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The effects of the calculation class in elementary school on student outcomes

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A B S T R A C T

We examine the impact of introducing a calculation class on the academic outcomes of elementary school students. The calculation class is characterized by instruction using an abacus (*soroban* in Japanese), a traditional calculation tool in Asia, and teaching by abacus instructors. The calculation class was introduced with time lags across schools and birth cohorts, which allows us to exploit the difference-in-differences strategy. Using administrative data from Amagasaki City in Japan, we find that the calculation class increases mathematics and Japanese scores by 0.145 and 0.0874 standard deviations, respectively. To explore possible mechanisms, we investigate the impact of the calculation class on students' non-cognitive skills, academic behaviors at home, and the classroom environment. The results indicate that the calculation class improves non-cognitive skills, such as grit and motivation for studying. Furthermore, we find heterogeneous effects across gender, socioeconomic status (SES), and previous academic scores. Our estimation results show that the calculation class has a larger impact on the mathematics scores of female students, students from low-SES families, and previously low-performing students. Finally, we explore the long-term effects and find that, for female students, the impact tends to persist for one year after the class ends, but after that, the effects fade out.

1. Introduction

Early academic outcomes are vital for later academic achievements and labor market outcomes. Especially, mathematics is important. Many studies have shown that mathematical skills affect later academic achievements, major choices, and thus labor market outcomes (Altonji, 1995; Levine and Zimmerman, 1995; Murnane et al., 1995; Hanushek, 2002; Rose and Betts, 2004; Joensen and Nielsen, 2009; Altonji et al., 2012; Heckman, 2013; Falch et al., 2014; Cortes et al., 2015; Hanushek and Woessmann, 2015; Dougherty et al., 2017; Goodman, 2019; Hemelt and Lenard, 2020; Hirata et al., 2006). However, existing studies have mixed results on what kind of educational interventions are effective in improving children's mathematics skills. They have focused on increasing additional instructional time (Taylor 2014; Cortes et al., 2015; Battistin and Meroni, 2016; Figlio et al., 2018), subject-based curricular acceleration (Hemelt and Lenard, 2020), supplementary education (Lavy, 2015; Bessho et al., 2019), curriculum changes (Cantoni et al., 2017; Alan and Ertac, 2018), and self-learning programs (Sawada et al., 2024).

This paper examines the effects of the calculation class, characterized by instruction using an abacus (*soroban* in Japanese) and teaching by abacus instructors, on the academic performance of elementary school students using an administrative dataset from Amagasaki City in Japan. The calculation class has three unique features. First, it uses an abacus, a supplementary calculation tool (shown in Fig. 1). Studies in neuroscience (Wang et al., 2017; 2019) find that abacus-based mental calculation has positive effects on brain functions and arithmetic test scores. In relation to these papers, we focus on the effects of the calculation class on children's academic outcomes from a wide range of socioeconomic status (SES) and aim to explore the possible mechanisms. Second, the class is taught by specialized abacus instructors. Finally, the calculation class increases the instructional time for mathematics, providing children with additional exposure to math learning.

The key feature of the calculation class introduction is that its timing varied across elementary schools and birth cohorts, even within the same year and municipality. The decision on which schools would

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Fig. 1. Abacus.
Source: Retrieved from https://www.free-materials.com.

introduce calculation classes was made by the local authority, considering regional balance and other factors. This variation allows us to employ the difference-in-differences (DID) estimation strategy. We use an administrative dataset from Amagasaki City in Japan, which contains rich information on individuals' educational outcomes, academic behaviors, and SES.

The results of a regression analysis of the effect of the calculation class on the test scores show that the calculation class increases mathematics and Japanese scores by 0.145 and 0.0874 standard deviations, respectively. To explore the possible mechanisms, we examine the impact of the calculation class on students' non-cognitive skills, academic behaviors at home, and the classroom environment. We find that the calculation class improves non-cognitive skills, such as grit and motivation for studying. Also, we find heterogeneous effects across gender, socioeconomic status (SES), and previous academic scores. Our results indicate that the calculation class has a larger impact on the mathematics scores of female students, students from low-SES families, and previously low-performing children. Finally, we explore the long-term effects and find that, for female students, the impact tends to persist for one year after the class ends, but after that, the effects fade out.

Our study contributes to the literature in three ways. First, we add to the research on interventions in mathematics education in schools. Existing studies suggest that mathematics education does not necessarily improve academic performance and that its impact may vary by gender, SES, or prior academic performance (Joensen and Nielsen, 2016; Hemelt and Lenard, 2020; Cortes et al., 2015; Berggren and Jeppsson, 2021). To investigate heterogeneous effects in detail, we conduct heterogeneity analysis across gender, SES, and previous academic scores.

Second, our study focuses on students in earlier grades, which is a key advantage over existing research. Most studies on mathematics education target high school or university students (Altonji, 1995; Joensen and Nielsen, 2016; Goodman, 2019; McEachin et al., 2020; Berggren and Jeppsson, 2021). However, both theoretical and empirical evidence suggests that improving mathematical skills requires relatively early intervention, as early as elementary school (Cunha and Heckman, 2007; Lai, 2010).[1] It is therefore essential to investigate the impacts of mathematics education on elementary school children.

Third, this study contributes to the literature on the effects of schooling on non-cognitive skills and academic behavior. To explore the mechanisms through which academic outcomes improve, we hypothesize that mathematics education enhances students' non-cognitive skills and academic behavior. Recent studies have found that schooling positively impacts non-cognitive skills and academic behavior (Alan and Ertac, 2018; Alan et al., 2019; Jagannathan et al., 2019; Knaus et al., 2020; Jepsen, 2003), which in turn appears to improve academic performance (Cunha and Heckman, 2007; Jacob, 2002).

The structure of this paper is as follows. Section 2 provides the relevant institutional background. Section 3 describes the dataset. Section 4 outlines hypotheses and empirical strategy. Section 5 presents the main results, heterogeneous effects, and long-term effects. Section 6 explores possible mechanisms. Section 7 concludes.

2. Institutional background

We leveraged a unique situation where the calculation class was introduced with time lags across schools and birth cohorts. While the introduction was not entirely random, we provide evidence in Section 4.2 that the timing of implementation after the initial phase was not systematically related to school or student characteristics, minimizing potential biases. To understand the background of the calculation class introduction, this section explains the Japanese educational system, the Amagasaki Special Zone for Education as an exception, the demographic characteristics of Amagasaki City, and the features of the calculation class.

2.1. Features of the calculation class in Amagasaki city

The Japanese school system consists of six-year elementary schools, three-year junior high schools, three-year senior high schools, and four-year universities. Compulsory education spans nine years, covering elementary and junior high school. Approximately 99 % of elementary schools and 92 % of junior high schools are public (Ministry of Education, Culture, Sports, Science and Technology, 2024). In public schools, the school they attend is determined by their residential address (school district), and changing schools generally requires relocating to a different district.

MEXT sets the National Curriculum Standards as broad standards for all schools in Japan, which outline class content and instructional hours. Local governments implement these standards, leaving little room for deviation. Class sizes and the number of teachers are automatically determined by the *Act on Standards for Class Formation and Fixed Number of School Personnel of Public Compulsory Education Schools*, further limiting local discretion in education policies. The central government decides baselines for all schools, and homogenous education is provided nationwide, which characterizes the Japanese school system. Basically, municipalities have limited freedom or authority to make independent decisions about the educational content and have no discretion over the class hours of each subject in public schools.

As an exception, the Special Zone for Education allows local governments to provide education that is different from the national baseline. Using the Special Zone for Education, Amagasaki City introduced a calculation class.[2] The introduction of the class does not change the total annual instructional hours or violate the Act governing class sizes. Each school was assigned an assistant teacher, and implementation complied with national standards.

Amagasaki City is an urban municipality adjacent to Osaka encompassing industrial, commercial, and residential areas with a population of approximately 460,000 (Statistics Bureau, 2024). In this city, children face a relatively low socioeconomic environment: about 4 % of the population receive welfare in the city, while the national average is about 1.5 %, and about 25 % of households with children receive financial assistance for school costs, while the national average is about 15 %. Academic performance in Amagasaki falls behind the national mean, as observed in the National Assessments of Academic Ability (nationwide standardized test). To address this, the local government

[1] Some studies show that the gender gaps in test scores related to mathematics and sciences emerge by the mid-teenage years, and the gap widens with age (Borgonovi et al. 2021; Speer 2017; Contini et al. 2017).

[2] Prior to the reform, Amagasaki City followed the National Curriculum Standards and the hours of abacus were the same as other municipalities in Japan.

introduced the calculation class. Specifically, they aim to improve students' cognitive and non-cognitive skills.

In the calculation class, students learn to calculate using an abacus, which is a traditional calculation tool used in Asia (Fig. 1). The city decided to start calculation class using the abacus for two reasons. First, Amagasaki City has been facing challenges in schools, such as low academic performance and an increased number of students struggling to focus on classes (Amagasaki City, 2004). Abacus-based calculations require students to carefully listen to teachers reading out numbers and to respond by performing calculations using the abacus. Policymakers expected that this practice would improve students' attitude toward listening to the teacher, as well as their calculation skills and motivation for learning. According to Amagasaki's reform plan, the expected effects of the calculation class include enhancing concentration, memory, listening, and reading skills by listening to the numbers read aloud by the teacher; improving information processing ability, insight, and creativity by learning the concept of quantity; and fostering perseverance through repeated quantitative tasks. It was also expected that improvements in focus and confidence obtained in the calculation class would have spillover effects on other subjects. Second, the abacus has historical roots in Amagasaki City, which flourished as a commercial hub where merchants widely used the abacus for calculation.

There are two features of the calculation class introduction. First, the calculation class was introduced by reducing other subjects' instructional time such as integrated studies or conventional mathematics (mathematics other than calculation class) in order to keep the total instruction time the same. Table A1 in the Appendix provides an example of the curriculum change in an elementary school in a certain year.[3] For instance, third graders had 910 h of total instructional time per year. The curriculum change added 50 h of calculation classes per year, but at the same time, it reduced conventional mathematics from 150 to 135 h (15 h were replaced with calculation) and also reduced the integrated studies from 105 to 70 h (35 h were replaced with calculation).[4] According to the National Curriculum Standards (enforced in 2002), the abacus had already been included in conventional mathematics classes, but its instructional time was minimal. For example, in 2003 (prior to the calculation class introduction), only 3rd graders had abacus instruction. Hours of abacus classes were only about 2 h per year (Keirinkan 2020; Tokyoshoseki 2020a; 2020b). Since the abacus is included in conventional mathematics, establishing the calculation class using the abacus means increasing the proportion of mathematics in the total instructional time. However, the calculation class is different from conventional mathematics instruction in the sense that the class uses the abacus and is taught by abacus instructors.

The second feature is that whether students have experienced calculation classes depends on their school and grade.[5] The calculation class gradually expanded to all elementary schools in the city between 2004 and 2009: one school introduced the calculation class in 2004, followed by 6 schools in 2005, 12 in 2006, 17 in 2007, 23 in 2008 and all 45 elementary schools in 2009. The Amagasaki Board of Education determined which schools and grades would introduce the calculation class each year, considering regional balance and other factors. Section 4.2 confirms that the timing of the calculation class introduction was not driven by school or student characteristics. Importantly, not all students in participating schools received the calculation class because targeted grades are limited. For example, in 2009, 22 schools newly introduced the calculation class, but the target was only third graders. Other graders did not receive the calculation class at this time.

2.2. Contents of calculation class

According to the *Plan for Special Reconstruction Zone* by Amagasaki, calculation classes have two purposes. One is to learn basic knowledge of quantity and calculation methods, and the other is to acquire stable computational skills. The former is similar to the conventional mathematics class, which is relatively passive learning. For example, 4th graders learn how to multiply and divide numbers using an abacus and mental calculation. The latter provides time for children to actively use the abacus and practice calculations repeatedly. For instance, an instructor reads several numbers aloud, and students carefully listen and sum up all the numbers. Fig. A1 displays actual class materials used in the calculation class. Panel A shows a textbook preface that emphasizes that accuracy is more important than speed, students have to verify their calculation results when they complete in time, and the importance of continuous practice to become proficient in abacus use.

