correspond to the effects of student SES at about .20 *SD* at the student level and the effects of school SES at about .27 *SD* at the school level when correlation of the prior measure is .15 with the current measure. Meanwhile, the above results correspond to the effects of student SES about at .03 *SD* at the student level and the effects of school SES at about .04 *SD* at the school level.

These results clearly show that the presence of a prior science achievement measure dramatically decreases both student SES effects and school SES effects in student science achievement, even after statistical control over important variables at student and school levels. The stronger the correlation between the prior science achievement measure and the present science achievement measure, the greater the decrease in both student SES effects and school SES effects.

Again, it is noteworthy that although all effects are statistically significant at the alpha level of .05 in Table 4.3, some effects have rather small effect sizes. Using 25 percent of a *SD* as the standard for practical importance, in the presence of student and school characteristics, phantom effects of school SES appear when a prior measure has a correlation of .45 (even .35) with the present measure. For example, compared with the base model, student SES effects and school SES effects in the model with .75 correlation between prior and present measures are decreased by 48 percent and 46 percent respectively.

Table 4.1 Description of independent variables

Variable	Mean	SD
Student-level variables (N = 5712)		
Male	0.50	0.5
Age	15.81	0.28
Student SES	0.078	1.00
Native	0.26	0.44
English as language at home (yes = 1, no = 0)	0.81	0.39
School-level variables (N = 177)		
School size	1251	887.26
City school	0.38	0.48
Town school	0.49	0.5
Rural school	0.13	0.34
Public school	0.94	0.24
School SES	0.069	0.54
Proportion of science teachers fully certified	0.93	0.18
Disciplinary climate	0.28	0.38
Teacher support	0.35	0.30
Principal instructional leadership	0.97	0.82

Note. N indicates the sample size. SD indicates standard deviation.

Table 4.2 Absolute Changes in the Effects of Student and School Socioeconomic Status (SES) after the Addition of the Prior Measure of Science Achievement in Various Correlations with the Current Measure of Science Achievement

	Student SES		School SES	
Correlation	Effects	SE	Effects	SE
No prior	22.84	.81	35.78	.84
.15	22.45	.80	34.92	.82
.25	21.72	.77	33.62	.79
.35	20.60	.72	31.72	.75
.45	19.06	.67	29.16	.69
.55	17.04	.62	25.88	.62
.65	14.49	.51	21.79	.52
.75	11.30	.40	16.76	.40
.85	7.37	.25	10.68	.27
.95	2.61	.08	3.52	.10

Note. SE = standard error. All effects are statistically significant at the alpha level of .05.

Table 4.3 Relative Changes in the Effects of Student and School Socioeconomic Status (SES) after the Addition of the Prior Measure of Science Achievement in Various Correlations with the Current Measure of Science Achievement

	Student SES		School SES	
Correlation	Effects	SE	Effects	SE
No prior	20.95	.87	27.16	.82
.15	20.67	.85	26.92	.80
.25	20.07	.82	26.24	.77
.35	19.11	.78	25.09	.73
.45	17.76	.72	23.42	.67
.55	15.97	.64	21.18	.60
.65	13.68	.54	18.25	.51
.75	10.78	.42	14.52	.39
.85	7.16	.27	9.78	.26
.95	2.66	.10	3.73	.10

Note. SE = standard error. All effects are statistically significant at the alpha level of .05.

CHAPTER 5. DISCUSSION

5.1 Summary of Principal Findings

The main purpose of this study is to demonstrate the extent of bias of estimated school SES effects on student science achievement when missing the important variable of prior science achievement. This study attempts to show the trend of diminishing school SES effects on student science achievement as a function of the strength of the student's prior science achievement. The null model results indicate that 20 percent of the total variance in science achievement is due to school level. The average science achievement is 494 for U.S. students, which is lower than the international average (i.e., 500).

The base model and full model showed that student and school SES effects associated with student science achievement are strong and statistically significant. The base model is a model which includes student SES and school SES variables only. The full model is a model in which all control variables both at the student level and at the school level are added to the base model. For the base model, at the student level, for one unit increase in student SES, student science achievement increases by 22.84 points (effect size = 0.23); at the school level, for one unit increase in school SES, student science achievement increases by 35.78 points (effect size = 0.36). For the full model, at the student level, students with high SES outperform students with low SES by 20.95 (effect size = 0.21); at the school level, students in high school SES outperform students in low school SES by 27.16 (effect size = 0.27).

