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Abstract

Education production functions are estimated using student-level achievement data for Japanese students, with emphasis on estimating the causal effect of class size on students' academic performance. The empirical results show that students' test scores are strongly affected by individual and family backgrounds, whereas school resource variables and teacher characteristics have a more limited impact. The causal effect of class size, which is currently being politically debated in Japan, is investigated using a regression discontinuity design. The estimation results suggest that class-size reduction has a weak impact on the academic performance of Japanese students.

Keywords

Education production function, Class size, Regression discontinuity design, Japan

JEL classification numbers

I21, I28

1 Introduction

A central issue for the economics of education and education policy has been the influence of schools on students' academic achievement, that is, whether schools and/or teachers can succeed in reducing the gaps in opportunities among students from different family backgrounds, given the stylized fact that family backgrounds are the major determinants of students' academic performance (Coleman et al., 1966; Hanushek, 2003, 2006; Wößmann, 2003). The underlying concern in the debates regarding reducing class size, improving teacher quality, increasing spending per pupil, etc., can be summarized as follows: Why do schools not influence student achievement?

Since the number of students in a class is considered to be not only a key variable in the production of learning but also a simple variable for policymakers to manipulate, many researchers, including economists, have long debated whether and how class size matters for student achievement. During the past half a century, hundreds of studies have literally been undertaken to identify the impact of class size on education outcomes. We can divide them into the following three groups: non-experimental studies, experimental studies, and instrumental variable approach.

The Coleman Report (Coleman et al., 1966) and subsequent studies can be categorized as non-experimental studies, because their statistical analyses are based on non-experimental survey data. Although the initial focus of the Coleman Report was not on investigating the effect of class size, the survey data, which collected students' test scores and information regarding students' family and school backgrounds, enabled researchers to estimate the so-called education production function and to identify the determinants of student achievement.

Coleman et al. (1966) found that family and community characteristics had a strong effect on student achievement and school-related variables such as pupil/teacher ratios, expenditures per pupil, and teacher characteristics had a weak effect on student achievement.[1] A main criticism against this finding is that the data used in the report are cross-sectional or snapshot, taken at a point in time. To the extent that students' achievement at time *t* is determined by current as well as past circumstances that students have experienced until the timing of the survey, there are many omitted variables in the regression equation using only current information. In addition, the class-size variable is potentially endogenous if school authorities and teachers prefer to teach lower-performing students in a smaller/larger class, or education-minded parents choose schools by moving residence.

The second set of studies analyze the effect of class size using data obtained from experimental design, wherein students are randomly assigned to classes of different sizes. The random assignment of students is equivalent to identifying the causal effect of class size, if the experiment is carefully conducted. An influential experiment was the Project STAR in Tennessee in the 1980s. Many researchers analyzed STAR data in order to identify the causal effect of class-size reduction, and some authors found statistically significant benefits of smaller classes, especially for minority students (Finn and Achilles, 1999; Krueger, 1999). On the other hand, some authors raised concern regarding the difficulties of the experiment: the motivation of teachers changes because they know they are participating in the experiment

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[1] Hanushek (1997) provided a review of empirical evidence after the Coleman Report.

(Hoxby, 2000). In addition, non-random selection of schools, non-random allocation of teachers, and attrition and late entry of students may affect the design of the experiment (Hanushek, 1999).

The third set of studies tried to avoid the endogeneity problem in quasi-experimental settings and identified the causal effect of class size by utilizing instrumental variable methods (Heinesen, 2010; Hoxby, 2000; Wößmann and West, 2006). Angrist and Lavy (1999) analyzed Israeli data and proposed an instrumental variable method utilizing information regarding the maximum class size rule in Israeli schools. An increasing number of studies are applying the maximum class size rule approach (Bonesrønning [2003] and Leuven et al. [2008] for Norway; Browning and Heinesen [2007] for Denmark; Gary-Bobo and Mahjoub [2006] for France; Urquiola [2006] for Bolivia; Wößmann [2005] for ten European countries). Because there are similarities in the institutional conditions between Japan and Israel, this paper applies the instrumental variable method for the Japanese case and investigates the causal effect of class-size reduction on the academic performance of Japanese students.

Empirical studies on Japanese education including education production function estimations have been scarce owing to limited data availability.[2] This paper, therefore, in addition to exploring the causal effect of class-size reduction, aims to contribute to this area of research by reporting the education production function estimates for Japanese students.

The remainder of the paper is structured as follows: Section 2 provides a brief description of the data. Section 3 explains the methodology of regression model analysis. Section 4 presents

[2] See Oshio and Senoh (2007) for related literature in Japan. Hojo and Oshio (2010) reported education production function estimates for five East Asian countries, including Japan.

the estimation results. We cannot reject the hypothesis that the effect of reducing class size is zero. Section 5 concludes the paper.

2 Data and descriptive analysis

The empirical analysis of this paper is based on the dataset for Japan collected from the Trends in International Mathematics and Science Study (TIMSS), which was conducted in 2007 under the auspices of the International Association for the Evaluation of Educational Achievement (IEA). Fifty-nine countries/regions participated in TIMSS 2007, and the survey in Japan was conducted by the National Institute for Educational Policy Research (NIER) in March 2007. TIMSS included four surveys: mathematics and science tests for the fourth and eighth graders. This paper will focus only on mathematics and science for eighth graders.[3]

The TIMSS assessment was administered to random samples of students from the target population, that is, the fourth and eighth graders in each country. Schools were selected with probability proportional to size, and classrooms with equal probabilities. In Japan, students were sampled in two stages: in the first stage, schools were randomly sampled and in the second stage, one or two classrooms were randomly chosen within each school and all of its students were tested. The number of sampled junior high schools is 146, and the number of sampled students is 4,312.

Student scores in TIMSS were normalized with an international mean of 500 and an

[3] This paper focuses on eighth graders because information of parental education is not available for fourth graders. I conducted empirical analysis similar to what is discussed below using the data of fourth graders. For the sake of brevity, I do not report the results of fourth graders, which are generally similar to those of eighth graders; however, they are available from the author upon request.

international standard deviation of 100. These score data can be linked to the background data from three types of background questionnaires. The student questionnaire asked students to provide information on their backgrounds, home and school lives, and their experiences in learning mathematics and science. The teacher questionnaire collected information from subject teachers regarding their backgrounds, course contents, and professional development. The school questionnaire asked the school principals to provide information on the school characteristics and the resources available to provide instruction.