Along with the introduction of the calculation class, part-time abacus instructors were assigned to each school. These instructors were teachers from abacus schools, recommended by the Amagasaki City Association for the Promotion of Abacus. The selection criteria for instructors included proficiency in abacus skills, experience teaching the abacus, and an understanding of the school's educational activities. Each abacus instructor was assigned to a specific school, with some instructors responsible for more than one school. In Japanese elementary schools, homeroom teachers typically teach all subjects. However, in calculation classes, both the homeroom teacher and the abacus instructor conduct the class together.[6] They could interact with each other, for example, by holding a meeting before the class. Since the calculation class introduction and the increase in teacher numbers occurred simultaneously for the same target students, we cannot separately identify the effects of these two factors. Similarly, we cannot separately identify the effect of the quality of the abacus instructors and the calculation class because there is no data on instructors.[7] Therefore, we focus on the overall effect of the calculation class, which includes both the impact of additional teachers and the quality of the abacus instructor.

3. Data

We exploit individual-level data collected from the *Amagasaki City Basic Survey on Academic Achievement and Daily Life* (hereafter, student-

[3] This is just an example. We do not have detailed data on how many hours of each subject were reduced in each elementary school each year.

[4] In the integrated studies class, students learn content that they do not study in other academic subjects. Each school has discretion regarding the content of integrated studies. Elementary schools in Amagasaki City provide, for example, international communications (English), welfare (disability experience workshop which aims to provide children with perspectives of disabled people), and food and nutrition education (rice planting experience). Since information on how many hours of integrated studies each school spent on which content before the reform and outcomes of integrated studies are not available, analysis regarding the effects of reduced hours of integrated studies is not possible. We assume that there is no correlation between whether or not a school provided mathematics or abacus instruction during integrated studies class before the reform and whether or not a school introduced the calculation class. If there is a positive correlation, the coefficient of the calculation class could be underestimated. In contrast, if there is a negative correlation, the coefficient of the calculation class could be overestimated. In the case that a school, which is highly motivated about introducing the calculation class provides mathematics or abacus instruction during the integrated studies class, the coefficient of the calculation class is expected to be underestimated.

[5] This means that the calculation class experience is almost exogenous to the students. In Japan, as long as students attend a public school, their place of residence automatically determines which school to attend. If they move to another school district, they can change schools. However, it is unrealistic to move just because of the calculation class.

[6] A single homeroom teacher taught elementary mathematics classes other than calculation classes, as is conventionally done.

[7] In general, data regarding teachers have not been accumulated in Japan. According to the Amagasaki Board of Education, there is no data remaining regarding abacus instructors from 2007 to 2009.

pupil panel data), conducted annually by Amagasaki City every April[8] between 2006 and 2015 except for 2013 and 2014. The survey targets all public elementary and junior high school students in Amagasaki City. The student-pupil panel data consists of academic achievement test scores and survey responses on daily life. Since the targeted grades are different by survey year, the data has an unbalanced panel structure.[9] This study focuses on the 1997 and 1998 cohorts for which academic scores are observable over consecutive periods around 2007 when the calculation class was expanding.

The student-pupil panel data does not include individual identifiers, which are necessary to merge it other administrative datasets. To address this, Amagasaki City first matched the student-pupil panel data with the Basic Resident Register (an individual-level administrative dataset containing individual identifiers), using individual names, grades, and addresses.[10] After matching, the data was hashed and provided to researchers, enabling anonymized individual identifiers to be assigned to the student-pupil panel data. These identifiers allow us to merge the panel data with other administrative datasets.

The other administrative datasets include information on welfare receipt during school enrollment, the number of students and classes in each school, and the information on the calculation class. We merged the student-pupil panel data with these datasets using year and individual identifiers or year, birth cohort, and school IDs as key variables. Each individual has a current elementary or junior high school ID and a past school ID. For instance, a junior high school student has an elementary school ID that he or she previously attended, enabling us to link past school information. A limitation of our dataset is that researchers do not have access to the names or locations of schools.

4. Empirical strategy

4.1. Hypotheses to be tested

The introduction of the calculation class is expected to improve children's outcomes. Our central hypothesis is that the calculation class improves children's academic scores through increased mathematics instructional time and the calculation using an abacus.[11] Existing literature shows that both increased mathematics instructional time and calculation using an abacus have a positive effect on students' academic outcomes. Taylor (2014) finds that increased mathematics instruction in middle schools raises students' mathematics scores. Cortes et al. (2015) find positive impacts of increased mathematics instructional time on low-skilled ninth graders' academic achievements. Wang et al. (2019) find that abacus-based mental calculation training has positive effects on mathematics scores and the function of visuospatial working memory from the perspective of neuroscience. In Wang et al. (2019), the settings are similar to ours: their targets are elementary school children, and the treatment group received 2 h of training per week for five school years. For the abacus, abacus-type mental calculation, in which an imaginary abacus is temporarily memorized and manipulated, has been shown to enhance executive function, a set of cognitive skills involved in self-regulatory behavior, and spatial visual working memory function (Wang et al., 2017; 2019).

The hypothesis to discuss the mechanism is that the calculation class improves children's non-cognitive skills, academic behaviors, and the classroom environment (Alan and Ertac, 2018; Angrist and Lavy, 2009). If the calculation class develops non-cognitive skills, enhanced non-cognitive skills can raise scores in other subjects (Cunha and Heckman, 2007). For example, Bessho et al. (2019) show that remedial education has a positive impact on whether an elementary school child perceives that studying is important. Another potential path is student behavior at home, such as doing homework. For instance, Lavy (2020) finds that added instructional time in school improves children's academic scores and concludes that the additional time spent on homework is likely a mechanism. The other possible mechanism is the improved classroom environment. Rivkin and Schiman (2015) show that instruction time increases academic achievement and the increase varies by classroom environment. Since calculation using an abacus requires children to concentrate on what their teachers say, it is less likely that they behave disruptively; the classroom environment possibly improves.

4.2. Empirical strategy

Our identification strategy relies on time lags in the calculation class implemented in public elementary schools in Amagasaki City. As mentioned in Section 2.1, the calculation class gradually expanded to all elementary schools in the city between 2004 and 2009. All schools in the city happen to be divided into six groups depending on the calculation class-conducted-year. The school groups were determined based on regional balance and other factors by the Amagasaki Board of Education. Table A2 shows treatment status by school group and cohort. Panels A and B present that for cohorts 1997 and 1998, all students in school groups 1, 2, and 3 were already treated in 2007. We did not use these observations in the estimation because we are interested in the comparison between the treated group and never treated group.[12] In 2007, school group 4 turned out to be treated. They are treated groups in our estimation. School groups 5 and 6 are never treated and they are the control group. Our main estimation sample consists of treated and control groups of cohorts 1997 and 1998.[13] Fig. 2 illustrates the timeline for these cohorts. Before is the outcome of 2006 and after is the outcome of 2007. Regarding treatment intensity, both cohorts had the same hours of calculation class (50 h per year) as shown in brackets in Table A2. When the calculation class was introduced, cohort 1997 was in 4th grade, and cohort 1998 was in 3rd grade. Since these cohorts were in the same school group and had the same treatment intensity, we can identify differences due to grades.

We separately conduct the estimation for cohort 1999, because the treated school group and treatment intensity is different from those of cohorts 1997 and 1998. For cohort 1999, not group 4 but group 5 is the treated group and only group 6 is the control group. As for the treatment intensity, cohort 1999 experienced 30 h of calculation class, which is 20 h less than cohort 1997 and 1998, as shown in brackets in Table A2. Table 1 shows the number of schools and students by treatment status in our estimation sample.

Since we have multiple time periods, one may suggest using staggered DID, but we decided not to use it. We use simple 2 $\times$ 2 DID (1 treatment group, 1 control group, 1 before period, and 1 after period).

[8] April is the start of the academic year in Japan.

[9] The purpose of the survey is not to evaluate the calculation class but to observe the student's academic performance. Therefore, which grades would be included in the survey was decided independently of the introduction of the calculation class.

[10] Since individual identifier was assigned based on a student's address and other information, we cannot identify students who changed their address and moved to other school districts as the same individuals. If students moved to other school districts, each of them would be assigned a new individual identifier.

[11] As shown in Table A1, conventional mathematics instruction was reduced by 15 hours per year, which was more than abacus hours prior to the reform (about 2 hours per year), and calculation class was increased by 50 hours.

[12] For cohort 1997, school groups 1, 2, and 3 are already treated groups. If we include these groups as control groups, we are to compare the effect of introducing 50 hours of calculation class and an additional 50 hours of calculation class, which is hard to interpret. Table A2 shows that for groups 1 and 2, their accumulated calculation class hours changed from 60 hours to 110 hours, and for group 3, accumulated calculation class hours changed from 50 hours to 100 hours.

[13] Even in 2009, there was a control group that did not receive calculation classes because the classes were introduced to not all grades but limited grades.

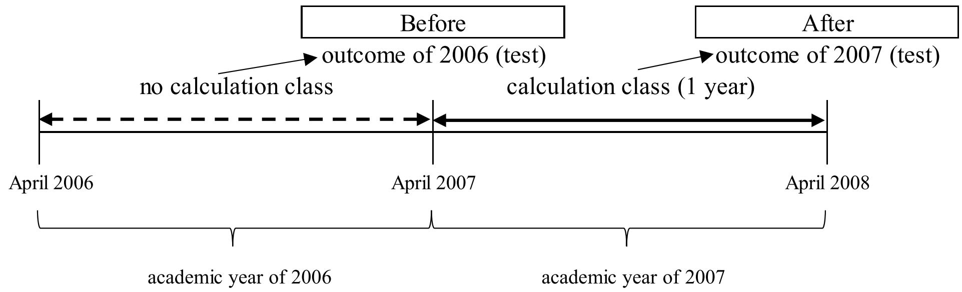

Fig. 2. Before and after period for main estimation.
Notes. The dashed arrow indicates that children did not have calculation classes in that period. The solid arrow shows that children experienced calculation class during the period. The calculation class was introduced in April 2007, and the academic test was conducted in April 2008. For cohort 1997, calculation class was introduced when they were in grade 4. For cohort 1998, calculation class was introduced when they were in grade 3.

Table 1
Number of schools and unique observations by treatment status.

	Number of schools	Number of students
Treatment Group	5	520
Control Group	28	4472

Notes. The treatment group had a calculation class since April 2007. The control group never had a calculation class.

The first reason for not using staggered DID is that the treatment intensity is different depending on the cohort. For cohorts 1997 and 1998, treatment is 50 h of calculation classes, but for cohort 1999, treatment is 30 h of calculation classes. Second, targeted schools are different depending on the cohort. For cohorts 1997 and 1998, the treated group is school group 4, but for cohort 1999, the treated group is school group 5. Considering the heterogeneous effect of calculation classes on different samples, we do not combine these two effects using a staggered DID strategy. We restricted our main analysis sample to cohorts born in the academic year 1997 and 1998 in order to use the 2×2 DID strategy. These cohorts can be followed as panel data and treatment intensity is the same between cohorts 1997 and 1998: The hours for the calculation class changed from 0 to 50 h for both cohorts. Moreover, the treated school groups are the same for these cohorts.

We apply 2×2 DID to identify the effect of the calculation class on student outcomes. Our main specification for the effect of the calculation class is given by

$$Y_{ijct} = \beta Calculation_{jct-1} + Controls_{ct-1} + \lambda_t + \alpha_i + u_{ijct} \tag{1}$$

where i denotes an individual, j denotes an elementary school, c denotes a cohort, t denotes academic year, Y_{ijct} is the outcome of interest, *Calculation* is a dummy variable that equals 1 if cohort c in school j has calculation classes at the time of t and 0 otherwise. We matched school-level data of the corresponding year. *Controls* is a vector of observables for student i in school j that includes grade dummy (we explain this in Section 4.3 in detail). We control for time fixed effects λ_t and individual-level fixed effects α_i. Our estimation strategy is a fixed-effect model, and the robust standard error is clustered at the school level. As the robustness checks, we use accumulated hours of calculation classes as a treatment variable that is an individual i in cohort c experienced until year t at school j.