With the above as the background, this study examined the influence of prior science achievement on student and school SES effects. The absolute influence is examined in a model in which (generated) prior science achievement measure in a certain correlation with present science achievement measure is added to the base model. The relative influence is examined in a model in which (generated) prior science achievement measure in a certain correlation with present science achievement measure is added to the full model. For the absolute influence, with correlation increasing from .15 to .95 (in an increment of .10), student SES effects decrease from 22.45 to 2.61, and school SES effects decrease from 35.78 to 3.52 (see Table 4.2). In terms of effect size, student SES effect size decreases from 0.22 to 0.026, and school SES effect size decreases from 0.36 to 0.035. For the relative influence, with correlation between present science academic achievement and prior science achievement increasing from .15 to .95, student SES effects decreases from 20.67 to 2.66 and school SES effect decreased from 27.16 to 3.73. (see Table 4.3). In terms of effect size, student SES effect size decreases from 0.21 to 0.026 and school SES effect size decreases from 0.27 to 0.037.

5.2 Characteristics of Phantom Effects

Mathematically, phantom effects refer to the effects of A (on some outcome) that are statistically significant in the absence of B but become statistically nonsignificant (i.e., tend to disappear) in the presence of B. Figures 5.1 and 5.2 are created to graphically illustrate the characteristics of phantom effects concerning student SES and school SES respectively. In general, based on the figures, phantom effects in this study can be characterized as such: The stronger the correlation between prior science achievement measure and present science achievement measure, the greater the chance that phantom effects occur in terms of both student SES effects and school SES effects. In fact, with the increasing correlation between prior science achievement and present science achievement, the association between school SES and student science achievement decreases dramatically. Using the 25 percent of a SD as the threshold for relative model (to overcome the overpower of a large sample size), phantom effects of school SES disappear when a prior science achievement reaches .45 (even .35) in correlation to present science achievement measurement. Meanwhile, with the increasing correlation between prior science achievement and present science achievement, the association between student SES and student science achievement decreases dramatically as well. In the relative model, all effects associated with student SES are below .25 SD. A smaller minimum cut-off value of the effect size (0.2 SD) is applied (see Hedges & Hedberg, 2007). Phantom effects of student SES disappear when a prior science achievement reaches .35 (even .25) in correlation to present science achievement measurement.

5.3 Implications for Empirical Research

In light of the findings in this study and evidences from other researchers (e.g., Marks, 2015; Televantou et al. 2015), it is noteworthy that for the contextual HLM model, missing information at the first level may attenuate the school (and student)

SES effects on student academic achievement. This study shows that, when the correlation between prior measurement and present measurement reaches .35 or even .25, phantom effects of school (and student) SES effects on student academic achievement may disappear. Because of the importance of student prior measurement, researchers need to make an effort to conduct a comprehensive data collection. In other words, data on student prior academic achievement measures should always be included in data analysis.

This study also offers a way to help create prior academic achievement measures when they are not available for data analysis. Researchers are encouraged to conduct a thorough literature review to locate possible correlations between prior academic achievement measures and current academic achievement measures. When these correlations are known, this study developed a procedure (in the programming language of R) to create prior academic achievement measurements, which will help researchers conduct data analysis based on correctly specified models.

5.4 Implications for Policy and Practice

Policymakers have issued many policies related to school SES that are based on previous research evidence generated from the contextual school effects model. In New Zealand and the United Kingdom, schools adopt a funding model that provides similar resources to all schools and provides additional funding to schools with high needs (e.g. rural school, high percentage of students from low SES, etc.) (Perry & McConney, 2010). Obviously, policymakers tried to promote student diversity in school and equalize each school SES. Similarly, in the U.S., policymakers issued a School Assignment Policy to equalize school SES. For example, in 2001, Cambridge, Massachusetts public school district applied a mixed method to assign students, which reduces race factor weight and considers students' SES when assigning students to elementary school (Reardon, Yun & Kurlaender, 2006).