As with any survey data, there were missing observations in the background questionnaires. Students with missing observations and those in private schools were dropped, and finally, the survey generated 4,960 observations for mathematics and 3,699 for science.[4]

Table 1 shows the descriptive statistics. The mean scores are 564 and 549 for mathematics and science, respectively, whereas the standard deviations are 78.4 and 71.1, respectively. In order to assess the distribution of student performance, Figure 1 graphically depicts the kernel density estimates of scores. Both mathematics and science scores have nearly symmetric distributions around the mean.

3 Method

3.1 Estimation model

We estimated the education production function for each grade in the following manner:

[4] The number of observations for mathematics, 4,690, exceeds the number of sampled students, 4,312, because some students are taught by multiple teachers. In the TIMSS dataset, students who are taught by two teachers are recorded as two observations.

$$A_{isc} = X_{isc}\beta + \alpha Z_{sc} + \epsilon_{isc}, \quad (1)$$

where A_{isc} is the TIMSS-normalized score of student *i* in class *c* of school s, X_{isc} is a set of individual-, teacher-, and school-level variables, and Z_{sc} is the size of class c in school s; ϵ_{isc} is an error term. Note that our class size measure is defined as the number of students at the instruction of each subject. If students are grouped at the instruction of certain subjects, the number of students at instruction could differ from the class size at homeroom.

Individual-level variables in X_{isc} are the gender and birth month of student i. As in other countries worldwide, the Japanese school system has a single cutoff date, that is, April 1, for school eligibility. This makes some students younger than others when they begin school, and younger students are likely to have some disadvantage in learning owing to physical and/or psychological immaturity. Recent studies have demonstrated that these initial maturity differences have long-lasting effects on student performance and schooling experiences (Bedard and Dhuey [2006] for OECD countries; Kawaguchi [2011] for Japan; and Mühlenweg and Puhani [2010] for Germany). We consider initial maturity differences for eighth graders, most of whom are 14 years old. Other individual-level variables are resources at students' homes (computer, dictionary, and Internet connection), number of books at home, and education level of parents.[5]

Teacher-level variables consist of teacher's gender, educational attainment (having

[5] In case a student answers his/her parental education as "unknown," a predicted value was calculated from the result of a regression of parental education on students' gender and birth month, number of books at home, resources at home, percentage of economically disadvantaged students, and the number of people in school-located districts. The empirical results reported are essentially similar when parental education levels are treated as categorical dummy variables.

obtained master's degree or not), and years of teaching experience. School-level variables are enrollment in each grade, the percentage of economically disadvantaged (PD) students, and the number of people in school-located districts.

3.2 Class-size effect and regression-discontinuity design

In estimating the education production functions given in Eq. (1), our focus is on the causal effect of class size, Z_{sc}, on student performance. The potential endogeneity of class size makes analyzing its effect rather difficult: schools, teachers, or parents may prefer to teach lower-performing students in a smaller/larger class. Angrist and Lavy (1999) tackled this issue by applying the instrumental variable method. They showed that the class size in Israeli public schools is strongly affected by Maimonides' rule: the twelfth century rabbinic scholar Maimonides proposed a maximum class size of 40. In other words, class size increases with grade enrollment until the threshold value of 40; however, it sharply declines once enrollment exceeds 40. Similarly, class size decreases each time the grade enrollment exceeds a multiple of 40.

Angrist and Lavy (1999) proposed an instrumental variable method that utilizes discontinuities in the relationship between grade enrollment and class size: instrumenting actual class size with the predicted one derived from Maimonides's rule. This can be viewed as an application of (fuzzy) regression discontinuity design. The predicted class size is determined solely by grade enrollment; thus, although it is largely exogenous to the school's preference or parental choices, it strongly correlates with the actual class size. Therefore, the predicted class size can be used as an instrument for the actual class size. The predicted class size is given by

$$Z_{sc}^{p} = \frac{\text{enrollment}}{\text{int}[(\text{enrollment}-1)/40]+1}, \tag{2}$$

where int[ ] defines the integer closest to the number in [ ].

Figure 2 shows the distribution of enrollment in the eighth grade. We do not observe apparent discontinuity around the threshold (multiples of 40); therefore, this suggests that grade enrollment is exogenously determined.[6] Figure 3 shows the distribution of the actual class size for mathematics (panel a) and science (panel b). Class size for mathematics is scattered to the left, indicating that in the case of mathematics students tend to be divided into smaller groups in some way. On the other hand, class size for science is less scattered.

Figure 4 depicts the actual and predicted class size for mathematics (panel a) and science (panel b), with grade enrollment on the horizontal axis. In Japan, it is mandatory for class sizes to not exceed 40.[7] As clearly seen from this figure, although the predicted class size successfully explains the actual class size for both the subjects, some observations are located apart from the line corresponding to the rule, especially in the case of mathematics.

Figure 5 illustrates the relationship between predicted class size and achievement. The solid line plots the predicted class size at intervals of 10 students, and the dashed lines show average scores. If smaller class size increases student achievement, then a jump in average

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[6] Urquiola and Verhoogen (2009) show that Chilean schools adjust their enrollments to avoid adding an additional classroom. This violates the assumptions underlying the regression discontinuity designs.

[7] The maximum class size, 40, is legally defined at the nation level, and the number of teachers allocated to a public school is determined on the basis of the grade enrollment divided by 40. However, at the same time, the maximum class size can be slightly modified at the local government level.

achievement around the thresholds should be observed. We found mirror patterns, though not perfect, for both subjects.

4 Estimation results

4.1 Ordinary least squares (OLS) estimates

Table 2 shows the estimation results of the education production function for both subjects using OLS.[8] Without any control variables (columns 1 and 4), the coefficient estimate of class size is positive and statistically insignificant. Controlling for individual characteristics (columns 2 and 5) and school characteristics (columns 3 and 6) does not change the class-size effect, indicating that conditioning on additional observables is not sufficient to correct for biases owing to selective placement by schools, teachers, or parents.

4.2 Instrumental variable estimation using maximum class size rule

Table 3 shows the results of the first-stage regression of two-stage least squares (2SLS). The coefficient estimate of predicted class size is positive and statistically significant in both regressions, suggesting that the predicted class size is a valid instrumental variable for the actual class size. Note that the coefficients are approximately 0.45 in the regressions for both subjects; thus, they are smaller than 1, suggesting that schools do not perfectly adhere to the maximum class size rule.

[8] In addition to OLS, we examined quintile regression because the structure of the education production function may differ between low- and high-performance students. The results of quintile regression were essentially similar to those of OLS.

Table 4 reports 2SLS estimation results for both subjects, using student-, teacher-, and school-level data. The estimate of class size is positive for mathematics and negative for science, although both are statistically insignificant. Therefore, we found no evidence that smaller class sizes increase Japanese eighth grade students' achievement in mathematics and science. This result is similar to that found in Leuven et al. (2008) for Norwegian students.