Since we employ the DID strategy, it is essential to verify whether the parallel trend assumption is satisfied. A common approach is to conduct an event study using pre-treatment data, assuming that counterfactual trends would remain the same after treatment because they were similar before treatment. However, since data from the pre-treatment period (i. e., data before 2004) is unavailable, we cannot apply this method. Instead, we show that the introduction of the calculation class is not driven by school or student characteristics. As Cunningham (2021) notes, "One situation where parallel trends would be obviously violated is if the treatment itself was endogenous." As a basic check, we examine whether schools with distinctive features, such as higher average math scores, introduced the calculation class earlier (or later). The results show no such trend, suggesting that the timing of the calculation class introduction does not depend on school or individual characteristics.[14]

Using school-level data, Table 2, Panel A, column 1 presents the effect of school characteristics observed one year before on the likelihood of at least one grade in that school introducing a calculation class between 2005 and 2008 using OLS.[15] The results show that the introduction of the calculation class is unrelated to school characteristics, such as average mathematics scores, female ratio, average class size and the percentage of students receiving public assistance. In Panel A, column 2, a fixed-effects model is used. While the strongest predictor of introducing a calculation class is the average class size, the effect is modest: an increase of one student in the average class size reduces the probability of introducing a calculation class by 3 percentage points. In Panel B, individual-level data is used to analyze the effect of individual and school characteristics observed one year earlier on the likelihood of having a calculation class. Since individual characteristics include time-invariant variables, OLS is used instead of a fixed-effects model. Similar to Panel A, the strongest predictor is the average class size from the previous year, but the effect is small: 1 increase in the average class size decreases the probability of introducing a calculation class by 1.29 percentage points. Overall, the results suggest that whether a child has experienced calculation class or not is unrelated to school or individual characteristics. In both panels A and B, the coefficient of the average class size tends to be statistically significant, but its effect size is modest. One possible reason for its statistical significance is that the average class size decreases over time, while the number of schools that have calculation classes increases.

4.3. Student's outcomes and characteristics

Our main dependent variables are scores on the academic achievement test. All students take Japanese and mathematics tests and only fifth and sixth graders have science and social sciences tests. We use mathematics and Japanese scores in the analysis as indicators of academic achievement. We standardized the scores with a mean of 0 and a

[14] We have heard from Amagasaki City that the initially introduced school (first wave) was special, which was highly motivated to introduce the calculation class, but after that, there were no such selections. Our main analysis focuses on the fourth wave, which is less likely to be highly motivated.

[15] The introduction of the calculation class began in 2004 and was implemented in all public elementary schools in the city by 2009. Since the data is available from 2006, elementary schools that introduced the calculation class in 2004 and 2005 are not included in this estimation.

Table 2
Effect of school and individual characteristics on calculation class introduction.

Panel A Dependent variable:Have calculation class at school level			Panel B Dependent variable:Have calculation class at individual level	
	(1) OLS	(2) Fixed Effect		(1) OLS
Average Math Score	0.109	−0.195	Math Score (last year)	−0.0119
	(0.313)	(0.212)		(0.0108)
Female Ratio (%)	0.652	0.301	Female	0.00937
	(1.064)	(0.771)		(0.0105)
Average Class Size	−0.0196	−0.0300***	Average Class Size (last year)	−0.0129*
	(0.0141)	(0.0101)		(0.00690)
Receive Public Assistance (%)	−1.964	1.019	Receive Public Assistance	0.0225
	(2.209)	(1.467)		(0.0202)
Average Relative Age	0.267**	0.0736	Relative Age	0.00340*
	(0.126)	(0.104)		(0.00167)
Constant	−0.769	0.617	Constant	0.496*
	(0.735)	(0.636)		(0.251)
Observations	126	168	Observations	4992
R-squared	0.061	0.086	R-squared	0.028
F-statistics	2.335	2.141	F-statistics	1.146
Number of schools	42	42	Number of students	4992

Notes. In Panel A, the dependent variable is whether an elementary school had a calculation class for at least one grade in a given year. The data used is from the years 2005 to 2008, during which the calculation class was expanding in Amagasaki City. Column 1 employs OLS using explanatory variables from one year before the dependent variable was observed. Column 2 applies a fixed-effects model. Panel B uses OLS at the individual level with data from the 1997 and 1998 cohorts for the years 2006 and 2007. Standard errors are clustered at the school level.

standard deviation of 1 within the grade and year. We limit the observations to students whose both mathematics and Japanese scores are observed in order to compare the results on mathematics and Japanese using the same observations.

As for students' characteristics, we have information on students' gender, relative age, and experience of receiving public assistance. Since these variables are time-invariant, they are controlled for as a child's fixed effect.

Table 3 presents the descriptive statistics of the sample we use in the main analysis. In our sample, about 12 % of the sample is classified into a treatment group. The male-female ratio is about 1. About four percent of the sample have received public assistance. As for non-cognitive skills, academic behaviors, and classroom environment, we provide a detailed explanation in Section 6.

5. The effect of calculation class on academic scores

5.1. Main results

Table 4 reports the impacts of the calculation class on academic scores. Panel A presents results for cohort 1997 and 1998 combined. These cohorts are in the same school group and thus have the same school-level characteristics, such as average SES. Also, treatment intensity is the same for these cohorts; they experienced 50 h of calculation class. The first two columns show estimated impacts on mathematics and Japanese scores for all samples. The estimates in columns 1 and 2 in Panel A are positive and significant, suggesting that the calculation class increases mathematics and Japanese scores by 0.145 and 0.0874 of a standard deviation, respectively. Columns 3 to 6 report the heterogeneous effect across gender. Columns 3 and 4 in Panel A present the coefficients of the calculation class on female students' mathematics and Japanese scores, which are positive and statistically significant. For female students, introducing calculation class increases mathematics and Japanese scores by 0.194 and 0.111 of a standard deviation, respectively. Columns 5 and 6 show the coefficient of the calculation class on male students' mathematics and Japanese scores, which are 0.0882 and 0.0622, respectively. They are positive but not significant. Comparing the size of the coefficients in columns 3 and 5 in Panel A, the difference between females (0.194) and males (0.0882) is statistically significant at a 10 % significance level, with a p-value of 0.0924. As for the effect on Japanese scores, there is no statistical difference between males and females.[16]

When the calculation class was introduced, cohorts 1997 and 1998 were in different grades, so we separated the sample by cohort. Panel B presents results for cohort 1997. For this cohort, the calculation class was introduced when they were 4th graders.

Panel C presents results for cohort 1998, who were 3rd graders when the calculation class was introduced. For this cohort, calculation class improves only mathematics scores, which is driven by the effect on females. Comparing Panels B and C, introducing the calculation class is more effective for older children when the SES and intensity are the same.

In order to discuss which aspects of the production function the treatment can address, we divide the treatment effect into the following four parts: (1) mathematics instruction, (2) alternative method (abacus), (3) additional teaching support (abacus instructor), and (4) removal of other subjects. Although we cannot clearly distinguish the effect of these four parts, we discuss which part is likely to generate a positive effect.

First, mathematics instruction is composed of conventional math instruction and abacus-based math instruction (calculation class). Due to the reform, the hours of conventional math instruction were decreased by 15 h, while math instruction using an abacus was increased by 50 h as shown in Table A1. Therefore, it is likely that the effect derives from math instruction using abacus rather than conventional math instruction.

Second, as for the alternative method, we disaggregate the scores by evaluation points and find that points related to the alternative method (abacus) are improved. Table A3 shows that the calculation class improves children's "Interest, motivation, and attitude" and "Mathematical thinking," and has no effect on other points which are related to diagrams.

Third, additional teaching support could affect children's scores. Especially, for girls, female teachers could have a positive effect on

[16] We disaggregate the scores by evaluation points, which are determined by the MEXT. Table A3 shows that the calculation class improves children's "Interest, motivation, and attitude" in both mathematics and Japanese scores. Additionally, "Mathematical thinking" in mathematics scores was also improved.

Table 3
Descriptive statistics.

	Control Group				Treatment Group			
	Before		After		Before		After	
	mean	sd	mean	sd	mean	sd	mean	sd
Experienced Calculation Class	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
Academic Scores								
Math Score	0.03	0.99	0.01	1.00	−0.12	0.99	0.01	0.99
Japanese Score	0.03	1.00	0.02	0.99	−0.06	0.93	0.02	0.96
Non-cognitive Skills								
Grit	0.03	0.98	0.00	0.99	−0.08	1.07	0.02	0.99
Like Myself	−0.00	0.99	0.00	1.00	−0.02	0.99	−0.02	1.02
Study for Grades	0.03	0.96	0.01	0.99	−0.10	1.10	0.01	1.02
Study for Job	0.02	0.98	−0.00	1.00	−0.10	1.12	0.04	0.99
Study for Teacher	0.02	0.98	−0.01	1.00	−0.11	1.07	0.04	1.03
Academic Behavior at Home								
Study Hours	0.03	1.01	0.03	1.02	−0.07	0.95	0.07	1.00
Do Homework	0.02	0.99	0.01	1.00	−0.02	0.98	0.04	0.96
Study Disliked Subject	0.04	0.97	0.01	0.99	−0.05	1.03	0.04	0.95
Study in Detail	−0.00	0.99	0.02	0.99	−0.03	1.03	−0.06	1.02
Classroom Environment								
Listen to Teacher	0.02	0.99	0.03	0.99	−0.16	1.05	−0.17	1.03
Quiet in Class	0.02	1.00	0.02	0.99	−0.02	0.95	−0.07	0.99
Individual Characteristics								
Female	0.50	0.50	0.50	0.50	0.52	0.50	0.52	0.50
Receive Public Assistance	0.04	0.19	0.04	0.19	0.05	0.22	0.05	0.22
Grade 3	0.51	0.50	0.00	0.00	0.53	0.50	0.00	0.00
Grade 4	0.49	0.50	0.51	0.50	0.47	0.50	0.53	0.50
Grade 5	0.00	0.00	0.49	0.50	0.00	0.00	0.47	0.50
Year								
2007	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
2008	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00
Observations	4472		4472		520		520	

Notes. About 10 % of the sample is classified into a treatment group. We standardized the academic scores, non-cognitive skills, academic behaviors (except for study hours), and classroom environment with mean 0 and standard deviation of 1 within grade and year.

scores (Lim and Meer, 2020).[17]

Last, we discuss the impacts of reducing the amount of time spent on other subjects. The hours for integrated studies were reduced the most. This class included international communications (English), welfare (disability experience workshop which aims to provide children with perspectives of disabled people), and food and nutrition education (rice planting experience), for example. We cannot observe the outcome of integrated studies since the integrated studies are not included in the academic test. Our main results show the total effect of reducing the hours of other subjects (integrated studies and conventional mathematics) and increasing the hours of mathematics using an abacus.

Our main results add to the literature on the impact of increased mathematics instruction time in school. Taylor (2014) finds that increased mathematics instruction in middle schools raises 0.16–0.18 standard deviations of mathematics scores, which is similar to the results shown in Table 4. Some papers find effects, especially on females. McEachin et al. (2020) find that enrolling in 8th-grade algebra raises 10th-grade female mathematics scores by 0.06 standard deviations. Cortes et al. (2015) report intensive mathematics instruction raises ninth-grade low-skilled female students' probability of passing mathematics courses. As for Japanese cases, Bessho et al. (2019) find that remedial classes do not affect third and fourth-graders mathematics scores. Compared to other educational interventions, such as class size reduction, calculation class has a substantial effect. Hojo and Senoh (2019) find that reducing the class size by 10 students increases the 0.18 standard deviation in the correct answer rate in mathematics for ninth graders. Ito et al. (2020) find effects of a 10-student reduction range between 0.01 and 0.07 standard deviations for four to nine graders. Compared to this literature, we obtained a substantial and significant effect, especially on female students' mathematics scores.

When we shed light on the literature on abacus-based education, existing studies find that abacus classes positively affect scores, but there is no significant difference between genders. Wang et al. (2019) find that abacus-based mental calculation increases elementary school children's arithmetic test scores without a significant difference. Wang et al. (2017) present that abacus-based mental calculation training increases fourth and sixth-graders mathematics scores, but again, no significant difference between gender is observed. Since this literature has quite limited sample sizes (<100 for both studies), a significant difference may not be observed.