The effectiveness of these policy practices is open to question based on the evidence in this and other studies. The association between school SES and student academic achievement may be attenuated by misspecified contextual models. In other words, student SES and school SES may not have as strong effects on student academic achievement as previous studies indicated, if the school contextual models are correctly specified. When a new policy related to school SES is issued, there appears to be a need to seriously consider the weight of school SES. Indeed, apart from the purpose of this study to examine the influence of missing prior student academic achievement measures, some other evidence has already shown that school SES effects on student academic achievement may disappear if variables such as school enrollment size and teacher academic expectation on students are properly controlled (see Lam & Lau, 2014; Rumberger & Palardy, 2005). In order to make appropriate policies, policymakers may want to encourage (e.g., fund) research projects that gather appropriate evidence with a fuller data collection from students and schools, particularly including prior student academic achievement measures.

5.5 Limitations of the Study

The findings of this study have to be seen in light of some limitations. The generalizability is limited. The first is data source. In this study, the data was from U.S. sample. Based on U.S. sample, phantom effects were found in misspecified contextual HLM model. The question then arises: Can phantom effects be found based on samples from other countries? The second limitation concerns dependent variable. In this study, the dependent variable is science achievement. Another question arises simultaneously: Can phantom effects be detected, when dependent variable is not science achievement? Marks (2015, 2017) provided information to answer those questions, but more comprehensive studies should be conducted.

5.6 Suggestions for Further Research

The results of this study indicate the importance of considering prior student academic achievement measures when considering school contextual effects such as school SES effects. Other variables for causing phantom effects of school contextual effects on student academic achievement may need to be explored, apart from prior student academic achievement measures. This approach focusing on missing important information needs to be continued to generate richer evidence for educational policies and practices.

On the other hand, the approach that focuses on potential measurement errors may also be explored further. Measurement error and model specification are often tangled up with each other to produce effects on parameter estimation. For example, after correcting measurement error based on a different correction method, how does school SES change? Pokropek (2015) examined three approaches to correct measurement error. Based on simulation study, the author gave a thumbs-up rule for applying each approach. Furthermore, what is the reaction between corrected model specification and each measurement error approach? Pokropek (2015) provides only limited information to answer some of the questions, but more comprehensive studies should be conducted.

5.7 Conclusion

The result of this study can be summarized by several important points. First, based on partial simulation procedure, phantom effects of school SES and student SES are real. Second, characteristics of phantom effects are generalized. The stronger the correlation between prior science achievement measure and present science achievement measure, the greater the decrease in both student SES effects and school SES effects. Third, the procedure of partial simulation provides a new angle to conduct theoretical studies (full simulation), which is entirely based on ideal assumption. Finally, the procedure of partial simulation offers researchers a way to create prior student academic achievement measures when they are not available for data analysis.

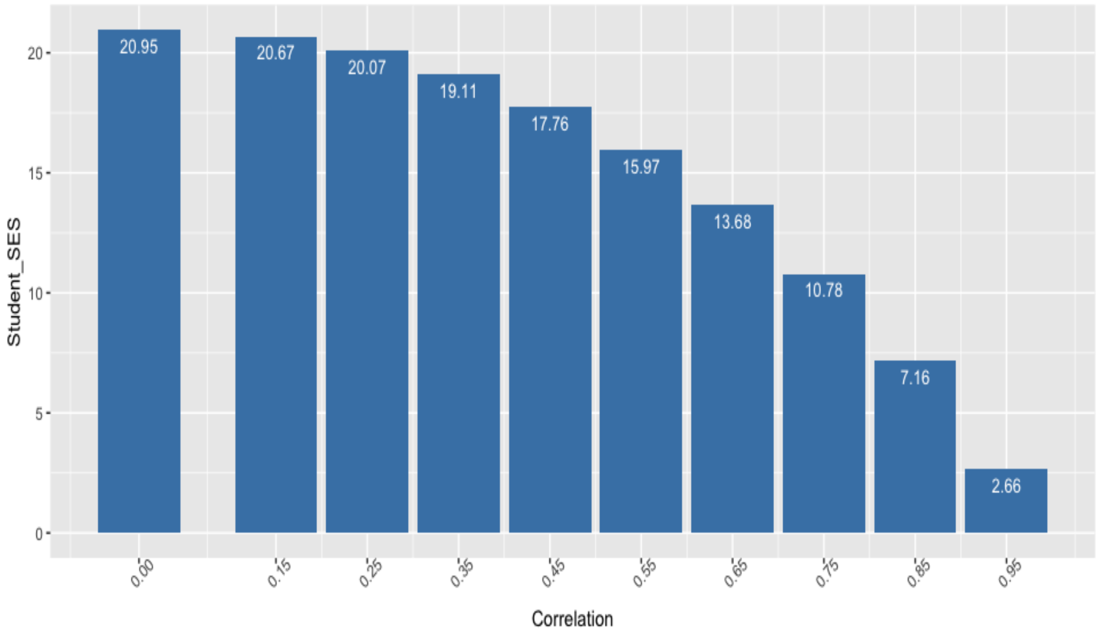

Figure 5.1 Change in effects of student SES on current science achievement, with addition of prior science achievement in various correlations with current science achievement.