In contrast to class size, we found strong evidence that individual-level variables have large and statistically significant influences on test scores. First, the younger students tend to score lower than older students. Since almost all eligible children in Japan enter school without delay or advancement (Kawaguchi, 2011), the coefficient estimates of birth month clearly reflect initial maturity differences. Students who were born from January to March score 10.5 points (0.13 standard deviations) lower for mathematics and 7.0 points (0.10 standard deviations) lower for science than those who were born from April to June.

Second, we found a positive correlation between test scores and attributes of students' homes. The number of books and resources at home (computers, dictionaries, and Internet connection) have strong positive effects on student-level test scores for both subjects. Third, higher parental education level is associated with higher performance for both subjects. All these results suggest strong effects of individual and family attributes, which are repeatedly shown in many preceding studies.

We found that test score is negatively correlated with the percentage of economically disadvantaged students. A student whose school is located in an economically disadvantaged area tends to score low (22.7 points for mathematics and 20.8 points for science). Among teacher-level variables, female teacher has a positive effect on mathematics scores. In Japan, teaching was considered an attractive job for women, and both men and women were treated more equally in schools than in private firms, in terms of employment opportunities and position advancement. Therefore, a positive effect for female teacher may indicate higher ability of female teachers. Among other school-level variables, students who are grouped according to their ability at instruction score higher than those who are not.

4.2 Robustness checks

We proceed to check the robustness of the 2SLS estimations. Table 5 shows the estimated class-size effects for various subsamples. The discontinuity sample (+5/-5) includes schools with enrollment levels at most five students short of or more than a multiple of 40 (hence, between 36 and 45, between 76 and 85, etc.). Row (2) reports the result for the subsample of students who are not grouped by ability at instruction, because the ability grouping is negatively correlated with actual class size (see Table 3). Row (3) reports the result for the subsample of girls. Row (4) shows the result for the subsample of schools located in economically disadvantaged areas, because the effect of class-size reduction may be large for students living in disadvantaged areas. Row (5) shows the results for the subsample of students with low-educated parents (both father and mother have less than 12 years of education). Row (6) shows class-size effects for all sample students; however, the predicted class size is calculated assuming that the maximum class size is 41 instead of 40. For all subsamples and the alternative rule of maximum class size, we cannot find any significant effects of class-size reduction for both subjects.

Hægeland et al. (2005) argued that input substitution may take place for equality or efficiency reasons. For example, large classes may be given more teacher hours or assigned able and/or veteran teachers (Jepsen and Rivkin, 2009). Students in large classes may tend to have more study hours at home with their parents (Datar and Mason, 2008). Mutual influences among students may decrease when their class size is small.

In order to simply check the possibilities of input substitution, Table 6 shows average values of potentially substitutable inputs for small and large classes. For mathematics, teachers assigned to large classes (class size ≥ 38) tend to assign homework and give opportunities of discussion more frequently than those assigned to small classes (class size ≤ 25). For science, teachers assigned to large classes have 4.8 years longer teaching experience than those assigned to small classes (class size ≤ 29). These input substitutions, though weak, may lessen the estimated class-size effects.

5 Conclusions

There is considerable debate in the educational community regarding the effect of class-size reduction on education outcomes of students. Although it is rather difficult to identify the causal effect of class size on student achievement owing to the potential endogeneity of class size, recent developments in econometric methods enable us to avoid biases in estimates. Using student-level data of Japanese public schools, this paper applied an instrumental variable estimation method to answer the following question: Are smaller classes better for Japanese students?

Student-level estimation results showed that the effect of class size on student achievement is statistically insignificant in both OLS and 2SLS estimations. Class-size effects are also insignificant for various subgroup regressions. Therefore, although we found no evidence that a smaller class increases mathematics and science performance of Japanese eighth grade students, we found strong effects of individual and family attributes, such as birth month, number of books at home, and parental education. Community characteristics measured by percentage of economically disadvantaged students also have strong effects. Among input-related variables, we found strong positive effects of female teachers and grouping by students' ability.

We should of course exercise considerable caution in interpreting the empirical results found in this paper. First, the evidence found in this paper is based only on mathematics and science for eighth graders. The effect of class-size reduction, or, more broadly, the process of education production, may differ with different subjects and/or different grades. Second, the impact of class size may have long-run consequences; in other words, the benefit of being in a smaller class may occur after several years (Krueger and Whitmore, 2001). Third, although this paper focuses only on the test scores of mathematics and science, other education outcomes are also important, such as increased motivation for studying, better relationships among students, etc. Fourth, class-size reduction may lessen the positive effects of classroom peers because the number of peers, and thus the heterogeneity of peers, decreases for students in small classes (Fertig, 2003). Fifth, owing to recent educational policy changes, a small class size does not necessarily mean a low pupil/teacher ratio in Japanese public schools. Multiple teachers may be assigned to instruction at large classes (called *team teaching*). Further accumulation of data and its increased availability would enable us to know the true impact and costs of class-size reduction in Japanese schools.

References

Angrist, J.D., Lavy, V., 1999. Using Maimonides' rule to estimate the effect of class size on scholastic achievement. Quarterly Journal of Economics 114, 533-575.

Bedard, K., Dhuey, E., 2006. The persistence of early childhood maturity: international evidence of long-run age effects. Quarterly Journal of Economics 121, 1437-1472.

Bonesrønning, H., 2003. Class size effects on student achievement in Norway: patterns and Explanations. Southern Economic Journal 69, 952-965.

Browning, M., Heinesen, E., 2007. Class size, teacher hours and educational attainment. Scandinavian Journal of Economics 109, 425-438.

Coleman, J.S. et al., 1966. Equality of Educational Opportunity. Washington, DC: US Government Printing Office.

Datar, A., Mason, B., 2008. Do reductions in class size 'crowd out' parental investment in education? Economics of Education Review 27, 712-723.

Fertig, M., 2003. Educational production, endogenous peer group formation and class composition: evidence from the PISA 2000 study. IZA Discussion Paper No. 714, Bonn.

Finn, J.P., Achilles, C.M., 1999. Tennessee's class size study: findings, implications and misconceptions. Educational Evaluation and Policy Analysis 21, 97-110.

Gary-Bobo, R.J., Mahjoub, M.B., 2006. Estimation of class-size effects, using "Maimonides' Rule": the case of French junior high schools. CEPR Discussion Paper No. 5754, London.

Hægeland, T., Raaum, O., Salvanes, K.G., 2005. Pennies from heaven? Using exogenous tax variation to identify effects of school resources on pupil achievements. IZA Discussion Paper No. 1459, Bonn.

