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Educational Production in East Asia: The Impact of Family Background and Schooling Policies on Student Performance

by

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Abstract:

East Asian students regularly take top positions in international league tables of educational performance. Using internationally comparable student-level data, I estimate how family background and schooling policies affect student performance in five high-performing East Asian economies. Family background is a strong predictor of student performance in South Korea and Singapore, while Hong Kong and Thailand achieve more equalized outcomes. There is no evidence that smaller classes improve student performance in East Asia. But other schooling policies such as school autonomy over salaries and regular homework assignments are related to higher student performance in several of the considered countries.

Keywords: Education production function, East Asia, family background, class size, school autonomy

JEL Classification: O15, I20, H52

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1. Introduction

Most of the high-performing East Asian economies have achieved universal enrollment of children in primary and secondary education. However, many people in these countries fear that their schooling systems do not provide the skills necessary to excel in a modern economy, such as analytical skills, creativity, and independence of mind.[1] It has been commented that "it is ironic that this debate … is taking place at a time when many in longer-established developed economies are urging a return to traditional educational systems" (Richardson 1996, p. 22) emphasizing basic skills and general rather than highly specialized education. Certainly, a strong foundation in basic skills is a prerequisite for success in more ambitious tasks. And the East Asian countries actually seem to do very well with regard to general education: Their students repeatedly take top places in international comparative studies of cognitive achievement in math, science, and reading literacy.

For example, the first four places in the ranking of the 39 participating countries in the middle-school math test of the 1995 Third International Mathematics and Science Study (TIMSS) are taken up by Singapore, Korea, Japan, and Hong Kong. With the exception of Hong Kong, these countries are also among the top four places in science. This extraordinary performance of East Asian countries had already been evident in previous cross-country studies, and it has been repeated in subsequent ones.[2] These achievement studies do not only test the basic knowledge of students in math and science, e.g. by multiple-choice questions, but also require students to accomplish a transfer and application of their knowledge to less familiar real-world tasks when solving more advanced open-ended questions. The lead of East Asian students over students from other continents is generally especially large in the latter, more difficult questions (cf. Beaton et al. 1996, pp. 57-98). The broad set of capabilities of Asian

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[1] For references for each of the countries dealt with in this paper, see Wrigley and Richardson (2001, p. 22); Ward and Richardson (2002a, p. 19); Ward and Richardson (2002b, pp. 17-18); Dosanjh and Richardson (2001, p. 13); and Bain and Richardson (2001, p. 13); see also Robitaille (1997).

[2] For example, middle-school Japanese children performed second in math and first in science in the first internationally comparative studies of the International Association for the Evaluation of Educational Achievement (IEA), conducted in 1964 and 1971, and the two East Asian countries participating in the 2000 OECD study Programme for International Student Assessment (PISA), Japan and Korea, took the first two places in math and science among the 31 participants.

students has also been verified in a series of cross-national studies conducted by psychologists in Asian and American metropolitan areas. Stevenson (1992, p. 32) concludes this research by stating that "contrary to popular stereotypes the high levels of achievement in Asian schools are not the result of rote learning and repeated drilling by overburdened, tense youngsters. Children are motivated to learn; teaching is innovative and interesting. Knowledge is not forced on children; instead the students are led to construct their own ways of representing this knowledge."[3]

The crucial question thus is how the high-performing East Asian economies have achieved their high educational performance, and how they can sustain the quality of their knowledge foundation and ensure a high-quality education for all children for their future development into a skill-based economy. Outside the United States, in-depth evidence on the impact of family background and school policies in educational production is very limited (cf. Hanushek 2002, pp. 3-4, 43-45). To my knowledge, recent comparable empirical evidence does not exist for East Asian countries.[4] This paper starts to provide such evidence by estimating the impact of family background, schooling resources, and other educational policies on student performance in five East Asian countries. Specifically, the estimated results provide answers to three important questions. First, they reveal which countries do best in supporting the performance of students with poor family backgrounds. Second, they show which role schooling resources, such as class size and teacher education and experience, play in the extraordinary achievement of East Asian students. Third, they estimate the impact of systemic features such as school autonomy and parental involvement on student performance, thereby shedding light on other policy options besides resource policies in the countries considered.

The evidence presented in this paper is based on student-level micro data from TIMSS, combining performance information with abundant data on students' family background and schools' resource endowments and institutional constraints (Section 2). The TIMSS database allows an estimation of education production functions for five

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[3] For Singapore, it has also been suggested that limited creativity might have more to do with a political system that lacks freedom to express own ideas than with the education system (Sjöholm 2002).

[4] A notable earlier exception is Jimenez et al.'s (1988) comparison of private and public schools in Thailand based on data from the Second International Mathematics Study.

East Asian countries: Hong Kong, Japan, South Korea, Singapore, and Thailand. Furthermore, the data and thus the estimated effects are directly comparable across these countries, as well as to countries in America and Europe. As discussed below, the multi-grade structure of the TIMSS sampling design also allows a credible identification of causal effects of class size on student performance in some of these countries, using a combination of school-fixed-effects and instrumental-variables estimation.

The first set of analyzed influence factors is the impact of family background on students' educational performance in the different countries (Section 3). The research question is to what extent the different schooling systems provide equal educational opportunities for children from different family backgrounds. For example, the strong priority placed on education in South Korea since its earliest days stems largely from the desire to put "smallholders on an equal educational footing with the owners of larger farms – which was an important aspect of avoiding polarization in the countryside and of enabling migrants from the countryside to adapt relatively easily to urban and industrial life" (Ward and Richardson 2002b, p. 17). The evidence presented in this paper allows an assessment both of the impact of family background on children's educational performance and of rural-urban performance differences, among other influences. The results suggest that the rural-urban performance difference is indeed relatively small in Korea. However, social background has a much larger impact on student performance in Korea, as well as Singapore, than in Hong Kong and Thailand. In terms of equalizing educational opportunities, Korea thus does not fare well. As a further student background factor, girls perform statistically significantly worse than boys in Hong Kong, Japan, and Korea, while no such between-gender difference exists in Singapore and Thailand.

One response to the concerns about schooling quality in these countries has been to raise the resource endowments of schools. For example, in Hong Kong, the government responded to these concerns by substantially increasing educational spending (Wrigley and Richardson 2001, p. 20). All of the countries concerned in this paper have substantially lowered their pupil-teacher ratios over the recent decades (Gundlach and Wößmann 2001, pp. 409-410). Can such policies help to ensure a high-quality education? In order to answer this question, Section 4 analyzes the impact of resource endowments on students' academic skills in the East Asian countries. Least-squares estimates of the coefficient on several resource measures such as endowment with materials, instruction time, and teacher characteristics reveal few statistically significant correlations between these variables and student performance. However, as these standard estimates may be substantially biased by non-random resource endowments, the paper combines instrumental-variables with school-fixed-effects estimation to disentangle the causal effect of class size on student performance from any effects of placements of students into differently sized classes between schools or within schools. The results show that many East Asian school systems indeed place lower-performing students into smaller classes in order to provide them with compensatory learning possibilities. The exception is Thailand, where higher-performing students end up in schools with smaller classes in what appears to be a regressive pattern of between-school student placements. Accounting for such resource endogeneity and omitted variable biases, class size does not seem to have a noteworthy causal effect on student performance in Japan and Singapore, the two countries for which the data allow a meaningful assessment. This contrasts, for example, with France, where there is some evidence of beneficial effects of smaller classes.

Given the dismal results for resource policies, the question arises whether other policy options can affect educational achievement in the East Asian countries (Section 5). For example, one complaint often heard all over the region is "that the government's administration of schools and universities is cumbersome, centralized and resistant to change" (Economist 1997). Rather than centralized administration, giving more autonomy to schools may induce more creativity and make better use of localized knowledge on effective teaching techniques. International evidence shows that school autonomy is particularly capable of raising student performance in school systems where performance is regularly accounted for in central examinations (Wößmann 2003b), and the East Asian countries are well known for their strong emphasis on examination results. Consistent with this evidence, large positive effects of salary autonomy are found in Japan and Singapore, but no such effects are evident in Hong Kong and Korea. Another policy to enhance student performance may be to make students study on their own by regularly assigning homework. Statistically significant positive effects of the amount of homework assigned are shown in Hong Kong, Japan, and Singapore.

It should be noted that the evidence presented in this paper mainly allows answers to questions relating to within-country variations in student performance. Thus, it shows the importance of different sets of influence factors for the performance variation within each country, and it allows for a comparison of the size of these effects across countries. By contrast, for questions relating to the most important determinants of the cross-country variation in test scores, the most promising way is to use the entire international dataset in order to link cross-country performance differences to cross-country differences in potential determinants. Such cross-country analyses have been performed elsewhere, both at the country level (e.g., Lee and Barro 2001) and at the student level (Wößmann 2003a). However, an analysis of the relative effects of the different influence factors on the within-country variation across countries can help to understand better how the East Asian countries achieve their high educational standards, and it can yield implications for educational and social policies both in these countries and in other countries that strive to learn from the East Asian education systems.

2. Data on Schooling in East Asia

Before describing the TIMSS database that is used to estimate education production functions for East Asian countries (Sections 2.2 – 2.4), Section 2.1 presents assessments from the literature on the importance of education for the East Asian growth experience, as well as basic data on educational attainment and expenditure in the countries analyzed in this paper.

2.1. Education Systems in East Asia

The World Bank (1993, pp. 5, 43-46) has argued that rapidly growing human capital was a principal engine of the East Asian miracle. Subsequent research validates that educational expansions played an important role in the East Asian growth experience (Young 1995; Collins and Bosworth 1996; McMahon 1998).[5] One shortcoming of these

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[5] The role of human capital accumulation in East Asian growth is not questioned in the recent reanalysis by Hsieh (2002), whose factor-market based estimates place some doubts on the relative importance of physical capital accumulation and total factor productivity growth in Singapore's growth

assessments is that they look only at the quantity of schooling while ignoring differences in the quality of schooling. Recent cross-country research shows that the quality of schooling, as measured by average student performance on achievement tests, has an even stronger impact on long-run economic growth than mere quantitative measures of schooling (Hanushek and Kimko 2000; Barro 2001).[6] The fact that East Asian countries excel on the qualitative measures suggests that the quantity-based studies potentially underestimate the present and future role of schooling in East Asia's economic development. The focus on the quality of education may also help to understand why many Latin American countries did not perform in a comparable way, despite relatively high quantitative levels of schooling in the 1960s. The recent financial crisis in many East Asian economies provides ample evidence that overly relying on volatile international capital markets appears to be an unsustainable development strategy. Given the relevance of education as a central determinant of long-run growth, understanding the sources of a high-quality education should prove to be a top priority for research.

However, the causes of East Asia's extraordinary educational performance record are largely unknown. To put the following analysis in perspective, Table 1 gives some quantitative assessment of educational attainment and expenditures in the countries concerned in this paper. In Hong Kong, Japan, and Korea, schooling is compulsory for children aged 6 through 15, and while there is no compulsory period of education in Singapore, every child there receives at least 10 years of general education (Robitaille 1997). Japan and Korea have achieved virtually universal enrollment in primary and secondary education. In Hong Kong and Singapore, enrollment in secondary education lies at about three quarters of the corresponding age group (lower and higher secondary education combined). In these four countries, basically all children reach grade 5. This data is not available for Thailand, but (gross) primary and secondary enrollment there lie at 87 and 54 percent, respectively. In Thailand, primary education is officially compulsory and free of charge for 6 years of study, and there are recent efforts to extent

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experience. Note also Booth's (1999) more diverse view which exposes educational conditions and progresses as one of the differences between the fast-growing economies of North and South East Asia.

[6] This reasoning is validated by Asian micro evidence that social rates of return to improving the quality of schooling may be higher than those to extending years of schooling (Behrman 1999).

this to 12 years (World Bank 2002b). However, enrollment ratios at the lower and upper secondary level in Thailand lag behind those of the other East Asian countries. As the TIMSS performance data pertains to students in grades 7 and 8, the selection of the student population in Thailand might be biased relative to other countries, but there is basically no sample selection in the other four countries.

