What factors determine student performance in East Asia?
New evidence from TIMSS 2007

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Abstract

This study investigates what factors determine students' academic performance in five major economies in East Asia, using the dataset from the 2007 survey of Trends in International Mathematics and Science Study (TIMSS). We explicitly consider initial maturity differences, endogeneity of class size, and peer effects in regression analysis. We find that a student's individual and family background is a key determinant of educational performance, while institutional and resource variables have a more limited effect. Peer effects are significant in general, but ability sorting at the school and/or class levels makes it difficult to interpret them in Hong Kong and Singapore.

Key words

Educational production function, Initial maturity differences, Peer effects, Class size, Asia

JEL classification numbers

I21, I22

1. Introduction

East Asian countries are often ranked very high in intergenerational comparisons of students' academic performance. The 2007 survey of Trends in International Mathematics and Science Study (TIMSS) revealed that five East Asian countries[1]—Taiwan, Korea, Singapore, Hong Kong, and Japan—occupied the top five places in the average mathematics scores of the eighth-grade students. Similarly, the 2006 survey of OECD Programme for International Student Assessment (PISA) revealed that Taiwan, Hong Kong, Korea, and Japan were in the top ten countries/regions for mathematical literacy of fifteen–year-old students.

Higher levels of student performance do not mean, however, that the within-country variation can be ignored. TIMSS normalized each student's score with an international mean of 500 and an international standard deviation of 100. In the five East Asian countries, the mean scores lie between 570 (Japan) and 598 (Taiwan), well above an unweighted mean of 450 for all countries participating in TIMSS. Meanwhile, the standard deviations lie between 85 (Japan) and 106 (Taiwan), compared to an unweighted mean of 85 for all TIMSS participants. This fact points to the relevance of understanding how important different factors are for the performance variation within each country in East Asia.

With regard to within-country variations, a central issue for education policies is how individual and family background affects student performance; in other words, to what extent education policies, school systems, and/or teaching quality succeed in reducing gaps in opportunities and prior attainments among students from different family backgrounds. Indeed, the effect of family income on child development has been a key issue explored empirically by many studies. It has been observed that family income has a positive association with life outcomes for children (Duncan, Yeung, Brooks-Gunn, and Smith, 1998; Bowles, Gintis, Groves, 2005). Those who have experienced poverty in childhood, regardless of its causes, are more likely to face circumstances unfavorable to their development.

Further, Carneiro and Heckman (2003) emphasized a limited rate of return from the education provided to children from poor families. Their analysis underscored the importance of family in creating a difference in both cognitive and noncognitive abilities that shape success in life and emphasized on the risk of a distinct transmission of poverty from older to younger generations. More recently, Oshio, Sano, and Kobayashi (2010) demonstrated that child poverty has a long-lasting and significant impact on subsequent life outcome, even after controlling the effect of educational attainment after the age of fifteen.

In a broader context, there is a voluminous literature on the determinants of student performance, as comprehensively surveyed by Hanushek (2006). A well-established view is that family background, such as family income and parents' educational attainment is a key determinant of student outcome, while there is no consensus about the impact of class size, ability grouping, or quality of teachers. Wößmann and his coauthors have published many articles that explicitly address these issues, by estimating educational production functions on the basis of a dataset obtained from TIMSS (Wößmann, 2003; Wößmann, 2005; Ammermüller, Hejike, and Wößmann, 2005; Wößmann and West, 2006). Their cross-country analyses consistently confirm the importance of family background.

With regard to East Asian countries, Wößmann (2005) made the first attempt at cross-country analysis of student performance using the TIMSS data. He estimated educational production functions for Hong Kong, Japan, Korea, Singapore, and Thailand, using the dataset of the 1995 survey of TIMSS. Although he confirmed the importance of family background, he found no evidence that education in smaller classes improves student performance. He also reported that some school policies related to higher student performance in some countries in East Asia. In Japan, Hojo (2010) also pointed out the substantial impact from a student's individual and family background using data on Japan from the 2007 survey of TIMSS.

In this study, we attempt to examine what factors determine students' academic performance in terms of mathematics scores of the eighth graders in Japan, Korea, Taiwan, Hong Kong, and Singapore—that is, the top five performers in TIMSS—using the dataset from the 2007 survey of TIMSS. We basically follow Wöβmann's (2005) methodology, but our analysis has three features distinguishing it from his analysis.

First, we explicitly consider the impact of initial maturity differences, or in other words, school entry-age effects. As in other countries worldwide, all education systems in East Asian countries have single cutoff dates for school eligibility. Single cutoff dates make some students younger than others when they begin school, and younger students are likely to have some disadvantage in learning at school. Indeed, Bedard and Dhuey (2006) demonstrated that these initial maturity differences have long-lasting effects on student performance across OECD countries. More recently, Mülenweg and Puhani (2010) and Kawaguchi (2010) provided evidence for such effects in Germany and Japan, respectively. We examine whether initial maturity differences affect academic performance of the eighth graders, most of whom are fourteen years old.

Second, we control for endogeneity of class size by employing Maimonides' rule. As stressed by Hoxby (2000), class size is sometimes affected by the students' mean ability, and its endogeneity is likely to cause estimation biases. For example, schools which have low-ability students may prefer to instruct them more intensively in smaller classes, while schools that select high-ability students can easily manage large classes. If so, it is difficult to hypothesize about causality between class size and student performance. We attempt to solve this problem by utilizing two instrumental variable methods. The first method involves utilizing the mean class size at the grade level as an instrument, as done in Ammermüller, Hejike, and Wößmann (2005), Wöβmann (2003), Wößmann (2005), Wößmann and West (2006), and others. The second method involves applying Maimonides' rule as proposed by Angrist and Lavy (1999);

that is, instrumenting the actual class size by the theoretical number of classes, which results from the application of a given threshold for opening new classes when the size of enrollment grows.

Third, we incorporate peer effects in regression analyses. The effect of classroom peers on a student's own performance has been examined by many researchers including Angrist and Lang (2004), Archidiacono and Nicholson (2005), Hanushek et al. (2003), Zimmerman (2003), and others, because it is closely related to the debate on educational reform. However, there is no consensus about the significance of these effects and there is limited evidence on their suitability for East Asian countries.[2] A technically important issue regarding peer effects is the reflection problem presented by Manski (1993), who pointed out the impossibility of separately identifying two types of social effects: endogenous (or behavioral) effects and contextual (or exogenous) effects. Peer effects are often measured as an estimated coefficient on peers' mean score, but it may also reflect the impact of the student's own score on the peers' score.

Hence, we alternatively utilize other variables that seem to be more exogenous, such as the mean number of books at the peers' homes, as done by Ammermüller and Pischke (2009), and the share of college graduates among the peers' parents. In addition, we stress that these variables tend to reflect the student's individual and family background rather than the peer effect in Hong Kong and Singapore, where students are sorted by ability at the school and/or class levels.

To our knowledge, this study is the first attempt at cross-country analysis of educational production functions that simultaneously addresses initial maturity differences, endogeneity of class size, and peer effects, at least for East Asian countries. The main insight gained from our study is that a student's individual and family background is a key determinant of educational performance in East Asian countries, in line with the results obtained by many existing studies. Institutional and resource variables in school education have more limited impact. In particular, we find no evidence that smaller classes enhance student performance. Peer effects are significant and substantial in general, but it is difficult to distinguish them from the effects of between-school and/or between-class ability sorting in Hong Kong and Singapore. Along with the fact that within-country variations in scores are not small in East Asian countries, these results suggest that school education cannot sufficiently reduce the ability gap among students hailing from families with different backgrounds.

The remainder of the paper is structured as follows. Section 2 provides a brief description of the data and some descriptive analysis. Section 3 explains the methodology of our regression model analysis. Section 4 presents our key estimation results. Section 5 concludes the paper.