Hanushek, E.A., 1997. Assessing the effects of school resources on student performance: an update. Educational Evaluation and Policy Analysis 19, 141-164.

Hanushek, E.A., 1999. Some findings from an independent investigation of the Tennessee STAR experiment and from other investigations of class size effects. Educational Evaluation and Policy Analysis 21, 143-164.

Hanushek, E.A., 2003. The failure of input-based schooling policies. Economic Journal 113, F64-F98.

Hanushek, E.A, 2006. School resources. In: Hanushek, E.A., Welch F. (Eds.). Handbook of The Economics of Education, Vol. II. Amsterdam: North-Holland, 865-908.

Heinesen, E., 2010. Estimating class-size effects using within-school variation in subject-specific classes. Economic Journal 120, 737-760.

Hojo, M., Oshio, T., 2010. What factors determine student performance in East Asia? New evidence from TIMSS 2007. PIE/CIS Discussion Paper No. 494, Institute of Economic Research, Hitotsubashi University.

Hoxby, C.M., 2000. The effects of class size on student achievement: new evidence from population variation. Quarterly Journal of Economics 115, 1239-1285.

Jepsen, C., Rivkin, S., 2009. Class size reduction and student achievement: The potential trade-off between teacher quality and class size. Journal of Human Resources 44, 223-250.

Kawaguchi, D., 2011. Actual age at school entry, educational outcomes, and earnings. Journal of the Japanese and International Economies 25, 64-80.

Krueger, A.B., 1999. Experimental estimates of education production functions. Quarterly Journal of Economics 114, 497-532.

Krueger, A.B., Whitmore, D.M., 2001. The effect of attending a small class in the early grades on college-test taking and middle school test results: evidence from project STAR. Economic Journal 111, 1-28.

Leuven, E., Oosterbeek, H., Rønning, M, 2008. Quasi-experimental estimates of the effect of class size on achievement in Norway. Scandinavian Journal of Economics 110, 663-693.

Mülenweg A.M., Puhani, P.A., 2010. The evolution of the school-entry age effect in a school tracking system. Journal of Human Resources 45, 407-438.

Oshio, T., Senoh, W., 2007. The economics of education in Japan: a survey of empirical studies and unresolved issues. The Japanese Economy 34, 46-81.

Urquiola, M., 2006. Identifying class size effects in developing countries: evidence from rural Bolivia. Review of Economics and Statistics 88, 171-176.

Urquiola, M., Verhoogen, E., 2009. Class-size caps, sorting, and the regression-discontinuity design. American Economic Review 99, 179-215.

Wößmann, L., 2003. Schooling resources, educational institutions and student performance: the international evidence. Oxford Bulletin of Economics and Statistics 65, 117-170.

Wößmann, L., 2005. Educational production in Europe. Economic Policy 20, 445-504.

Wößmann, L., West, M., 2006. Class-size effects in school systems around the world:

evidence from between-grade variation in TIMSS. European Economic Review 50, 695-736.