Both relative to GDP per capita and in purchasing power parity (PPP) terms, expenditure per student at the secondary level in the East Asian countries lay between the values in France and Spain, with the exception of Thailand in the absolute PPP measure. As a share of GDP, total public spending on education in the five East Asian countries lies between 2.9 and 4.0 percent. Given the relatively high enrollment rates and reasonable overall resource endowments in these East Asian countries, the main issue is thus not to increase the coverage of schooling by a larger educational budget but to ensure a high quality of the given amount of schooling.

One salient feature of the school systems in all five East Asian countries is their strong emphasis on examinations. All have central examination systems, and students' future fate depends heavily on examination results. The "examination hell" that students have to go through in Japan and Korea has become proverbial (cf. Ward and Richardson 2002a, b). The stringent examination system has sometimes been linked to an emphasis on rote learning. As discussed before, the education systems all over East Asia are generally characterized by a high degree of centralization of administration and curriculum. The centralization tends to introduce uniformity of educational standards, which is also often associated with a lack of flexibility and creativity. But the evidence presented by Stevenson (1992) points out that such a prejudice does not necessarily reflect the reality of learning in the classroom, at least in the case of Japan.

In Hong Kong, Japan, and Korea, there is no official policy on within-school streaming at least up to grade 8, and public elementary and lower secondary schools are not tracked (Robitaille 1997, pp. 162, 220, 228). Students generally follow the same curriculum, but some schools in Hong Kong offer remedial lessons in which low-ability students are grouped together for math instruction. With regard to streaming and tracking, Singapore is an outlier in the region in that at the end of grade 4, students are streamed according to their abilities (Robitaille 1997, p. 331).

2.2. The TIMSS Database

The database used to estimate education production functions for the five East Asian countries draws from a large-scale cross-country comparative test of student achievement, the Third International Mathematics and Science Study (TIMSS). It combines individual student-level performance data in math and science with information from student, teacher, and school-principal background questionnaires for nationally representative samples of students in each of the countries. TIMSS was conducted in 1995 under the auspices of the International Association for the Evaluation of Educational Achievement (IEA), an independent cooperation of national research institutes and governmental research agencies. The target population of middle school students to which each participating country administered the test was defined as those students enrolled in the two adjacent grades that contained the largest proportion of 13-year-old students at the time of testing. These are the first two grades of secondary school in all East Asian countries dealt with in this paper, representing the seventh and eighth year of formal education in all the countries.[7]

Each participating country randomly sampled the schools to be tested in a stratified sampling design, and within each of these schools, generally one class was randomly chosen from each of the two grades and all of its students were tested in both math and science, yielding a representative sample of students within each country. Schools in geographically remote regions, extremely small schools, and schools for students with special needs were excluded from the target population. Within sampled schools, disabled students who were unable to follow even the test instructions were excluded; students who merely exhibited poor academic performance or discipline problems were required to participate (Foy et al. 1996). The overall exclusion rate was not to exceed 10 percent of the total student population.

The number of sampled schools that participated in the TIMSS test in each country is about 150, with the exception of Hong Kong, where it is 86 (Table 2a). In Singapore, all eligible schools were included in TIMSS (Martin and Kelly 1998, p. B-23). The sampling procedure yielded a sample size between 5827 students in Korea and 11643 students in Thailand. To allow a comparison of the East Asian findings to countries

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[7] In Hong Kong, Singapore, and Thailand, the relevant grades are called “Secondary 1 and 2;” in Japan, “1st and 2nd Grade Lower Secondary;” and in Korea, “1st and 2nd Grade Middle School.”

from other regions in the world, all estimations are also executed for the United States, France, and Spain, the latter two being major European countries with reasonably complete TIMSS data sets. Thus, Table 2a also presents sample sizes for these three countries, which are comparable to the East Asian samples.

TIMSS gave rigorous attention to quality control, using standardized procedures to ensure comparability in school and student sampling, to prevent bias, and to assure quality in test design and development, data collection, scoring procedures, and analysis. The TIMSS achievement tests were developed through an international consensus-building process involving inputs from international experts in math, science, and measurement, and were endorsed by all participating countries. Students were tested in a wide array of content dimensions in math and science. In math, the content areas were: fractions and number sense; geometry; algebra; measurement; proportionality; and data representation, analysis, and probability. In science, they included: earth science; life science; physics; chemistry; and environmental issues and the nature of science. Many different kinds of performances were expected of students, encompassing categories such as understanding simple information, performing routine procedures, using complex procedures, solving problems, proving, communicating, and investigating the natural world. A quarter of the test items (meant to cover a third of the testing time) were in free-response format, sometimes requiring extensive responses, while the remainder of the items were multiple-choice questions. A test-curriculum matching analysis performed by TIMSS which restricted the analysis to items definitely covered in each country's curriculum showed that the overall achievement patterns were hardly affected by this.

Student performance in math and science were measured separately using an international achievement scale with scores having an international mean of 500 and an international standard deviation of 100. Table 2a reports the mean performance of students for the countries considered in this paper. Students from Hong Kong, Japan, Korea, and Singapore excelled on the tests, with the exception of Hong Kong in science. The latter performance was still above the international average, though, as was the performance of Thai students in both subjects. The variation in performance as indicated by the standard deviation of test scores in each country was relatively low in

Thailand (both in absolute terms and relative to mean performance), and it was relatively high in Korea and Hong Kong.

The performance data are merged with the specific background data from three different TIMSS background questionnaires for each individual student. From the student background questionnaires, I draw information on age and sex of the student, on whether the student was born in the country and lives with both parents, the level of the parents' education, and the number of books at home. The math and science teacher background questionnaires contain data on the actual sizes of the respective math and science classes, as well as on teacher characteristics such as sex, years of experience, and education level. They also report the amount of homework assignments per week and whether teaching was thought to be limited by uninterested or interested parents. The school-principal background questionnaires provide information on the community location of the school, shortage of materials, instruction time, average class sizes in the two relevant grades, and on whether the school had responsibility for determining teacher salaries. Most of these background variables based on qualitative survey data were transformed into dummy variables for the estimations of this paper.

Given the international standardization of the test results, the cooperative nature of the test development, its endorsement by all participating countries, and the substantial efforts to ensure high-quality sampling and testing in all countries, the TIMSS student performance and background data should be comparable across countries. This should also make the empirical estimates presented in this paper directly comparable across the different countries. This makes the database uniquely capable of using student, class, and school level data to analyze the determination of student performance in the five East Asian countries.

2.3. Descriptive Statistics on East Asian Schooling Systems

Table 2b presents descriptive statistics on the student and family background data. The descriptives are weighted by the sampling probabilities of each students so as to give representative means and standard deviations for each country. The samples are rather evenly divided between seventh and eighth grade in each country. The average age of the students varies between 13.7 and 13.9 years. Girls make up nearly 60 percent of the Thai students, while they make up slightly less than half in the other four East Asian countries. Nearly all the Korean and Thai students were born in the country. In Hong Kong and Singapore, there is a share of about 10 percent of students not born in the country. These data were reported as being not administered or not internationally comparable in Japan, as is the case for the other family background data as well.

Parental education is the highest educational level attained by one of the parents, measured in five categories: primary; some secondary; finished secondary; some after secondary; and finished university. The share of students with parents whose highest educational level was primary education was 8 percent in Korea and about 20 percent in Hong Kong and Singapore, and it is as high as 64 percent in Thailand. On the other extreme, children of parents with university degrees made up between 7 and 11 percent in Hong Kong, Singapore, and Thailand, but 24 percent in Korea. The number of books in the students' home, a further proxy for the educational and social background of the students' family, is likewise measured in five categories, ranging from less than one shelf to more than two bookcases. About half the students in Hong Kong and Thailand had at least one bookcase of books in their homes; the same is true for about two thirds of students in Singapore and 80 percent in Korea. The share of students from families with more than one bookcase of books ranged between 18 and 26 percent in Hong Kong, Singapore, and Thailand but was 47 percent in Korea. As a rough comparison among the East Asian countries, both of these family background measures suggest a relatively large share of students from highly educated backgrounds in Korea, and a relatively large share of students from lowly educated backgrounds in Thailand and Hong Kong. In both categorical variables, the lowest category was dropped as the residual category in the estimations of the following sections. The community location of the school is measured in two categories, geographically isolated and close to the center of a town or city, with the remainder of schools being located in village areas or at the outskirts of a town or city.[8]

Table 2c reports descriptive statistics on the data on resource endowments of the schools. The smallest class sizes in the country sample are observed in Singapore with an average of about 33 students per class. In Korea and Thailand, average class sizes are as high as 50 students per class. Nearly three quarters of school principals in Singapore,

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[8] While the data on age, sex, parental education, and community location generally come from the student background questionnaires, they were obtained from the ministry in Singapore.

and nearly two thirds in Hong Kong, report that their schools' instructional capacity was not at all affected by the shortage or inadequacy of instructional materials; this was true for only 11 percent of school principals in Thailand. On the other hand, 45 percent of Thai principals reported a lot of shortage problems, but less than 8 percent in Hong Kong, Japan, and Singapore. Instruction times in the East Asian countries range between 837 and 995 hours (of 60 minutes) per year, or – assuming a 45-week instruction year with 5 days a week – roughly between 3.7 and 4.4 hours a day. This is substantially higher than in the United States, France, and Spain, where instruction time ranges between 3.1 and 3.4 hours a day (under the same assumption).

In Japan, only 18 percent of science teachers and 25 percent of math teachers are female, while between 60 and 70 percent of the teaching force in Singapore and Thailand are female. Teachers in Hong Kong and Thailand have on average an experience of about 9 years of teaching; average teacher experience in Singapore is as high as 17.5 years in math and 15.8 years in science. Only in Singapore are there a few teachers who did not complete secondary education. About 90 percent of teachers in Korea and Thailand have the equivalent of a BA degree; this share is between one half and two thirds in Hong Kong and Singapore. The fraction of teachers with the equivalent of an MA or PhD degree is relatively small in all the East Asian countries.

Table 2d reports descriptive statistics on a few other schooling policy variables. While at most 10 percent of schools in Hong Kong, Japan, and Singapore have autonomy in the determination of teacher salaries, nearly all schools in Thailand have such an autonomy. Homework assignments are smallest in Japan and highest in Thailand. Rather few teachers report that their teaching is severely limited by parents uninterested in their children's learning and progress; the fraction ranges from 4 percent in Singapore in science to 14 percent in Thailand in math. Likewise, few East Asian teachers reported that interested parents limit how they teach their class. Thus, there is not much variation in these observations in the East Asian countries.

2.4. Imputation of Missing Data

Complete performance data is available for all the students participating in TIMSS. In the background questionnaires, however, some students, teachers, and school principals failed to answer some questionnaire items. Table A1 in the appendix reports the share of missing values for each variable in each country. Since dropping all students with missing data on some explanatory variables from the analyses deletes the information available on the other explanatory variables, reduces the sample size, and might introduce bias if observations are not missing at random, I chose instead to impute missing values within each country for the analyses in this paper. The method used to impute data for missing responses in the TIMSS questionnaires is based on least-squares, probit, and ordered-probit models relating the observations from students with original data to a set of "fundamental" explanatory variables available for all students.

Specifically, I first chose the following set of "fundamental" variables F with data available for virtually all students: grade level; student sex; student age; four dummies for the parents' education level; four dummies for the number of books in the student's home; and three dummies for the community location of the schools. The small amount of missing data within F was imputed by the median category observed at the lowest level available; that is, either the class median, the school median, or the country median was imputed.

The variables in F were then used to impute missing data on each variable M for each student i within each country. Let S denote the set of students j with available data for M. Using the students in S, the variable M was regressed on F:

$$M_{j \in S} = F_{j \in S} \phi + \varepsilon_{j \in S} \tag{1}$$

For M being a discrete variable, the regression model was a least-squares estimation, weighting each student by its sampling probability. For M being a dichotomous (binary) variable, an equally weighted probit model was used. For M being a polychotomous qualitative variable with multiple categories, a weighted ordered-probit model was estimated.

