Private and Public Education:
A Cross-National Exploration with TIMSS 2003

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Abstract

This article investigates cross-national mathematics and science achievement differences between public and private schools. Using the TIMSS 2003 data, we empirically examine differences through a set of multilevel models that attempt to control for select student background factors. We also attempt to correct for selection bias using propensity score matching methods. A number of methodological issues including the treatment of missing data and the construction of a quality student background measure are also addressed. While our analysis supports previous findings of higher private school achievement, we have found that higher private school achievement is not uniform across educational systems or content domains analyzed. This variation is significant in light of the blanket privatization policy currently promoted by powerful international organizations.

Keywords: *TIMSS, private schools, multilevel models, propensity score matching*

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In the past several decades a range of policy actions have created a space for the promotion of private educational systems throughout the world. For example, as part of an education initiative, the World Bank, (incidentally, the world's largest external funder of education) has created a collaborative of researchers to explore the benefits of public-private partnerships in education. As recently as June 2007, the World Bank sponsored a conference to discuss the benefits of the privatization of education and presented case studies codifying this assumption (World Bank, 2007). Papers presented at this conference as well as work done within the broader privatization project assume the dominant paradigm in most economic based educational research, which suggests that private educational institutions outperform their publicly funded peer institution cross-nationally. Further, when discussion moves to the global level of discourse, benefits to privatization often become the dominant way of discussing educational reform. However, whether the benefits of privatization are robust is unclear. Further, it is uncertain whether the private school advantage is consistent around the world. Therefore, this paper aims to investigate the magnitude of the private school achievement advantage in and across a number of educational systems.

Studies of private education benefits have proven robust if for nothing else but for their perseverance. Historically, Friedman (1955) positioned himself as an early proponent of private education, who argued that similar to private industry, free markets in the educational sector would lead to improved educational institutions. This line of argument continued unabated over the next 50 years. Institutions such as the World Bank and authors such as Tooley and Dixon

(2006) continue Friedman's legacy by attempting to demonstrate the benefits of private schools while simultaneously arguing for the reduction of public institutions.

The World Bank's conviction to the superior performance of private educational systems is one example of how the organization is attempting to introduce free market principles to educational governance. Internationally and, especially, within the United States, a number of organizations and institutes also spend significant time and resources advocating the benefits of a private school model. While the World Bank clearly has the largest (and therefore most influential) pocketbook, organizations such as the Cato Institute, the Adam Smith Institute and the Futures of Freedom Foundation all unconditionally support a broad based private school model nationally and around the world.

By what criteria are researchers concluding a private school advantage? While measures of private school success typically vary, evidence of superior performance at the national and international level is often presented via differences in standardized assessment achievement (for example, Fuchs & Woessman, 2007; Woessman, 2003). Using these data allow for a low cost examination of benefits; however, previous findings have been based on what we believe are less optimal methods or a failure to fully consider the context. As such, the current paper seeks to investigate whether private schools have higher mathematics and science achievement than their public school counterparts on the 2003 Trends in International Mathematics and Science Study (TIMSS). TIMSS provides data resulting from a reliable international assessment of fourth and eighth grade students on the mathematics and science achievement. Using what we reason are the most appropriate and up to date methods, we aim to better understand the relationship between institution type and achievement in a number of educational systems.

Theoretical Debate

Educational privatization notions are closely linked to neo-classical theories that promote free markets as the most efficient way of providing a product or service (education) to the customer (students and parents). Friedman's (1955) theories on the privatization of education were and continue to be supported by researchers who contended that public educational institutions lacked incentives to improve educational systems. Among others, Chubb and Moe (1990) and Coleman (1997) argued that allowing school choice, mainly through the promotion of private schools, would improve educational markets. In 1995, forty years after his seminal work in education, Milton Friedman continued to posit, "the only way to make a major improvement in our educational system is through privatization to the point at which a substantial fraction of all educational services is rendered to individuals by private enterprises" (online). Aligned with basic economic principles of supply and demand, these privatization advocates argued that increased marketization of education would spur competition, which would ultimately lead to improved quality.

Unfortunately, the debates surrounding the privatization of education are not straightforward. In particular, economists such as Friedman acknowledge that education results in some public good and therefore deserves funding from the public sector. However, the neo-classical approach to education typically views the benefits of education as individual. As such, compulsory public schooling violates this economic tenet. Further, it is argued that public schools have become an inefficient bureaucracy, accountable for very little and often with little or no incentive to improve. Finally, neo-classical economic theory argues if the commodity of education is allowed to enter the free market, providers will have an incentive to meet customers' needs or risk extinction.

In the United States and around the world, privatization is often packaged as a voucher system, whereby students choose a school within certain parameters and the government provides to the chosen institution an allotment for that student. While appeasing privatization advocates by giving students limited choices, voucher systems often manage to also placate detractors who argue that private school access is exclusive and limited to children of the wealthy. Vouchers are also seen as a way to preserve school autonomy while making public funding available (Buchanan & Tullock, 1962; Epple & Romano, 1998). Despite the popularity of voucher systems, benefits of a broad based privatization approach remain unclear (Witte, 1999; Manski, 1992). In the U.S., Rouse (1998) indicated a small benefit to school choice in mathematics achievement with mixed results in reading while others found no significant achievement advantage for the school choice models (Bettinger, 2005; Levin, 1998; Mayer, Peterson, Myers, Tuttle, & William, 2002). Internationally, findings are also equivocal (McEwan & Carnoy, 2000; West, 2001, Angrist et al., 2002; Bradley & Taylor, 2002; Filer & Münich, 2000). Finally, Miron and Nelson (2002), argue that more research about the effects of these types of school models is needed.

Private school proponents often operate under the assumption that private schools are relatively more effective than public schools at improving student outcomes. However, as McEwan (2004) acknowledged, the mounting research on the benefits of private education “does not specify exactly why private schools might produce better outcomes than public schools” (p. 68). Conjecturing about the nature of some causes, McEwan went on to state:

> One possibility is that private schools use more resources than public schools or allocate the same resources differently. Another possibility is that private schools enroll students with different characteristics, on average, than public schools … and that private students benefit from exposure to “better” peers. (p. 68)

Factors, such as the socio-economic status (SES) of students and the community in which they learn as well as the student background, may account for higher private school performance relative to their public peers. While there exists a wealth of research comparing the outcomes of private and public schools, it is the intention of this paper to analyze the differences at the national level across several nations. A paucity of studies in this particular area exists in spite of heavy private school promotion internationally by large organizations that typically fund these types of reforms. The following includes a short summary of studies that have used LSA data to address the difference between public and private schools.