Table A4 reports the impact of the calculation class on academic scores of students born in 1999. Overall, the coefficients are insignificant for mathematics scores, which means the results are different from the main estimation. Possible reasons are that the characteristics of treated and control groups differ from the samples in the main estimation in three points. First, the treated school group (group 5) has higher SES than those in the main estimation. Table A5 shows that only 3 % of students in school group 5 have received public assistance, while 5 % of students in school group 4 (treated group of cohorts 1997 and 1998) have received public assistance. Second, the hours of calculation classes they had were less than cohorts 1997 and 1998. Table A2 shows that the treated group of cohorts 1997 and 1998 have 50 h of calculation class per year, but those of cohort 1999 only receive 30 h a year. Less treated hours for cohort 1999 could lead to an insignificant effect of the calculation class on mathematics scores. Third, children were relatively young when calculation class was introduced. As Table 4 shows, the effect for younger graders tends to be smaller and insignificant.

When we replace the dummy indicating calculation class with a continuous variable indicating accumulated calculation class hours, the main results do not change. Table A6 reports the impacts of 100 h of increase in calculation class hours on scores, using the continuous

[17] Since we do not have any information on classroom teachers and abacus instructors when the calculation class was introduced, this issue is left for future research.

Table 4
Effect of the calculation class on scores.

	All		Female		Male	
	(1) Math	(2) Japanese	(3) Math	(4) Japanese	(5) Math	(6) Japanese
Panel A:Cohort 1997 & 1998						
Experienced Calculation Class	0.145**	0.0874***	0.194***	0.111***	0.0882	0.0622
	(0.0549)	(0.0290)	(0.0594)	(0.0289)	(0.0701)	(0.0706)
Observations	9984	9984	4982	4982	5002	5002
R-squared	0.004	0.002	0.009	0.004	0.004	0.002
Number of personid	4992	4992	2491	2491	2501	2501
Panel B: Cohort 1997 (introduced when Grade 4)						
Experienced Calculation Class	0.186**	0.119**	0.181**	0.146**	0.191**	0.0909
	(0.0753)	(0.0499)	(0.0793)	(0.0565)	(0.0755)	(0.0649)
Observations	4900	4900	2462	2462	2438	2438
R-squared	0.007	0.003	0.007	0.006	0.007	0.004
Number of personid	2450	2450	1231	1231	1219	1219
Panel C: Cohort 1998 (introduced when Grade 3)						
Experienced Calculation Class	0.109*	0.0596	0.205**	0.0838	−0.0142	0.0338
	(0.0641)	(0.0406)	(0.0804)	(0.0579)	(0.0731)	(0.0906)
Observations	5084	5084	2520	2520	2564	2564
R-squared	0.002	0.001	0.010	0.003	0.004	0.000
Number of personid	2542	2542	1260	1260	1282	1282

Notes. Dependent variables are standardized to have a mean zero and a standard deviation of one within grade and year. The explanatory variable is a dummy indicating whether or not an individual has experienced calculation classes. In columns 3 and 4, we limit the observations to female students, and in columns 5 and 6, we limit the observations to male students. In Panels A and C, the coefficients of mathematics scores between the female and male groups are statistically different at a 10 % and 5 % significance level, respectively. The symbols ***, **, and * indicate that the coefficients are statistically significant at the 1, 5, and 10 % levels, respectively. Standard errors are allowed for clustering at the school level.

variable. The size of the coefficients of the continuous variable is twice as large as that of the dummy variable in Table 4. This is because, in the main results when the dummy equals one, it corresponds to 50 h of increase in calculation class hours. Since this relationship between dummy and hours always holds, we will not show the coefficients of calculation class hours in subsequent sections.

5.2. Heterogeneous effects

We investigate heterogeneous impacts based on children's socioeconomic status and previous academic scores. Existing research shows that math-related educational interventions are the most effective for low-SES students or low-performing students (McEachin et al. 2020; Cortes et al. 2015; Hojo and Senoh 2019). To check whether heterogeneous effects exist across SES and previous academic scores, we divide the sample by SES and by scores before the treatment.

5.2.1. Socioeconomic status

As a proxy for SES, we use the number of books at home,[18] which is a predictor of parental educational attainment in Japan (Kawaguchi 2016). We obtained the variable from the questionnaire, specifically in response to the question "Approximately how many books do you have at home (not including magazines, newspapers, and textbooks)." Students select one from the following options: 1 (0–50 books), 2 (51–100 books), 3 (101–300 books), and 4 (>300 books). Since about half of the sample chose 1, we define students with 51 books or more as students from high-SES families.

Table 5 reports the estimates for mathematics and Japanese scores across SES. Panel A shows the results for children from low SES families and Panel B displays the results for children from high SES. Columns 1 and 2 report estimates based on the full sample. Columns 3 to 6 divide the sample by gender. The table indicates that the coefficients on mathematics scores tend to be significant and larger for children from low SES backgrounds. In particular, column 3 reports that the calculation class has a large impact (0.29 standardized scores) on low-SES females' mathematics scores and column 5 shows the effect is 0.185 for low-SES males.

5.2.2. Previous scores

Hereafter, we split the sample into groups by academic scores one year before the treatment: mathematics and Japanese scores in 2007. We define a student's performance as low when his or her corresponding subject's standardized scores in 2007 are below the median. Table 6 reports the effects of calculation class on academic scores across previous scores. Panel A shows the results for previously low-performed children and Panel B presents the results for previously high-achieved children. Columns 1 and 2 report estimates based on the full sample. Columns 3 to 6 split the sample by gender. The table indicates that for the previously low-performed group, the effect of calculation class on mathematics scores is driven by females, and for the high-performed group, the effect is driven by males. The impact is largest (0.217 standardized scores) for low-performed females.

Our results are consistent with results from existing literature. Cortes et al. (2015) examine the impact of intensive mathematics instruction on low-skilled students and find that the impact was largest for students with below-average reading skills because their intensive mathematics instruction focuses on the verbal exposition of mathematical concepts. As in their study, the content of abacus classes may be relevant to our results. Generally, the abacus class starts with very basic calculations, such as adding a digit. This may allow low-performing students to review what they should have learned in the previous grades.

5.3. Long-term effect

In this section, we explore whether the effects fade out over time using data when children become older. At most, data includes information when they were junior high school students. The observations

[18] Although we have information on whether or not a student has received public assistance, only 4% of the sample has ever received welfare, and we would not have sufficient observations for them. Still, we check the number of books at home and having received public assistance have the same tendency: those who have received public assistance tend to have fewer books.

Table 5
Heterogeneous effects on scores across SES.

	All		Female		Male	
	(1) Math	(2) Japanese	(3) Math	(4) Japanese	(5) Math	(6) Japanese
Panel A: Low SES						
Experienced Calculation Class	0.240***	0.0855*	0.290***	0.0758*	0.185*	0.0941
	(0.0650)	(0.0430)	(0.0809)	(0.0379)	(0.0937)	(0.0881)
Observations	5160	5160	2714	2714	2446	2446
R-squared	0.011	0.002	0.017	0.001	0.011	0.003
Number of personid	2580	2580	1357	1357	1223	1223
Panel B: High SES						
Experienced Calculation Class	0.0260	0.0792***	0.0599	0.137***	−0.0167	0.0277
	(0.0521)	(0.0257)	(0.0506)	(0.0391)	(0.0678)	(0.0692)
Observations	4712	4712	2220	2220	2492	2492
R-squared	0.002	0.002	0.002	0.009	0.003	0.006
Number of personid	2356	2356	1110	1110	1246	1246

Notes. Dependent variables are standardized to have a mean zero and a standard deviation of one within grade and year. The focal variable is a dummy indicating whether or not an individual has experienced calculation classes. In Panel A, we limit the observations to students from low SES backgrounds, and in Panel B, we limit the observations to students from high SES backgrounds. Students with low SES have 0 to 50 books at home and those with high SES have 51 or more books at home. The symbols ***, **, and * indicate that the coefficients are statistically significant at the 1, 5, and 10 % levels, respectively. Standard errors are allowed for clustering at the school level.

Table 6
Heterogeneous effects on scores across previous scores.

	All		Female		Male	
	(1) Math	(2) Japanese	(3) Math	(4) Japanese	(5) Math	(6) Japanese
Panel A: Low Pre-Score						
Experienced Calculation Class	0.147**	0.0339	0.214***	0.0490	0.0541	0.0180
	(0.0698)	(0.0441)	(0.0467)	(0.0573)	(0.117)	(0.0921)
Observations	5038	5002	2548	2058	2490	2944
R-squared	0.039	0.048	0.068	0.071	0.022	0.035
Number of personid	2519	2501	1274	1029	1245	1472
Panel B: High Pre-Score						
Experienced Calculation Class	0.0938*	0.116***	0.0762	0.123**	0.110**	0.103*
	(0.0461)	(0.0409)	(0.0523)	(0.0511)	(0.0487)	(0.0520)
Observations	4946	4982	2434	2924	2512	2058
R-squared	0.089	0.109	0.092	0.120	0.087	0.098
Number of personid	2473	2491	1217	1462	1256	1029

Notes. Dependent variables are standardized to have a mean zero and a standard deviation of one within grade and year. The focal variable is a dummy indicating whether or not an individual has experienced calculation classes. In Panel A, we limit the observations to low-performing children in a previous year, and in Panel B, we limit the observations to high-performing children in a previous year. The low-performing children are those who scored below the median in the test of the corresponding subject. The symbols ***, **, and * indicate that the coefficients are statistically significant at the 1, 5, and 10 % levels, respectively. Standard errors are allowed for clustering at the school level.

used here are different from those of the main estimation. When we examine the long-term effect, we have to compare the effect when children are in elementary schools and in junior high schools. When children became junior high school students, about 15–20 % of them dropped from our data mainly because they entered private junior high schools while we can only observe students in public schools. Since relatively high-performing children tend to go to private schools, observations for elementary schools and junior high schools will be different and not comparable. Thus, we limit the observations to the students who went to public junior high schools in order to make the observations comparable.[19]

Once the calculation class was introduced, children continued to experience the class for 2 or 3 consecutive years. As shown in Fig. 3, the duration is different depending on cohorts: for cohort 1997, the calculation class was introduced when they were 4th graders, the class was continued when they were in grade 5, and no calculation class was conducted in grade 6. Cohort 1997 experienced 50 h of calculation class per year, 100 h in total. For cohort 1998, the calculation class was introduced when they were 3rd graders, the class was continued when they were in grades 4 and 5, and no calculation class in grade 6. Cohort 1998 experienced 50 h of calculation per year, 150 h in total. Since grades when they experienced calculation class, duration of calculation class, and total experienced hours, are different between cohorts, we separate the observations by cohort.

To estimate the long-run effect of the calculation class on academic outcomes, we estimate the following equation separately for each cohort.

$$\textbf{Cohort } 1997: \; Y_{ijkt} = \sum_{k \in K_{1997}} \beta_k \left(Calculation_{jg=4,\ t=2007} \times ElapsedYears_k \right) + \sum_{k \in K_{1997}} ElapsedYears_k + \alpha_i + u_{ijkt}. \tag{2}$$

[19] We have checked that the results are almost the same when we do not limit the sample.