Finally, the coefficients ϕ from these regressions and the data on F_i were used to impute the value of M_i for the students with missing data:

$$\widetilde{M}_{i \notin S} = F_{i \notin S} \phi \tag{2}$$

For the probit models, the estimated coefficients were used to forecast the probability of occurrence associated with each category for the students with missing data, and the category with the highest probability was imputed. This data imputation technique was applied within each country individually, resulting in a complete data set for all the students sampled in TIMSS.

3. Family Background and Student Performance in East Asia

3.1. The Empirical Model

To assess the influence of the students' family background on their educational performance in the different East Asian countries, I estimate education production functions for each country of the following form:

$$T_{ics} = B_{ics}\alpha_1 + D^B_{ics}\delta_1 + \left(D^B_{ics}B_{ics}\right)\delta_2 + \varepsilon_{ics} \quad , \tag{3}$$

where T is the test score of student i in class c in school s and B is the vector of family background variables. The coefficient vectors α_1, δ_1, and δ_2 are to be estimated. The inclusion of the imputation controls D^B and the structure of the error term ε are discussed below. The estimation does not control for other school characteristics, such as schools' resource endowments or teaching policies, because in this section I am interested in the total impact of family background on student performance, including any effect that might work through families' differential access to schools or their influence on school policies.

It helps to clarify in advance what the estimates of the coefficients α_1 on the family-background variables (and of the coefficients on the other explanatory variables in later sections), and especially differences in the estimates across countries, mean and do not mean. Because the TIMSS data were generated by the same data-generating process in the different countries and are therefore directly comparable across countries, the prior from a technical point of view should be that the coefficient estimates should be the same everywhere. Given the technical constraints on the pedagogical process, the size of the *effect* of any family-background characteristic on students' educational performance should be expected to be the same in any school system. If this is not the case, this implies that there must be differences in how the school systems work. This does *not* reflect different *distributions* of family-background characteristics in the different populations, as they are apparent from the descriptive statistics in Table 2. Different distributions of family-background characteristics would not be an a priori reason for the gap in student performance between students with two different characteristics to be different. For example, the performance gap between children of parents with university degrees and children of parents without secondary education may be expected to be independent of the relative number of parents with different educational degrees in the population. If this gap is 25 TIMSS test-score points in one country but 50 points in another country, this would rather be a sign that the school systems work differently in the two countries, resulting in a different effect of parental education on student performance.

As discussed in the previous section, some of the data are imputed rather than original. Generally, data imputation introduces measurement error in the explanatory variables, which should make it more difficult to observe statistically significant effects. Still, to make sure that the results are not driven by imputed data, a vector of dummy variables D^B is included as controls in the estimation. The vector D^B contains one dummy for each variable in the family-background vector B which takes the value of 1 for observations with missing and thus imputed data and 0 for observations with original data. The inclusion of D^B as controls in the estimation allows the observations with missing data on each variable to have their own intercepts. The inclusion of the interaction term between imputation dummies and background data, $D^B B$, allows them to also have their own slopes for the respective variable. These imputation controls for every variable with missing values ensure that the results are robust against possible bias arising from data imputation.

Further problems in the econometric estimation equation (3) are that the explanatory variables in this study are measured at different levels, with some of them not varying within classes or schools; that the performance of students within the same school may not be independent from one another; and that the primary sampling unit (PSU) of the two-stage clustered sampling design in TIMSS was the school, not the individual student (see Section 2.2). As shown by Moulton (1986), a hierarchical structure of the data requires the addition of higher-level error components to avoid spurious results. Therefore, the error term ε of equation (3) has a school-level and a class-level element in addition to the individual-student element:

$$\varepsilon_{ics} = \eta_s + \nu_c + \upsilon_i \quad , \tag{4}$$

where η is a school-specific error component, ν is a class-specific error component, and υ is a student-specific error component. Clustering-robust linear regression (CRLR) is used to estimate standard errors that recognize this clustering of the survey design. The CRLR method relaxes the independence assumption and requires only that the observations be independent across the primary sampling units, which are schools in the case of TIMSS. By allowing any given amount of correlation within the primary sampling units, CRLR estimates appropriate standard errors when many observations share the same value on some but not all independent variables (cf. Deaton 1997).

Finally, TIMSS used a stratified sampling design within each country, which produced varying sampling probabilities for different students (Martin and Kelly 1998). To obtain nationally representative coefficient estimates from the stratified survey data, weighted least squares (WLS) estimation using the sampling probabilities as weights is employed. The WLS estimation ensures that the proportional contribution to the parameter estimates of each stratum in the sample is the same as would have been obtained in a complete census enumeration (DuMouchel and Duncan 1983; Wooldridge 2001).

3.2. Results

Table 3a presents the results of an estimation of equation (3) for each of the sample countries for TIMSS math performance, and Table 3b presents the equivalent results for science. With respect to students' characteristics, students in the upper grade (eighth grade) perform statistically significantly better than students in the lower grade (seventh grade) in all countries, with the gap being largest in Singapore and smallest in Japan. In Japan, much of the superior performance of older students seems to be captured by students' age rather than grade level, as older students perform statistically significantly better in both subjects in Japan. In Hong Kong, Korea (only math), and Singapore, older students perform statistically significantly worse once the grade level is held constant.

In Hong Kong, Japan, and Korea, girls perform substantially worse than boys in both subjects – a result similarly found in the three advanced economies (United States, France, and Spain). Singapore and Thailand show no such performance difference between genders. In both countries, there is no statistically significant difference between the performance of boys and girls, with the performance of girls being slightly higher in math and the reverse finding in science. In interpreting these findings, it should be borne in mind that girls make up two thirds of the student population at the respective levels in Thailand, while universal enrollment in the other countries make the student population being evenly split between the two genders.

The performance gap between native and immigrant children is quite different between the East Asian countries. In Korea and Thailand, children born in the respective country performed better – although the share of immigrant children is very low in these two countries. But in Hong Kong, children not born in the country actually performed better. No statistically significant performance difference between natives and immigrants is found in Singapore. Students living with both parents perform better in math in Hong Kong and Korea and in science in Singapore.[9]

Two sets of dummy variables reflect the educational background of the students' families: the highest level achieved by the parents and the number of books in the students' home. In all the countries, children from more favorable backgrounds on both measures perform consistently better. The largest performance difference between children of parents with a university degree relative to children of parents without secondary education are found in Singapore. The same is true when comparing parents who finished university to parents who finished secondary school. The size of the coefficient says that, for example, the performance gap between students of parents with a university degree and students of parents without secondary education in Singapore in math was 52.7 test-score points – slightly more than half an international standard deviation in TIMSS test scores, and slightly less than the average difference in performance between seventh and eighth grade in Singapore.

Because parental education levels may be slightly differently defined in the different countries, possibly reflecting different years and courses of education, it is illuminating to look at the performance levels of students with different numbers of books at home, which can work as an internationally comparable additional proxy for the educational background of a student's family. Using this measure, the impact of family background on students' educational achievement is again substantially larger in Korea and Singapore than it is in Hong Kong and Thailand. This is true irrespective of whether one

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[9] In Japan, there is no data on many of the family-background variables.

compares the highest category of books at home to the lowest one, the highest one to some intermediate one, or an intermediate one to the lowest one. On this measure, the impact of family background in Korea is even stronger than in the United States, a country with a schooling system generally known to produce relatively large performance differences between students from different backgrounds. In Hong Kong and Thailand, the measure points to a smaller impact of family background than the one found in any of the three advanced economies.

The statistically significant and quantitatively substantial coefficients on the family-background variables cannot necessarily be interpreted in the sense that, for example, increasing parental education for the whole population in the different countries would increase educational performance of the students by the amount estimated. Rather, the coefficient estimates may to some extent reflect heritable ability in that more able parents, who may have obtained more education because of their higher ability levels, have more able children, who then perform better on the performance tests. Heritable ability has been shown to be a likely source of the whole correlation between the quantitative educational attainment of mothers and their children in data on Minnesota twins (Behrman and Rosenzweig 2002). This was not true for fathers, however, and other evidence shows that there was a causal impact of increased women's schooling on their children's schooling, working through home teaching, in the setting of rural India during the green revolution (Behrman et al. 1999). Whatever the sources and channels of transmission may be, the reduced-form results of Table 3 still represent the observed performance gap between children from different family backgrounds in the schooling systems of the different East Asian countries.

Student performance also differs by community location in most of the East Asian countries. In Hong Kong, Korea, Singapore, and Thailand, students in schools close to the center of a town perform statistically significantly better in both math and science than students in schools located in villages or at the outskirts of a town. This rural-urban performance gap is smaller in Korea than in the other three countries, and it is not statistically significant in Japan, France, and Spain. In the United States, inner-city students actually performed statistically significantly worse in science. Student performance in geographically isolated areas is generally even worse than performance in village or outskirt areas, although except for Thailand, none of the TIMSS samples in the East Asian countries contains a noteworthy share of geographically isolated schools.[10]

The explanatory power of the family-background regressions, as measured by the proportion of the variation in test scores explained by the family-background variables (the R^2), ranges from 8.7 percent in Hong Kong in science to 23.0 percent in Singapore in science (without considering the variation "explained" by the imputation controls).[11] The standard finding of a large residual in microeconometric student-level estimations may be attributed to unobserved heterogeneity in the innate ability of students entering the error term in student-level education production functions. A proportion of the test-score variation of nearly one quarter attributed to observed family-background measures is actually relatively large in comparison to most previous research. In both subjects, the explained performance variation is relatively small in Hong Kong and Thailand, both in comparison to Korea and Singapore and to the three more advanced economies. Compared across subjects, the explanatory power of the math models is larger than of the science models in most countries.

4. Resource Endowments and Student Performance in East Asia

4.1. Least-Squares Coefficients on Resources and Teacher Characteristics

The standard procedure to estimate the relationship between schools' resource endowments and their students' performance is to simply introduce resources into the previously estimated equation:

$$T_{ics} = B_{ics}\alpha_2 + R_{cs}\beta_1 + D^B_{ics}\delta_3 + \left(D^B_{ics}B_{ics}\right)\delta_4 + D^R_{cs}\delta_5 + \left(D^R_{cs}R_{cs}\right)\delta_6 + \varepsilon_{ics} \quad , \qquad (5)$$

where R is a vector of resource measures such as class size, the availability of instructional materials, and teacher characteristics. The imputation controls D^R again ensure that the results are robust against possible bias arising from missing and thus imputed data in the resource variables. Assuming that the resource-performance relationship is constrained by a pedagogical process, the education production function

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[10] The number schools classified as being located in geographically isolated areas is only 2 in the Hong Kong sample, 1 in Korea, 4 in Japan, and 0 in Singapore.

[11] The low R^2s of the Japanese regressions obviously reflect the fact that most of the family background data are missing in Japan.

(5) describes the maximum amount of schooling output in the form of student performance that can be achieved by a given amount of schooling inputs. In economic theory, someone fully informed about the education production function would allocate a fixed budget across schooling inputs in order to maximize student performance.

Under the assumption that the resource endowment is exogenous to student performance – an assumption shown to be wrong in the next section at least in the case of class sizes in most countries – the coefficient vector β_1 estimated in a least-squares regression would reflect the impact of resources on student performance. The coefficient vector on resources obtained by this standard procedure may be substantially biased, however. One potential reason for bias is that the resource endowment may to some extent be endogenous to student performance, for example if weaker students are sorted into smaller classes (cf. West and Wößmann 2003). Another potential reason for bias is the impact of further omitted variables which, like sorting, could be related to the resource endowment.