Existing Research

The literature concerning public and private school effectiveness is extensive and vastly international. Inspiring a line of research and discussion in the United States, Coleman, Hoffer, and Kilgore (1981) argued that a positive private school effect was evident in United States high school level data. However, Coleman, Hoffer, and Kilgore's work was soon criticized by a number of authors to include Goldberger and Cain (1982), who argued that the assessment methods used fell "below the minimum standards for social scientific research" (p. 103). In part, what can be viewed as a response to critics of their initial study, Coleman and Hoffer (1987), along with others such as Chubb and Moe (1990) and Bryk, Lee, and Holland (1993) provided further evidence that private institutions (mostly in the form of Catholic Schools) outperform their public counterparts. Internationally, a number of studies using a variety of methods and data attempted to test the private effect. For example, in Indonesia, Bedi and Garg (2000); in India, Kingdon (1996); in Tanzania, Lassibille and Tan (2001); and Glewwe and Patrinos (1998) in Vietnam provide a range of national studies mostly showing positive effects for private institutions. Filer and Münich (2000) argued that the introduction of a voucher system in the

Czech Republic has led to the creation of private schools in areas where public schools were performing poorly; hence inferring the superiority of the private system. Moreover, Dronkers (2001) empirically examined the difference between privately managed religious schools and their public counter parts in Europe. Finally, concentrating on Latin America, Somers, McEwan, and Willms (2004) provided an excellent summary of a number of studies conducted in this region examining the private school effect. The authors found no consistent or strong effect for private schools when controlling for socio economic status (SES). While the above research informed the present project, our focus is international and large-scale assessment (LSA) evidence based in that it attempts to examine the difference in educational attainment in public and privately managed schools when using the same assessment cross nationally.

To date, a small number of studies have attempted to use international LSA data to examine the difference in student performance in both public and private schools. Unfortunately, many of these studies either ignored the structure of the data or used scantily researched methods to examine the differences between the two institution types. In two studies, Woessmann (2003) and Fuchs and Woessman (2007), utilize TIMSS and the Programme for International Student Assessment (PISA) data, respectively, in an attempt to explain international variation in student performance in both assessments. While the focus of both studies is not explicitly concentrated on the difference in educational attainment between private and public institutions, both studies find higher private achievement. Woessmann claimed that “students in countries with larger shares of enrolment in privately managed educational institutions scored statistically significantly higher in both mathematics and science” (p. 149). The 2007 study found that publicly funded, privately managed schools outperform their publicly funded, publicly managed and privately funded, privately managed counterparts. Surprisingly, Woessman (2003) contends that “there is no significant variation in many institutional features within a single country” (p. 120). As a result, the author aggregates all data to the international level. This tendency may introduce a host of problems including aggregation bias and a shift of meaning. Further, in neither study do the authors report or acknowledge considering intra-class correlations, which may have had an impact on the decision to conduct analyses at the international level.

Similarly, Vandenberghe and Robin (2003) utilized the PISA data to show that for four of nine included educational systems, private schools outperform public schools in a number of subjects. While relatively sophisticated methods were used to control for selection bias (a possibly significant problem in survey analysis research), the hierarchical structure of the data is ignored, rendering the significance of findings questionable.

With advancements in methodologies along with the expansion of high quality data, the way in which LSAs are analyzed has recently seen a transformation. Using multilevel modeling to account for the clustered structure of the data, Lubienski and Lubienski (2006) used the National Assessment of Educational Progress (NAEP) data to show that after controlling for home background factors, there appears to be little to no statistically significant benefits to private education on standardized test scores when compared to public systems in the United States. This differs from a large group of previous studies that did not utilize such models and subsequently came to different conclusions. As Lubienski and Lubienski show, there appears to be a relationship between studies that do not use the most appropriate models for educational data and the positive effects of private schools when compared to public schools. Therefore, it is our intent to adjust for home background and community SES levels while using techniques that account for the unique structure and attributes of educational LSA data. In particular, we fit multilevel models with and without propensity score matching (Rosenbaum & Rubin, 1983) to account for the structure of the data and to attempt to correct for the possible biases that may result from systematic differences between public and private school students. We also fit ordinary least-squares regression models with robust standard errors to compare against the multilevel models.

Research Question

At the international level a dominant paradigm is emerging, which assumes that private educational institutions are superior to their public counterparts. However, as recent studies have shown there is a continued need to examine the hypothesized advantage in light of a variety of factors. For example, much of the above evidence suggests that private educational systems are superior to public educational systems. It is important to note that many of the studies with a focus on public and private educational systems, especially at the international level, operate under strong economic assumptions. As a result, the way in which LSA data is often analyzed assumes very narrow guidelines and envisions the school as a unit of production. However, the aims of education and the purpose of schools in educational systems can differ greatly from the aims and purposes as envisioned by economists and economic organizations. As such, we utilize TIMSS data, which measures achievement based on educational curriculum rather than an LSA such as PISA, which measures workforce knowledge.

Our overall research question is as follows: for educational systems that indicated a public-private distinction in the TIMSS international data base, is there a significant difference between public and private schools in terms of mathematics and science achievement after accounting for school SES and select student background variables? To address this question, a number of methodological research issues arose in this study including: what is the best possible background index that can be created from the data at hand? Also, what is the most appropriate method for accounting for missing data in the TIMSS data set? Additionally, a policy relevant research question is discussed: To what extent do educational systems differ in their results? The theoretical debate and policy controversy surrounding the benefits of private educational systems are ongoing and constantly evolving. As such, the debates should be informed by and updated with the latest and most appropriate data and methodological tools. Using the TIMSS 2003 data and up to date multilevel modeling software and selection bias methods, we empirically investigate the above research questions.

Research Methods

Data

TIMSS 2003 is the third in a continuing cycle of curriculum-based international assessments in mathematics and science. The target population of TIMSS is all students at the end of 4th and 8th grades in participating educational systems. In addition to assessing mathematics and science achievement of 4th and 8th graders internationally, TIMSS also collects a wealth of background data from students, teachers and principals of participating schools. The resulting database is a rich resource for policy makers and researchers interested in educational achievement and possible correlates. According to the TIMSS 2003 Assessment Framework and Specifications (Mullis et al., 2003), the 4th grade sample is defined as the upper of the two adjacent grades with the most 9-year-olds. The 8th grade sample includes children aged 13 and 14, and is defined as the upper of the two adjacent grades with the most 13-year-olds. To maintain consistency with earlier privatization studies that utilized international LSA data, we have limited our investigation to 8th grade data. In 2003, 46 educational systems and four benchmarking educational systems were measured at the 8th grade. Further, given our research questions, we were limited to educational systems that made a school-type distinction in the data set (public or private). This resulted in a data set that included the following nine educational systems: Bahrain, the Flemish region of Belgium, Chile, Iran, Japan, Lebanon, the Philippines, and the United States. For these educational systems, sample sizes, achievement averages and proportion of students in the sample that attend private schools can be found in Table 1.

Insert Table 1 about here

According to the International Association for the Evaluation of Educational Achievement (IEA), TIMSS 2003 primarily used a two-stage stratified-cluster sample design[1]. The first stage consists of a sample of schools (in most educational systems about 150), which may be stratified; the second stage consists of a sample of one or more classrooms from the target grade in sampled schools. All of the students in the sampled class(es) were selected to participate in the TIMSS testing (Foy & Joncas, 2004).