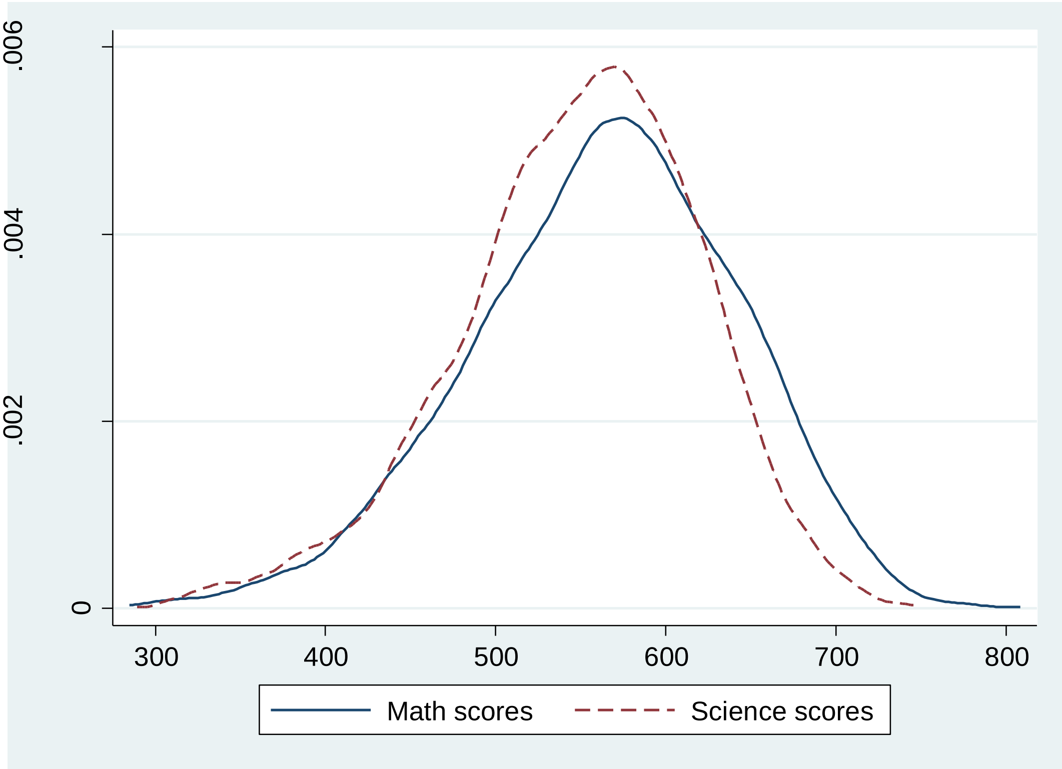


Figure 1 Kernel density estimates

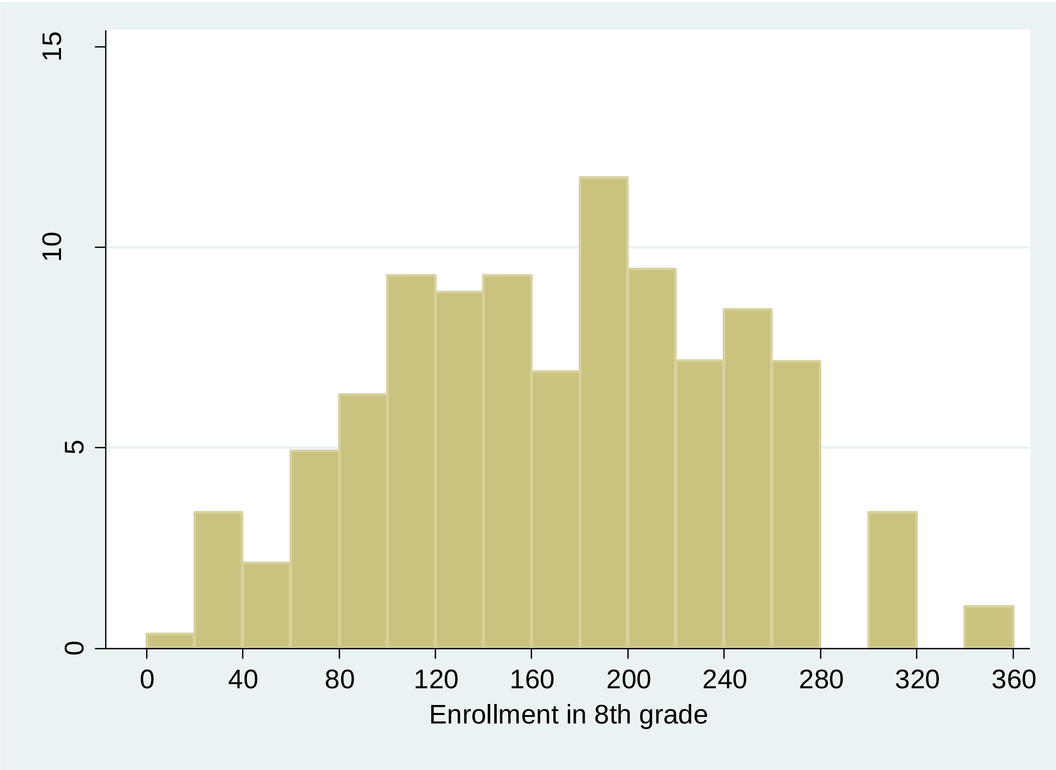


Figure 2 Distribution of grade enrollment

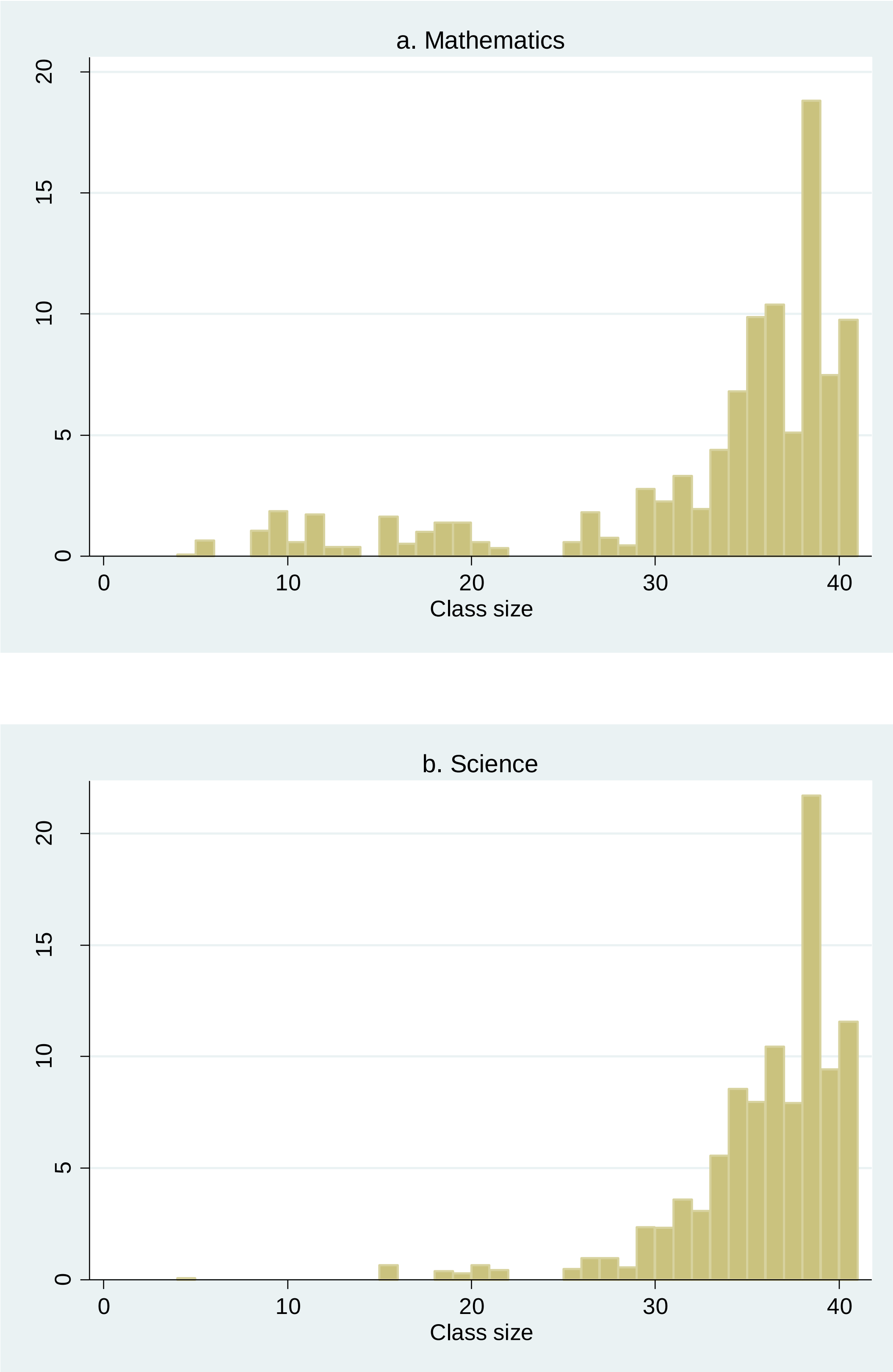
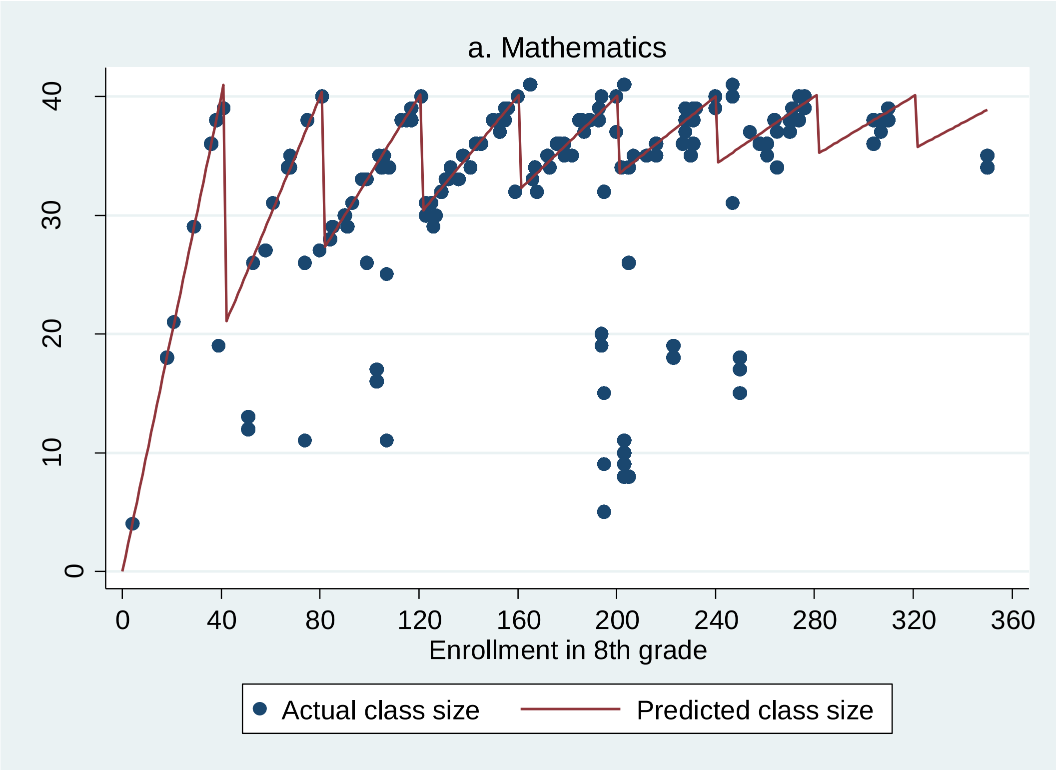