Tables 4a and 4b present the estimated least-squares coefficients on resources, controlling for all the family-background variables reported in Table 3 and for all the imputation controls. Resource endowment is measured by various variables, beginning with class size. Class size is measured in natural logarithm units because the proportional impact of a one-student reduction in class size is greater the smaller the initial size of the class. Except for Thailand and for math in Korea, the estimated coefficients on log class size are statistically significant and positive in the East Asian countries; that is, higher test scores are related to larger classes. If one were to interpret these coefficients causally, as much previous work for other countries has done (e.g., Hanushek 1997; Krueger 2003), one would come to the somewhat counterintuitive conclusion that in most East Asian countries, students learn more in larger classes.

In terms of endowment with instructional materials and instruction time, there is some evidence that students whose school principal reported no shortage of materials perform statistically significantly better in some of the East Asian countries than students whose principal reported some shortages. However, students whose principal reported a lot of shortage do not perform statistically significantly worse, and in Japan, they even perform statistically significantly better.[12] Only in Thailand in math is the length of instruction time statistically significantly related to student performance.

With respect to teacher characteristics, students of female teachers performed statistically significantly worse than students of male teachers in math in Japan, but statistically significantly better in science in Hong Kong, Singapore, and Thailand. Teacher experience, measured in logs so as to allow for decreasing returns to experience, is statistically significantly positively related to student performance only in math in Singapore and Thailand; in math in Korea, there is a statistically significant negative relation. The teachers' educational level also does not seem to be strongly related to student performance. In math in Thailand, students of teachers with the equivalent of a BA actually performed statistically significantly lower than students of teacher with less education than a BA, while the residual categories that drive the other statistically significant coefficients are made up of a maximum of two teachers.

In conclusion, there is basically not much of a positive relationship between student performance and additional units of any of the measured resource variables. These findings mirror prior research in this field that found no strong or systematic relationship between larger resource endowments and student performance in the United States and in several developing countries (Hanushek 1995, 1997; Hanushek and Luque 2003). Note also that the increase in the explained proportion of the test-score variation (R^2) relative to the family-background regressions of Table 3 is minimal in most cases, and where it is not, this is nearly exclusively driven by the counterintuitive correlation between student performance and class size.

4.2. School-Fixed-Effects Instrumental-Variables Estimates of Class-Size Effects

While the family-background measures B in the estimated equations (3) and (5) can reasonably be expected to be exogenous to student performance because there appears to be no plausible inverse link from student performance to family background, there may potentially be endogeneity of schooling resources R. The quantitative estimates of the resource effects will be biased if the resources spent on students are determined by

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[12] For Korea, Paik (2001) reports that despite the widespread availability of calculators and computers in Korean schools, they are rarely used in class. The low dependence on calculator technologies has been related to the high problem-solving skills of Korean students.

student performance *T*, that is if additional schooling resources are systematically allocated either to above-average performing students or to below-average performing students. The estimates of resource effects would also pick up the correlation between student performance and any omitted variable that is correlated with resource endowment. In both cases, unbiased econometric estimates can only result if the endogenous nature of schooling resources is properly accounted for (Hoxby 2000).

In the case of the estimated coefficients on class size, I can exploit specific characteristics of the TIMSS data in a quasi-experimental estimation design in order to obtain unbiased estimates of the effects of class size on student performance. Akerhielm (1995) suggests to instrument the actual class size C_{cs} (one vector in the resource matrix R_{cs} of equation (5)) by the average class size in the school A_s in a two-stage least-squares estimation to control for the problem of endogenous resource allocation within schools.[13] The grade-average class size promises to be a valid instrument for actual class size: It is generally strongly linked to the size of the class actually tested in TIMSS; within each school, it is exogenous to the performance of the students (although this might not be the case between schools, a fact that I will return to shortly); and there is no reason to expect that it affects student performance in any other way than through the size of the class in which they are actually taught.[14] The first-stage estimation regresses (log) C_{cs} on (log) A_s and all other exogenous variables X_{ics}:

$$C_{cs} = \chi_1 A_s + X_{ics}\chi_2 + \mu_{ics} \quad , \tag{6}$$

where X_{ics} includes the family-background measures and the imputation controls. The second stage then employs $\hat{C}_{cs} = C_{cs} - \mu_{ics}$ instead of C_{cs} in lieu of R_{cs} in the estimation of equation (5). This specification eliminates any bias in the estimated class-size effects that would result from within-school sorting of low-performing students, at a given grade level, to smaller classes.

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[13] Akerhielm (1995) also uses the overall grade-level enrollment of a school as a second instrument in addition to average class size. However, this may be a false instrument as there might be a direct relationship between overall enrollment and student performance that is unrelated to differences in class size (Angrist and Lavy 1999). Moreover, none of the coefficients on enrollment in Akerhielm's first-stage regressions are statistically significant, suggesting that it is anyway not a good instrument.

[14] See Wößmann and West (2002) for a more detailed discussion of the validity of the instrument.

However, these IV estimates may still be biased by between-school sorting effects. If parents tend to send low-performing children to schools with smaller classes, the estimated resource effect would again be biased downward. But it could also go the other way if parents tend to send high-performing children to schools with smaller classes. Between-school sorting might also be relevant if students are tracked into different schools according to their ability, as is the case in Singapore (cf. Section 2.1).

In order to exclude any effects of either within- or between-school sorting from the estimates of class-size effects, Wößmann and West (2002) suggest an identification strategy specifically designed to exploit the multi-grade nature of the TIMSS database. They combine the aforementioned IV strategy with a school-fixed-effects estimation which disregards any between-school variation, as this may reflect between-school sorting effects. The combined school-fixed-effects instrumental-variables (SFE-IV) estimation then is:

$$T_{ics} = B_{ics}\alpha_3 + \hat{C}_{cs}\beta_2 + S_s\varphi + D^B_{ics}\delta_7 + \left(D^B_{ics}B_{ics}\right)\delta_8 + D^C_{cs}\delta_9 + \left(D^C_{cs}C_{cs}\right)\delta_{10} + \varepsilon_{ics} \quad , \qquad (7)$$

where S_s is a complete set of school dummies and $\hat{C}_{cs}$ is again the result of a first-stage regression that instruments actual class size by grade-average class size and all other exogenous variables as in equation (6).[15] Because equation (7) includes school fixed effects, and because every class size at a given grade level is instrumented by the same average class size, this SFE-IV strategy requires comparable information on student performance from more than one grade level in each school. This is exactly the structure of the TIMSS data.

The grade-level dummy included in the background measures *B* controls for the average difference in performance between students from the two adjacent grades. Therefore, the remaining performance difference between students from the different grades is idiosyncratic to each school. Equation (7) relates this idiosyncratic variation in student performance to that part of the actual class-size difference between the two grades that is due to differences in average class size between the two grades. Thereby,

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[15] The imputation dummies D^C for the class-size variable used in this section equal 1 if either the observation on actual class size or the observation on grade-average class size (the instrument) is imputed. In the IV and SFE-IV regressions, in addition to instrumenting class size, the interaction term $D^C C$ between the imputation dummy and actual class size is also instrumented, using an interaction term $D^C A$ between the imputation dummy and grade-average class size as an additional instrument.

the SFE-IV identification strategy effectively excludes both between-school and within-school sources of student sorting: Between-school sorting is eliminated by controlling for school fixed effects; within-school sorting is filtered out by instrumenting actual class sizes by grade-average class size. Arguably, the remaining variation in class size between classes at different grades of a school is caused by random fluctuations in cohort sizes between the two adjacent grades in each school, presumably reflecting natural fluctuations in student enrollment. The coefficient estimate β_2 can thus be interpreted as an unbiased estimate of the causal impact of class size on student performance.

As there is no comparable quasi-experimental identification strategy for the other resource measures, these are not included in equations (6) and (7). Therefore, the resulting coefficient estimates on class size should be interpreted as the effect on student performance of class size and any other resource with which class size may be associated.

Tables 5a and 5b report the coefficient estimates on class size obtained by implementing the different identification strategies for the East Asian countries. The first row presents the standard weighted least-squares (LS) estimates, where the slight differences to the coefficients reported in Tables 4a and 4b stem from the exclusion of the other resource variables.[16] The second row reports results of the straight IV regression without controlling for school fixed effects, which should exclude biases due to within-school sorting but not due to between-school sorting. The third row reports results of a least-squares regression that does not instrument for class size but includes the whole set of school fixed effects (SFE), which excludes any effects of between-school sorting but might still be biased by within-school sorting effects. And finally, the fourth row reports results of the combined SFE-IV identification strategy that excludes both between- and within-school sorting effects.

The SFE-IV estimation is extremely demanding in terms of data requirements, because the variation on which it is based excludes both any between-school variation and any within-grade variation within schools. If the remaining within-school between-

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[16] In order to be able to implement the school-fixed-effects strategy, I also had to exclude one school from the Hong Kong sample and one from the Thai sample which tested only classes at one of the two grade levels. In the United States, France, and Spain, this exclusion rate was slightly larger.

grade variation is low, this will be reflected in imprecise estimates of the class-size coefficient estimated by the SFE-IV strategy (cf. Wößmann and West 2002). This is the case in Hong Kong and Thailand, where the standard errors of the SFE-IV estimates are too large to make any confident statement about the existence or magnitude of class-size effects in these countries. By contrast, in Japan and Singapore the SFE-IV estimates are very precise, with standard errors between 20.8 and 29.2. These standard errors are so small that if a 10 percent reduction in class size were to change TIMSS test scores by just 4 to 6 test-score points or 4 to 6 percent of an international standard deviation, the change would be statistically significant at the 5 percent level.[17] In other words, the random variations in class size identified by the SFE-IV strategy have considerable power to detect class-size effects in these two countries.

The SFE-IV estimates of the causal effect of class size on student performance are statistically indistinguishable from zero in both math and science in Japan and Singapore. Given the precision of their estimation, they are equivalent to what Hoxby (2000, p. 1280) calls "rather precisely estimated zeros."[18] These results suggest that there is no causal effect of class size on student performance in Japan and Singapore. By contrast, the SFE-IV estimate for France in math is marginally statistically significant (at the 15 percent confidence level) and negative, suggesting a potential beneficial effect of reduced class sizes there.

The strong prevalence of statistically significant positive estimates of the coefficient on class size in least-squares estimations in East Asian countries is clearly linked to the sorting of students of different ability levels into differently sized classes. Once the estimation is based on credibly exogenous variations in class size in the SFE-IV estimation, no statistically significant effect of class size on student performance is found in the East Asian countries. While the existence of any sizable causal effect of class size on student performance can be rejected in Japan and Singapore, no confident

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[17] With a standard error of 20 [30] and the standard asymptotic *t* value of 1.96 for a 5 percent confidence level, the threshold point for a test-score change ensuing from a 10 percent reduction in class size (equivalent to a change of 0.10 in log class size) to be statistically significant would be of $0.10*20*1.96 \cong 4$ [$0.10*30*1.96 \cong 6$].

[18] For example, two of the standard errors of the coefficient on log class size in Hoxby's (2000) Table IV are bigger than 0.20. Given that her test scores are divided by their standard deviation, this would be equivalent to a standard error of 20 in this paper, as the test scores here are measured on the TIMSS test-score scale which has an international standard deviation of 100 (rather than 1).

evaluation is possible in the other three countries. The individual IV and SFE regressions suggest that the existence of beneficial effects of smaller class sizes might be feasible in Korea and Thailand; however, these estimates are still biased by between-school sorting in the case of IV estimates and by within-school sorting in the case of SFE estimates. The imprecision of the SFE-IV estimation does not allow for the validation or rejection of the existence of class-size effects in these countries.

4.3. Implications for the Sorting of Students into Differently Sized Classes

A comparison of the estimated coefficients on class size between the four estimation strategies reported in Table 5 allows to assess the sorting effects of how students of different performance levels are placed into differently sized classes. The differences in the estimated coefficients imply that there is substantial sorting of students according to achievement levels in the East Asian school systems – student performance affects the choices of parents, teachers, and school principals with respect to class sizes.