2. Data and descriptive analysis

2.1 Data

Our empirical analysis is based on the dataset for five East Asian economies collected from TIMSS, which was conducted in 2007 under the auspices of the International Association for the Evaluation of Educational Achievement (IEA). We also use the data on Sweden, a non-Asian country, for comparison purposes, because the country had a mean score of 491, close to the international average (500) among the TIMSS participating countries, and complete information about individual, family, school, class, and teacher attributes, which makes comparisons with the five East Asian countries possible. TIMSS included four surveys: mathematics and science for the fourth and eighth graders, respectively, and we focus on mathematics results for the eighth graders who were fourteen years old in most cases.[3]

The TIMSS assessment was administered to random samples of students from the target population in each country. The basic design of the sample used was a two-stage stratified cluster design. The first stage consisted of a sampling of schools, and the second stage of a sampling of intact classrooms from the target grade in the sampled schools. Schools were selected with probability proportional to size, and classrooms with equal probabilities. For each country, 150–164 schools were sampled in each country. In Singapore, two classes were sampled per school and a sample of 19 students was drawn in each class. In Sweden, two classes were sampled per school whenever possible. In Japan and Taiwan, two classes were sampled per school having at least 230 (Japan) or 185 (Taiwan) students, and one class otherwise. In Korea and Hong Kong, only one class was sampled per school.

Student scores in TIMSS were normalized with an international mean of 500 and an international standard deviation of 100, as mentioned above. These score data can be matched with the background data from three types of background questionnaires in each country. The school questionnaire asked the school principals to provide information on the school contexts and the resources available for instruction. The teacher questionnaire collected information from the teachers about their backgrounds, preparation, and professional development. Finally, the student questionnaire addressed students' home and school lives and their experiences in learning mathematics and science.

2.2 Cross-country comparisons of student performance

Table 1 summarizes the key statistics with regard to mathematics scores in each country, using the TIMSS original data. The top part of the table shows that student scores are between 570 (Japan) and 598 (Taiwan), well above 451, which is the unweighted mean among countries participating in TIMSS. It should be also noted, however, that within-country variations lie between 85 (Japan) and 106 (Taiwan), compared to an unweighted average of 85 for all TIMSS participants. In Sweden the mean and standard deviation of the scores are 491 and 70, respectively; both the measures lower than that in East Asian countries.

The middle part of Table 1 summarizes between- and within-school variations for each country, and the bottom part between- and within-class variations. Each part compares the shares of variances between and within groups. We observe interesting differences across the six countries. First, judging by the ratio of the standard deviation to the mean as well as the Gini coefficient of the scores, student performance is most equally distributed in Japan (with the lowest mean), while it is least equally distributed in Taiwan (with the highest mean). In addition, the score distribution in all of the five countries is more unequal than in Sweden. To help assess cross-country differences in the distribution of student performance, Figure 1 graphically depicts kernel density estimations of scores. Japan and Sweden have almost symmetric distributions around the mean, although the levels for the two countries are quite different. The other four countries have distributions somewhat skewed to the right end. In addition, Taiwan, Hong Kong, and to a lesser extent, Singapore, have a kinked slope in the left tail of the curve. This suggests that these countries have two groups of students classified according to ability; the first group is the majority and has relatively high scores, while the second, the minority one, has lower scores. In these countries, high levels of mean scores reflect higher performance of the students in the first group, while large nationwide deviations are attributable to the dual structure of student performance.

Second, we observe from the middle part of the table that the East Asian countries can be divided into two groups: the first group (Japan, Korea, and Taiwan) where within-school deviations are larger than between-school ones, and the second group (Hong Kong and Singapore) where the opposite is true. Sweden has the same feature as the first group. All the countries have statistically significant *F*-statistics, meaning that scores differ significantly between schools, while their values are much higher in the second group. This finding probably reflects ability sorting at the school and/or class levels in Hong Kong and Singapore. Indeed, schools are explicitly ordered using thirty ranks on the basis of student performance in Singapore. In Hong Kong, schools are divided into 18 groups by financing, language, and gender, and it is reasonable to suspect that students are effectively sorted at the school level. However, this does not rule out the possibility that students are sorted further at the class level, because only one class was sampled per school in the country.

Finally, the bottom part of Table 1 shows between- and within-class deviations. The results in the middle and bottom parts are the same in Korea and Hong Kong, where only one class was sampled per school, and nearly the same in Japan and Taiwan, where two classes were sampled only for large schools. In Singapore, the share of between-class deviation (82 percent) is large and well above that of between-school one (53 percent), in contrast with Sweden, where two classes were sampled but both the shares of between-school and between-class deviations were relatively small (14 and 21 percent, respectively). This suggests that schools in Singapore sort students by ability at the class level as well as the school level.

3. Method

3.1 Benchmark models

We estimate education production functions for each country as follows:

$$A_{sci} = \beta_0 + \boldsymbol{F}_i \beta_1 + \boldsymbol{T}_{\boldsymbol{c}} \beta_2 + \boldsymbol{Z}_s \beta_3 + \varepsilon_{sci}. \tag{1}$$

or

$$A_{sci} = \beta_0 + \boldsymbol{F}_i \beta_1 + \boldsymbol{T}_c \beta_2 + \boldsymbol{Z}_s \beta_3 + \beta_4 P_i + \varepsilon_{sci}. \tag{2}$$

Here, A_{sci} is the TIMSS-normalized mathematics score of student i in class c of school s. $\boldsymbol{F}$ is a set of individual-level variables. $\boldsymbol{T}_c$ and $\boldsymbol{Z}_s$ are sets of class- and school-level variables, respectively, and they are categorized into institutional and resource variables. Because only one class is sampled per school in most cases, we deal with class- and school-level variables almost interchangeably in actual estimations. P denotes the peers' attributes such as peers' mean score. $\boldsymbol{\varepsilon}$ is an error term. We consider two types of regression models—without the peer effect (eq. (1))

and with it (eq. (2)) —because it is difficult to distinguish between the conventional peer effect and the impact of ability sorting when students are sorted by ability at the school and/or class levels. For both types of models, we apply clustering-robust linear regressions to obtain standard errors robust to the within-school clustering of the data.

3.2 Initial maturity differences

Using eq. (1) or (2) as the benchmark model, we address three issues. The first focus is on initial maturity differences. Each country has a single cutoff date for school eligibility, and it is important to control for initial maturity differences because it is well known that they have long-lasting impacts on educational attainment and even earnings. In Japan, for example, school starts on April 1, and children who become seven years old between April 2 in year X and April 1 in year X+1 are eligible to enter primary school in year X. It is reasonable to suspect that younger students, who were born just before April, have some disadvantage in learning for biological and/or psychological reasons.

Table 2 summarizes the dates of starting school and eligibility conditions for going to elementary school in each country. For each country, we divide students into four groups by birth month: those born in Q1, Q2, Q3, and Q4, each of which consists of three months. Students born in Q1 are the oldest among the surveyed students and are followed by those born in Q2, Q3, and Q4. Figure 2 compares mean scores across the four groups in each country (without controlling for other variables), highlighting the initial maturity differences in the five East Asian countries. Lower-level performances by the youngest students (who were born in Q4) are most remarkable in Taiwan and Japan. Younger students tend to have lower scores in general in the other three countries in East Asia as well, while the differences are more limited in Sweden. In regression estimations, we included dummy variables for Q2–Q4, using Q1 as the reference to see whether their coefficients are negative.

3.3 Class size

The second issue to be addressed is class size, which has been a central issue closely linked to education policy. Potential endogeneity of class size makes analyzing its effect on student performance quite difficult: schools may want to teach lower-performing children in a smaller class and parents with these children want to send them to schools with smaller classes.

Ammermüller, Hejike, and Wößmann (2005) and Wößmann (2005) tackled this issue by using the grade-mean class size in the school as an instrumental variable and controlling for school-fixed effects. This strategy effectively excludes both between- and within-school sources of student sorting. Unfortunately, we cannot precisely estimate the grade-mean class size from the 2007 TIMSS dataset, because we have data for only one class in Japan, Korea, Taiwan, and Hong Kong in most cases and the data for two classes in Singapore and Sweden.