Figure 3 Distribution of actual class size



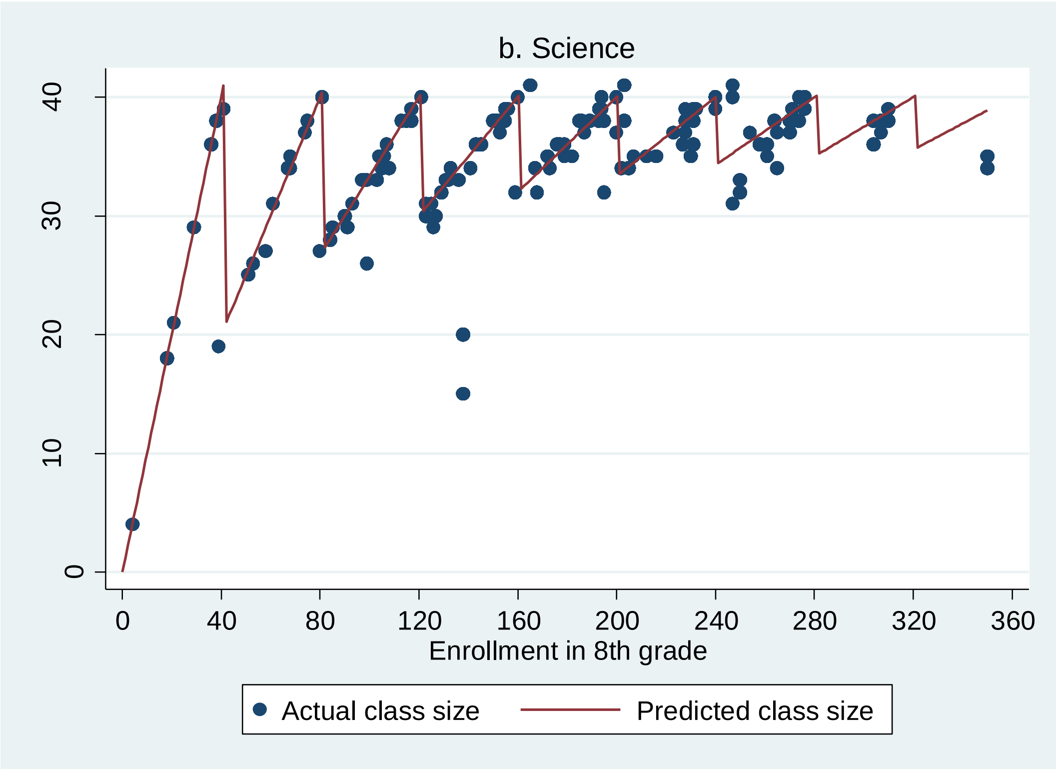
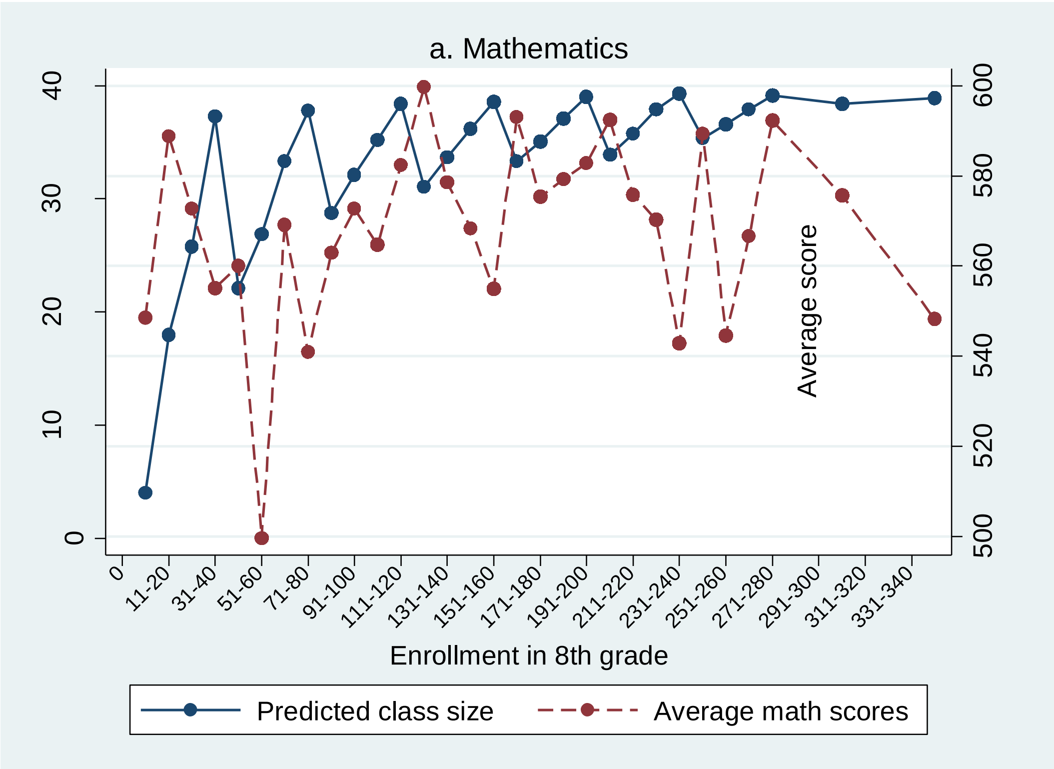