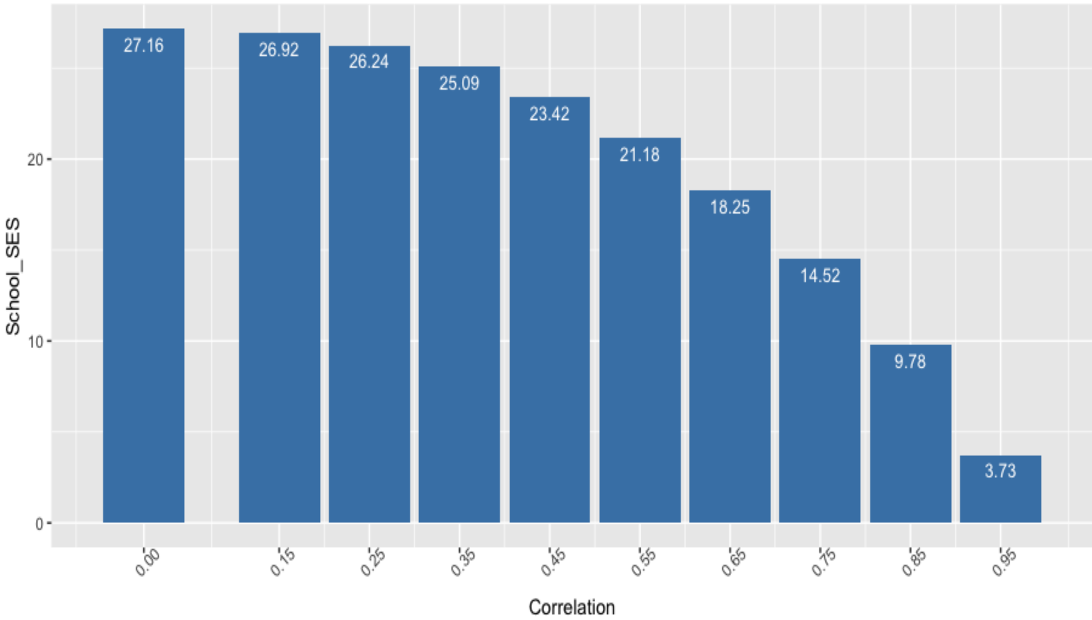

Figure 5.2 Change in effects of school SES on current science achievement, with addition of prior science achievement in various correlations with current science achievement.

APPENDICES

APPENDIX 1. Description of Independent Variables at the Student Level

Variable	Item	Coding
Age	On what date were you born?	Continuous
Gender	Are you female or male?	0 = Female and 1 = Male
Language at Home	What language do you speak at home most of the time? (English or Other language)	0 = Other Language and 1 = English
Immigration Status	In what country were you and your parents born? (Native or Immigrant)	0 = Native and 1 = Immigrant
Index of Economic, Social and Cultural Status (Student SES)	Parental education, parental occupation, and home possessions	Composite index. Continuous.
Disciplinary Climate in Science Classes	How often does the following happen? 1. Students don't listen to what the teacher says. 2. There is noise and disorder. 3. The teacher has to wait a long time for students to quiet down. 4. Students cannot work well. 5. Students don't start working until a long time after the lesson begins. (Every Lesson, Most Lessons, Some Lessons, Never or Hardly Ever)	Valid average for each student. Continuous.
Teacher Support in Science Class	How often does the following happen? 1. The teacher shows an interest in every student's learning. 2. The teacher gives extra help to students with their learning. 3. The teacher continues	Valid average for each student. Continuous.

	teaching until the students understand. 4. The teacher continues teaching until the students understand. 5. The teacher gives students an opportunity to express opinions. (Every Lesson, Most Lessons, Some Lessons, Never or Hardly Never)	
Parental Support for Learning at Home	How often does the following happen? 1. Discuss how well my child is doing at school. 2. Eat a meal with my child around a table. 3. Spending time just talking with my child. 4. Help my child with his/her science homework. 5. Ask how my child is performing in science classes. 6. Obtain science-related materials (e.g. applications, software, study guides etc.) for my child. 7. Discuss with my child how science is used in everyday life. 8. Discuss science-related career options with my child. (Never or Hardly Never, Once or Twice a Year, Once or Twice a Year, Once or Twice a Week, Every Day or Almost Every Day)	Valid average for each student. Continuous.