For simplicity, we estimate the number of classes by (i) estimating the number of classes as the integer closest to the ratio of the total eighth-grade enrollment of the actual size of the sampled class, and then (ii) dividing the enrollment by this estimated number of classes. We recognize, however, that this methodology might be misleading, if the size of the sampled class is so small or large compared to the enrollment that it suggests some adjustment of class size by ability or for other reasons. Hence, we additionally explore the instrumental variable method using Maimonides' rule, which was proposed by Angrist and Lavy (1999). The estimated number of classes is that which results from the application of a given threshold for opening new classes when enrollment grows. Then, the estimated class size is given by

$$\text{Estimated class size} = \text{enrollment}/\{\text{int}\,[(\text{enrollment}-1)/\text{threshold}]+1\}, \qquad (3)$$

where int [ ] defines the integer closest to the number in [ ]. The estimated class size is determined solely by enrollment and institutional factors and is largely exogenous to choices by schools or parents.

The problem with this methodology is that we do not know the threshold for each country, and the rule may not be strictly applied in actual school management. In this study, we seek the threshold value that can explain the actual class size most precisely, judging by (i) the graphical relationship between the estimated and actual class sizes and (ii) the goodness of fit and *t*-value of the coefficient on the predicted class size in OLS models that regress the estimated class size on the actual one. On the basis of this methodology, we obtain the most plausible values of the threshold as 40 (Japan), 40 (Korea), 35 (Taiwan), 45 (Hong Kong), 40 (Singapore), and 30 (Sweden). We calculate the theoretical class size by using these numbers in eq. (3) in each country.

Figure 3 depicts the actual and estimated class sizes for each country, with the enrollment on the horizontal axis. As clearly seen from this figure, Maimonides' rule is most suitable for Japanese data with the threshold of 40. Unlike in Japan, the rule does not successfully explain within-country variations of actual class sizes in other countries: the thresholds do not seem very binding and a substantial portion of actual class sizes are located apart from the line corresponding to the rule. This indicates limited validity of Maimonides' rule for estimating the class size, except for Japan.

3.4 Peer effects

The third issue is that of peer effects. As already demonstrated by many studies, each student's performance is affected by his/her peers' performance. We add the peers' mean score as an explanatory variable and examine how it affects the student score. As pointed out by Manski (1993), however, the peers' mean score is likely to be affected by the student's own score especially if the class size is small. To mitigate this reflection problem, we explore the mean number of books at the peers' homes and the share of college graduates among the peers' parents. These variables are likely more exogenous than the peers' mean score. With regard to the number of books, TIMSS asked the students to choose one from among "none or very few

(0–10 books),” “enough to fill one shelf (11–25 books),” “enough to fill one bookcase (26–100 books),” “enough to fill two bookcases (101–200 books),” and “enough to fill three or more bookcases (more than 200 books)” to the question: “About how many books are there in your home? (Do not count magazines, newspapers, or your school books).” We transformed these categorical answers to numerical ones, taking the middle value of the range in each value (using 300 for “more than 200 books”).

3.5 Other explanatory variables

In addition to addressing these three issues, we explore various factors as explanatory variables at student, teacher, class, and school levels, which are summarized in three categories:

- Background variables: a student’s gender, month of birth, country of birth, number of books at home, belongings (computer, study desk, dictionary, and internet connection) at home, and parents’ educational attainment;
- Institutional variables: the eighth-grade enrollment, the share of economically disadvantaged students, school location, and school stratification;
- Resource variables: shortage of instructional materials, classrooms, and teachers, class size, ability grouping, the teacher’s gender, educational attainment (having obtained a master degree or not), and years of experience.

With regard to school stratification in the category of school institutional variables, we specifically consider: school type (public or private) in Japan; gender (boys, girls, or co-educational) in Korea; financing (government, aided, direct subsidy scheme, or private), language (Chinese or English), and gender (boys, girls, or co-educational) in Hong Kong; school rank (30 different ranks based on the students’ performance) in Singapore; and principal organizer (public or independent) in Sweden. School stratification is an institutional aspect of the school, but it provides a reasonable reflection of the student’s individual and family background as well. Indeed, Singapore conducts explicit ability-sorting between schools (UNESCO, 2006). More generally, school choices are highly dependent on the students' family background, including family income, which is not available in the TIMSS dataset. Hence, we consider school stratification separately from other institutional variables.[4]

After excluding respondents missing key variables, we obtain the numbers of observations as 4909, 3574, 3166, 1836, 3713, and 2978 for Japan, Korea, Taiwan, Hong Kong, Singapore, and Sweden, respectively.

4. Results

4.1 Benchmark model without the peer effect

We estimate the benchmark model, eq. (1), which instruments the actual class size by the estimated mean class size and does not include the peer variable, in the framework of the two-stage least squares (2SLS) regression. In addition, we employ TIMSS-provided sampling weights to obtain nationally representative coefficient estimates.

The estimation results are summarized in Table 3. We observe various noteworthy findings in this table. With regard to the individual attributes of students, boys show better performance in Japan, Korea, Taiwan, and Sweden, while the opposite is true in Singapore. More interestingly, students who were born in later months tend to show lower-level performance, except in Hong Kong and Sweden. For example, the mean score of the youngest students (born in Q4) is nearly 16 points lower than that of the oldest one in Taiwan. If we use those born in Q2 (who show the best performance in Hong Kong, as seen in Figure 2) as the reference, the coefficient on those born in Q4 turns negative and significant at the 5% level (not reported in Table 3). These findings indicate that initial maturity differences generally matter for student performance in East Asia. Finally, those born in the current country of residence tend to show better performance in Taiwan, Hong Kong, Sweden and poorer performance in Singapore.

Family background factors have a significant impact on student performance in general. The more books they have at home, the better their performance tends to be, judging by the magnitudes of the coefficients on each dummy variable for the number of books. This is not a surprising result, given that the number of books at home probably reflects the cultural level of the family. Similarly, family belongings such as computer, study desk, dictionary, and internet connection have positive associations with student performance, albeit differently across countries. Furthermore, we observe a positive impact of parents' educational attainment on student performance in most countries, notably in Japan. The father's graduation from college or a higher level of education increases student scores, except in Hong Kong.

Turning to institutional variables, we notice that a higher share of economically disadvantaged students tends to reduce student performance, except in Taiwan. Although this variable is based on the principal's subjective assessment, it represents a general level of family income among students who attend the school. The population size of the area in which the school is located matters in Taiwan and Korea, where smaller population size tends to reduce student performance.

The coefficients on the variables of school stratification are not reported to save space, but we observe some interesting facts. In Japan, the coefficient on the private school is 83 when the public school is the reference. In Hong Kong, the coefficients on each type of school are in the range between 64 (private/Chinese/co-educational) and 174 (government/English/boys), when using the aided/Chinese/boys schools as the reference. In Singapore, the coefficient on the top school is as high as 265 when the bottom (30^{th}) school is the reference. These findings suggest that school stratification makes between-school ability sorting substantial, whether explicitly or implicitly, in these countries. By contrast, school stratification has no significant association with student scores in Korea and Sweden.

Finally, we find virtually no uniform impact of any resource variable in all countries. Most importantly, a smaller class size does not improve student performance. Instead, we observe a positive and significant correlation between class size and student scores in Taiwan, Hong Kong, and Singapore. We will examine the robustness of the results using other model specifications, as discussed below. As for the other variables, ability grouping significantly improves student performance in Japan, but it is not effective in the other countries. Shortages of instructional materials, classrooms, or teachers, as well as the teacher's gender, master degree, or experience do not affect student performance uniformly or significantly.