While the standard LS coefficient estimate on class size reflects the combined effects of between- and within-school sorting and true class-size effects, the SFE coefficient estimate, which controls for school fixed effects, reflects only within-school sorting and true class-size effects. Thus, the difference between the LS coefficient and the SFE coefficient reflects the extent of between-school sorting. Likewise, the SFE-IV coefficient estimate reflects the causal effect of class size on student performance. Thus, subtracting the SFE-IV coefficient from the SFE coefficient yields estimates of the extent of within-school sorting in a school system.[19]

The estimates of Table 5 reveal that both between- and within-school sorting effects are substantial in many of the analyzed school systems. In Japan, Singapore, and Hong Kong, there are strong progressive (compensatory) between-school sorting effects, in that low-performing students are placed into smaller classes. In Korea and Thailand, there is not much evidence of between-school sorting on the basis of achievement. In Singapore, as well as in France, there is also evidence of substantial progressive sorting within schools.

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[19] See West and Wößmann (2003) for a detailed derivation of the identification of sorting effects.

5. Institutional Features and Student Performance in East Asia

The lack of consistent evidence that resource endowments matter for student performance suggests that resources are inefficiently used in the school systems analyzed. In other countries, such inefficiencies have been related to the lack of suitable performance incentives in the school system (e.g., Hanushek et al. 1994). This opens the possibility for other schooling policies that focus on institutions rather than on resources to affect student performance. Theoretical work suggests that the institutional structure of the school system generates the incentives that drive actors' behavior in educational production and thus the performance achieved (cf., e.g., Bishop and Wößmann 2003).

Because institutional features generally do not vary substantially within school systems, but rather across countries, empirically the institutional effects should be mainly an issue in cross-country rather than within-country research. Wößmann (2002, 2003a) shows that many schooling institutions are strongly linked to the cross-country variation in student performance. As is apparent from Table 2d, the TIMSS background data reveal that some institutional features do also vary within some of the East Asian systems. Particularly, there is some limited variation in schools' autonomy in salary decisions, homework policies, and parental involvement in the education process. This section analyzes whether these within-country differences in institutional schooling policies add to an understanding of the within-country differences in student performance in East Asia.

As institutional features of the school systems may be viewed as largely exogenous to student performance, reasonable estimates of institutional effects may be obtained by adding the vector of institutional measures I as explanatory variables to the education production function of equation (5):

$$\begin{aligned} T_{ics} &= B_{ics}\alpha_4 + R_{cs}\beta_3 + I_{cs}\gamma \\ &\quad + D^B_{ics}\delta_{11} + \left(D^B_{ics}B_{ics}\right)\delta_{12} + D^R_{cs}\delta_{13} + \left(D^R_{cs}R_{cs}\right)\delta_{14} + D^I_{cs}\delta_{15} + \left(D^I_{cs}I_{cs}\right)\delta_{16} + \varepsilon_{ics} \end{aligned} \quad . \qquad (8)$$

D^I is again a set of imputation dummies to control for possible effects of the data imputation. The estimation keeps controlling for all family background and resource variables of Tables 3 and 4, as well as for their respective imputation controls.[20]

The coefficient estimates on the institutional variables are reported in Tables 6a and 6b for math and science. Students in schools that had autonomy in determining their teachers' salaries performed statistically significantly better than students in schools without salary autonomy in both subjects in Japan and Singapore. In these countries, school autonomy in determining teacher salaries seems to positively affect students' educational performance.[21] A small opposite effect is found in science in Hong Kong.

The amount of homework assigned by the teacher is statistically significantly and positively related to math performance in Japan and Singapore and to science performance in Hong Kong. Thus, to the extent that teachers' homework assignments can be viewed as exogenous to student achievement, they seem to favorably affect achievement in the East Asian countries, with the exceptions of Korea, where actually a small negative coefficient is found in science, and Thailand.[22] The estimates on homework assignments should be interpreted with care, however, as they may be particularly prone to endogeneity and omitted-variable biases.

In Hong Kong, students whose teachers reported that their teaching was limited by parents uninterested in students' progress performed statistically significantly worse than students whose teachers did not report limitations by uninterested parents. Interestingly, students whose teachers reported that their teaching was limited by interested parents performed statistically significantly better in math than students whose teachers did not report such limitations. Apparently, even though teachers judged the interventions of interested parents as limiting their teaching, this "limitation" was

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[20] Excluding the resource variables and their imputation controls, because their estimation may be biased by sorting effects, does not make any qualitative difference to the estimated coefficients on the institutional variables.

[21] The lack of such an effect in Korea may be attributable to the fact that much of the monetary rewards of teachers in Korea come directly from parents (cf. Paik 2001).

[22] The coefficient estimates in science may be attenuated as the variable measures only the homework assigned by the main science teacher of each student, while in many countries, different science subjects are taught by different teachers.

positively related to the performance of their students – a result similarly found in the United States. No comparable results are found in the other East Asian countries.[23]

6. Conclusions

Given the pivotal role of students' educational performance for the future economic prospects of societies, the empirical results of education production functions estimated for the five high-performing East Asian countries in this paper could have substantial implications for educational and social policies in the region and in other, lower-performing countries alike. For the East Asian countries, the evidence for the first time reveals the impact of family background and schooling policies in the different school systems. And by examining how the East Asian countries achieved their high educational performance, other countries can learn for their own educational production.

Although the fact that all East Asian countries performed extraordinarily well in international comparisons of student performance seems to suggest that they are very homogenous, the evidence presented in this paper reveals that their schooling systems actually feature a lot of heterogeneity. For example, family background is a much stronger predictor of children's educational performance in Korea and Singapore than in Hong Kong and Thailand, both in terms of estimated effect sizes and explanatory power. If providing more equal opportunities for successful learning independent of parental education and social status is an important goal of the education systems, the different size of family-background effects across countries reveals that the different schooling systems achieve this goal to a different extent. Furthermore, the evidence from the different countries suggests that those school systems that allow family background to exert its beneficial impact on student performance achieve the highest overall performance levels. In reverse, this may mean that although school systems that try to equalize educational performance for students from different backgrounds may be able to lower the variation in educational performance in the population, the overall educational performance of the system may suffer.

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[23] The large negative coefficient on interested parents in Japan in math is due to only 2 teachers reporting limitations by interested parents.

The high educational performance of East Asian countries also suggests that their schooling systems are highly efficient. While this is true in the sense of a cross-country comparison between East Asian countries and countries from other parts of the world, the internal efficiency of the East Asian school systems is less clear. The evidence presented in this paper reveals that resource endowments and especially class sizes do not seem to be strongly related to students' educational achievement. As in many other countries in the world, East Asian schools that are better equipped with educational resources do not seem to make efficient use of the additional resources. This cross-sectional finding mirrors the time-series evidence of Gundlach and Wößmann (2001) that increased spending and smaller class sizes did not lead to substantially better performance over time in the analyzed East Asian school systems.

With respect to other, more institutional schooling policies, giving schools autonomy in their salary decisions might strengthen educational performance, especially in Japan and Singapore. Given that performance standards are centrally set and examined in all the East Asian systems considered, additional autonomy might allow schools to find the best ways of how to achieve these standards. Additional focus on homework policies, which allow students to practice their knowledge at home, might be a worthwhile policy option, especially in Hong Kong, Japan, and Singapore. In Hong Kong, increased parental involvement in the teaching process also promises superior student performance.

It remains to be seen whether the conclusions of this paper also apply for other subjects and skills than middle-school mastery of math and science. Some evidence suggests that East Asian students are not just capable of rote learning, but also do well in more creative tasks. Learning the cognitive foundations is certainly a prerequisite for the mastery of more advanced applications, so that the two are complements rather than substitutes. To sustain the quality of this knowledge base and to tap the full potential of their student populations, East Asian school systems would be well advised to ensure an excellent educational performance for students from all family backgrounds and to care more for policies that ensure efficient educational production than for resource policies.

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Table 1: Basic Statistics on Educational Attainment and Expenditures

1995 unless otherwise noted.

	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Gross enrollment rate (%)								
Preprimary	82.1	48.6	84.4	19.5	57.1	70.7	84.0	71.6
Primary	94.0	102.5	95.3	95.2	86.5	101.8	106.1	109.0
Secondary	73.0	103.4	100.9	73.4	54.1	97.4	111.3	122.1
Tertiary	25.0	41.7	52.0	33.7	20.1	80.9	51.0	47.8
Net enrollment rate (%)								
Primary	89.5	102.7 [h]	93.3	93.3	76.9 [i]	94.5	100.1	104.5
Secondary	69.0	98.6 [h]	96.0	–	55.2 [i]	90.0	94.4	91.6 [i]
Persistence to grade 5, total (% of cohort)	100.0 [h]	100.0 [g]	98.5	97.2 [a]	–	–	96.4 [d]	98.5 [f]
Number of students								
Primary	467 718	8 370 246	3 915 848	261 648	5 961 855	24 045 968	4 065 005	2 799 960
Secondary	473 817	9 878 568 [h]	4 706 541	205 683 [g]	3 794 290	21 473 692	5 980 518	8 234 104
Average years of schooling [k]	9.3	9.2	10.6	6.7	6.1	11.9	7.4	6.8
Illiteracy rate, total								
Adult (% of people aged 15 and above)	8.2	–	3.1	9.3	5.9	–	–	2.9
Youth (% of people aged 15-24)	1.0	–	0.2	0.4	1.4	–	–	0.3
Expenditure per student (% of GDP per capita)								
Primary	7.8	19.0 [h]	17.4	–	15.5	18.0 [h]	15.3	14.5
Secondary	12.6	18.7 [h]	11.9	13.3 [g]	11.6	23.1 [h]	26.3	10.4
Tertiary	51.3 [e]	13.6 [h]	5.5	34.1	29.7	23.9 [h]	25.5	16.0
Expenditure per student (PPP) [j]								
Primary	1 748	4 590	2 401	–	975	5 081	3 245	2 249
Secondary	2 825	4 526	1 645	2 582	728	6 526	5 557	1 606
Tertiary	11 509	3 294	761	6 632	1 866	6 750	5 392	2 467
Public spending on education, total (% of GDP)	2.9	3.5 [h]	3.4	3.1	4.0	5.2 [h]	6.0	4.7

[a] 1980. – [b] 1982. – [c] 1984. – [d] 1990. – [e] 1991. – [f] 1992. – [g] 1993. – [h] 1994. – [i] 1998. –

[j] Purchasing power parity, in 1995 current international $. Calculated by multiplying the percentage values above with 1995 data on GDP per capita. – [k] Of the total population aged 15 and above.

Sources: World Bank (2002a), on the basis of UNESCO data; except for Average years of schooling: Barro and Lee (2001).

Table 2a: Descriptive Statistics: Sample Size and Student Performance

Sample size: Absolute numbers. – Student performance: International test scores. Standard deviation in parentheses. Standard deviation in percent of country mean test score in brackets.

	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Sample size								
Students	6752	10271	5827	8285	11643	10973	6014	7596
Classes	171	302	300	274	293	529	253	309
Schools	86	151	150	137	147	183	134	154
Student performance								
Math score	575.8	588.3	592.3	622.3	508.3	487.8	514.4	467.6
Standard deviation	*(100.8)*	*(100.5)*	*(107.8)*	*(93.2)*	*(83.4)*	*(90.9)*	*(78.3)*	*(74.2)*
Standard deviation/score (in percent)	*[17.5]*	*[17.1]*	*[18.2]*	*[15.0]*	*[16.4]*	*[18.6]*	*[15.2]*	*[15.9]*
Science score	508.7	551.5	550.1	576.2	508.9	521.4	473.9	497.1
Standard deviation	*(88.7)*	*(90.4)*	*(93.9)*	*(102.7)*	*(72.6)*	*(106.2)*	*(78.9)*	*(81.4)*
Standard deviation/score (in percent)	*[17.4]*	*[16.4]*	*[17.1]*	*[17.8]*	*[14.3]*	*[20.4]*	*[16.7]*	*[16.4]*
Position in international ranking								
Math, 7th grade (out of 37 countries)	4	3	2	1	17	22	19	30
Math, 8th grade (out of 39 countries)	4	3	2	1	19	27	13	29
Science, 7th grade (out of 37 countries)	15	4	2	1	17	11	28	25
Science, 8th grade (out of 39 countries)	23	3	4	1	20	16	27	25

Table 2b: Descriptive Statistics: Student and Family Background

Country means. Standard deviations in parentheses. – Only non-imputed data. Weighted by sampling probabilities.