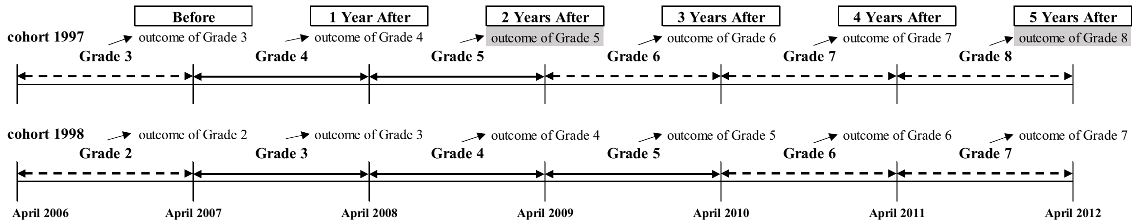

Fig. 3. Timeline of the Calculation Class.
Notes. Dashed arrows indicate that children did not have calculation classes in that grade. Solid arrows show that children experienced calculation class during the grade. The outcomes highlighted in gray indicate that they were not observed.

$$\textbf{Cohort 1998}: \; Y_{ijkt} = \sum_{k \in K_{1998}} \beta_k \left(Calculation_{jg=3,\ t=2007} \times ElapsedYears_k \right) + \sum_{k \in K_{1998}} ElapsedYears_k + \alpha_i + u_{ijkt}. \tag{3}$$

where i denotes an individual, j denotes an elementary school, k denotes the number of years since the introduction of the calculation class, t denotes an academic year, and g denotes a grade. Y represents standardized mathematics and Japanese scores. K is the set of observable years since the introduction of the calculation class, specifically, $K_{1997} = \{1, 3, 4\}$ for cohort 1997 and $K_{1998} = \{1, 2, 3, 4, 5\}$ for cohort 1998. The long-term effect is captured by the coefficient β_k of the interaction term between $Calculation_{jgt}$ and $ElapsedYears_k$. $Calculation_{jgt}$ is a dummy variable that equals 1 if grade g in school j in academic year t has the calculation class and 0 otherwise. $ElapsedYears_k$ is a dummy variable indicating the number of years since the calculation class was introduced.[20] Specifically, for cohort 1997, β_k captures the effect of 1, 3, and 4 years after the introduction of the calculation class at grade 4 ($g = 4$). For cohort 1998, β_k captures the effect of 1 to 5 years after the introduction of the calculation class at grade 3 ($g = 3$). α_i is an individual fixed effect and u_{ijkt} is the error term.

Fig. 4 Panel A shows the long-term effect of the calculation class for cohort 1997. For this cohort, the effect on mathematics scores persists for 3 years since the class was introduced (1 year after the end of the class), but it fades out 4 years after the introduction (2 years after the end of the class). The effect on Japanese scores seems different between genders. For females, the effect is significant just after the introduction of the class, but for males, the effect becomes significant 3 years after the introduction (1 year after the end of the class) and it persists for another year.[21]

For cohort 1998, the effect is statistically significant 3 years after the introduction (just after the end of the calculation class), and for female students, it persists for another year (1 year after the end of the class), but after that, it fades out.[22] Overall, the effects tend to persist for 1 year after the end of the calculation class for female students, but after that, the effects fade out.

6. Possible mechanisms

In this section, we focus on why calculation class improves academic scores. Possible mechanisms are as follows: (1) direct path, where calculation class improves mathematics scores directly, and (2–1) indirect path, where calculation class improves non-cognitive skills, academic behavior at home, or classroom environment, leading to better academic scores (Alan and Ertac, 2018; Angrist and Lavy, 2009; Rivkin and Schiman, 2015) and (2–2) indirect path, where calculation class improves mathematics score and it improves non-cognitive skills leading to better academic scores of other subjects. We believe that path (1) alone is insufficient to explain our results because not only mathematics but also Japanese language scores are improved, especially for girls. To address why calculation class improves Japanese scores, we explore path (2). Investigating the effects on non-cognitive skills, academic behavior at home, and classroom environment could facilitate the understanding of the mechanisms by which the calculation class affects children.

6.1. Effects of calculation class on non-cognitive skills

Non-cognitive skills are measured by the degree to which a respondent (student) agreed with the following statements: "When I begin something, I go all the way to the end" (grit), "I like myself," "I study to get a good grade," "I study to get a good job in the future," and "I study for the teacher." Students select one from four choices: 1 (the statement does not describe me at all), 2 (the statement does not describe me), 3 (the statement somewhat describes me), and 4 (the statement describes me fairly well). For all indicators, we treated "I do not know" and no answer as missing values. We standardized the measurement for non-cognitive skills within grade and survey year.

Table 7 presents the effect of the calculation class on non-cognitive skills. Panel A reports the results for the full sample, and Panel B and C present the results for female and male students, respectively. The table indicates that coefficients of having experienced calculation classes are positive for all non-cognitive indicators except for self-affirmation in column 2. Columns 1, 3, and 4 show that the coefficients of calculation class are positive and significant for grit and motivation to study for grades and job, regardless of the child's gender.[23] These enhanced non-cognitive skills could improve academic scores. Indeed, we cannot deny the possibility that causality runs reverse: improved academic scores may lead to better non-cognitive skills.

6.2. Effects of calculation class on academic behavior at home

The survey asks students about their academic behaviors at home. Students report how many hours they study at home. Students select one from seven choices: (almost zero), (within 30 min), (between 30 min and 1 hour), (between 1 and 2 h), (between 2 and 3 h), (between 3 and 4 h), and (>4 h). We converted discrete choice into a continuous variable by taking the mean of each choice (we converted ">4 h" into 4 h). Students report the degree by how much they agreed with the following statements: "I do homework at home," "I study hard at home even if I dislike the subject," and "I study in detail at home what I learned in class." Students select one of the four choices presented in 6.1. We standardized

[20] We only use observations which are observed at all of the observation timing: as for cohort 1997, we use observations which are observed 4 times, and as for cohort 1998, we use observations which are observed 6 times.

[21] We explore possible mechanisms and find that only males' motivation to study for grades improved.

[22] For cohort 1999, nothing is statistically significant.

[23] For all non-cognitive skills, the differences in effect size between females and males are not statistically different from zero.

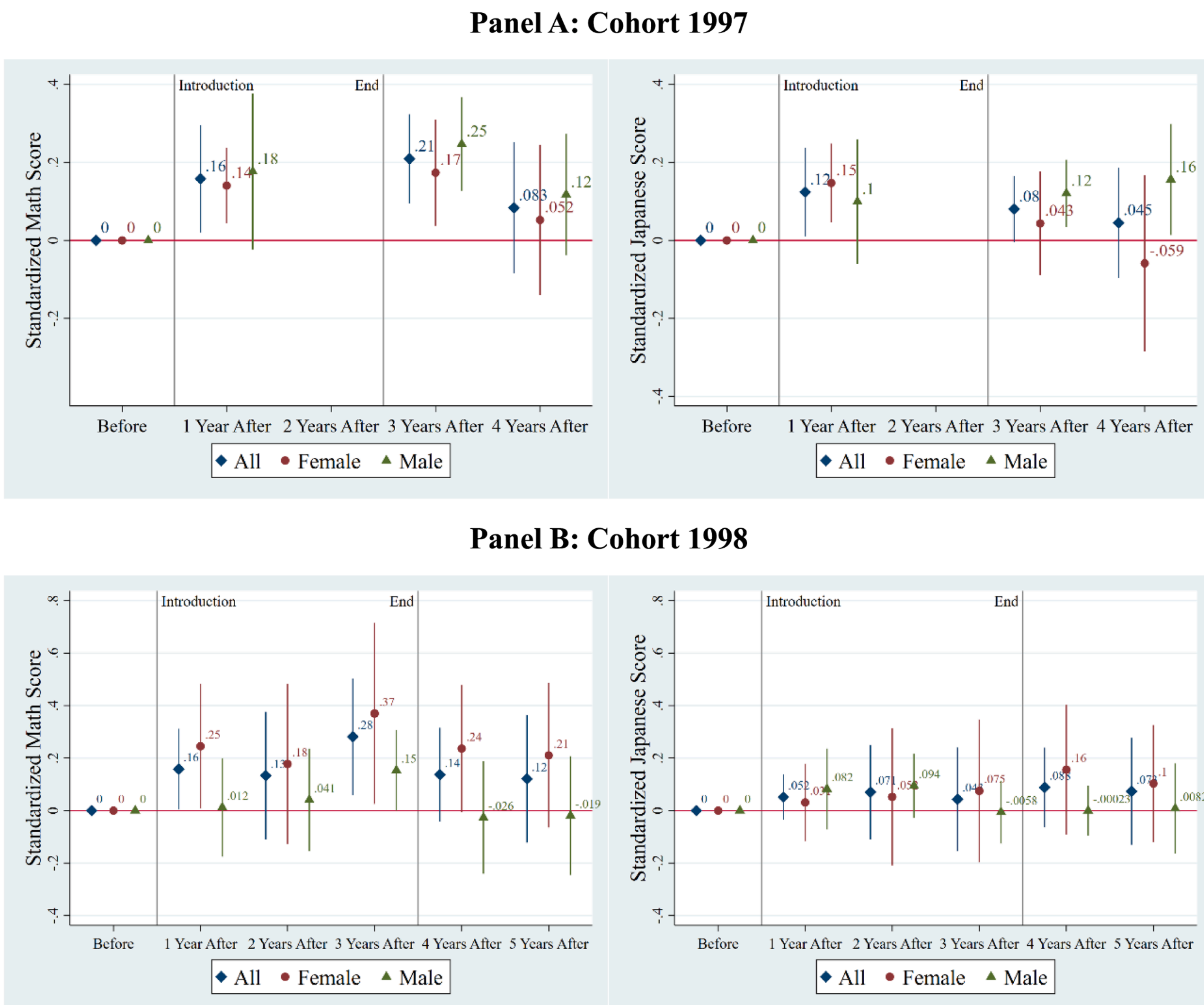

Fig. 4. Long-term Effects of the Calculation Class.
Notes. Panel A: Cohort 1997 Panel B: Cohort 1998 Notes. The symbols represent point estimates, and the bars indicate 95 % confidence intervals. The diamond, circle, and triangle symbols correspond to the point estimates for all students, female students, and male students, respectively. For cohort 1997, the calculation class was introduced when they were in 4th grade, and for cohort 1998, it was introduced when they were in 3rd grade. Since our panel data is unbalanced, cohort 1997 can be observed 1 year before the introduction and 1, 3, and 4 years after the introduction (i.e., when they were in grades 3, 4, 6, and 7). Cohort 1998 can be observed 1 year before the introduction and 1, 2, 3, 4 and 5 years after the introduction (i.e., when they were in grades 2, 3, 4, 5, 6, and 7). Cohort 1997 experienced calculation classes in grades 4 and 5, with 50 h per year, totaling 100 h. Cohort 1998 experienced calculation classes in grades 3, 4, and 5, with 50 h per year, totaling150 h. The vertical lines indicate the timing of the introduction and the end of the calculation class.

these indicators within grade and survey year.

Table 8 reports estimates of the effect of calculation class on academic behavior at home: study hours, intensity to do homework, study disliked subject, and study in detail. Panel A presents estimates based on the full sample and Panel B and C show the effect on female and male, respectively. In Panel A, the estimated coefficient of the calculation class on study hours (column 1) and intensity to do homework (column 2) are statistically significant and 0.139 and 0.0642, respectively. The estimated coefficient was not significantly different from zero for other behaviors, intensity to study disliked subject and study in detail (columns 3 and 4). The significant results in Panel A seem to be derived from each gender. Panel B shows the calculation class positively affects females' intensity to do homework, but it has no significant effect on other behaviors. Panel C reports the calculation class has a positive impact on males' study hours, but it has no significant effect on other behaviors. The effect sizes on the study hours at home (0.0625 for females and 0.218 for males) are statistically different between females and males with p-values of 0.005. Although the size of the coefficient for study hours is noticeable, the actual impact seems to be small. A 0.2-hour increase in study hours corresponds to a 13 min increase in study hours per day.

6.3. Effects of calculation class on classroom environment

The survey asks students about the classroom environment and students report the degree by how much they agreed with the following statements: "I listen to my teacher well in class" (which means students focus on the class), and "I do not chat in class." We standardized the indicators within grade and survey year.

Table 9 reports the estimated effects of the calculation class on the classroom environment. Panel A presents estimates based on the full sample and Panel B and C show the effect on female and male, respectively. In Panel A, the estimated coefficient of the calculation class on listening to the teacher (column 1) and being quiet in class (column 2) are not significantly different from zero. However, estimates by gender seem to be a little different. Panel B exhibits that the calculation class

Table 7
Effect of calculation class on non-cognitive skills.