4.2 Benchmark model with the peer effect

Next, we additionally explore peer effects by estimating eq. (2), which includes peers' mean score as an explanatory variable. Instead of again presenting a large table for a full set of estimation results, let us concentrate on two things. The first are the estimated coefficients on the peers' mean score, which are presented in the bottom part of Table 3. It can be seen that the peers' mean score has a positive and highly significant impact on student performance for all countries. A closer look at the results reveals that six countries can be divided into two country groups: Hong Kong and Singapore vs. the other four countries.

In the first country group, the coefficient on peers' mean score is very close to unity, and the goodness of fit measured by adjusted R^2 improves substantially from the case without the peer effect. This result is not surprising, because students are sorted by ability at the school and/or class levels in Hong Kong and Singapore, making their own scores very close to the peers' mean. Hence, the peers' mean score in these countries is most likely to reflect the student's own performance, rather than capture the peer effect in its true sense. In the second country group, by contrast, the coefficient on peers' mean score is in the lower range between 0.358 and 0.579 and the improvement in the goodness of fit is more limited. This is probably because between-school or between-class ability sorting is more modest in the second group.

Second, we compare the estimated coefficients on the background variables between the models without and with the peer effect. Figure 4 compares the results for Japan and Singapore as representatives for each country group. We observe from this figure that including the peers' mean score reduces the magnitudes of the estimated coefficients in Japan, while it substantially reduces their magnitudes in Singapore. This result is consistent with the view that the peers' mean score reflects the students' own ability, which in turn is mostly dependent on individual and family background, in Singapore, where students are sorted by ability at the school and class levels.

4.3 Relative importance of each category of variables

The observations from the benchmark models suggest that student performance is largely determined by individual and family background variables, rather than school institutional or resource variables. We now move to comparisons of the relative importance of each category of variables, following the approach taken by Ammermüller, Hejike, and Wößmann (2005).

Table 4 presents (unadjusted) R^2 for the regressions including all variables and the percentage reduction in R^2 when categories of variables are excluded from the regression for the models without the peer effect (top part) and with it (bottom part). Although R^2 cannot be linearly decomposed, this table can help roughly assess the relative importance of each category of variables. We additionally examine the impact of excluding background variables and school stratification together, considering that school stratification is potentially linked to the student's background, including family income, which is not included in the TIMSS background variables.

We again confirm from the top part of the table (without the peer effect) that the student's individual and family background is a key determinant of student performance in Korea and

Sweden, and to a lesser extent, Taiwan and Japan. When the background variables are excluded, R^2 declined over 80% in Korea and Sweden, 64% in Taiwan, and 51% in Japan. By contrast, a reduction in R^2 is modest in Hong Kong (6%) and Singapore (15%). When both the background variables and school stratification are excluded, a reduction in R^2 becomes larger even in Singapore and Taiwan. Excluding institutional variables (except for school stratification) or resource variables reduces R^2 more modestly.

The bottom part of the table summarizes the results for the models with the peer effect. Compared to the results for the models without the peer effect, a reduction in R^2 by excluding individual and family background is smaller, but still largest in Japan, Korea, Taiwan, and Sweden. In Hong Kong and Singapore, excluding individual and family background as well as other variables has only a marginal impact, while the peer effect is a dominant determinant of student scores. This result confirms that the peers' mean score reflects the student's individual and family background in Hong Kong and Singapore, where students are sorted by ability at the school and/or class levels.

Despite the differences in the role played by school stratification across the countries, these findings altogether confirm a dominant role played by the student's individual and family background in determining student performance. They also imply that country-level differences in student performances in East Asia are attributable to the differences in individual and family background across the countries to some extent.

4.4 Class size and peer effect: alternative specifications

Finally, we examine the robustness of the estimation results using alternative model specifications. First, we focus on the impact of class size on student performance. Table 5 compares the estimated coefficients on class size across six different specifications. The top part summarizes the results of the models without the peer effect obtained by: (i) assuming that class size is exogenous in an OLS specification; (ii) instrumenting actual class size by the estimated mean class size in a 2SLS specification (the benchmark model); and (iii) instrumenting it by the estimated class size based on class size estimated by Maimonides' rule in a 2SLS specification. The second part of the table compares these three results for models with the peer effect (using the peers' mean score). We observe some positive and significant coefficients for five countries other than Japan. However, no country has consistent results across six different specifications. More importantly, there is no case in which class size has a negative and significant coefficient. In line with many existing studies, these results confirm that smaller classes cannot enhance student performance.

However, we should be cautious about the validity of Maimonides' rule in the six countries. As already suggested by Figure 3, the rule cannot trace the actual class size, and the variation of the estimated class sizes is much smaller than that of the actual one in five countries other than Japan. Correspondingly, in the case of Maimonides' rule, the magnitude of the coefficient on class size tends to be much larger than those for other specifications, except in Japan.

The final focus is on the peer effect. For the benchmark models, we use the peers' mean score, but it is not free from the reflection problem. Hence, we utilize three alternative variables for the peer effect: (i) the mean number of books at the peers' home, (ii) the share of college graduates among the peers' fathers, and (iii) the share of college graduates among the peers' mothers. We additionally consider (iv) the case where both the mean and standard variation of the peers' scores are included, to examine whether within-class ability deviation reduces student performance.

Table 6 summarizes the estimated coefficients on these variables for peer effects, with other explanatory variables unchanged from the benchmark models. First, we observe from this table that the coefficients on alternative variables are positive and very significant in most cases. This confirms that the peer effect matters for student performance in general, even after controlling for its endogeneity. Second, we notice that the coefficients on the standard deviation of the peers' scores are mixed and not significant. This is consistent with the result that smaller classes do not improve student performance, considering that they probably reduce within-class deviation. We should be cautious in interpreting the results in Hong Kong and Singapore, however, because the peers' scores and attributes reflect the student's own ones due to ability sorting in these countries.

5. Conclusion

We examined students' academic performance in terms of mathematics scores of the eighth graders in five major economies: Japan, Korea, Taiwan, Hong Kong, and Singapore, using an international dataset from the 2007 survey of TIMSS.

From the descriptive analysis, we found that while student performance is relatively high in all East Asian countries, its distribution differs substantially across them. Student scores are distributed most symmetrically around the mean in Japan, while they are skewed to the high end in other countries, especially in Taiwan. Correspondingly, student performance distribution is most equal in Japan and most unequal in Taiwan. We also noticed that between-class deviations of student performance are higher than within-class deviations in Hong Kong and Singapore, while the opposite is true in other countries. This is probably the result of ability sorting at the school and/or class levels in these two countries.

In our regression analysis, we explicitly considered initial maturity differences, endogeneity of class size, and peer effects. The estimation results showed that a student's individual and family background is a key determinant of educational performance, in line with the results of many existing studies. In addition to educational attainment of the parents and family belongings such as books and other cultural artifacts or media, initial maturity differences significantly affect student performance.

The relationship between school stratification—in terms of school type, gender, financing, language, school rank, and principal organizer—and student performance is remarkable as well. It presumably reflects the student's individual attributes (including his/her prior attainment) and family background (including family income, which cannot be collected directly from the TIMSS dataset), which affect between-school sorting.

By contrast, institutional and resource variables have more limited effect in general. Notably, we did not find any evidence that smaller classes improve student performance. We obtain the same result even after controlling for potential endogeneity of class size, by utilizing the expected grade-mean class size and Maimonides' rule. Enrollment size, school location, resource availability, teacher quality, and ability grouping do not much affect student performance in general. We also confirmed that peer effects are significant in all countries, whether they are captured by the peers' mean score, the mean number of books at home, or the share of college graduates among the peers' parents. In Hong Kong and Singapore, however, these variables probably reflect the effect of ability sorting, making it difficult to interpret peer effects in these countries.