Figure 4 Actual and predicted class size



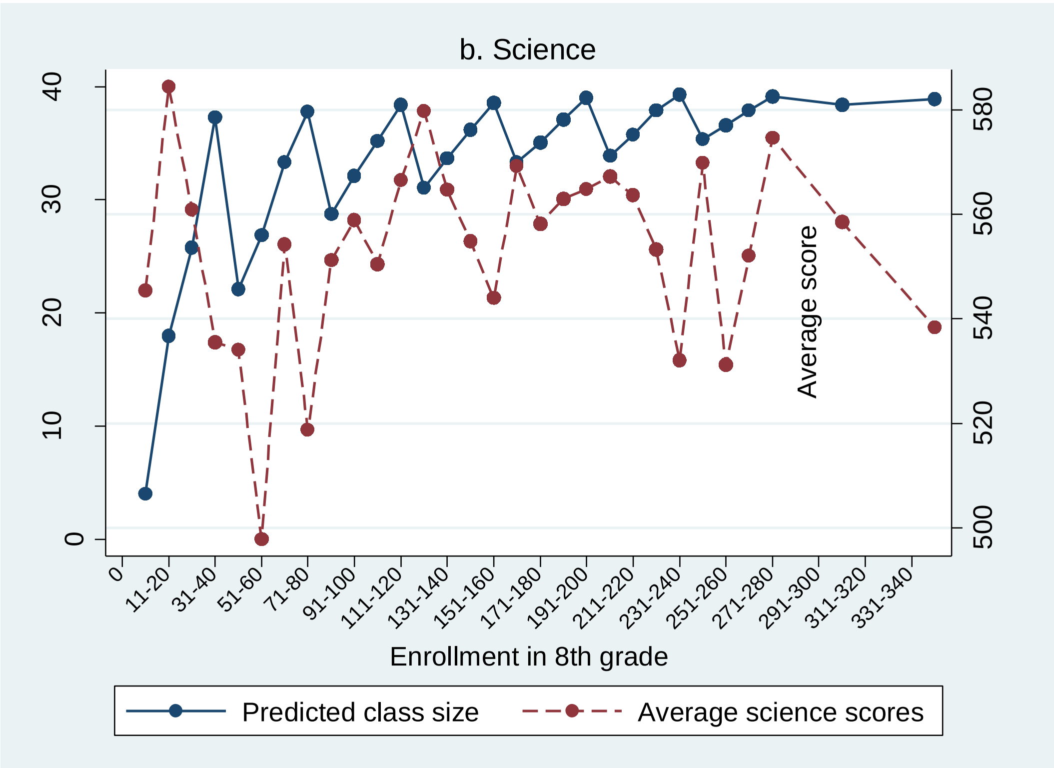


Figure 5 Predicted class size and achievement

Table 1 Summary Statistics

	Mathematics (N=4690)		Science (N=3699)	
	Mean	Std. Dev.	Mean	Std. Dev.
Score	563.76	78.36	548.81	71.09
Class size	33.39	6.92	34.83	4.75
Individual characteristics				
Girl	0.50	0.50	0.50	0.50
Born from April to June	0.25	0.43	0.25	0.44
Born from July to September	0.26	0.44	0.26	0.44
Born from October to December	0.25	0.43	0.25	0.43
Born in January-March	0.24	0.43	0.24	0.43
ln (Number of books at home)	3.74	1.50	3.75	1.50
Computer at home	0.87	0.34	0.87	0.34
Dictionary at home	0.99	0.12	0.98	0.12
Internet connection at home	0.76	0.43	0.76	0.43
Mother's years of education	13.17	1.59	13.17	1.59
Father's years of education	13.44	1.92	13.43	1.93
School characteristics				
ln (Population size in school district)	12.07	1.39	12.07	1.40
PD: 0-10%	0.55	0.50	0.54	0.50
PD: 11-25%	0.35	0.48	0.36	0.48
PD: more than 50%	0.10	0.31	0.11	0.31
Enrollment in 8th grade	158.32	70.11	157.52	70.20
Grouped by ability at instruction	0.32	0.47	0.04	0.19
Teacher characteristics				
Female	0.42	0.49	0.13	0.34
Master's degree	0.06	0.24	0.12	0.32
Years of experience	15.49	9.33	17.14	10.38

Note: Author's calculation from TIMSS 2007. TIMSS-provided sampling weights are used. National and private schools are dropped.

Table 2 OLS estimates: dependent variable=test scores

	Mathematics			Science		
	(1)	(2)	(3)	(4)	(5)	(6)
Class size	0.498 (0.444)	0.185 (0.290)	0.356 (0.288)	0.423 (0.625)	0.024 (0.479)	0.479 (0.403)
Individual characteristics						
Girl		-4.119 (2.354)	-4.284 (2.306)		-3.727 (1.987)	-3.881 (1.928)*
June-September		-0.508 (3.066)	0.040 (3.104)		1.582 (2.978)	2.038 (2.972)
October-December		-4.313 (3.311)	-3.603 (3.204)		-1.775 (3.079)	-0.934 (2.940)
January-March		-11.741 (3.247)**	-10.791 (3.145)**		-8.085 (3.277)*	-6.973 (3.220)*
ln (Number of books at home)		8.552 (0.858)**	8.245 (0.887)**		10.205 (0.801)**	10.033 (0.830)**
Computer at home		7.808 (4.252)	7.038 (4.086)		9.755 (4.136)*	9.361 (3.997)*
Dictionary at home		76.575 (14.571)**	73.955 (15.618)**		76.947 (11.505)**	73.853 (12.023)**
Internet connection at home		14.643 (3.875)**	15.801 (3.959)**		3.514 (3.511)	4.951 (3.453)
Mother's education		3.158 (0.851)**	3.086 (0.845)**		2.752 (0.761)**	2.640 (0.724)**
Father's education		7.771 (0.807)**	7.529 (0.785)**		6.294 (0.747)**	6.233 (0.713)**
School characteristics						
PD: 11-25%			-2.630 (3.943)			-1.380 (3.390)
PD: more than 25%			-22.711 (7.424)**			-21.234 (7.551)**
ln (Population size in school district)			-1.535 (1.287)			-1.986 (1.357)
Grouped by ability			11.067 (3.766)**			30.682 (4.776)**
Teacher characteristics						
Female			8.395 (3.126)**			-3.661 (4.826)
Master's degree			-11.246 (6.678)			1.851 (6.047)
Years of experience			-0.147 (0.183)			0.123 (0.168)
adj.R-squared	0.002	0.168	0.182	0.001	0.168	0.183
N observations	4690	4690	4690	3699	3699	3699
N schools	129	129	129	128	128	128

All estimations use TIMSS-provided sampling weights.