	Non-cognitive Skills				
	(1) Grit	(2) Like Myself	(3) Study for Grades	(4) Study for Job	(5) Study for Teacher
Panel A: All					
Experienced Calculation Class	0.107**	−0.0132	0.137**	0.154***	0.165*
	(0.0428)	(0.0782)	(0.0635)	(0.0353)	(0.0971)
Observations	9718	9592	9808	9578	9592
R-squared	0.001	0.000	0.001	0.002	0.002
Number of personid	4859	4796	4904	4789	4796
Panel B: Female					
Experienced Calculation Class	0.0989*	0.00380	0.134*	0.141***	0.191**
	(0.0502)	(0.0681)	(0.0732)	(0.0410)	(0.0779)
Observations	4870	4826	4914	4810	4818
R-squared	0.001	0.003	0.003	0.002	0.005
Number of personid	2435	2413	2457	2405	2409
Panel C: Male					
Experienced Calculation Class	0.119*	−0.0258	0.143**	0.175***	0.138
	(0.0693)	(0.102)	(0.0679)	(0.0460)	(0.124)
Observations	4848	4766	4894	4768	4774
R-squared	0.001	0.003	0.001	0.002	0.001
Number of personid	2424	2383	2447	2384	2387
p-value of *t*-test between female & male	0.814	0.686	0.876	0.492	0.441

Notes. Dependent variables are standardized to have mean zero and standard deviation one within grade and year. The explanatory variable is a dummy indicating calculation classes. Panel A reports estimates based on the full sample. Panel B limits the observations to females. Panel C limits the observations to males. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 % level, respectively. Standard errors are allowed for clustering at the school level.

positively affects girls' intensity to listen to the teacher, but it has no significant effect on the degree of being quiet in class. Panel C shows no significant effect on the male's classroom environment. The effect size on the intensity of listening to the teacher (0.0926 for females and −0.139 for males) is statistically different between females and males with p-values of 0.0132. Listening to the teacher could have a substantial effect on scores if students focus on the whole instructional time (about 4.5 h of classes per day at school: 45 min multiplied by six classes).

Our results are consistent with some existing research explaining the gender difference in school achievements. For example, Golsteyn and Schils (2014) find that boys and girls employ their skills differently, leading to different academic achievements. Cornwell et al. (2013) suggest that boys tend to behave negatively.

6.4. *Effects across SES and previous score*

Tables A7 to A9 reports the estimates on academic scores, non-cognitive skills, academic behaviors, and classroom environment across gender and SES, gender and previous mathematics scores, and previous Japanese scores. The tables suggest the existence of heterogeneous effects across those groups, but we could not find a clear pattern.

Table 8
Effect of calculation class on academic behavior at home.

	Behavior at Home			
	(1) Study Hours	(2) Do Homework	(3) Study Disliked Subject	(4) Study in Detail
Panel A: All				
Experienced Calculation Class	0.143*	0.0663*	0.119	−0.0419
	(0.0802)	(0.0349)	(0.0813)	(0.0497)
Observations	9876	9894	9840	9802
R-squared	0.002	0.000	0.001	0.000
Number of personid	4938	4947	4920	4901
Panel B: Female				
Experienced Calculation Class	0.0696	0.116*	0.116	−0.0428
	(0.0742)	(0.0634)	(0.0888)	(0.109)
Observations	4938	4944	4926	4902
R-squared	0.002	0.003	0.002	0.000
Number of personid	2469	2472	2463	2451
Panel C: Male				
Experienced Calculation Class	0.220**	0.00616	0.129	−0.0432
	(0.0944)	(0.0582)	(0.0957)	(0.0479)
Observations	4938	4950	4914	4900
R-squared	0.003	0.002	0.002	0.001
Number of personid	2469	2475	2457	2450
p-value of *t*-test between female & male	0.00546	0.279	0.888	0.998

Notes. In column 1, the unit of study hours is hours and in columns 2 to 4, dependent variables are standardized to have mean zero and standard deviation one within grade and year. The explanatory variable is a dummy indicating calculation classes. Panel A reports estimates based on the full sample. Panel B limits the observations to females. Panel C limits the observations to males. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 % level, respectively. Standard errors are allowed for clustering at the school level.

Table 9
Effect of calculation class on classroom environment.

	Classroom Environment	
	(1) Listen to Teacher	(2) Quiet in Class
Panel A: All		
Experienced Calculation Class	−0.0151	−0.0499
	(0.0490)	(0.0550)
Observations	9682	9676
R-squared	0.000	0.000
Number of personid	4841	4838
Panel B: Female		
Experienced Calculation Class	0.0961**	−0.0219
	(0.0355)	(0.0691)
Observations	4854	4842
R-squared	0.001	0.000
Number of personid	2427	2421
Panel C: Male		
Experienced Calculation Class	−0.139	−0.0798
	(0.0886)	(0.0594)
Observations	4828	4834
R-squared	0.001	0.000
Number of personid	2414	2417
p-value of *t*-test between female & male	0.0117	0.386

Notes. Dependent variables are standardized to have mean zero and standard deviation one within grade and year. The explanatory variable is a dummy indicating calculation classes. Panel A reports estimates based on the full sample. Panel B limits the observations to females. Panel C limits the observations to males. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 % level, respectively. Standard errors are allowed for clustering at the school level.

Each table reports the estimates on academic scores (columns 1–2), non-cognitive skills (columns 3–7), academic behaviors at home (columns 8–11), and classroom environment (columns 12–13) across gender and SES.

In Table A7, columns 1 and 2 present that coefficients of calculation class tend to be statistically significant for low SES groups. Columns 3 to 7 show that the calculation class increases motivation to study for all groups, but only females from low SES families improve their grit. Columns 8 to 11 indicate that academic behavior at home tends to be improved for low SES groups. Columns 12 and 13 show that females from low SES improve their classroom environment, but males from low SES deteriorate it.

Table A8 reports the estimation results across gender and previous mathematics scores. Panels A and B show that for low-performing females, calculation class improves scores, motivation to study, intensity to do homework, and listening to the teacher, but for high-performing females, nothing is statistically different from zero. For males, the calculation class increases motivation to study for both groups, but only low-performing males improve their grit. Also, only low-performing males deteriorate the classroom environment.

Table A9 reports estimated results across gender and previous Japanese scores. Table A9 suggests that there might be a heterogeneous effect across groups, but we observe no clear pattern.

7. Conclusion

This paper analyzes the effects of the calculation class characterized by the abacus and teaching by specialized instructors. Since there is a time lag in the introduction of the class among schools and cohorts, we can detect the impacts of the calculation class using DID after controlling for student-fixed effects.

Using administrative data from a city in Japan, we find that the calculation class increases mathematics and Japanese scores by 0.145 and 0.0882 of standard deviations, respectively. To explore the possible mechanisms, we examine the impacts of the calculation class on students' non-cognitive skills, academic behaviors at home, and the classroom environment. We find that calculation class improves non-cognitive skills, such as grit and motivation for studying. Also, we find heterogeneous effects across gender, SES, and previous academic scores. Our estimation results show that calculation class has a larger impact on mathematics scores of female students, students from low-SES families, and previously low-performing children. Finally, we explore the long-term effects and find that for female, the effects tend to persist for one year after the class ends, but after that, the effects fade out.

This paper is one of the few studies that exploit longitudinal administrative data in Japan. However, our analysis has an important limitation. We cannot decompose the effect of the calculation class, such as factors related to teachers or changes in curriculum composition. An analysis using information on teachers will be an important direction for future research.

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CRediT authorship contribution statement

Mayuko Abe: Writing – review & editing, Investigation, Formal analysis. **Fumio Ohtake:** Supervision, Methodology, Funding acquisition, Conceptualization. **Shinpei Sano:** Writing – original draft, Methodology, Investigation, Data curation.

Declaration of competing interest

None.

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Appendix

Table A1
Example of a Curriculum Change Due to the Introduction of Calculation Class.

	grade 1	grade 2	grade 3	grade 4	grade 5	grade 6
Elementary Math	114	155	**150**	**150**	**150**	**150**
Integrated Studies	0	0	**105**	**105**	**110**	**110**
Living Environment Studies	102	**105**	0	0	0	0
Japanese Language	272	280	235	235	180	175
Social Studies	0	0	70	85	90	100
Science	0	0	70	90	95	95
Music	68	70	60	60	50	50
Arts and Handcrafts	68	70	60	60	50	50
Home Economics	0	0	0	0	60	55
Physical Education	90	90	90	90	90	90
Ethics	34	35	35	35	35	35
Special Activities	34	35	35	35	35	35
Total	782	840	910	945	945	945

	grade 1	grade 2	grade 3	grade 4	grade 5	grade 6
Calculation	**0**	**10**	**50**	**50**	**50**	**50**
Elementary Math	114	155	**135**	**135**	**140**	**140**
Integrated Studies	0	0	**70**	**70**	**70**	**70**
Living Environment Studies	102	**95**	0	0	0	0
Japanese Language	272	280	235	235	180	175
Social Studies	0	0	70	85	90	100
Science	0	0	70	90	95	95
Music	68	70	60	60	50	50
Arts and Handcrafts	68	70	60	60	50	50
Home Economics	0	0	0	0	60	55
Physical Education	90	90	90	90	90	90
Ethics	34	35	35	35	35	35
Special Activities	34	35	35	35	35	35
Total	782	840	910	945	945	945

Notes. The unit is hours: 50 corresponds to 50 h of in-classroom learning. For example, third graders have 910 h of total instructional time per year. The curriculum change adds 50 h of calculation classes per year. At the same time, it reduces elementary math class hours from 150 to 135 h (15 h were replaced with calculation) and also decreases the integrated studies hours from 105 to 70 h (35 h were replaced with calculation).

Table A2
Treatment status by school group and cohort.

	School group	Number of Schools	Number of Students	2006 treated or not	2006 accum. hours	2007 treated or not	2007 accum. hours	2008 treated or not	2008 accum. hours
Panel A: cohort 1997				Grade 3		Grade 4		Grade 5	
Already treated	1	1	49	1	[60]	1	[110]		
	2	5	99	1	[60]	1	[110]		
	3	6	416	1	[50]	1	[100]		
Treated Group	4	5	242	0	[0]	1	[50]		
Control Group	5	6	428	0	[0]	0	[0]		
	6	22	1780	0	[0]	0	[0]		
Panel B: cohort 1998				Grade 2		Grade 3		Grade 4	
Already treated	1	1	55	1	[10]	1	[60]		
	2	5	113	1	[10]	1	[60]		
	3	6	435	1	[10]	1	[60]		
Treated Group	4	5	278	0	[0]	1	[50]		
Control Group	5	6	414	0	[0]	0	[0]		
	6	22	1850	0	[0]	0	[0]		
Panel C: cohort 1999				Grade 1		Grade 2		Grade 3	
Already treated	1	1	65			1	[10]	1	[60]
	2	5	120			1	[10]	1	[60]
	3	6	434			1	[10]	1	[60]
	4	5	271			1	[10]	1	[60]
Treated Group	5	6	433			0	[0]	1	[30]
Control Group	6	22	1838			0	[0]	0	[0]

Notes. In the main estimation, we use the treated and control groups from cohorts 1997 and 1998. For Table A4, we use the treated and control groups from cohort 1999. Rows highlighted in gray represent already treated groups and are not used in any estimation. The timing (year) and grade of introduction varied depending on the cohort.

Table A3
Effect of the calculation class on disaggregated scores.