In all, this study confirmed that within-country deviation in student scores is largely attributable to the student's individual and family background. Significant peer effects point to the possibility that high-ability students, if sorted by ability, can further improve their ability, which will eventually enhance academic performance in society as a whole. The benefit from such school education is not equally enjoyed, however. Indeed, limited impact of institutional and resource variables observed from the TIMSS dataset implies a risk that school education fails to sufficiently help students of low ability or with economic disadvantages enhance their academic performance. It underscores the importance of providing policy support beyond school education to children for whom socio-economic conditions are unfavorable.

Footnotes

1. The term "country" used in this paper includes a region of a certain country (Hong Kong SAR) and an area whose independence is ambiguous (Taiwan/Chinese Taipei). In tables and figures in this paper, JPN, KOR, TWN, HKG, SGP, and SWE stand for Japan, Korea, Taiwan, Hong Kong, Singapore, and Sweden, respectively.
2. Kan's (2007) worldwide cross-country analysis found a significantly positive association between peers' performance and students' own achievement for most countries participating in the 1995 survey of TIMSS.
3. We conducted empirical analysis similar to what is discussed below using data of science scores. We do not report the results of science, which were generally in line with those of math, to save space, but they are available from the authors upon request.
4. Wößmann (2005) utilized some school characteristics—such as schools' autonomy in salary decisions, homework studies, and parental involvement in the education process—as institutional variables in regression analysis. Instead of using these specific factors, we include dummies for school stratification, which are expected to completely capture major institutional differences across schools.

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Table 1. Basic statistics of math scores by country

	JPN	KOR	TWN	HKG	SGP	SWE
Mean	570	597	598	572	593	491
Standard deviation	85	92	106	94	93	70
Standard deviation/Mean	0.149	0.154	0.177	0.164	0.157	0.143
Gini coefficient	0.0822	0.0840	0.0953	0.0855	0.0853	0.0768
Between-school variation (%, A)	23.7	12.9	25.2	67.9	52.5	14.1
Within-school variation (%, B)	76.3	87.1	74.8	32.1	47.5	85.9
(A)/(B)	0.31	0.15	0.34	2.11	1.11	0.16
F -statistics	11.5	4.14	8.80	60.6	31.3	5.78
Between-class variation (%, A)	24.0	12.9	26.6	67.9	82.0	20.8
Within-class variation (%, B)	76.0	87.1	73.4	32.1	18.0	79.2
(A)/(B)	0.32	0.15	0.36	2.11	4.57	0.26
F -statistics	10.1	4.14	9.27	60.6	62.5	4.65
Number of schools	146	150	150	120	164	159
Number of classes	169	150	153	120	326	307
Number of students	5524	4298	4046	3534	4770	5722

Note: TIMSS (2007).

Figure 1. Estimated Kernel density of math scores

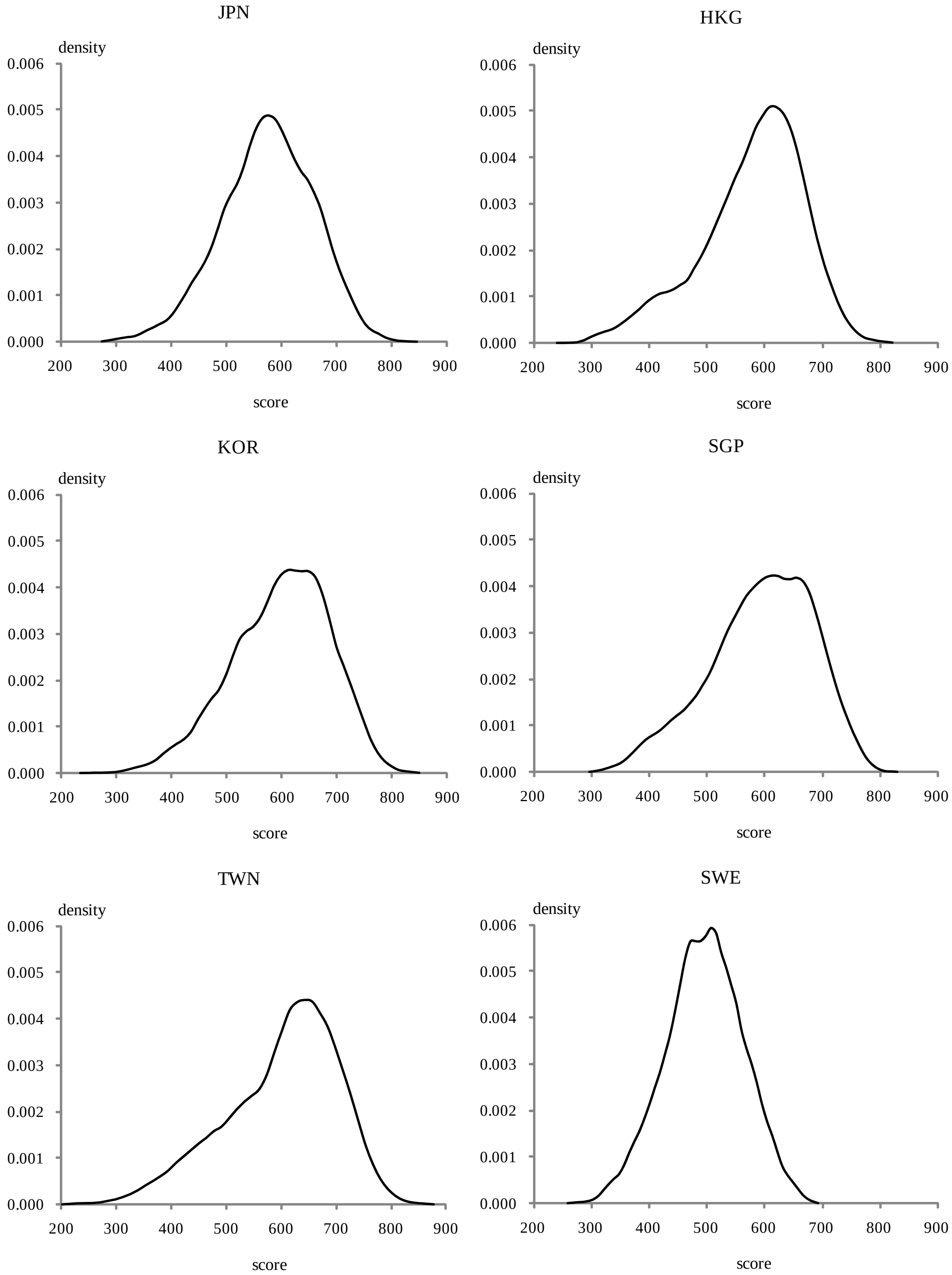


Table 2. School years and definitions of birth-quarters in this paper

Country	Dates of starting school	Children supposed to start going to elementary school in year *X*	Definitions of birth-quarters Q1	Q2	Q3	Q4
JPN	April	Those who become seven years old between April 2 in year *X* and April 1 in year *X* +1	Apr-Jun in 1992	Jul-Sep in 1992	Oct-Dec in 1992	Jan-Mar in 1993
KOR	March	Those who become six years old between March 1 in year *X* -1 and the end of Feburuary in year *X* .	Mar-May in 1992	Jun-Aug in 1992	Sep-Nov in 1992	Dec-Feb in 1993
TWN	September	Those who become six years old by August 31 in year X.	Sep-Nov in 1992	Dec-Feb in 1993	Mar-May in 1993	Jun-Aug in 1993
HKG	September	Those become six years old by December 31 in year *X*	Jan-Mar in 1993	Apr-Jun in 1993	Jul-Sep in 1993	Oct-Dec in 1993
SGP	January	Those become six years old between January 3 in year X-1 and January 2 in year *X*	Jan-Mar in 1992	Apr-Jun in 1992	Jul-Sep in 1992	Oct-Dec in 1992
SWE	August	Tho who become seven years old by December 31 in year *X* .	Jan-Mar in 1992	Apr-Jun in 1992	Jul-Sep in 1992	Oct-Dec in 1992

Note: The rule in Korea was the one before the revision in 2008.