Standard errors are reported in parentheses and are robust to clustering at the school level.

Stars indicate statistical significance as follows: * p<0.05, ** p<0.01.

Table 3 The impact of predicted class size on actual class size

	Mathematics		Science	
	Coef.	(SE)	Coef.	(SE)
Predicted class size	0.449	(0.214)*	0.463	(0.174)**
Enrollment	0.152	(0.086)	0.053	(0.060)
Enrollment squared/100	-0.081	(0.048)	-0.014	(0.030)
Enrollment cubed/10000	0.013	(0.009)	0.001	(0.005)
Individual characteristics				
Girl	0.090	(0.140)	0.004	(0.102)
June-September	-0.509	(0.223)*	-0.233	(0.115)*
October-December	-0.094	(0.228)	-0.114	(0.131)
January-March	-0.412	(0.256)	-0.164	(0.205)
ln (Number of books at home)	-0.131	(0.102)	-0.097	(0.046)*
Computer at home	-1.071	(0.459)*	-0.434	(0.292)
Dictionary at home	1.961	(1.225)	0.235	(0.559)
Internet connection at home	0.576	(0.370)	0.183	(0.209)
Mother's education	0.036	(0.066)	-0.048	(0.043)
Father's education	0.078	(0.063)	0.073	(0.043)
School characteristics				
PD: 11-25%	-1.423	(1.083)	-0.859	(0.615)
PD: more than 25%	0.981	(2.412)	0.500	(1.382)
ln (Population size in school district)	0.220	(0.445)	0.548	(0.237)*
Grouped by ability	-2.293	(1.527)	-1.136	(3.918)
Teacher characteristics				
Female	1.713	(0.798)*	1.631	(0.902)
Master's degree	-1.622	(1.755)	0.870	(0.661)
Years of experience	0.027	(0.045)	0.067	(0.033)*
adj.R-squared	0.247		0.527	
F (Prob > F)	7.87	(0.000)	18.82	(0.000)
N observations	4690		3699	
N schools	129		128	

All estimations use TIMSS-provided sampling weights.
Standard errors are reported in parentheses and are robust to clustering at the school level.
Stars indicate statistical significance as follows: * p<0.05, ** p<0.01.

Table 4 2SLS estimation results of the education production functions

	Mathematics		Science	
	Coef.	(SE)	Coef.	(SE)
Class size (instrumented)	0.848	(1.357)	-0.206	(1.288)
Enrollment	-0.003	(0.462)	0.159	(0.312)
Enrollment squared/100	0.005	(0.246)	-0.072	(0.163)
Enrollment cubed/10000	-0.001	(0.041)	0.011	(0.028)
Individual characteristics				
Girl	-4.325	(2.293)	-3.919	(1.909)*
June-September	0.257	(3.133)	1.907	(2.959)
October-December	-3.628	(3.200)	-1.028	(2.909)
January-March	-10.478	(3.176)**	-6.989	(3.222)*
ln (Number of books at home)	8.339	(0.874)**	9.939	(0.788)**
Computer at home	7.719	(4.413)	9.036	(4.178)*
Dictionary at home	72.871	(15.223)**	73.978	(12.024)**
Internet connection at home	15.176	(4.087)**	5.080	(3.519)
Mother's education	3.019	(0.850)**	2.622	(0.719)**
Father's education	7.466	(0.771)**	6.265	(0.707)**
School characteristics				
PD: 11-25%	-1.913	(4.174)	-2.101	(3.475)
PD: more than 25%	-22.699	(7.819)**	-20.753	(7.923)**
ln (Population size in school district)	-2.122	(1.425)	-1.756	(1.472)
Grouped by ability	12.321	(5.349)*	29.172	(4.472)**
Teacher characteristics				
Female	7.762	(3.665)*	-2.364	(5.032)
Master's degree	-11.071	(7.156)	2.365	(6.149)
Years of experience	-0.166	(0.190)	0.189	(0.206)
adj.R-squared	0.179		0.181	
N observations	4690		3699	
N schools	129		128	

All estimations use TIMSS-provided sampling weights.
Standard errors are reported in parentheses and are robust to clustering at the school level.
Stars indicate statistical significance as follows: * p<0.05, ** p<0.01.

Table 5 Estimated class size effects for sub-groups

	Mathematics			Science		
	Effect	(SE)	N obs.	Effect	(SE)	N obs.
(1) +5/-5 discontinuity sample	2.943	(3.115)	1070	-6.979	(49.412)	811
(2) Not grouped by ability	1.453	(1.143)	2831	-0.243	(1.283)	3554
(3) Girls	1.512	(1.358)	2314	-0.089	(1.094)	1826
(4) Disadvantaged areas	5.643	(8.536)	2197	6.575	(11.107)	1797
(5) Low-educated parents	-0.845	(2.923)	1092	-1.957	(3.507)	847
(6) Threshold=41	-0.381	(1.194)	4690	-0.901	(0.882)	3699

Coefficient estimates of class size using 2SLS are reported.

All estimations use TIMSS-provided sampling weights.

Standard errors are reported in parentheses and are robust to clustering at the school level.

Stars indicate statistical significance as follows: * $p<0.05$, ** $p<0.01$.

Table 6 Potential input substitution: difference in inputs between small and large classes

	Mathematics				Science			
	CS≦25	CS≧38	difference	(S.E)	CS≦29	CS≧38	difference	(S.E)
(1) Instruction minutes (a week)	158.664	154.260	-4.404	(6.755)	150.828	152.155	1.327	(1.470)
(2) Teacher: master's degree	0.044	0.059	0.015	(0.054)	0.109	0.148	0.038	(0.117)
(3) Teacher: female	0.329	0.498	0.169	(0.106)	0.135	0.161	0.026	(0.113)
(4) Teacher: experience (years)	12.473	14.543	2.070	(2.268)	16.563	21.355	4.792	(3.548)
(5) Frequency assign homework	0.145	0.318	0.173	(0.096)*	0.119	0.014	-0.106	(0.113)
(6) Frequency discuss small groups	0.010	0.062	0.051	(0.036)	0.494	0.340	-0.154	(0.203)

Weighted average values and differences are reported.

Large class is defined as one which has 38 students or more, while small class is defined as one which has 25 (Mathematics) or 29 (science) students or less.

Stars indicate statistical significance as follows: * $p<0.10$