	Math			
	(1) point 1 Interest, motivation, and attitude	(2) point 2 Mathematical thinking	(3) point 3 Representation and processing of quantities and diagrams	(4) point 4 Knowledge and understanding of quantities and diagrams
Panel A: All				
Experienced Calculation Class	0.187***	0.0959*	0.0894	0.0660
	(0.0511)	(0.0557)	(0.0913)	(0.0673)
Observations	9,984	9,984	9,984	9,984
R-squared	0.003	0.001	0.001	0.001
Number of personid	4,992	4,992	4,992	4,992
Panel B: Female				
Experienced Calculation Class	0.223***	0.177***	0.0899	0.102
	(0.0480)	(0.0574)	(0.0657)	(0.0833)
Observations	4,982	4,982	4,982	4,982
R-squared	0.005	0.006	0.002	0.006
Number of personid	2,491	2,491	2,491	2,491
Panel C: Male				
Experienced Calculation Class	0.141	0.0144	0.0871	0.0166
	(0.0842)	(0.0740)	(0.123)	(0.0793)
Observations	5,002	5,002	5,002	5,002
R-squared	0.004	0.002	0.002	0.006
Number of personid	2,501	2,501	2,501	2,501

	Japanese				
	(1) point 1 Interest, motivation, and attitude	(2) point 2 Speaking and listening skills	(3) point 3 Writing skills	(4) point 4 Reading skills	(5) point 5 Knowledge and understanding of language
Panel A: All					
Experienced Calculation Class	0.186***	0.0772	-0.0353	0.0301	0.104**
	(0.0663)	(0.0512)	(0.0299)	(0.0528)	(0.0399)
Observations	9,984	9,984	9,984	9,984	9,984
R-squared	0.003	0.001	0.000	0.000	0.001
Number of personid	4,992	4,992	4,992	4,992	4,992
Panel B: Female					
Experienced Calculation Class	0.201**	-0.00365	0.0191	0.0313	0.192***
	(0.0832)	(0.0429)	(0.0632)	(0.0577)	(0.0572)
Observations	4,982	4,982	4,982	4,982	4,982
R-squared	0.009	0.000	0.000	0.000	0.006
Number of personid	2,491	2,491	2,491	2,491	2,491
Panel C: Male					
Experienced Calculation Class	0.171**	0.159**	-0.0941	0.0284	0.0168
	(0.0813)	(0.0759)	(0.0583)	(0.0830)	(0.0800)
Observations	5,002	5,002	5,002	5,002	5,002
R-squared	0.005	0.004	0.001	0.001	0.004
Number of personid	2,501	2,501	2,501	2,501	2,501

Notes. Dependent variables are standardized scores disaggregated by evaluation points, which are determined by the MEXT. Mathematics scores were disaggregated into 4 points, and Japanese scores were disaggregated into 5 points.

Table A4
Effect of the calculation class on scores (Cohort 1999).

	All		Female		Male	
	(1) Math	(2) Japanese	(3) Math	(4) Japanese	(5) Math	(6) Japanese
Cohort 1999 (introduced when Grade 3)						
Experienced Calculation Class	-0.0112	0.0214	0.0452	0.0737*	-0.0579	-0.0294
	(0.287)	(0.0681)	(0.291)	(0.0404)	(0.291)	(0.106)
Observations	4,542	4,542	2,262	2,262	2,280	2,280
R-squared	0.006	0.000	0.003	0.003	0.012	0.002
Number of personid	2,271	2,271	1,131	1,131	1,140	1,140

Notes. We conduct 2×2 DID for cohort 1999 using the calculation class introduced in 2007. Dependent variables are standardized to have mean zero and standard deviation one within grade and year. The explanatory variable is a dummy indicating whether or not an individual has experienced calculation classes. In columns 3 and 4, we limit the observations to female students, and in columns 5 and 6, we limit the observations to male students. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 % level, respectively. Standard errors are allowed for clustering at the school level.

Table A5
Descriptive statistics by school group.

	Group 1				Group 2				Group 3			
	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Experienced Calculation Class	1.00	0.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	0.00	1.00	1.00
Accum. Calculation Class Hours (in 100 hours)	0.49	0.34	0.10	1.10	0.50	0.34	0.10	1.10	0.48	0.31	0.10	1.00
Academic Scores												
Math Score	-0.06	1.03	-3.62	1.45	0.05	0.93	-4.61	1.60	0.06	0.95	-4.13	1.60
Japanese Score	-0.13	1.03	-3.55	1.92	0.05	0.90	-3.24	1.89	-0.01	0.99	-4.02	1.98
Non-cognitive Skills												
Grit	-0.14	1.04	-2.77	1.13	0.07	0.96	-2.77	1.13	-0.01	1.00	-2.77	1.13
Like Myself	0.03	0.93	-1.42	1.64	-0.01	1.01	-1.42	1.64	-0.02	1.02	-1.42	1.64
Study for Grades	-0.14	1.10	-4.09	0.67	-0.06	1.05	-3.88	0.67	-0.00	0.99	-4.09	0.67
Study for Job	-0.13	1.04	-3.45	0.66	0.03	0.98	-3.45	0.66	0.01	0.99	-3.45	0.66
Study for Teacher	-0.01	0.98	-3.19	0.94	-0.02	1.04	-3.19	0.94	-0.01	1.00	-3.19	0.94
Academic Behavior at Home												
Study Hours	-0.11	0.77	-1.22	2.88	-0.12	0.95	-1.22	3.08	-0.04	1.00	-1.22	3.08
Do Homework	-0.11	0.99	-3.99	0.60	0.02	0.94	-3.92	0.60	-0.02	0.99	-3.99	0.60
Study Disliked Subject	-0.10	1.02	-3.26	0.85	0.03	1.02	-3.26	0.85	-0.03	1.01	-3.26	0.85
Study in Detail	-0.23	0.98	-1.62	2.03	-0.01	1.03	-1.62	2.03	-0.05	1.00	-1.62	2.03
Classroom Environment												
Listen to Teacher	-0.15	0.98	-3.18	1.07	0.12	0.92	-3.18	1.07	0.01	1.00	-3.18	1.07
Quiet in Class	0.26	0.91	-1.83	1.43	-0.15	0.97	-1.83	1.43	-0.07	1.01	-1.83	1.43
Individual Characteristics												
Female	0.43	0.50	0.00	1.00	0.51	0.50	0.00	1.00	0.51	0.50	0.00	1.00
Receive Public Assistance	0.07	0.25	0.00	1.00	0.02	0.14	0.00	1.00	0.02	0.16	0.00	1.00
Low SES (have 0-50 books)	0.65	0.48	0.00	1.00	0.61	0.49	0.00	1.00	0.51	0.50	0.00	1.00
Grade 3	0.36	0.48	0.00	1.00	0.35	0.48	0.00	1.00	0.34	0.47	0.00	1.00
Grade 4	0.50	0.50	0.00	1.00	0.50	0.50	0.00	1.00	0.50	0.50	0.00	1.00
Grade 5	0.14	0.35	0.00	1.00	0.15	0.36	0.00	1.00	0.16	0.37	0.00	1.00
Observations	338				664				2570			

	Group 4				Group 5				Group 6			
	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Experienced Calculation Class	0.67	0.47	0.00	1.00	0.17	0.38	0.00	1.00	0.00	0.00	0.00	0.00
Accum. Calculation Class Hours (in 100 hours)	0.28	0.25	0.00	0.60	0.05	0.11	0.00	0.30	0.00	0.00	0.00	0.00
Academic Scores												
Math Score	0.01	0.96	-4.56	1.60	-0.05	1.02	-5.49	1.60	0.01	1.00	-5.54	1.60
Japanese Score	-0.05	0.95	-3.82	1.89	-0.02	1.02	-4.21	2.04	0.03	0.99	-5.17	2.10
Non-cognitive Skills												
Grit	-0.00	1.01	-2.77	1.13	-0.01	1.01	-2.77	1.13	0.01	0.99	-2.77	1.13
Like Myself	0.02	1.00	-1.42	1.64	0.01	0.99	-1.42	1.64	-0.00	1.00	-1.42	1.64
Study for Grades	-0.06	1.06	-4.09	0.67	0.03	0.98	-4.09	0.67	0.02	0.97	-4.09	0.67
Study for Job	-0.05	1.07	-3.45	0.66	0.03	0.97	-3.45	0.66	0.01	0.99	-3.45	0.66
Study for Teacher	-0.07	1.07	-3.19	0.94	0.04	0.97	-3.19	0.94	0.01	0.99	-3.19	0.94
Academic Behavior at Home												
Study Hours	-0.03	0.97	-1.22	3.08	0.03	1.03	-1.22	3.08	0.02	1.00	-1.22	3.08
Do Homework	-0.02	1.03	-3.99	0.60	-0.02	1.00	-3.99	0.60	0.03	0.98	-3.99	0.60
Study Disliked Subject	-0.03	1.01	-3.26	0.85	-0.02	0.99	-3.26	0.85	0.03	0.98	-3.26	0.85
Study in Detail	-0.07	1.01	-1.62	2.03	0.04	0.99	-2.40	2.03	0.03	1.00	-2.40	2.03
Classroom Environment												
Listen to Teacher	-0.08	1.02	-3.18	1.07	-0.02	1.01	-3.18	1.07	0.01	0.99	-3.18	1.07
Quiet in Class	-0.01	0.98	-1.83	1.43	0.03	1.03	-1.83	1.43	0.01	0.99	-1.83	1.43
Individual Characteristics												
Female	0.50	0.50	0.00	1.00	0.49	0.50	0.00	1.00	0.50	0.50	0.00	1.00
Receive Public Assistance	0.05	0.22	0.00	1.00	0.03	0.16	0.00	1.00	0.04	0.19	0.00	1.00
Low SES (have 0-50 books)	0.55	0.50	0.00	1.00	0.50	0.50	0.00	1.00	0.52	0.50	0.00	1.00
Grade 3	0.35	0.48	0.00	1.00	0.33	0.47	0.00	1.00	0.34	0.47	0.00	1.00
Grade 4	0.50	0.50	0.00	1.00	0.50	0.50	0.00	1.00	0.50	0.50	0.00	1.00
Grade 5	0.15	0.36	0.00	1.00	0.17	0.37	0.00	1.00	0.16	0.37	0.00	1.00
Observations	1582				2550				10936			

Note: The sample is composed of the cohorts 1997 and 1998 from the years 2006 and 2007, and the cohort 1999 from the years 2007 and 2008. The school groups were determined based on regional balance and other factors by the Amagasaki Board of Education.

Table A6
Effect of accumulated calculation class hours on scores.

	All		Female		Male	
	(1) Math	(2) Japanese	(3) Math	(4) Japanese	(5) Math	(6) Japanese
Cohort 1997 & 1998						
Accum.Calculation Class Hours	0.290**	0.175***	0.388***	0.223***	0.176	0.124
	(0.110)	(0.0579)	(0.119)	(0.0578)	(0.140)	(0.141)

(*continued on next page*)

Table A6 (*continued*)

	All		Female		Male	
	(1) Math	(2) Japanese	(3) Math	(4) Japanese	(5) Math	(6) Japanese
Observations	9,984	9,984	4,982	4,982	5,002	5,002
R-squared	0.004	0.002	0.009	0.004	0.004	0.002
Number of personid	4,992	4,992	2,491	2,491	2,501	2,501

Notes. Dependent variables are standardized to have mean zero and standard deviation one within grade and year. The explanatory variable is accumulated hours of abacus classes in 100 h. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 % level, respectively. Standard errors are allowed for clustering at the school level.

Table A7
Heterogeneous effects on scores, non-cognitive skills, academic behavior at home and classroom environment across gender and SES.