Figure 2. Mathematics scores by birth quarter

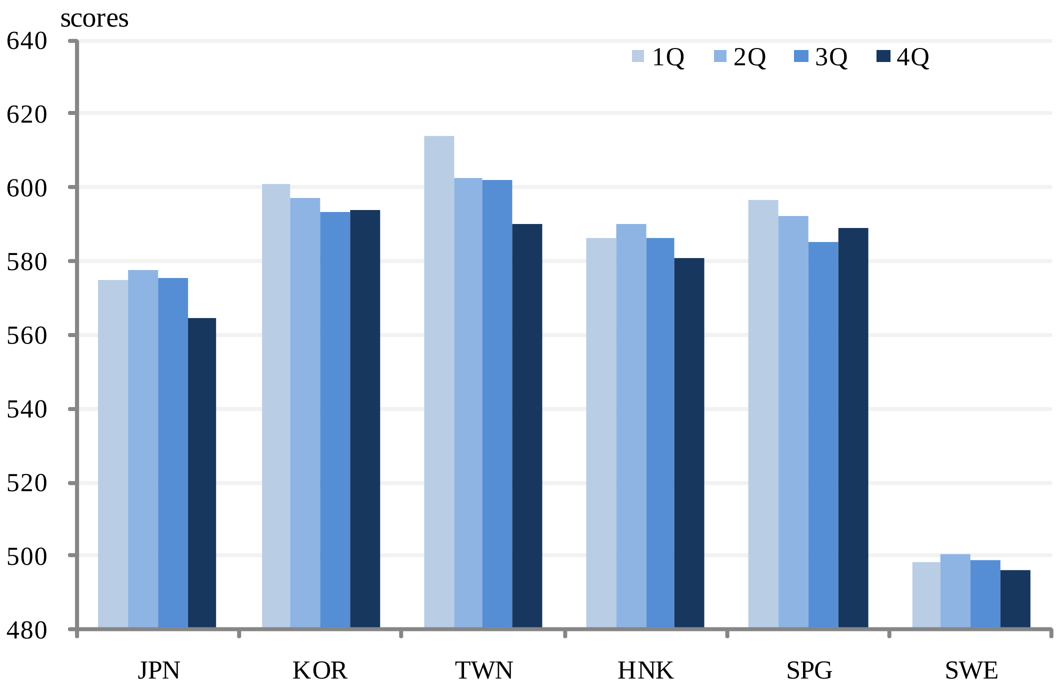
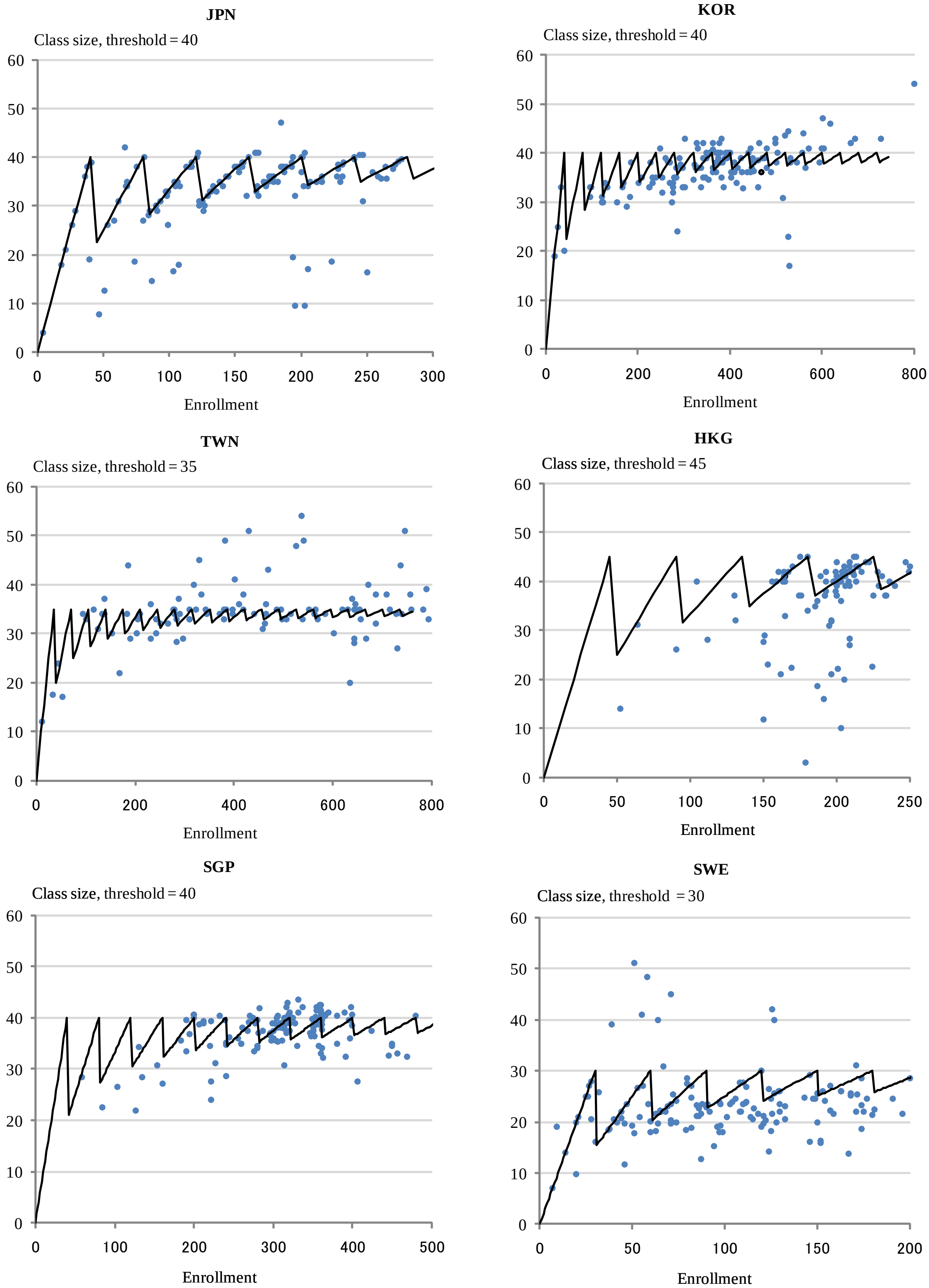


Figure 3. Actual class size and estimated class size based on Maimonides' rule



Note: Dots indicates the actual class sizes and the lines indicates the estimated ones.

Table 3. Regressions for mathematics score (the 8th graders)