Measures

We used TIMSS 2003 mathematics and science achievement scores along with student and principal background questionnaire responses for a number of educational systems. To improve the efficiency of the TIMSS sample design and to ensure that samples were representative of the population, stratification methods were used in the sampling procedures. In many cases, the school type (public or private) was used as the stratification variable. In those educational systems that used a public/private distinction as a stratification variable, we created a binary indicator for later analysis (see Foy & Joncas, 2004 for a detailed explanation of the intended use of the stratification variables). As a proxy for the average SES of the school, we

[1] In some countries TIMSS included a third stage, sub-sampling students within large classrooms.

selected from the principal questionnaire the proportion of students in the community who were from disadvantaged homes. Through an exploratory analysis (discussed in the section titled *Student Background Measure*), we chose several variables to control for the effects of student background on mathematics and science achievement. These variables included *student gender*, *number of books in the home*, *home possessions* (a composite variable indicating home possession of dictionary, calculator, desk and computer), and *parent's education*. The measure of *parent's education* is a derived index variable available in the international database that uses the highest education level of one (for single-parent homes) or both parents reported by the respondent.

Student Background Measure

To investigate achievement differences on TIMSS 2003 mathematics and science assessments between public and private schools, we elected to control for factors in the data that we believed to be beyond the control of the school. This decision was made based on previous studies that showed reduced private school effects when proxies for student socio-economic status were included in the model (Lubienski & Lubienski, 2006). While we agree that SES was an important predictor of student achievement, our approach valued more than simply proxies for SES. We also postulate that the latent construct for which we are trying to control is not limited to SES. Instead, we wanted to capture those student attributes that accounted for variance in achievement scores but were out of the explicit control of the school system. Our initial exploration of these variables was based on a number of studies, (Lamb & Fullarton, 2002; Dronkers & Robert, 2003; Woessman, 2003; Postlethwaite & Ross, 1992; Martin et al. 2000; Kyriakides, Gagatis & Charalambous, 2000; Baker, Goesling, & LeTendre, 2002; Van den Broeck, Opdenakker, & Van Damme, 2003), that used student background or SES attributes as either control variables or variables to inform their results. While to a certain degree, our ability to incorporate a good measure of student background was limited by available data, the TIMSS background questionnaires collect a number of measures dealing with student attributes.

An extensive exploratory analysis included selecting candidate measures based on previous research (referenced above) along with our approach to the research question. Using a set of variables collectively referred to as *student background*, we aimed to account for as much of the variance as possible in mathematics and science achievement for which the school could not control. Utilizing the above literature we were left with a collection of the following indicators: *home possessions (book, calculator, desk, dictionary)*; *mother's education*; *father's education*; *father born in country*; *mother born in country*; *gender of student*; *frequency that language of the test is spoken at home*; *family size*; and *single parent family*. In order to account for the greatest amount of variance in test scores and keep the model as parsimonious as possible, we settled on a multiple regression model as an exploratory tool to obtain the best possible indicator.

Using the above variables, we fit a number of multiple regression models with math and science achievement as the outcome. As a measure of variance accounted for in the model, we used the coefficient of determination, or R^2. The coefficient of determination is defined as the proportion of variability in the response variable (math or science achievement) explained by adding predictors to the model. Using R^2 is a simple, yet effective way to determine whether a predictor or set of predictors account for variance in TIMSS math or science achievement. We proceeded by adding and subtracting variables from the multiple regression model until we arrived at a model such that adding additional candidate variables did not markedly account for more variance in achievement. As mentioned above, this resulted in a measure of student background that included *number of books in the home*, *parent's education*, and a composite indicator of *home possessions*.

Missing Data

Many social science and natural science data sets are plagued by missing data. Further, the mechanism for the missingness is often unknown and unknowable. Until recently, applied researchers have had few practical means at their disposal to handle missing data other than listwise deletion (also referred to as complete case analysis) or other unacceptable procedures. Rules of thumb suggest that listwise deletion is acceptable for missing rates of up to five percent (Graham, Cumsille & Elek-Fisk, 2003); however, in our data set parent's education had close to a 20 percent missing rate in some educational systems. This left listwise deletion as an untenable option, particularly given the necessary missing completely at random (MCAR) assumption. Given advances in missing data research, the means (while not perfect) are available to deal with missing data so as to achieve the least biased, most efficient population estimates.

As an alternative to listwise deletion, we opted to use the SAS 9.1 (2003) multiple imputation procedure (PROC MI) to impute missing values for cases in the TIMSS 2003 data set. We cautiously chose to use multiple imputation, particularly given the nature of the TIMSS 2003 data and the pattern of missingness in the data. While multiple imputation procedures assume that data are missing at random (MAR), Collins, Schafer and Kam (2001) demonstrated that incorrectly assuming MAR has only a minor impact on estimates and standard errors. Additionally, the imputation model assumes that data are distributed normally. While this is a safe assumption for the response variables (mathematics and science achievement), our student background variables were either binary (gender) or at best, ordinal (categories representing number of books in the home). Simulation studies indicate that parameter estimates based on multiply imputed categorical data has better coverage and less bias than estimates resulting from complete case analysis (Allison, 2005). Finally, given the large sample size for each educational system, we were fairly confident that our results would be robust.

The process of multiple imputation requires three related steps. First, a pre-specified number of data sets are created, such that each data set represents a different imputed value (plausible value) for each of the missing values. The number of data sets typically ranges in number from three to 10; however, for the current analysis we chose five, which is consistent with the IEA protocol for imputation. The second step includes separately and identically analyzing each of the five data sets. Finally, the parameter estimates from the five analyses are combined to arrive at a single set of parameter estimates and standard errors. All three steps were conducted within the SAS environment; however, only the combined parameter estimates are reported.

To impute missing data in the TIMSS 2003 data set, we chose for the imputation model all variables that we wanted to include as predictors and response variables in the multilevel model. Variables were chosen according to these criteria in part as an attempt to ensure that the imputer's model was the same as the analyst's model. We reasoned that variables used to measure student background should also be included in an imputation model since these variables are related and may increase the possibility of capturing the missing mechanism, thereby reasonably allowing for an MAR assumption.

In SAS, it is possible in the first imputation step to impose realistic range limits on the imputed values. For instance, imputed values for binary data can be limited for values not greater than one and not less than zero. Based on missing categorical data research indicating that unrounded imputed values had better coverage and less bias than rounded imputed values

(Allison, 2005), we first attempted to impose relevant range limits on imputed values but without rounding the results. Unfortunately, the MI procedure failed for a number of educational systems. To correct for this failure, we relaxed the range restrictions during imputation and imposed the range restrictions on the resulting five imputed data sets *ex post facto*. While this approach results in undesirable rounding of extreme imputed values, we found that the distributions of these variables were not markedly changed when we rounded extreme values to match the value limits on the variables. Additionally, we felt it was important to limit the range of imputed variables in the data set to what would have realistically been found if all data were present. Imputed values within the acceptable range limits were left unrounded.