APPENDIX 2. Description of Independent Variables at School Level

Variable	Item	Coding
School location	What best describes the community in which your school is located? (Rural, Town, City)	Town (town = 1 and others = 0) City (city = 1 and others = 0)
School Size	What is the total school enrollment (number of student)?	Continuous
School Type	What is your school's ownership? (Private independent, Private Government-dependent, Public)	Public (Public = 1 and others = 0)
School SES	Aggregated from the student level	Continuous
Proportion of science teachers fully certified	What is the proportion of science teachers fully certified?	Continuous
Instructional leadership	How often does the following happen? 1. I use student performance results to develop the school's educational goals. 2. I make sure that the professional development activities of teachers are in accordance with the teaching goals of the school. 3. I ensure that teachers work according to the school's educational goals. 4. I promote teaching practices based on recent educational research. 5. I praise teachers whose students are actively participating in learning. 6. When a teacher has problems in his/her classroom, I take the initiative to discuss matters. 7. I draw teachers' attention to the importance of pupils'	Valid average for each school. Continuous.

	development of critical and social capacities. 8. I pay attention to disruptive behavior in classrooms. 9. I provide staff with opportunities to participate in school decision-making. 10. I engage teachers to help build a school culture of continuous improvement. 11. I ask teachers to participate in reviewing management practices. 12. When a teacher brings up a classroom problem, we solve the problem together. 13. I discuss the school’s academic goals with teachers at faculty meetings. (Didn’t occur, 1-2 times during the year, 3-4 times during the year, Once a month, Once a week, More than once a week)	
Teacher Support in a Science Class (as Academic Pressure)	Aggregated from the student level	Continuous
Parental Support for learning at Home (as Parental involvement)	Aggregated from the student level	Continuous
Disciplinary Climate in Science Classes	Aggregated from the student level	Continuous

APPENDIX 3. Results of Full Multilevel Model as Basis to Examine Effects of Student and School Socioeconomic Status (SES) on Science Achievement

	Coefficients	SE
Constant	272.11*	17.48
Student-level variables		
Male (vs female = 0)	7.25*	1.11
Age	11.47*	1.09
Student SES	20.95*	0.87
Immigrant (vs native = 0)	-5.33*	1.54
English as language at home (yes = 1, no = 0)	10.69*	1.84
School-level variables		
School size (per 100 students)	0.34*	0.09
City school (vs rural school)	-24.52*	1.61
Town school (vs rural school)	-13.29*	1.52
Public school (vs private school)	26.43*	2.00
School (mean) SES	27.16*	0.82
Proportion of science teachers fully certified	4.02	3.50
Disciplinary climate	47.86*	0.91
Teacher support	-12.02*	2.14
Principal instructional leadership	0.55	0.66

Note. * $p < .05$. At the student level, male students outperform female students by 7.25. Older students outperform younger students by 11.47. Students with high SES outperform students with low SES by 20.95. Native (born) students outperform foreign (born) students by 5.33. Students with English as language at home outperform students with other language at home by 10.69. At the school level, students in big school outperform students in small school by 0.34. Students in rural schools outperform students in city schools by 24.52. Students in rural schools outperform students in town schools by 13.29. Students in private schools outperform students in public schools by 26.43. Students in schools with high school SES outperform student in schools with low school SES by 27.16. Students in schools with good disciplinary climate outperform students in schools with poor disciplinary climate by 47.86. Students in schools with less teacher support outperform students in schools with more teacher support by 12.02. Finally, other variables are not statistically significant at the school level.

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Qiu, C., Dueber, D. M., Toland, M. D., Berney, E. C., Zhou, H., Blevins, J., Kehrwald, N., & Clement, T. (2019, August). *RA and resident belongingness: Multilevel longitudinal analysis.* Poster accepted for presentation at the 127th American Psychological Association Conference, Chicago, IL.

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