Dependent variable = mathematics score

	JPN		KOR		TWN		HKG		SGP		SWE	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Individual and family background												
Girls	-6.14	(2.38) ***	-6.18	(3.55) *	-11.01	(3.31) ***	-0.15	(4.06)	4.70	(2.63) *	-6.12	(2.49) **
Born in 2Q	-0.45	(2.92)	-5.68	(3.72)	-5.96	(3.99)	9.03	(4.37) **	-5.34	(3.04) *	2.19	(3.04)
Born in 3Q	-5.67	(3.10) *	-10.16	(3.45) ***	-11.35	(3.94) ***	7.87	(4.16) *	-7.12	(3.09) **	0.82	(3.05)
Born in 4Q	-11.05	(2.98) ***	-9.28	(3.69) **	-16.15	(3.98) ***	-1.47	(4.62)	-3.48	(3.26)	0.79	(3.61)
Born in the country	14.23	(15.47)	2.00	(30.41)	84.12	(7.87) ***	13.57	(6.82) **	-12.98	(4.62) ***	22.83	(5.99) ***
Number of books at home (11-25)	15.21	(4.16) ***	18.90	(6.21) ***	41.21	(6.44) ***	14.74	(6.73) **	17.18	(3.85) ***	19.54	(4.95) ***
Number of books at home (26-100)	29.92	(4.02) ***	44.93	(5.42) ***	59.59	(5.83) ***	20.81	(6.52) ***	38.67	(3.99) ***	30.60	(4.95) ***
Number of books at home (101-200)	34.40	(4.28) ***	64.25	(5.38) ***	75.26	(6.70) ***	25.37	(7.41) ***	35.03	(4.71) ***	41.23	(5.36) ***
Number of books at home (201+)	40.31	(4.74) ***	84.00	(5.66) ***	80.45	(6.34) ***	26.17	(7.58) ***	38.45	(4.59) ***	61.56	(4.87) ***
Computer at home	8.46	(4.16) **	18.91	(18.19)	42.55	(8.05) ***	8.54	(22.46)	13.30	(6.25) **	1.84	(12.86)
Study desk at home	19.89	(6.71) ***	8.87	(8.09)	7.26	(6.88)	-18.21	(4.69) ***	14.32	(3.83) ***	17.39	(7.46) **
Dictionary at home	67.16	(14.22) ***	62.10	(13.68) ***	21.88	(15.60)	31.16	(16.47) *	37.32	(11.26) ***	9.78	(3.97) **
Internet connection at home	17.21	(4.00) ***	54.59	(9.10) ***	10.49	(6.91)	18.08	(14.28)	31.82	(4.94) ***	16.62	(8.22) **
Father's education: high school	16.57	(7.86) **	6.27	(7.57)	4.22	(4.90)	-1.39	(5.03)	3.06	(3.69)	6.52	(5.79)
Father's education: junior college	23.76	(8.74) ***	9.54	(10.44)	21.04	(6.41) ***	-7.46	(7.15)	2.91	(4.46)	6.21	(5.86)
Father's education: college or more	46.31	(8.10) ***	27.27	(7.93) ***	33.71	(7.03) ***	-5.29	(6.02)	12.52	(5.07) **	14.96	(6.29) **
Father's education: unknown	18.88	(8.18) **	-16.33	(8.64) *	-3.19	(7.66)	-9.57	(6.31)	0.51	(4.45)	0.40	(5.30)
Mother's education: high school	22.08	(8.47) ***	7.14	(5.99)	10.07	(4.11) **	-6.19	(4.70)	4.17	(3.69)	2.54	(5.99)
Mother's education: junior college	34.90	(8.66) ***	19.75	(10.19) *	21.15	(6.05) ***	4.49	(6.00)	-2.74	(4.45)	21.46	(6.13) ***
Mother's education: college or more	26.01	(8.81) ***	17.22	(6.92) **	12.23	(6.61) *	-5.59	(7.00)	-1.98	(4.92)	1.60	(6.45)
Mother's education: unknown	19.11	(8.33) **	-1.49	(7.84)	-12.08	(7.86)	-4.34	(6.25)	-9.20	(4.45) **	-1.36	(6.21)

(to be continued)

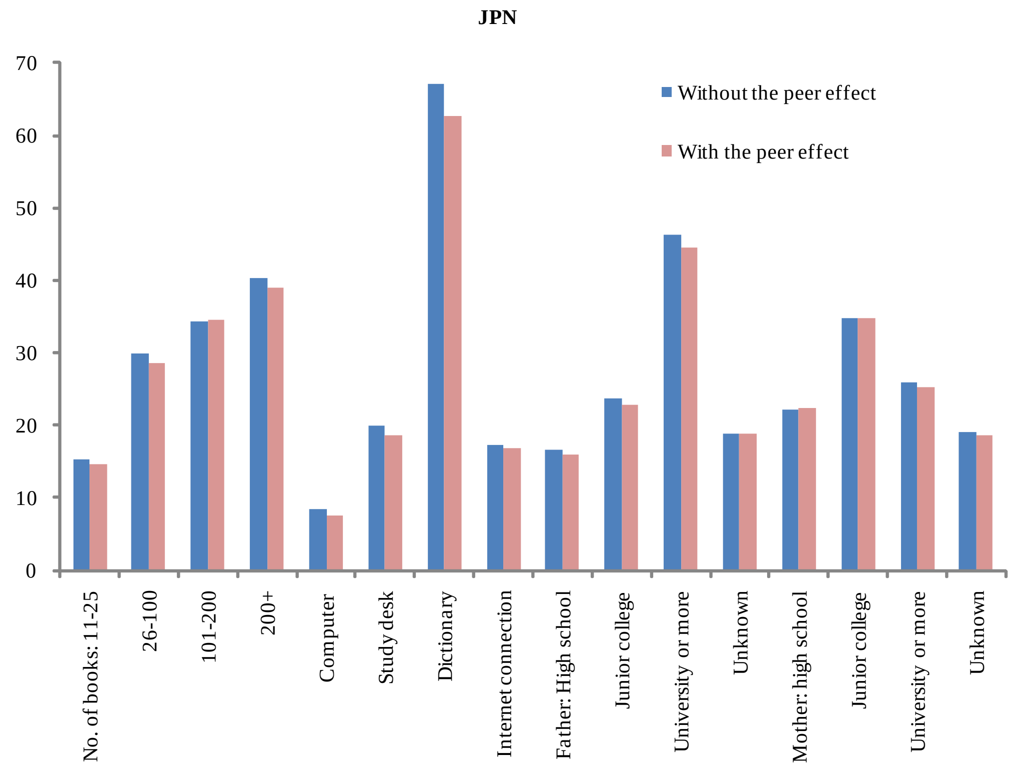
Table 3 (continued)

	JPN		KOR		TWN		HKG		SGP		SWE	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Institutional variables												
Enrollment in the 8th grade	0.02	(0.03)	-0.01	(0.02)	0.00	(0.01)	0.04	(0.27)	-0.22	(0.06) ***	0.06	(0.04)
Disadvantaged students: 11-25%	-2.89	(3.98)	-17.11	(4.59) ***	6.16	(5.96)	-30.36	(17.34) *	8.45	(6.22)	-8.26	(3.81) **
Disadvantaged students: 26% or more	-23.85	(7.34) ***	-16.51	(4.45) ***	-6.24	(9.42)	-49.04	(17.47) ***	0.48	(9.00)	-5.27	(7.42)
School location: 100,001-500,000 people	2.88	(4.78)	-0.91	(3.88)	-5.19	(7.17)	-18.94	(16.22)			-11.26	(10.09)
School location: 50,001-100,000 people	-5.84	(5.32)	-0.50	(8.13)	-10.72	(8.45)	10.32	(16.79)			-12.29	(9.41)
School location: 15,001-50,000 people	4.68	(5.73)	-27.89	(8.85) ***	-37.49	(9.54) ***	-24.78	(18.34)			-11.63	(8.60)
School location: 15,000 people or less	18.26	(7.25) **	-8.40	(8.29)	-73.43	(18.82) ***					-18.33	(9.31) **
School stratification	Included		Included		Not included		Included		Included		Included	
Resource variables												
Shortage: instructional materials	0.71	(5.28)	10.30	(6.97)	-0.65	(13.21)	-19.07	(15.92)	35.53	(12.71) ***	-2.55	(5.41)
Shortage: classrooms	-3.15	(4.56)	0.02	(4.13)	12.45	(7.93)	-3.58	(11.65)	-11.08	(9.51)	8.91	(3.99) **
Shortage: teachers	4.23	(3.82)	-12.61	(5.75) **	4.35	(9.55)	-2.61	(36.59)	-6.66	(13.76)	-6.88	(6.83)
Class size	0.36	(0.27)	0.17	(0.55)	2.05	(0.50) ***	1.88	(0.91) **	2.88	(1.04) ***	0.54	(0.40)
Ability grouping	10.65	(3.95) ***	-7.09	(4.84)	-4.72	(8.91)	-15.31	(11.38)	2.68	(6.2)	6.05	(3.88)
Teacher: female	7.55	(3.18) **	5.91	(5.32)	-7.28	(5.68)	6.61	(12.05)	11.64	(6.31) *	-0.98	(3.86)
Teacher: master degree	-2.71	(6.96)	6.67	(5.27)	0.61	(6.63)	-17.66	(15.88)	-1.82	(15.00)	4.92	(4.04)
Teacher: years of experience	-0.23	(0.18)	-0.15	(0.26)	-0.16	(0.35)	-0.29	(0.59)	0.23	(0.30)	0.15	(0.19)
Constant	361.4	(27.6) ***	411.9	(39.0) ***	332.6	(26.0) ***	376.7	(58.8) ***	319.5	(37.8) ***	379.6	(23.3) ***
Adjusted R^2	0.2764		0.2725		0.3312		0.3986		0.4957		0.1858	
Including the peer effect												
Peers' mean score	0.423	(0.05) ***	0.358	(0.06) ***	0.579	(0.04) ***	0.966	(0.02) ***	0.930	(0.01) ***	0.563	(0.04) ***
Adjusted R^2	0.2912		0.2828		0.3801		0.6730		0.7924		0.2414	
Number of observations	4909		3574		3166		1836		3713		2972	
Number of clusters	133		138		125		91		145		116	

Note: The estimated coefficients on variables of school stratification in the top part and all variables other than the peers' mean score in the bottom part are not reported to save space.