Models

Several two-level models were fit to the TIMSS 2003 data set in an effort to answer the research question regarding the efficacy of private schools versus public schools. At the outset, we fit a null model for each educational system to provide justification for a multilevel modeling approach via the intra-class correlation. At level one, this model is of the form:

$$Y_{ij} = \beta_{0j} + R_{ij}, \tag{1}$$

where Y_{ij} is the math or science achievement score for student *i* in class *j*, β_{0j} is the intercept for group *j* and R_{ij} is the level-one residual for $i = 1,\ldots,n_j$ and $j = 1,\ldots,N$.

At level two, the model is of the form:

$$\beta_{0j} = \gamma_{00} + U_{0j} \tag{2}$$

where the intercept, β_{0j}, is a function of a fixed average intercept term, γ_{00}, and a random group term or level-two residual, U_{0j}. The intra-class correlation is defined as the proportion of the total variance in the response attributable to between group differences and is written as:

$$\rho_I = \frac{\tau^2}{\tau^2 + \sigma^2} \tag{3}$$

where var(Y_{ij}) = $\text{var}(U_{0j} + R_{ij}) = \text{var}(U_{0j}) + \text{var}(R_{ij}) = \tau^2 + \sigma^2$.

The next group of models included the school type as a level-two predictor. These models are referred to as *intercepts-as-outcomes* models. While the level-one model remains identical to the null model, the level-two specification changes as follows:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(private_j) + U_{0j}\,. \tag{4}$$

Where $private_j$ is a binary indicator for whether a school is public or private. A significant parameter estimate indicates that the mean achievement level is significantly different for private schools when compared with public schools. The combined level-one and level-two model that includes the school type is written as:

$$Y_{ij} = \gamma_{00} + \gamma_{01}(private_j) + U_{0j} + R_{ij}\,. \tag{5}$$

A third set of models was created for each educational system that included the student background variables as level-one predictors and the addition of school SES as a level two predictor. At level-one, these models were as follows:

$$Y_{ij} = \beta_0 + \beta_1(gender_{ij}) + \beta_2(books_{ij}) + \beta_3(pared_{ij}) + \beta_4(home_{ij}) + R_{ij}\,, \tag{6}$$

where β_1 is the estimated coefficient for gender, β_2 is the estimated coefficient for number of books in the home, β_3 is the estimated coefficient for the highest level of parent's education, and β_4 is the estimated coefficient for the home possession composite. Combined with the level-two terms, these models are written as follows for each educational system:

$$Y_{ij} = \gamma_{00} + \gamma_{01}(private_j) + \gamma_{02}(SES_j) + \gamma_{10}(books_{ij}) + \gamma_{20}(home_{ij}) + \gamma_{30}(pared_{ij}) + U_{0j} + R_{ij}\,, \tag{7}$$

where γ_{00} is the model intercept, γ_{01} represents the effect of school type, γ_{02} represents the effect of school SES, and γ_{h1} represents a level-one estimated effect. The random effects, U_{0j} and R_{ij} are assumed normally distributed with constant variance.

Propensity Score Matching Method

As noted by a number of authors (e.g. Rosenbaum & Rubin, 1983; Cuddeback, Wilson, Orme & Combs-Orme, 2004), selection bias is an issue with which to contend in cross-sectional, observational studies. Selection bias arises in observational studies when the composition of comparison groups differs systematically (Schneider, Carnoy, Kilpatrick, Schmidt & Shavelson, 2007), resulting in biased estimates of the *treatment* effect – in our case school type. To correct for the possibility of selection biased results, we also implemented a propensity score matching analysis for comparison with the multi-level model results. An important feature of propensity score matching methods is this method can correct for bias due to unobserved variables – a real possibility given the limited background data collected in the types of study used in this analysis.

In propensity score matching analyses, students in private and public schools are matched, one-to-one, based on the conditional probability of attending private school. This conditional probability was generated using a logistic regression model with student background and community SES variables as predictors. Matching in such a way allowed us to compare a limited subset of students from each country who have similar probabilities of attending private school, thereby minimizing extraneous or unobserved factors such as economic disadvantage or cultural capital. We matched students by country using a nearest neighbor algorithm. The resulting data set is a much smaller subset than the original data and contains students who are similar on important background measures. These data sets were subsequently analyzed in a simple regression model that featured only school type as a covariate. To account for bias in the standard errors due to the data structure, we report robust standard errors. This type of analysis allows us to make quasi-experimental inferences about the private school advantage.

Results

Empty Model

To investigate the appropriateness of a multilevel modeling approach, we examined the mean intra-class correlation (ICC) for all five plausible values of mathematics and science achievement. The ICC averaged across the five plausible values for each educational system is located in Table 2. In the United States and Bahrain two classes per school were sampled for mathematics. As a result, the ICC for these countries may also reflect some variance between teachers as well as between schools.

Insert Table 2 about here

In each educational system and for each ICC, the proportion of variance in achievement that can be explained by between-school differences provides ample evidence of the need for multilevel modeling (Hox, 1998). In Chile, the Philippines, the U.S. and Flemish Belgium more than half of the variance in mathematics achievement is explained by between-school differences. In Flemish Belgium and the U.S., over half of the science achievement is explained by between-school differences.

Private School Effect When Student Background and School SES Is Not Controlled

Given sufficiently large between-school differences, described in the previous section, we next set out to explain these differences by adding a school type effect – either public or private – to the null model for math and science. Science results for this second set of models are included in Table 3. Mathematics results are located in Table 4.

Insert Table 3 about here

Insert Table 4 about here

The mean private school differences in mathematics and science achievement are significantly higher for all educational systems. Further, the between school variance accounted for by the addition of a private school effect varies widely across educational systems and topics. For instance, by adding an effect for school-type, between-school variance is reduced by just one percent in mathematics achievement for the United States where between-school variance is reduced by nearly 60 percent for Chile in mathematics achievement. Finally, in most educational systems we see that the private school effect accounts for slightly more between school variance on the science achievement than the math achievement. This suggests that school type may matter slightly more for science than for mathematics.

Private School Effect When Student Background and School SES Is Controlled

To further explain achievement differences, particularly with regard to the private school effect found in the previous models, we added a number of covariates to control for student background and school SES. Results for the science and mathematics models that include level-one effects for books in the home, home possessions and parent's education and level-two effects for school type and school SES are included in Table 5 and Table 6, respectively. Positive private school effects are significant in all educational systems on both assessments with the exception of math and science achievement in the United States and science achievement in Bahrain and Flemish Belgium. Community SES was also frequently associated with improved math and science achievement; however, this finding did not hold in Lebanon for math or science. We also found no significant effect for community SES in Bahrain (science), Lebanon (science), Japan (math) and the Philippines (math). In several cases, better home background conditions also predict higher science and mathematics achievement after controlling for the school type and community SES effects. Exceptions to this trend include non-significant home possession effects for Chile, Belgium (Flemish) in both science and mathematics achievement, the Philippines in mathematics achievement, and Iran and the United States on science achievement. We also found that books in the home are neither significant predictors of science achievement in the Philippines nor significant predictors of mathematics achievement in Flemish Belgium. Surprisingly, parent's education did not significantly predict science achievement in Iran.