	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Upper grade	0.500	0.512	0.504	0.502	0.492	0.502	0.487	0.499
	(0.500)	*(0.500)*	*(0.500)*	*(0.500)*	*(0.500)*	*(0.500)*	*(0.500)*	*(0.500)*
Age	13.688	13.902	13.710	13.939	13.884	13.735	13.805	13.757
	(0.884)	*(0.576)*	*(0.611)*	*(0.835)*	*(0.716)*	*(0.719)*	*(0.910)*	*(0.860)*
Sex (female)	0.449	0.483	0.438	0.492	0.594	0.498	0.496	0.503
	(0.497)	*(0.500)*	*(0.496)*	*(0.500)*	*(0.491)*	*(0.500)*	*(0.500)*	*(0.500)*
Born in country	0.870	–	0.991	0.920	0.989	0.926	–	0.971
	(0.337)		*(0.096)*	*(0.272)*	*(0.105)*	*(0.261)*		*(0.167)*
Living with both parents	0.901	–	0.876	0.907	0.852	0.791	0.862	0.885
	(0.299)		*(0.330)*	*(0.290)*	*(0.355)*	*(0.406)*	*(0.345)*	*(0.319)*
Parents' education								
Primary	0.189	–	0.079	0.229	0.636	0.015	0.092	0.430
	(0.392)		*(0.269)*	*(0.420)*	*(0.481)*	*(0.122)*	*(0.289)*	*(0.495)*
Some secondary	0.394	–	0.178	0.000	0.113	0.059	0.246	0.160
	(0.489)		*(0.383)*	*(0.000)*	*(0.317)*	*(0.235)*	*(0.431)*	*(0.367)*
Finished secondary	0.280	–	0.414	0.565	0.114	0.192	0.334	0.102
	(0.449)		*(0.493)*	*(0.496)*	*(0.318)*	*(0.394)*	*(0.472)*	*(0.302)*
Some after secondary	0.053	–	0.090	0.134	0.027	0.375	0.145	0.123
	(0.224)		*(0.286)*	*(0.341)*	*(0.161)*	*(0.484)*	*(0.352)*	*(0.329)*
Finished university	0.084	–	0.238	0.072	0.111	0.359	0.183	0.185
	(0.278)		*(0.426)*	*(0.259)*	*(0.314)*	*(0.480)*	*(0.387)*	*(0.388)*
Books at home								
Less than one shelf (<=10)	0.208	–	0.088	0.108	0.187	0.081	0.054	0.048
	(0.406)		*(0.283)*	*(0.310)*	*(0.390)*	*(0.273)*	*(0.226)*	*(0.213)*
One shelf (11-25)	0.281	–	0.109	0.219	0.301	0.124	0.186	0.184
	(0.450)		*(0.312)*	*(0.413)*	*(0.459)*	*(0.330)*	*(0.389)*	*(0.387)*
One bookcase (26-100)	0.301	–	0.335	0.408	0.334	0.279	0.361	0.333
	(0.459)		*(0.472)*	*(0.491)*	*(0.472)*	*(0.449)*	*(0.480)*	*(0.471)*
Two bookcases (101-200)	0.103	–	0.240	0.145	0.093	0.209	0.196	0.189
	(0.304)		*(0.427)*	*(0.352)*	*(0.290)*	*(0.407)*	*(0.397)*	*(0.392)*
More than two bookcases (>200)	0.107	–	0.228	0.120	0.086	0.306	0.204	0.246
	(0.309)		*(0.420)*	*(0.325)*	*(0.280)*	*(0.461)*	*(0.403)*	*(0.431)*
Community location								
Geographically isolated	0.026	0.012	0.007	0.000	0.165	0.034	0.000	0.007
	(0.160)	*(0.107)*	*(0.081)*	*(0.000)*	*(0.371)*	*(0.180)*	*(0.000)*	*(0.081)*
Close to town center	0.679	0.382	0.540	0.392	0.234	0.442	0.391	0.225
	(0.467)	*(0.486)*	*(0.498)*	*(0.488)*	*(0.423)*	*(0.497)*	*(0.488)*	*(0.418)*

Table 2c: Descriptive Statistics: Resources

	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Math class size	38.838	36.556	55.934	33.196	53.591	27.400	25.376	28.402
	(5.583)	*(4.026)*	*(24.807)*	*(7.074)*	*(28.312)*	*(15.637)*	*(3.277)*	*(8.850)*
Science class size	40.404	36.526	48.587	33.348	51.566	38.247	24.992	29.568
	(2.801)	*(4.046)*	*(12.698)*	*(6.941)*	*(26.130)*	*(34.856)*	*(3.889)*	*(9.646)*
Grade-average class size	40.136	36.302	49.893	32.515	42.804	25.624	25.357	28.269
	(3.687)	*(4.584)*	*(5.282)*	*(6.251)*	*(5.395)*	*(4.541)*	*(2.570)*	*(6.911)*
Shortage of materials								
None	0.629	0.521	0.367	0.733	0.115	0.456	0.385	0.544
	(0.483)	*(0.500)*	*(0.482)*	*(0.442)*	*(0.319)*	*(0.498)*	*(0.487)*	*(0.498)*
A lot	0.058	0.071	0.180	0.024	0.452	0.064	0.178	0.043
	(0.234)	*(0.256)*	*(0.384)*	*(0.153)*	*(0.498)*	*(0.245)*	*(0.383)*	*(0.204)*
Instruction time	8.625	–	9.247	8.366	9.947	7.683	7.039	7.132
(in 100 hours of 60 minutes per year)	*(1.615)*		*(1.829)*	*(0.512)*	*(1.544)*	*(2.228)*	*(1.506)*	*(1.385)*
Math teacher's sex (female)	0.386	0.248	0.496	0.599	0.690	0.688	0.484	0.405
	(0.487)	*(0.432)*	*(0.500)*	*(0.490)*	*(0.463)*	*(0.463)*	*(0.500)*	*(0.491)*
Math teacher's experience	9.124	13.273	12.095	17.540	9.739	15.076	19.784	21.390
(in years)	*(8.985)*	*(9.166)*	*(9.185)*	*(12.378)*	*(7.651)*	*(9.751)*	*(10.297)*	*(8.735)*
Math teacher's education								
Less than secondary	0.000	–	–	0.089	0.000	–	0.007	0.095
	(0.000)			*(0.285)*	*(0.000)*		*(0.086)*	*(0.294)*
Secondary only	0.354	–	0.003	0.350	0.053	–	0.338	0.198
	(0.478)		*(0.058)*	*(0.477)*	*(0.224)*		*(0.473)*	*(0.399)*
BA or equivalent	0.617	–	0.907	0.512	0.908	0.568	0.396	0.667
	(0.486)		*(0.291)*	*(0.500)*	*(0.289)*	*(0.495)*	*(0.489)*	*(0.471)*
MA/PhD	0.028	–	0.090	0.048	0.039	0.432	0.259	0.039
	(0.166)		*(0.286)*	*(0.215)*	*(0.194)*	*(0.495)*	*(0.438)*	*(0.194)*
Science teacher's sex (female)	0.372	0.184	0.494	0.696	0.646	0.573	0.534	0.439
	(0.484)	*(0.387)*	*(0.500)*	*(0.460)*	*(0.478)*	*(0.495)*	*(0.499)*	*(0.496)*
Science teacher's experience	9.311	14.545	12.508	15.805	8.911	13.908	19.739	18.480
(in years)	*(8.110)*	*(9.168)*	*(8.756)*	*(10.991)*	*(7.109)*	*(9.836)*	*(10.446)*	*(8.945)*
Science teacher's education								
Less than secondary	0.000	–	–	0.037	0.000	–	0.000	0.077
	(0.000)			*(0.189)*	*(0.000)*		*(0.000)*	*(0.267)*
Secondary only	0.226	–	0.006	0.229	0.007	–	0.241	0.218
	(0.418)		*(0.079)*	*(0.420)*	*(0.085)*		*(0.428)*	*(0.413)*
BA or equivalent	0.696	–	0.831	0.672	0.889	0.575	0.298	0.658
	(0.460)		*(0.375)*	*(0.470)*	*(0.314)*	*(0.494)*	*(0.457)*	*(0.474)*
MA/PhD	0.078	–	0.163	0.062	0.103	0.425	0.462	0.047
	(0.269)		*(0.369)*	*(0.242)*	*(0.304)*	*(0.494)*	*(0.499)*	*(0.211)*

Table 2d: Descriptive Statistics: Institutional Features

Country means. Standard deviations in parentheses. – Only non-imputed data. Weighted by sampling probabilities.

	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
School responsibility for determining teacher salaries	0.103	0.076	0.374	0.067	0.961	0.892	0.000	0.095
	(0.305)	*(0.265)*	*(0.484)*	*(0.249)*	*(0.194)*	*(0.310)*	*(0.000)*	*(0.294)*
Math								
Homework assignment (in hours per week)	1.362	0.716	1.268	2.636	3.417	1.647	1.542	1.631
	(0.936)	*(0.747)*	*(1.027)*	*(1.444)*	*(2.290)*	*(1.075)*	*(0.693)*	*(1.144)*
Teaching limited by								
Uninterested parents	0.100	–	0.071	0.090	0.142	0.149	0.128	0.217
	(0.299)		*(0.257)*	*(0.286)*	*(0.349)*	*(0.356)*	*(0.335)*	*(0.412)*
Interested parents	0.055	0.008	0.021	0.030	0.062	0.043	–	0.163
	(0.228)	*(0.089)*	*(0.145)*	*(0.170)*	*(0.241)*	*(0.204)*		*(0.370)*
Science								
Homework assignment (in hours per week)	0.401	0.310	0.547	0.726	1.288	0.961	0.468	0.997
	(0.300)	*(0.330)*	*(0.528)*	*(0.447)*	*(1.297)*	*(0.923)*	*(0.400)*	*(0.832)*
Teaching limited by								
Uninterested parents	0.082	–	0.051	0.035	0.050	0.088	0.089	0.165
	(0.274)		*(0.219)*	*(0.184)*	*(0.218)*	*(0.283)*	*(0.285)*	*(0.371)*
Interested parents	0.053	0.000	0.020	0.017	0.031	0.033	–	0.137
	(0.224)	*(0.000)*	*(0.139)*	*(0.131)*	*(0.172)*	*(0.179)*		*(0.344)*

Table 3a: Family Background and Math Performance

Least-squares regression within each country, weighted by students' sampling probabilities.
Dependent variable: TIMSS math test score. Clustering-robust standard errors in parentheses.