A full set of estimation results is available from the authors upon request.

Figure 4. Estimated coefficients on the background variables: with and without the peer effect



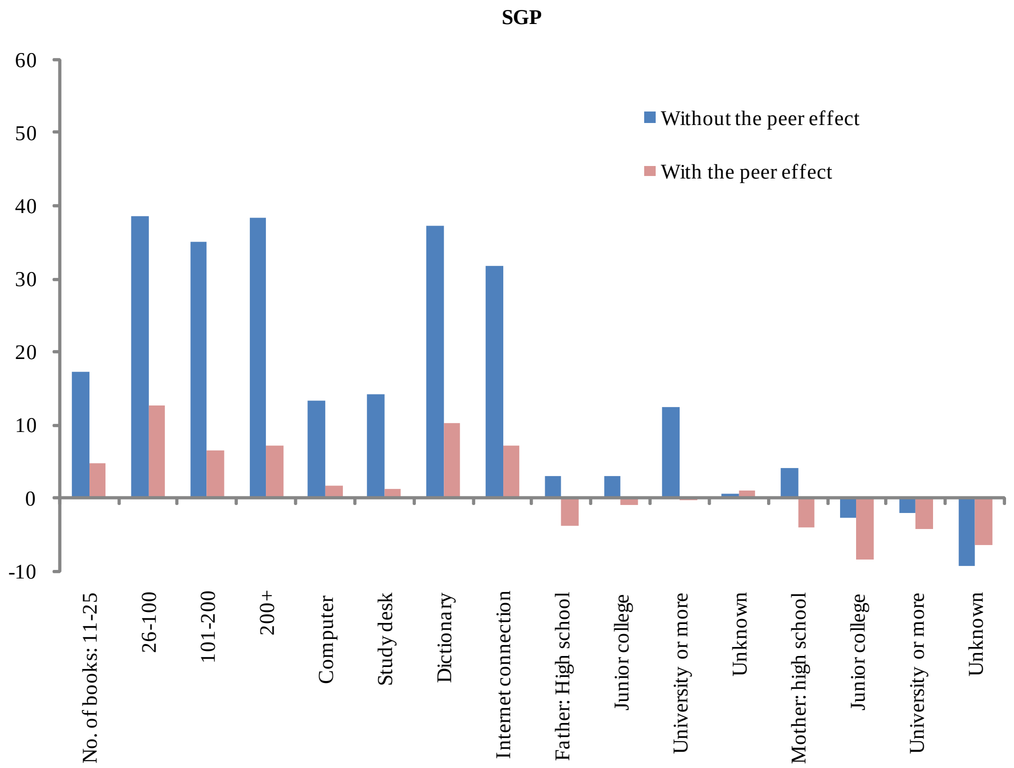


Table 4. R^2 and percentage decreases in R^2 when categories of variables are excluded

	JPN	KOR	TWN	HKG	SGP	SWE
Models without the peer effect						
R^2	0.2763	0.2726	0.3293	0.4004	0.4904	0.1822
Excluded category						
Individual and family background and school stratification	74.1	82.3	64.2	29.3	69.2	80.6
Individual and family background	50.7	81.4	64.2	6.2	15.3	80.1
School stratification	13.9	0.4	0.0	19.7	31.4	0.1
Institutional factors (excl. school stratification)	3.8	3.0	4.7	7.6	2.7	3.2
Resources	2.6	1.8	5.7	11.0	3.2	5.6
Models with the peer effect						
R^2	0.2912	0.2828	0.3801	0.6731	0.7924	0.2364
Excluded category						
Individual and family background and school stratification	46.3	72.6	41.2	2.0	0.8	50.9
Individual and family background	44.0	72.2	41.2	1.8	0.7	50.9
School stratification	1.8	0.2	0.0	0.4	0.1	0.7
Institutional factors (excl. school stratification)	0.7	0.6	0.3	0.1	0.0	0.5
Resources	0.6	1.2	0.4	0.1	0.0	1.4
Peer effects (peers' mean score)	5.1	3.6	13.4	40.5	38.1	22.9

Note: Class size was instrumented by the estimated mean class size at the eighth grade.

Table 5. The coefficient on class size

	JPN		KOR		TWN		HKG		SGP		SWE	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Without the peer effect												
OLS	0.37	(0.26)	0.05	(0.56)	2.19	(0.52) ***	1.80	(0.79) **	3.71	(0.93) ***	1.22	(0.38) ***
2SLS-IV (Instrument = estimated mean class size)	0.36	(0.27)	0.17	(0.55)	2.05	(0.50) ***	1.88	(0.91) **	2.88	(1.04) ***	0.54	(0.40)
2SLS-IV (Instrument = Maimonides' rule)	-0.37	(0.86)	4.22	(1.83) **	-1.60	(2.46)	10.61	(6.48)	8.68	(6.14)	4.12	(4.67)
With the peer effect												
OLS	0.15	(0.14)	-0.03	(0.36)	0.39	(0.18) **	0.01	(0.17)	0.15	(0.10)	1.08	(0.31) ***
2SLS-IV (Instrument = estimated mean class size)	0.14	(0.15)	0.09	(0.31)	0.40	(0.18) **	0.12	(0.16)	0.18	(0.13)	0.34	(0.24)
2SLS-IV (Instrument = Maimonides' rule)	-0.19	(0.42)	2.86	(1.25) **	-0.82	(0.60)	-0.55	(1.51)	1.87	(1.02) *	0.53	(2.15)

Table 6. The coefficients on alternative variables of the peer effect

Peer effect variable	JPN		KOR		TWN		HKG		SGP		SWE	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Mean score	0.423	(0.05) ***	0.358	(0.06) ***	0.579	(0.04) ***	0.966	(0.02) ***	0.930	(0.01) ***	0.563	(0.04) ***
Mean number of books at home	-0.004	(0.07)	0.252	(0.06) ***	0.470	(0.08) ***	0.720	(0.20) ***	0.844	(0.08) ***	0.115	(0.04) **
Share of college graduates: fathers	38.5	(13.7) ***	47.2	(11.7) ***	131.5	(26.0) ***	17.6	(52.4)	188.6	(25.9) ***	49.4	(16.4) ***
Share of college graduates: mothers	38.8	(14.5) ***	46.7	(13.0) ***	144.2	(24.6) ***	8.8	(51.4)	148.7	(29.3) ***	20.6	(18.7)
Mean score	0.417	(0.05) ***	0.364	(0.07) ***	0.596	(0.04) ***	0.945	(0.02) ***	0.932	(0.01) ***	0.558	(0.04) ***
with standard deviation	-0.059	(0.11)	0.045	(0.13)	0.068	(0.10)	-0.251	(0.17)	0.045	(0.05)	-0.097	(0.09)

Note: Class size is instrumented by the estimated mean class size.