An examination of the variance components for the science and mathematics models indicate that between school variance is further reduced by introducing home background and school SES variables in all educational systems. Conversely, within school variance is only slightly reduced in all educational systems except Japan (11 to 12 percent of within school variance explained) when home background effects and school SES are added to the model. Given the reduction in between-school variance when student background and school SES is controlled, later discussion is limited to the full model, which includes student background and school SES effects.

Insert Table 5 about here

Insert Table 6 about here

Our study found that, depending on the educational system and the assessment, private school achievement was from about 13 points (Bahrain, science) to slightly more than 71 points (Chile, mathematics) higher on average when student background and school SES were controlled. We also found that private school results varied within an educational system and across assessments. For instance, private schools in Bahrain outperformed their public counterparts by nearly 40 points in mathematics but only about 13 points in science. Conversely, math achievement is about 71points higher on average for Chilean private schools while mathematics achievement is about 45 points higher.

The variance between schools attributed to differences in public versus private institutions also varied substantially across educational systems and assessments. For example, only 20 percent of between school variance in mathematics achievement in the Philippines was accounted for by the full model including student background; however, nearly 80 percent of between school variance on science achievement was accounted for in Chile.

Comparison of Imputed Data to Complete Case Data

The parameter estimates above are unbiased under the assumption that our imputed variables were normally distributed and that the data are missing at random. Given that none of the imputed variables were normally distributed and that the missing mechanism for these data is unknown, we considered the extent to which results were changed by using data resulting from the imputation model versus the complete case data set. This additional step was not necessary for the null model or for the model that includes only a school-type effect, as we did not impute data for these models.

For both the mathematics and science models that included home background and school SES fixed effects, with few exceptions only slight changes in the parameter estimates and standard errors were noted. Results for the science model are located in Table 7, while results for the mathematics model are located in Table 8. Notable differences between the complete case data and the imputed data are marked in bold. For the science model, school type in Belgium (Flemish) was significant when the imputed data was used. Differences between the complete data set and the imputed data set are slightly more pronounced in the mathematics model. Most notably, community SES in Japan and the Philippines and home possessions in the United States and Iran were significant when the imputed data set was used.

Insert Table 7 about here

Insert Table 8 about here

Comparison of propensity matching methods to multilevel models

To correct for the possibility of selection bias, we include for comparison the results of propensity matching methods for both the science and mathematics models. Results for this analysis are found in Tables 9 and 10. In general, the private school advantage did not notably change between the multilevel models and the regression models that used propensity score matching methods. Exceptions to this trend include Iran in science achievement where the private school was halved and the Philippines where the private school effect fell by about 20 points using the propensity score matching method. In mathematics, we observed about a 20 point decline in Chile’s private school advantage and again a halving of the private school effect in Iran. Using the propensity score matching method we found a significant private school advantage for every country on both assessments. This appears to provide some evidence of selection bias, particularly in Iran and in those countries where the private school effect was not significant using multilevel methods.

Insert Table 9 about here

Insert Table 10 about here

Limitations

As analysts of secondary data, we no doubt suffer from limitations to our study. Given that not all educational systems made a school-type distinction, our analysis was limited to those study participants who did make this distinction. It may be that with a larger number of educational systems for analysis, additional exceptions to the private school advantage may have emerged. Further, the availability of student background measures was limited to those items administered on the TIMSS background questionnaire. It is important to consider that the variables we used for student background may not have been optimal as covariates of a student’s economic and home situation. It may be that improved measures of socioeconomic status and home background would have done a better job of accounting for variance within and between schools. To better capture the variance in test scores attributable to student background differences, a more comprehensive measure is likely necessary. We also reported non-uniform effects for all of the background variables used in our analysis. As such, it is worth noting that these variables may not be strictly comparable across the countries analyzed; however, this is a frequent limitation of international comparisons. A further limitation of the TIMSS 2003 data is that a distinction between publicly-funded, privately managed and privately-funded, privately-managed schools is not made for each country. This distinction may have allowed for a further investigation into the nature of the private school effects.

Our paper uses only 8th grade data from TIMSS 2003. Other research (e.g., Lubienski & Lubienski, 2006) has shown a stronger public school advantage at the 4th grade. Finally, the cross-sectional nature of the data limits what we can say about our findings and what we are able to measure, even with correction for selection bias. Longitudinal data of this type would allow for change over time and for an examination of whether the private school advantage extends to development as well as achievement. Limitations notwithstanding, our analyses do show a clear but highly varied advantage for private schools across nine educational systems that participated in 2003 TIMSS. The large sample sizes and well established design and implementation of TIMSS allow us to feel fairly confident in our findings.

Discussion

While a substantial amount of quantitatively-based research in the area of school privatization exists, most of the knowledge that uses LSA data as evidence about private school effects is generated by a limited cohort of researchers. The perspective brought to bear by this group of scholars often brings with it a host of targeted viewpoints and assumptions, the most predominant of which is the superior performance of private schools under most circumstances. Additionally, policy recommendations that result from this sort of research are typically of a one-size-fits-all variety. Across the board privatization is the order of the day.

Similar to earlier private school studies (McEwan, 2000; Vandenberghe & Robin, 2003; Fuchs & Woessman, 2007; Woessman, 2003), we found significant private school effects across educational systems. While our analysis largely supports the findings of a private school advantage after controlling for student background, we have found that higher private school achievement is not uniform across educational systems or assessments analyzed in this study. In fact, the advantage gained by private schools varies within an educational system and across assessments with occurrences of a much stronger private school advantage for one assessment over the other in a given educational system. Findings from this study indicate that a standardized prescription of privatization may not benefit educational systems equally and such policy recommendations should not be considered in a vacuum.

It is a worthy effort to shed some light on the private school effect and what it might really mean. Carnoy (1998) is a particularly germane source, especially given the high private school advantage that our paper found for Chile. Carnoy indicates that several factors are at work in Chile that may explain higher private school advantage. Perhaps most importantly, he offers by way of explanation the highly selective nature of Chilean private schools and the negative impact on public schools of a voucher system implemented in 1981. This impact tapered in the 1990s with increased educational funding; however, whether ground lost in the 1980s by public schools has been recovered is unclear. This may suggest that the private advantage is not so much a matter of improved performance of private schools but diminished performance of public schools over time as resources and students are channeled elsewhere.

Our findings also indicate that, while a private advantage largely prevailed, the between-school variance attributed to school-type varied widely across educational systems. This suggests that for some educational systems, the type of institution was sufficient to explain a large proportion of school differences (Chile); however, in other systems, such as the Flemish region of Belgium, few between school differences were explained by institution type. These findings should encourage researchers and educationalists to dig deeper into factors that may account for between-school differences in 8^{th} grade mathematics and science achievement internationally.