MATH	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Upper grade	37.795*	10.636^{+}	38.731*	61.346*	26.377*	45.988*	67.387*	59.248*
	(6.040)	*(4.502)*	*(4.406)*	*(5.021)*	*(4.296)*	*(4.439)*	*(4.359)*	*(2.452)*
Age	-11.571*	23.389*	-4.601	-14.685*	1.802	-22.088*	-24.737*	-20.969*
	(2.881)	*(3.850)*	*(3.975)*	*(1.922)*	*(2.180)*	*(2.610)*	*(2.358)*	*(1.440)*
Female	-13.519^{+}	-10.385*	-15.926*	1.643	3.194	-9.006*	-10.691*	-9.696*
	(6.433)	*(3.254)*	*(3.182)*	*(4.320)*	*(3.121)*	*(2.335)*	*(2.044)*	*(2.049)*
Born in country	-17.544*	–	26.578	-5.065	28.679*	1.565	–	14.370*
	(5.204)		*(17.753)*	*(3.914)*	*(9.100)*	*(4.566)*		*(5.061)*
Living with both parents	9.258^{+}	–	9.156^{+}	5.222	0.400	15.476*	7.819*	0.504
	(4.285)		*(4.395)*	*(3.977)*	*(2.847)*	*(2.888)*	*(2.461)*	*(2.570)*
Parents' education								
Some secondary	0.019	–	0.738	–	1.204	11.061	8.377	7.822*
	(3.185)		*(6.294)*		*(3.872)*	*(8.632)*	*(6.642)*	*(2.574)*
Finished secondary	13.341*	–	12.408°	13.754*	15.808*	17.203°	19.628*	22.188*
	(3.716)		*(6.410)*	*(3.008)*	*(5.596)*	*(8.831)*	*(6.884)*	*(2.989)*
Some after secondary	29.154*	–	0.419	41.491*	39.924*	31.478*	21.237*	8.903*
	(6.997)		*(7.844)*	*(4.520)*	*(6.283)*	*(8.288)*	*(7.155)*	*(3.191)*
Finished university	34.259*	–	41.639*	52.672*	40.557*	52.663*	38.249*	19.775*
	(6.215)		*(7.218)*	*(5.738)*	*(9.150)*	*(9.160)*	*(6.936)*	*(3.674)*
Books at home								
One shelf (11-25)	17.943*	–	19.571*	8.573^{+}	3.373	9.746^{+}	-4.621	15.326*
	(4.487)		*(6.704)*	*(3.597)*	*(2.208)*	*(3.779)*	*(4.977)*	*(4.477)*
One bookcase (26-100)	23.566*	–	57.779*	32.684*	9.736*	34.571*	8.747°	31.117*
	(4.774)		*(4.997)*	*(3.611)*	*(3.076)*	*(3.560)*	*(4.672)*	*(4.283)*
Two bookcases (101-200)	18.297*	–	84.691*	43.718*	13.437*	53.481*	16.634*	42.602*
	(5.353)		*(5.344)*	*(4.851)*	*(3.468)*	*(4.229)*	*(4.927)*	*(4.755)*
More than two bookcases (>200)	21.669* *(5.908)*	–	97.397* *(5.235)*	47.075* *(5.387)*	10.980* *(3.930)*	62.607* *(4.747)*	11.165^{+} *(5.234)*	49.806* *(4.507)*
Community location								
Close to town center	25.968°	-7.190	12.042*	16.791^{+}	34.353^{+}	-4.106	2.253	2.370
	(14.083)	*(6.467)*	*(3.589)*	*(8.124)*	*(13.548)*	*(6.639)*	*(5.232)*	*(4.523)*
Geographically isolated	-49.538°	-18.230	0.659	–	-10.975	-28.904*	–	-46.097*
	(25.728)	*(20.163)*	*(3.923)*		*(7.237)*	*(7.948)*		*(2.223)*
Imputation controls	yes	yes	yes	yes	yes	yes	yes	yes
Students [Unit of observation]	6752	10271	5827	8285	11643	10973	6014	7596
Schools [Unit of clustering]	86	151	150	137	147	183	134	154
R^2	0.144	0.038	0.179	0.154	0.119	0.185	0.230	0.205
R^2 (without imput. controls)	0.102	0.037	0.169	0.152	0.115	0.175	0.211	0.199

Significance levels (based on clustering-robust standard errors): * 1 percent. – $^{+}$ 5 percent. – $^{\circ}$ 10 percent.

Table 3b: Family Background and Science Performance

Least-squares regression within each country, weighted by students' sampling probabilities.
Dependent variable: TIMSS science test score. Clustering-robust standard errors in parentheses.

SCIENCE	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Upper grade	35.884*	22.444*	27.541*	88.783*	31.063*	43.012*	60.682*	54.494*
	(5.148)	*(3.567)*	*(3.863)*	*(5.171)*	*(2.653)*	*(4.922)*	*(2.888)*	*(2.641)*
Age	-7.683*	17.748*	5.230	-20.171*	1.403	-17.244*	-16.407*	-15.603*
	(2.095)	*(3.078)*	*(3.372)*	*(2.063)*	*(1.507)*	*(2.919)*	*(1.767)*	*(1.785)*
Female	-20.731*	-13.553*	-24.011*	-7.126	-2.294	-15.139*	-19.693*	-21.637*
	(4.372)	*(2.497)*	*(2.650)*	*(4.968)*	*(2.030)*	*(2.682)*	*(2.374)*	*(1.959)*
Born in country	-12.289*	–	39.988*	-0.743	23.298*	17.611*	–	12.500+
	(3.141)		*(14.496)*	*(5.114)*	*(8.975)*	*(4.971)*		*(5.627)*
Living with both parents	-1.347	–	-0.203	10.249+	-0.686	14.374*	4.937°	0.228
	(3.735)		*(4.828)*	*(3.969)*	*(1.984)*	*(3.506)*	*(2.974)*	*(3.208)*
Parents' education								
Some secondary	1.706	–	-6.783	–	0.246	-9.812	5.602	10.600*
	(2.997)		*(6.907)*		*(2.936)*	*(10.158)*	*(5.913)*	*(2.873)*
Finished secondary	11.281*	–	0.513	20.117*	7.545+	5.216	12.387°	19.569*
	(3.419)		*(5.690)*	*(3.313)*	*(3.681)*	*(10.181)*	*(6.385)*	*(3.742)*
Some after secondary	20.526*	–	-12.565°	55.740*	25.357*	18.546°	21.298*	9.628*
	(5.925)		*(6.929)*	*(5.436)*	*(4.628)*	*(9.681)*	*(6.859)*	*(3.533)*
Finished university	24.160*	–	15.070+	67.116*	27.322*	34.474*	26.840*	19.174*
	(5.944)		*(6.340)*	*(6.571)*	*(4.569)*	*(10.081)*	*(6.246)*	*(3.932)*
Books at home								
One shelf (11-25)	13.570*	–	15.984*	10.426*	0.361	15.781*	8.948	12.228+
	(3.453)		*(5.956)*	*(3.573)*	*(2.254)*	*(4.815)*	*(5.466)*	*(4.913)*
One bookcase (26-100)	16.234*	–	45.938*	36.816*	5.738+	48.239*	24.644*	28.580*
	(3.305)		*(4.165)*	*(3.963)*	*(2.228)*	*(4.806)*	*(4.883)*	*(4.679)*
Two bookcases (101-200)	16.119*	–	62.636*	56.224*	11.052*	67.216*	33.231*	38.801*
	(4.386)		*(4.532)*	*(4.559)*	*(4.026)*	*(5.160)*	*(5.357)*	*(4.976)*
More than two bookcases	14.865*	–	75.152*	57.052*	8.170+	79.101*	29.401*	45.334*
(>200)	*(4.291)*		*(4.526)*	*(4.632)*	*(3.725)*	*(6.005)*	*(5.268)*	*(5.075)*
Community location								
Close to town center	17.486°	-2.948	6.021+	21.886+	17.948+	-13.793+	2.813	2.860
	(9.321)	*(4.913)*	*(2.886)*	*(8.468)*	*(8.325)*	*(6.074)*	*(3.701)*	*(4.344)*
Geographically isolated	-33.201*	-1.410	-6.704+	–	-11.975+	-40.684*	–	-37.696*
	(12.529)	*(14.381)*	*(3.092)*		*(5.209)*	*(9.112)*		*(1.917)*
Imputation controls	yes	yes	yes	yes	yes	yes	yes	yes
Students [Unit of observation]	6752	10271	5827	8285	11643	10973	6014	7596
Schools [Unit of clustering]	86	151	150	137	147	183	134	154
R^2	0.118	0.058	0.139	0.234	0.102	0.174	0.183	0.165
R^2 (without imput. controls)	0.087	0.058	0.131	0.230	0.097	0.161	0.171	0.158

Significance levels (based on clustering-robust standard errors): * 1 percent. – + 5 percent. – ° 10 percent.

Table 4a: Resources, Teacher Characteristics, and Math Performance

Least-squares regression within each country, weighted by students' sampling probabilities.
Dependent variable: TIMSS math test score. Clustering-robust standard errors in parentheses.

MATH	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Class size (log)	106.206*	123.908*	-3.469	137.201*	7.850	-3.716	63.962*	9.469 °
	(35.471)	*(36.010)*	*(4.188)*	*(11.681)*	*(7.408)*	*(6.441)*	*(18.845)*	*(4.973)*
Shortage of materials								
None	16.000	7.754 °	0.921	13.521 °	24.237	-1.669	7.886	5.013
	(12.714)	*(4.360)*	*(3.680)*	*(7.151)*	*(18.338)*	*(6.055)*	*(5.076)*	*(3.853)*
A lot	-29.598	20.216^{+}	-0.087	-7.418	7.108	-28.585^{+}	4.839	20.353 °
	(32.201)	*(9.986)*	*(5.036)*	*(9.545)*	*(6.085)*	*(11.636)*	*(5.848)*	*(11.920)*
Instruction time	-3.288	–	-0.769	7.376	4.473 °	-1.939	1.030	0.616
	(5.108)		*(1.358)*	*(5.474)*	*(2.367)*	*(1.608)*	*(1.794)*	*(1.129)*
Teacher characteristics								
Female teacher	0.867	-9.718^{+}	3.898	2.989	-9.153	8.819 °	5.556	-1.577
	(9.028)	*(4.051)*	*(3.133)*	*(4.766)*	*(6.275)*	*(5.278)*	*(3.943)*	*(3.484)*
Teacher's experience (log)	-2.638	-0.387	-3.771 °	8.191*	9.181*	2.873	2.370	1.670
	(4.339)	*(3.212)*	*(1.974)*	*(2.589)*	*(3.223)*	*(2.979)*	*(2.290)*	*(2.977)*
Teacher's education								
Secondary only	–	–	–	12.496	–	–	59.804*	9.714
				(9.451)			*(13.942)*	*(6.332)*
BA or equivalent	-10.856	–	46.182*	16.233	-18.566 °	–	52.564*	7.858
	(9.264)		*(6.495)*	*(10.260)*	*(10.569)*		*(14.666)*	*(5.745)*
MA/PhD	13.777	–	47.056*	11.998	-7.008	9.954 °	53.272*	-9.922
	(21.598)		*(8.427)*	*(14.651)*	*(21.552)*	*(5.880)*	*(15.372)*	*(8.676)*
Family background controls	yes	yes	yes	yes	yes	yes	yes	yes
Imputation controls	yes	yes	yes	yes	yes	yes	yes	yes
Students [Unit of observation]	6722	10271	5827	8285	11643	10973	6014	7596
Schools [Unit of clustering]	86	151	150	137	147	183	134	154
R^2	0.203	0.063	0.182	0.278	0.159	0.203	0.259	0.216
R^2 (without imput. controls)	0.150	0.062	0.172	0.270	0.141	0.187	0.229	0.208

Significance levels (based on clustering-robust standard errors): * 1 percent. – $^{+}$ 5 percent. – ° 10 percent.

Table 4b: Resources, Teacher Characteristics, and Science Performance

Least-squares regression within each country, weighted by students' sampling probabilities.
Dependent variable: TIMSS science test score. Clustering-robust standard errors in parentheses.