The TIMSS study used in this paper distinguishes itself from other international student achievement studies in that the focus is on curriculum rather than the amorphous target of work force knowledge, which may differ significantly across educational systems depending on the nature of the economy and the level of a nation's economic development. While we understand that curricular differences exist across educational systems surveyed in the TIMSS study, the collaborative and cooperative nature of the study development ensures that departures from a test-curriculum match are minimized. Further, the methods used to examine a private school advantage are the most appropriate for the structure of survey data.

Finally, a global initiative promoted by the World Bank appears to support the advancement of private institutions in education. Our research partially supports these findings;

however, it is our intent that the findings of this paper add to a much needed increase in dialogue within the educational community to dispute the one-size fits all recommendations (stemming from LSA) so often transmitted by the Bank and free market researchers in education. As noted in our limitations, more research along with improved data is needed before any resolute policy recommendations should take place. Further, as can be seen by the findings of this paper, cross-educational system comparisons show varying degrees of benefits, which should act to temper blanket policy recommendations.

Conclusion

This study attempted to better understand the link between school type (public versus private) and mathematics and science achievement as measured by 2003 TIMSS assessment results. Using two-level models that attempt to control for student background, our findings indicate that in all educational systems, private schools have significantly higher achievement. While our study validates previous work indicating that private schools do, on average, outperform their public counterparts, we found that these effects were neither uniform across educational systems nor were they uniform within an educational system across content domain. Further, variance in math and science achievement attributable to school type was highly varied across countries. Findings from this study provide evidence that caution on the part of national level policy makers is necessary before adopting policies that do not perform equally well across educational systems.

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Table 1

Sample Sizes, Achievement Means, and Private School Enrollment by Country

Educational System	ID	N	Math Mean	SE	Science Mean	SE	Private School Enrollment %
Bahrain	48	4199	401	-1.7	438	-1.8	9
Belgium (Flemish)	956	4970	537	-2.8	516	-2.5	93.98
Chile	152	6377	387	-3.3	413	-2.9	21.98
Iran	364	4942	411	-2.4	453	-2.3	9.77
Japan	392	4856	570	-2.1	552	-1.7	5.33
Lebanon	422	3814	433	-3.1	393	-4.3	52.67
Philippines	608	6917	378	-5.2	377	-5.8	19.46
USA	840	8912	504	-3.3	527	-3.1	5.04
International Average		4777	467	0.5	474	-0.6	Not applicable

Table 2

Intra-Class Correlations for Mathematics and Science Achievement by Country

Science

Educational System	Average ICC
Bahrain	0.10
Chile	0.38
Iran	0.26
Japan	0.11
Lebanon	0.44
Phillipines	0.47
USA	0.54
Flemish Belgium	0.58

Mathematics

Educational System	Average ICC
Bahrain	0.17
Chile	0.56
Iran	0.34
Japan	0.14
Lebanon	0.47
Philippines	0.54
USA	0.62
Flemish Belgium	0.71

Table 3

Science Intercepts as Outcomes Models with Only Private School Effect by Country

Educational System	Effect	Estimate	SE	Between Schools Variance Explained
Bahrain	Intercept γ_{00}	436.28*	2.44	0.11
	Private, γ_{01}	33.35*	7.81	
Chile	Intercept γ_{00}	402.35*	3.17	0.56
	Private, γ_{01}	101.00*	6.90	
Iran	Intercept γ_{00}	447.93*	2.77	0.31
	Private, γ_{01}	70.98*	8.71	
Japan	Intercept γ_{00}	547.56*	1.86	0.40
	Private, γ_{01}	65.19*	8.35	
Lebanon	Intercept γ_{00}	359.06*	6.55	0.29
	Private, γ_{01}	66.79*	9.05	
Phillipines	Intercept γ_{00}	363.34*	6.45	0.18
	Private, γ_{01}	71.78*	13.13	
USA	Intercept γ_{00}	521.40*	3.01	0.02
	Private, γ_{01}	31.40*	11.04	
Flemish Belgium	Intercept γ_{00}	476.41*	11.69	0.04
	Private, γ_{01}	41.93*	12.15	

*$p < 0.05$.

Table 4

Mathematics Intercepts as Outcomes Models with Only Private School Effect by Country

Educational System	Effect	Estimate	SE	Between Schools Variance Explained
Bahrain	Intercept γ_{00}	397.96*	2.72	0.29
	Private, γ_{01}	60.02*	8.23	
Chile	Intercept γ_{00}	373.15*	3.85	0.59
	Private, γ_{01}	126.66*	7.99	
Iran	Intercept γ_{00}	403.63*	3.01	0.33
	Private, γ_{01}	86.51*	9.77	
Japan	Intercept γ_{00}	563.22*	2.19	0.48
	Private, γ_{01}	94.00*	9.59	
Lebanon	Intercept γ_{00}	406.72*	4.78	0.31
	Private, γ_{01}	51.97*	6.59	
Phillipines	Intercept γ_{00}	367.06*	5.92	0.13
	Private, γ_{01}	56.42*	12.22	
USA	Intercept γ_{00}	498.84*	3.18	0.01
	Private, γ_{01}	25.52*	11.70	
Flemish Belgium	Intercept γ_{00}	479.88*	13.82	0.06
	Private, γ_{01}	61.18*	14.37	

*$p < 0.05$.

Table 5

Science Intercepts as Outcomes Models with Level-One Effects for Books, Home and Parent's Education and Level-Two Effects for School-Type and Community SES

Educational System	Effect	Estimate	SE	School Variance Explained	
				Between	Within
Bahrain	Intercept, γ_{00}	385.70	8.57*	0.33	0.07
	Private, γ_{01}	12.97	8.77		
	Comm. SES, γ_{02}	-4.93	2.81		
	Books, γ_{10}	4.75	1.07*		
	Home, γ_{20}	6.06	1.88*		
	Parent's Ed., γ_{30}	7.94	1.18*		
Chile	Intercept, γ_{00}	385.89	8.94*	0.79	0.04
	Private, γ_{01}	45.18	6.22*		
	Comm. SES, γ_{02}	-16.79	2.64*		
	Books, γ_{10}	9.96	1.11*		
	Home, γ_{20}	0.02	1.47		
	Parent's Ed., γ_{30}	12.37	1.38*		
Iran	Intercept, γ_{00}	452.84	8.76*	0.46	0.02
	Private, γ_{01}	48.19	8.83*		
	Comm. SES, γ_{02}	-9.68	3.14*		
	Books, γ_{10}	6.48	1.18*		
	Home, γ_{20}	0.13	1.24		
	Parent's Ed., γ_{30}	1.95	0.96*		
Japan	Intercept, γ_{00}	424.85	10.68*	0.59	0.12
	Private, γ_{01}	49.43	7.34*		
	Comm. SES, γ_{02}	-12.32	6.11*		
	Books, γ_{10}	10.89	0.81*		
	Home, γ_{20}	15.07	1.98*		
	Parent's Ed., γ_{30}	11.81	1.53*		
Lebanon	Intercept, γ_{00}	308.64	13.77*	0.44	0.01
	Private, γ_{01}	54.52	8.76*		
	Comm. SES, γ_{02}	-0.70	4.44		
	Books, γ_{10}	7.26	1.40*		
	Home, γ_{20}	7.56	2.92*		
	Parent's Ed., γ_{30}	5.65	1.20*		
Philippines	Intercept, γ_{00}	350.71	15.55*	0.28	0.04

	Private, γ_{01}	53.48	12.98*		
	Comm. SES, γ_{02}	-10.42	5.92		
	Books, γ_{10}	-0.45	1.10		
	Home, γ_{20}	3.70	1.64*		
	Parent's Ed., γ_{30}	9.70	1.49*		
U.S.A.	Intercept, γ_{00}	484.43	7.28*	0.42	0.08
	Private, γ_{01}	16.06	9.36		
	Comm. SES, γ_{02}	-14.28	1.83*		
	Books, γ_{10}	9.68	0.80*		
	Home, γ_{20}	2.56	1.66		
	Parent's Ed., γ_{30}	6.46	0.90*		
Belgium (Fl)	Intercept, γ_{00}	510.85	18.38*	0.42	0.05
	Private, γ_{01}	18.20	10.05		
	Comm. SES, γ_{02}	-42.48	5.08*		
	Books, γ_{10}	4.83	0.66*		
	Home, γ_{20}	3.28	2.51		
	Parent's Ed., γ_{30}	3.42	0.76*		

*$p < 0.05$.

Table 6

Mathematics Intercepts as Outcomes Models with Level-One Effects for Books, Home and Parent's Education and Level-Two Effects for School-Type and Community SES

				School Variance Explained	
Educational System	Effect	Estimate	SE	Between	Within
Bahrain	Intercept, γ_{00}	342.66	10.40*	0.40	0.06
	Private, γ_{01}	37.64	8.20*		
	Comm. SES, γ_{02}	-7.96	3.09*		
	Books, γ_{10}	6.23	0.99*		
	Home, γ_{20}	9.08	2.15*		
	Parent's Ed., γ_{30}	6.67	0.86*		
Chile	Intercept, γ_{00}	377.67	8.74*	0.78	0.04
	Private, γ_{01}	71.12	7.89*		
	Comm. SES, γ_{02}	-21.62	3.33*		
	Books, γ_{10}	8.26	0.98*		
	Home, γ_{20}	0.02	1.08		
	Parent's Ed., γ_{30}	10.21	1.16*		
Iran	Intercept, γ_{00}	408.11	9.18*	0.48	0.02
	Private, γ_{01}	60.27	9.74*		
	Comm. SES, γ_{02}	-11.37	3.41*		
	Books, γ_{10}	7.88	1.07*		
	Home, γ_{20}	2.53	1.15*		
	Parent's Ed., γ_{30}	0.47	0.93		
Japan	Intercept, γ_{00}	416.43	11.88*	0.66	0.11
	Private, γ_{01}	74.63	8.17*		
	Comm. SES, γ_{02}	-13.13	7.10		
	Books, γ_{10}	10.80	0.93*		
	Home, γ_{20}	16.35	2.17*		
	Parent's Ed., γ_{30}	16.95	1.28*		
Lebanon	Intercept, γ_{00}	376.95	10.97*	0.40	0.02
	Private, γ_{01}	44.83	6.43*		
	Comm. SES, γ_{02}	0.19	3.12		
	Books, γ_{10}	2.50	1.05*		
	Home, γ_{20}	4.92	1.38*		
	Parent's Ed., γ_{30}	3.84	0.82*		
Philippines	Intercept, γ_{00}	368.81	13.54*	0.20	0.01

	Private, γ_{01}	44.53	12.39*		
	Comm. SES, γ_{02}	-8.35	4.71		
	Books, γ_{10}	-1.96	0.83*		
	Home, γ_{20}	1.89	1.08		
	Parent's Ed., γ_{30}	5.79	0.93*		
U.S.	Intercept, γ_{00}	480.09	6.63*	0.26	0.04
	Private, γ_{01}	12.16	10.25		
	Comm. SES, γ_{02}	-14.07	2.34*		
	Books, γ_{10}	6.28	0.54*		
	Home, γ_{20}	2.74	1.38*		
	Parent's Ed., γ_{30}	4.31	0.64*		
Belgium (Fl)	Intercept, γ_{00}	533.86	20.31*	0.33	0.00
	Private, γ_{01}	39.72	12.66*		
	Comm. SES, γ_{02}	-42.25	6.38*		
	Books, γ_{10}	0.98	0.78		
	Home, γ_{20}	0.82	2.39		
	Parent's Ed., γ_{30}	3.01	0.75*		

*$p < 0.05$.

Table 7

Science Model Comparison between Complete and Imputed Data

Educational System	Effect	Imputed Estimate	Imputed SE	Not Imputed Estimate	Not Imputed SE
Bahrain	Intercept, γ_{00}	385.70	8.57*	390.12	8.02*
	Private, γ_{01}	12.97	8.77	11.23	10.18
	Comm. SES, γ_{02}	-4.93	2.81	-5.10	2.05
	Books, γ_{10}	4.75	1.07*	4.77	1.22*
	Home, γ_{20}	6.06	1.88*	7.04	2.09*
	Parent's Ed., γ_{30}	7.94	1.18*	7.22	1.05*
Chile	Intercept, γ_{00}	385.89	8.94*	377.30	7.83*
	Private, γ_{01}	45.18	6.22*	38.85	7.90*
	Comm. SES, γ_{02}	-16.79	2.64*	-13.58	2.17*
	Books, γ_{10}	9.96	1.11*	10.99	1.27*
	Home, γ_{20}	0.02	1.47	0.31	1.51
	Parent's Ed., γ_{30}	12.37	1.38*	11.74	1.52*
Iran	Intercept, γ_{00}	452.84	8.76*	452.51	7.45*
	Private, γ_{01}	48.19	8.83*	37.87	9.63*
	Comm. SES, γ_{02}	-9.68	3.14*	-8.02	2.59*
	Books, γ_{10}	6.48	1.18*	6.85	1.15*
	Home, γ_{20}	0.13	1.24	-0.98	1.37
	Parent's Ed., γ_{30}	1.95	0.96*	2.26	1.00*
Japan	Intercept, γ_{00}	424.85	10.68*	415.97	9.67*
	Private, γ_{01}	49.43	7.34*	45.71	7.74*
	Comm. SES, γ_{02}	-12.32	6.11*	-6.07	2.79*
	Books, γ_{10}	10.89	0.81*	11.60	1.09*
	Home, γ_{20}	15.07	1.98*	14.85	2.42*
	Parent's Ed., γ_{30}	11.81	1.53*	11.79	1.49*
Lebanon	Intercept, γ_{00}	308.64	13.77*	308.32	15.18*
	Private, γ_{01}	54.52	8.76*	55.38	8.85*
	Comm. SES, γ_{02}	-0.70	4.44	1.87	4.46
	Books, γ_{10}	7.26	1.40*	6.97	1.65*
	Home, γ_{20}	7.56	2.92*	7.38	2.52*
	Parent's Ed., γ_{30}	5.65	1.20*	5.50	1.28*
Philippines	Intercept, γ_{00}	350.71	15.55*	349.75	15.96*