SCIENCE	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Class size (log)	174.606*	86.505*	8.017^{+}	141.419*	-7.426	3.990	9.452	5.604
	(49.075)	*(29.523)*	*(3.149)*	*(11.016)*	*(6.315)*	*(6.591)*	*(9.821)*	*(4.618)*
Shortage of materials								
None	10.876	7.794^{+}	-0.783	13.115	19.208^{+}	-3.795	1.330	2.417
	(8.571)	*(3.672)*	*(3.150)*	*(8.392)*	*(8.716)*	*(5.648)*	*(3.948)*	*(3.357)*
A lot	-22.224	19.014*	0.947	-14.831	5.896	-27.755*	-2.517	6.799
	(16.323)	*(6.642)*	*(3.983)*	*(17.364)*	*(4.841)*	*(10.026)*	*(4.053)*	*(10.688)*
Instruction time	-2.702	–	1.454	5.892	1.598	-0.515	-1.522	0.283
	(3.143)		*(0.985)*	*(5.744)*	*(1.556)*	*(1.412)*	*(1.877)*	*(0.968)*
Teacher characteristics								
Female teacher	16.993*	0.491	-1.765	19.016*	10.587^{+}	2.878	4.215	4.380
	(6.206)	*(4.247)*	*(2.838)*	*(5.926)*	*(4.516)*	*(5.186)*	*(3.475)*	*(3.144)*
Teacher's experience (log)	-0.320	2.119	-0.212	-0.778	1.972	1.717	1.590	-2.318
	(2.585)	*(2.148)*	*(1.873)*	*(2.815)*	*(2.365)*	*(3.032)*	*(2.246)*	*(2.331)*
Teacher's education								
Secondary only	–	–	–	4.106	–	–	–	-9.731°
				(17.413)				*(5.425)*
BA or equivalent	-1.136	–	-14.747*	-2.359	12.485°	–	-1.418	-11.040^{+}
	(7.530)		*(3.885)*	*(16.789)*	*(7.083)*		*(3.816)*	*(4.802)*
MA/PhD	9.094	–	-21.008*	-1.822	22.838^{+}	-6.633	1.877	-1.594
	(16.945)		*(4.896)*	*(19.504)*	*(9.791)*	*(5.338)*	*(4.437)*	*(8.921)*
Family background controls	yes	yes	yes	yes	yes	yes	yes	yes
Imputation controls	yes	yes	yes	yes	yes	yes	yes	yes
Students [Unit of observation]	6752	10271	5827	8285	11643	10973	6014	7596
Schools [Unit of clustering]	86	151	150	137	147	183	134	154
R^2	0.158	0.075	0.142	0.338	0.120	0.182	0.189	0.170
R^2 (without imput. controls)	0.121	0.073	0.133	0.332	0.109	0.166	0.173	0.161

Significance levels (based on clustering-robust standard errors): * 1 percent. – $^{+}$ 5 percent. – ° 10 percent.

Table 5a: The Coefficient on Log Class Size in Math

Regressions within each country, weighted by students' sampling probabilities. Dependent variable: TIMSS math test score.
Controlling for family-background variables and imputation controls. Clustering-robust standard errors in parentheses.

MATH	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
LS	107.924 *	126.077 *	-5.566	138.002 *	10.742	-3.294	60.824 *	9.456
	(30.775)	*(39.352)*	*(4.538)*	*(11.984)*	*(8.680)*	*(6.656)*	*(21.424)*	*(5.966)*
IV	261.893	151.598 *	66.028 $^{+}$	155.356 *	-1926.856	-25.978	-13.591	18.766
	(160.843)	*(53.952)*	*(27.462)*	*(16.581)*	*(4666.453)*	*(25.666)*	*(32.477)*	*(11.666)*
SFE	96.727 *	-10.286	-13.245 $^{+}$	89.849 *	4.899	-0.808	43.019 °	-2.182
	(20.298)	*(15.222)*	*(5.547)*	*(15.366)*	*(5.999)*	*(7.903)*	*(21.838)*	*(5.766)*
SFE-IV	249.479	1.509	-46.547	11.093	-585.839	52.385	-81.209	-12.253
	(752.850)	*(21.177)*	*(40.134)*	*(20.792)*	*(2075.300)*	*(42.658)*	*(53.996)*	*(88.898)*
Students	6712	10271	5827	8285	11610	10831	5669	7556
Schools	85	151	150	137	146	179	119	152

Methods of estimation: LS = Least squares. – IV = Instrumental variables. – SFE = School fixed effects. – SFE-IV = Combination of school fixed effects and instrumental variables. See text for details on the four methods of estimation.

Significance levels (based on clustering-robust standard errors): * 1 percent. – $^{+}$ 5 percent. – ° 10 percent.

Table 5b: The Coefficient on Log Class Size in Science

Regressions within each country, weighted by students' sampling probabilities. Dependent variable: TIMSS science test score.
Controlling for family-background variables and imputation controls. Clustering-robust standard errors in parentheses.

SCIENCE	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
LS	179.803 *	87.866 *	6.661 $^{+}$	149.994 *	-8.720	7.483	8.382	3.224
	(47.300)	*(31.216)*	*(3.128)*	*(10.826)*	*(6.243)*	*(5.760)*	*(9.842)*	*(5.134)*
IV	330.140 *	122.347 $^{+}$	24.446	151.825 *	-421.048	10.166	4.334	-21.434
	(59.487)	*(49.099)*	*(27.366)*	*(16.154)*	*(537.430)*	*(25.149)*	*(28.694)*	*(108.010)*
SFE	99.388 $^{+}$	-15.235	1.613	100.887 *	-4.224	9.731	-5.055	1.470
	(43.329)	*(13.409)*	*(6.414)*	*(16.283)*	*(5.276)*	*(6.003)*	*(15.244)*	*(7.229)*
SFE-IV	3220.834	4.383	-7.000	10.625	-42.607	340.332	-42.511	58.538
	(12012.380)	*(29.239)*	*(93.685)*	*(20.996)*	*(737.196)*	*(2410.341)*	*(40.457)*	*(329.424)*
Students	6712	10271	5827	8285	11610	10831	5669	7556
Schools	85	151	150	137	146	179	119	152

Methods of estimation: LS = Least squares. – IV = Instrumental variables. – SFE = School fixed effects. – SFE-IV = Combination of school fixed effects and instrumental variables. See text for details on the four methods of estimation.

Significance levels (based on clustering-robust standard errors): * 1 percent. – $^{+}$ 5 percent. – ° 10 percent.

Table 6a: Institutions and Math Performance

Least-squares regression within each country, weighted by students' sampling probabilities.
Dependent variable: TIMSS math test score. Clustering-robust standard errors in parentheses.

MATH	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
School responsibility for determining teacher salaries	0.537	64.160 *	0.113	60.400 *	18.209	3.000	–	2.099
	(13.839)	*(13.400)*	*(3.771)*	*(9.993)*	*(11.780)*	*(8.805)*		*(4.629)*
Homework	6.121	8.547 $^{+}$	1.936	4.177 $^{+}$	-1.952	14.265 *	4.582	-0.336
	(4.408)	*(4.218)*	*(1.323)*	*(1.628)*	*(1.399)*	*(2.381)*	*(2.813)*	*(1.585)*
Teaching limited by								
Uninterested parents	-62.004 *	–	4.348	-10.258	4.247	-17.825 $^{+}$	-17.097 $^{+}$	0.636
	(17.329)		*(7.662)*	*(7.962)*	*(8.411)*	*(7.057)*	*(7.067)*	*(6.323)*
Interested parents	58.296 *	-46.875 *	-13.949	14.285	19.899	34.660 $^{+}$	–	6.193
	(21.940)	*(18.010)*	*(9.189)*	*(16.046)*	*(12.724)*	*(16.754)*		*(6.988)*
Family background controls	yes	yes	yes	yes	yes	yes	yes	yes
Resource controls	yes	yes	yes	yes	yes	yes	yes	yes
Imputation controls	yes	yes	yes	yes	yes	yes	yes	yes
Students [Unit of observation]	6722	10271	5827	8285	11643	10973	6014	7596
Schools [Unit of clustering]	86	151	150	137	147	183	134	154
R^2	0.239	0.094	0.183	0.299	0.164	0.231	0.267	0.220
R^2 (without imput. controls)	0.180	0.090	0.172	0.292	0.149	0.207	0.235	0.209

Significance levels (based on clustering-robust standard errors): * 1 percent. – $^{+}$ 5 percent. – ° 10 percent.

Table 6b: Institutions and Science Performance

Least-squares regression within each country, weighted by students' sampling probabilities.
Dependent variable: TIMSS science test score. Clustering-robust standard errors in parentheses.

SCIENCE	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
School responsibility for	-15.521 $^{+}$	59.339 *	2.154	72.032 *	5.178	9.852	–	-5.881
determining teacher salaries	*(6.650)*	*(12.527)*	*(3.082)*	*(8.073)*	*(5.872)*	*(8.788)*		*(4.936)*
Homework	22.774 *	-1.912	-7.166 $^{+}$	1.500	0.788	4.267	2.699	-1.105
	(8.049)	*(4.944)*	*(2.820)*	*(5.499)*	*(1.419)*	*(3.785)*	*(3.037)*	*(1.664)*
Teaching limited by								
Uninterested parents	-50.668 *	–	-3.674	-19.438	-10.066	-15.117	-4.689	-2.015
	(11.884)		*(6.661)*	*(23.056)*	*(8.082)*	*(11.335)*	*(6.634)*	*(4.512)*
Interested parents	22.900	–	8.855	30.221	-13.844 $^{+}$	32.437	–	-8.433 °
	(16.423)		*(11.838)*	*(36.499)*	*(6.989)*	*(21.341)*		*(4.308)*
Family background controls	yes	yes	yes	yes	yes	yes	yes	yes
Resource controls	yes	yes	yes	yes	yes	yes	yes	yes
Imputation controls	yes	yes	yes	yes	yes	yes	yes	yes
Students [Unit of observation]	6752	10271	5827	8285	11643	10973	6014	7596
Schools [Unit of clustering]	86	151	150	137	147	183	134	154
R^2	0.186	0.098	0.144	0.369	0.123	0.188	0.191	0.173
R^2 (without imput. controls)	0.140	0.096	0.133	0.356	0.111	0.169	0.173	0.163

Significance levels (based on clustering-robust standard errors): * 1 percent. – $^{+}$ 5 percent. – ° 10 percent.

Table A1: Missing Values

Unweighted percentage of students with missing data.

	HON	JAP	KOR	SIN	THA	USA	FRA	SPA
Age	0.008	0.006	0.000	0.001	0.014	0.001	0.065	0.000
Sex	0.001	0.000	0.000	0.000	0.009	0.000	0.035	0.000
Born in country	0.028	1.000	0.019	0.006	0.011	0.018	1.000	0.013
Living with both parents	0.018	1.000	0.001	0.008	0.006	0.020	0.037	0.007
Parents' education	0.122	1.000	0.058	0.003	0.069	0.101	0.450	0.158
Books at home	0.020	1.000	0.003	0.007	0.017	0.023	0.044	0.010
Community location	0.113	0.006	0.013	0.000	0.116	0.150	0.107	0.065
Math class size	0.190	0.006	0.069	0.006	0.592	0.320	0.135	0.225
Science class size	0.225	0.010	0.113	0.026	0.620	0.574	0.174	0.217
Grade-average class size	0.111	0.000	0.009	0.003	0.136	0.205	0.122	0.124
Shortage of materials	0.111	0.016	0.020	0.016	0.123	0.152	0.097	0.065
Instruction time	0.218	1.000	0.064	0.000	0.162	0.320	0.396	0.171
Math teacher characteristics								
Teacher's sex	0.064	0.006	0.036	0.006	0.355	0.138	0.074	0.049
Teacher's experience	0.048	0.017	0.043	0.010	0.413	0.140	0.103	0.065
Teacher's education	0.070	1.000	0.036	0.020	0.359	0.142	0.092	0.063
Science teacher characteristics								
Teacher's sex	0.099	0.010	0.067	0.026	0.353	0.232	0.066	0.050
Teacher's experience	0.080	0.025	0.070	0.035	0.393	0.246	0.081	0.060
Teacher's education	0.105	1.000	0.067	0.035	0.350	0.230	0.077	0.062
School determines teacher salaries	0.123	0.020	0.020	0.007	0.308	0.172	0.123	0.080
Math								
Homework assignment	0.132	0.026	0.054	0.011	0.376	0.280	0.124	0.186
Uninterested parents limit	0.131	1.000	0.066	0.025	0.358	0.287	0.103	0.194
Interested parents limit	0.137	0.010	0.070	0.023	0.358	0.290	1.000	0.194
Science								
Homework assignment	0.183	0.094	0.084	0.033	0.372	0.524	0.172	0.208
Uninterested parents limit	0.175	1.000	0.070	0.039	0.358	0.532	0.168	0.212
Interested parents limit	0.170	0.017	0.063	0.045	0.358	0.534	1.000	0.218