	Private, γ_{01}	53.48	12.98*	47.91	14.29*
	Comm. SES, γ_{02}	-10.42	5.92	-8.77	5.93
	Books, γ_{10}	-0.45	1.10	0.43	1.41
	Home, γ_{20}	3.70	1.64*	3.77	1.92
	Parent's Ed., γ_{30}	9.70	1.49*	9.01	1.41*
U.S.	Intercept, γ_{00}	484.43	7.28*	500.69	6.89*
	Private, γ_{01}	16.06	9.36	7.81	10.42
	Comm. SES, γ_{02}	-14.28	1.83*	-20.40	2.22*
	Books, γ_{10}	9.68	0.80*	9.45	0.82*
	Home, γ_{20}	2.56	1.66	2.11	1.91
	Parent's Ed., γ_{30}	6.46	0.90*	5.47	0.82*
Belgium (Fl)	Intercept, γ_{00}	510.85	18.38*	476.47	15.55*
	Private, γ_{01}	**18.20**	**10.05**	**23.21**	**10.51***
	Comm. SES, γ_{02}	-42.48	5.08*	-33.44	3.25*
	Books, γ_{10}	4.83	0.66*	5.64	0.86*
	Home, γ_{20}	3.28	2.51	3.37	2.78
	Parent's Ed., γ_{30}	3.42	0.76*	3.37	0.90*

*$p < 0.05$.

Table 8

Mathematics Model Comparison between Complete and Imputed Data

Educational System	Effect	Imputed		Not Imputed	
		Estimate	SE	Estimate	SE
Bahrain	Intercept, γ_{00}	342.66	10.40*	346.08	9.97
	Private, γ_{01}	37.64	8.20*	32.81	10.86*
	Comm. SES, γ_{02}	-7.96	3.09*	-7.39	2.31*
	Books, γ_{10}	6.23	0.99*	6.50	1.08*
	Home, γ_{20}	9.08	2.15*	9.36	2.42*
	Parent's Ed., γ_{30}	6.67	0.86*	6.05	0.94*
Chile	Intercept, γ_{00}	377.67	8.74*	368.41	7.47*
	Private, γ_{01}	71.12	7.89*	57.88	8.49*
	Comm. SES, γ_{02}	-21.62	3.33*	-18.39	2.51*
	Books, γ_{10}	8.26	0.98*	8.85	1.08*
	Home, γ_{20}	0.02	1.08	-0.12	1.18
	Parent's Ed., γ_{30}	10.21	1.16*	10.48	1.07*
Iran	Intercept, γ_{00}	408.11	9.18*	408.12	7.47*
	Private, γ_{01}	60.27	9.74*	48.28	10.33*
	Comm. SES, γ_{02}	-11.37	3.41*	-9.85	2.68*
	Books, γ_{10}	7.88	1.07*	7.93	1.12*
	Home, γ_{20}	**2.53**	**1.15***	**1.95**	**1.17**
	Parent's Ed., γ_{30}	0.47	0.93	0.66	0.98
Japan	Intercept, γ_{00}	416.43	11.88*	412.46	10.68*
	Private, γ_{01}	74.63	8.17*	71.25	8.65*
	Comm. SES, γ_{02}	**-13.13**	**7.10**	**-7.16**	**3.35***
	Books, γ_{10}	10.80	0.93*	11.04	1.05*
	Home, γ_{20}	16.35	2.17*	15.59	2.65*
	Parent's Ed., γ_{30}	16.95	1.28*	16.38	1.40*
Lebanon	Intercept, γ_{00}	376.95	10.97*	370.75	10.67*
	Private, γ_{01}	44.83	6.43*	48.65	6.75*
	Comm. SES, γ_{02}	0.19	3.12	3.80	3.32
	Books, γ_{10}	2.50	1.05*	2.40	1.02*
	Home, γ_{20}	4.92	1.38*	4.79	1.62*
	Parent's Ed., γ_{30}	3.84	0.82*	3.50	1.01*
Philippines	Intercept, γ_{00}	368.81	13.54*	376.98	15.05*

	Private, γ_{01}	44.53	12.39*	37.51	13.46*
	Comm. SES, γ_{02}	**-8.35**	**4.71**	**-10.41**	**5.60***
	Books, γ_{10}	-1.96	0.83*	-2.33	0.92*
	Home, γ_{20}	1.89	1.08	1.85	1.13
	Parent's Ed., γ_{30}	5.79	0.93*	5.48	1.00*
U.S.	Intercept, γ_{00}	480.09	6.63*	494.43	7.06*
	Private, γ_{01}	12.16	10.25	6.75	12.09
	Comm. SES, γ_{02}	-14.07	2.34*	-20.41	2.55*
	Books, γ_{10}	6.28	0.54*	6.07	0.60*
	Home, γ_{20}	**2.74**	**1.38***	**2.03**	**1.52**
	Parent's Ed., γ_{30}	4.31	0.64*	3.70	0.69*
Belgium (Fl)	Intercept, γ_{00}	533.86	20.31*	502.29	15.92*
	Private, γ_{01}	39.72	12.66*	38.81	12.49*
	Comm. SES, γ_{02}	-42.25	6.38*	-40.61	3.81*
	Books, γ_{10}	**0.98**	**0.78**	**1.89**	**0.79***
	Home, γ_{20}	0.82	2.39	2.54	2.72
	Parent's Ed., γ_{30}	3.01	0.75*	3.04	0.89*

*$p < 0.05$.

Table 9

Science Model, Propensity Score Matching Analysis Results

	Effect	Estimates	SE
Bahrain	Intercept	476.34	3.64*
	Private	15.77	2.72*
Chile	Intercept	496.24	3.70*
	Private	41.81	2.32*
Iran	Intercept	508.95	2.95*
	Private	22.87	2.47*
Japan	Intercept	612.81	3.07*
	Private	41.86	2.48*
Lebanon	Intercept	416.21	2.67*
	Private	42.35	2.11*
Phillipines	Intercept	419.25	2.94*
	Private	34.81	2.23*
USA	Intercept	561.91	2.53*
	Private	13.00	2.27*
Belgium (Fl)	Intercept	524.26	4.38*
	Private	26.46	2.71*

*$p < 0.05$.

Table 10

Math Model, Propensity Score Matching Analysis Results

	Effect	Estimates	SE
Bahrain	Intercept	466.67	2.92*
	Private	41.38	2.72*
Chile	Intercept	491.81	8.24*
	Private	54.04	5.14*
Iran	Intercept	480.92	3.70*
	Private	28.77	2.50*
Japan	Intercept	657.47	3.34*
	Private	67.28	2.67*
Lebanon	Intercept	453.82	1.99*
	Private	38.51	1.78*
Phillipines	Intercept	409.09	2.20*
	Private	24.00	2.09*
USA	Intercept	534.91	2.12*
	Private	9.18	2.32*
Belgium (Fl)	Intercept	540.75	5.22*
	Private	40.32	2.70*

*$p < 0.05$.