	Scores		Non-cognitive Skills					Behavior at Home				Classroom Environment	
	(1) Math	(2) Japanese	(3) Grit	(4) Like Myself	(5) Study for Grades	(6) Study for Job	(7) Study for Teacher	(8) Study Hours	(9) Do Homework	(10) Study Disliked Subject	(11) Study in Detail	(12) Listen to Teacher	(13) Quiet in Class
Panel A: Female, Low SES													
Experienced Calculation Class	0.290***	0.0758*	0.117**	-0.0319	0.154	0.0305	0.188*	0.207*	0.145	0.0861	-0.0361	0.238***	-0.0212
	(0.0809)	(0.0379)	(0.0497)	(0.141)	(0.0916)	(0.0697)	(0.0944)	(0.102)	(0.0870)	(0.0739)	(0.122)	(0.0434)	(0.0968)
Observations	2,714	2,714	2,638	2,628	2,674	2,608	2,612	2,692	2,700	2,688	2,670	2,636	2,640
R-squared	0.017	0.001	0.004	0.003	0.004	0.003	0.009	0.004	0.002	0.003	0.000	0.006	0.001
Number of personid	1,357	1,357	1,319	1,314	1,337	1,304	1,306	1,346	1,350	1,344	1,335	1,318	1,320
Panel B: Female, High SES													
Experienced Calculation Class	0.0599	0.137***	0.0800	0.0312	0.105	0.257***	0.193**	-0.0893	0.0899	0.149	-0.0562	-0.0697	0.00848
	(0.0506)	(0.0391)	(0.0720)	(0.104)	(0.0741)	(0.0738)	(0.0863)	(0.0718)	(0.0964)	(0.129)	(0.117)	(0.0665)	(0.121)
Observations	2,220	2,220	2,190	2,156	2,196	2,158	2,162	2,200	2,198	2,192	2,188	2,172	2,160
R-squared	0.002	0.009	0.003	0.002	0.002	0.009	0.004	0.010	0.006	0.002	0.002	0.001	0.001
Number of personid	1,110	1,110	1,095	1,078	1,098	1,079	1,081	1,100	1,099	1,096	1,094	1,086	1,080
Panel C: Male, Low SES													
Experienced Calculation Class	0.185*	0.0941	0.215	-0.0748	0.118	0.207**	0.290**	0.295**	-0.0396	0.317*	0.136*	-0.179*	-0.146*
	(0.0937)	(0.0881)	(0.144)	(0.140)	(0.108)	(0.101)	(0.131)	(0.110)	(0.100)	(0.176)	(0.0719)	(0.0916)	(0.0736)
Observations	2,446	2,446	2,372	2,326	2,398	2,330	2,340	2,416	2,414	2,396	2,388	2,350	2,348
R-squared	0.011	0.003	0.005	0.008	0.001	0.004	0.006	0.014	0.005	0.007	0.002	0.004	0.002
Number of personid	1,223	1,223	1,186	1,163	1,199	1,165	1,170	1,208	1,207	1,198	1,194	1,175	1,174
Panel D: Male, High SES													
Experienced Calculation Class	-0.0167	0.0277	0.0598	0.0150	0.230**	0.177***	-0.0106	0.0936	0.0403	-0.143	-0.263***	-0.0867	-0.0233
	(0.0678)	(0.0692)	(0.0959)	(0.101)	(0.0851)	(0.0565)	(0.152)	(0.0740)	(0.0857)	(0.0980)	(0.0952)	(0.108)	(0.0595)
Observations	2,492	2,492	2,416	2,384	2,436	2,378	2,374	2,460	2,474	2,456	2,452	2,422	2,426
R-squared	0.003	0.006	0.003	0.001	0.004	0.002	0.002	0.003	0.002	0.003	0.005	0.001	0.001
Number of personid	1,246	1,246	1,208	1,192	1,218	1,189	1,187	1,230	1,237	1,228	1,226	1,211	1,213

Notes. All dependent variables are standardized to have mean zero and standard deviation one within grade and year, except for study hours. The unit of study hours is hours. The explanatory variable is a dummy indicating whether or not an individual has experienced calculation classes. Panels A and B report estimates based on the observations of females from low and high SES backgrounds, respectively. Panels C and D report estimates based on the observations of males from low and high SES backgrounds, respectively. Students with low SES have 0 to 50 books at home and those who with high SES have 51 or more books at home. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 % level, respectively. Standard errors are allowed for clustering at the school level.

Table A8
Heterogeneous effects across gender and previous math score.

	Scores		Non-cognitive Skills					Behavior at Home				Classroom Environment	
	(1) Math	(2) Japanese	(3) Grit	(4) Like Myself	(5) Study for Grades	(6) Study for Job	(7) Study for Teacher	(8) Study Hours	(9) Do Homework	(10) Study Disliked Subject	(11) Study in Detail	(12) Listen to Teacher	(13) Quiet in Class
Panel A: Female, Low Pre-math Score													
Experienced Calculation Class	0.217***	0.139**	0.113	0.0382	0.218	0.171	0.265**	0.0775	0.135**	0.0852	0.0273	0.166***	0.0969
	(0.0467)	(0.0550)	(0.0872)	(0.0619)	(0.140)	(0.105)	(0.103)	(0.123)	(0.0606)	(0.121)	(0.195)	(0.0560)	(0.0861)
Observations	2,490	2,490	2,406	2,386	2,448	2,384	2,390	2,460	2,464	2,452	2,432	2,406	2,392
R-squared	0.070	0.005	0.001	0.001	0.004	0.004	0.007	0.001	0.004	0.003	0.002	0.003	0.002
Number of personid	1,245	1,245	1,203	1,193	1,224	1,192	1,195	1,230	1,232	1,226	1,216	1,203	1,196
Panel B: Female, High Pre-math Score													
Experienced Calculation Class	0.0791	0.0623	0.0717	-0.0872	0.0114	0.0778	0.0727	0.0916	0.0834	0.150	-0.134	-0.0151	-0.200

(*continued on next page*)

Table A8 (*continued*)

	Scores		Non-cognitive Skills					Behavior at Home				Classroom Environment	
	(1) Math	(2) Japanese	(3) Grit	(4) Like Myself	(5) Study for Grades	(6) Study for Job	(7) Study for Teacher	(8) Study Hours	(9) Do Homework	(10) Study Disliked Subject	(11) Study in Detail	(12) Listen to Teacher	(13) Quiet in Class
	(0.0514)	(0.0467)	(0.0610)	(0.132)	(0.0729)	(0.120)	(0.0947)	(0.0576)	(0.0930)	(0.109)	(0.128)	(0.0479)	(0.150)
Observations	2,492	2,492	2,464	2,440	2,466	2,426	2,428	2,478	2,480	2,474	2,470	2,448	2,450
R-squared	0.089	0.010	0.002	0.016	0.004	0.007	0.009	0.012	0.002	0.005	0.005	0.002	0.004
Number of personid	1,246	1,246	1,232	1,220	1,233	1,213	1,214	1,239	1,240	1,237	1,235	1,224	1,225
Panel C: Male, Low Pre-math Score													
Experienced Calculation Class	0.0597	0.0869	0.253*	0.00888	0.159*	0.119	0.111	0.248*	0.0689	0.170	0.00815	-0.268**	-0.207**
	(0.106)	(0.0950)	(0.126)	(0.124)	(0.0907)	(0.164)	(0.155)	(0.125)	(0.126)	(0.147)	(0.0877)	(0.121)	(0.0927)
Observations	2,458	2,458	2,336	2,292	2,380	2,294	2,308	2,420	2,422	2,388	2,384	2,332	2,348
R-squared	0.023	0.004	0.005	0.013	0.003	0.002	0.005	0.008	0.001	0.001	0.003	0.005	0.002
Number of personid	1,229	1,229	1,168	1,146	1,190	1,147	1,154	1,210	1,211	1,194	1,192	1,166	1,174
Panel D: Male, High Pre-math Score													
Experienced Calculation Class	0.105*	0.0354	-0.0201	-0.0683	0.123**	0.227**	0.163	0.199**	-0.0618	0.0860	-0.0953	-0.0124	0.0498
	(0.0572)	(0.0791)	(0.0568)	(0.0788)	(0.0584)	(0.107)	(0.164)	(0.0735)	(0.0776)	(0.0906)	(0.0707)	(0.0883)	(0.0726)
Observations	2,544	2,544	2,512	2,474	2,514	2,474	2,466	2,518	2,528	2,526	2,516	2,496	2,486
R-squared	0.086	0.001	0.002	0.000	0.003	0.006	0.007	0.005	0.006	0.006	0.001	0.001	0.000
Number of personid	1,272	1,272	1,256	1,237	1,257	1,237	1,233	1,259	1,264	1,263	1,258	1,248	1,243

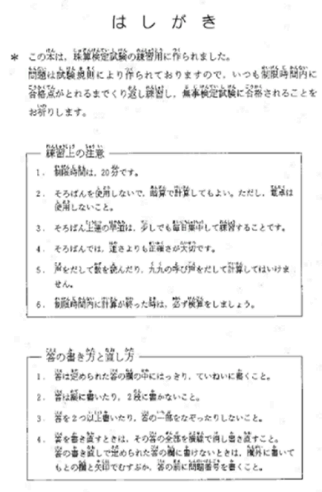
Notes. All dependent variables are standardized to have mean zero and standard deviation one within grade and year, except for study hours. The unit of study hours is hours. The explanatory variable is a dummy indicating whether or not an individual has experienced calculation classes. Panels A and B report estimates based on the observations of females who were low- and high-performing in mathematics in the previous year, respectively. Panels C and D report estimates based on the observations of males who were low- and high-performing in mathematics in the previous year, respectively. The low-performing children are those who scored below the median. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 % level, respectively. Standard errors are allowed for clustering at the school level.

Table A9
Heterogeneous effects across gender and previous Japanese score.

	Scores		Non-cognitive Skills					Behavior at Home				Classroom Environment	
	(1) Math	(2) Japanese	(3) Grit	(4) Like Myself	(5) Study for Grades	(6) Study for Job	(7) Study for Teacher	(8) Study Hours	(9) Do Homework	(10) Study Disliked Subject	(11) Study in Detail	(12) Listen to Teacher	(13) Quiet in Class
Panel A: Female, Low Pre-Japanese Score													
Experienced Calculation Class	0.205**	0.0529	0.263***	-0.00855	0.0918	0.126	0.125	0.0593	0.144*	0.110	0.0281	0.141**	0.161*
	(0.0992)	(0.0603)	(0.0655)	(0.0594)	(0.0994)	(0.0950)	(0.113)	(0.132)	(0.0741)	(0.113)	(0.135)	(0.0664)	(0.0885)
Observations	2,040	2,040	1,964	1,948	2,004	1,950	1,952	2,018	2,020	2,006	1,990	1,968	1,956
R-squared	0.013	0.075	0.005	0.002	0.001	0.003	0.001	0.001	0.006	0.005	0.002	0.004	0.008
Number of personid	1,020	1,020	982	974	1,002	975	976	1,009	1,010	1,003	995	984	978
Panel B: Female, High Pre-Japanese Score													
Experienced Calculation Class	0.178***	0.120**	-0.0324	0.00609	0.164*	0.150**	0.239***	0.0879	0.0864	0.117	-0.102	0.0517	-0.182
	(0.0456)	(0.0498)	(0.0710)	(0.120)	(0.0933)	(0.0564)	(0.0556)	(0.0723)	(0.0910)	(0.0947)	(0.124)	(0.0427)	(0.115)
Observations	2,942	2,942	2,906	2,878	2,910	2,860	2,866	2,920	2,924	2,920	2,912	2,886	2,886
R-squared	0.009	0.121	0.001	0.009	0.007	0.005	0.012	0.006	0.004	0.005	0.002	0.002	0.007
Number of personid	1,471	1,471	1,453	1,439	1,455	1,430	1,433	1,460	1,462	1,460	1,456	1,443	1,443
Panel C: Male, Low Pre-Japanese Score													
Experienced Calculation Class	0.0877	0.0161	0.146	-0.0530	0.157*	0.195*	0.0428	0.214*	0.0743	0.272*	0.0681	-0.226	-0.127**
	(0.0904)	(0.0923)	(0.110)	(0.123)	(0.0830)	(0.106)	(0.101)	(0.114)	(0.124)	(0.144)	(0.0639)	(0.153)	(0.0605)
Observations	2,924	2,924	2,804	2,756	2,848	2,752	2,766	2,876	2,882	2,850	2,850	2,786	2,798
R-squared	0.006	0.036	0.001	0.010	0.002	0.002	0.002	0.009	0.001	0.004	0.002	0.003	0.001
Number of personid	1,462	1,462	1,402	1,378	1,424	1,376	1,383	1,438	1,441	1,425	1,425	1,393	1,399
Panel D: Male, High Pre-Japanese Score													
Experienced Calculation Class	0.0980*	0.102*	0.0761	0.00408	0.123	0.147	0.281	0.265**	-0.108	-0.109	-0.212***	-0.00664	0.0110
	(0.0508)	(0.0519)	(0.0754)	(0.0990)	(0.0728)	(0.0869)	(0.182)	(0.103)	(0.115)	(0.146)	(0.0723)	(0.0744)	(0.197)
Observations	2,078	2,078	2,044	2,010	2,046	2,016	2,008	2,062	2,068	2,064	2,050	2,042	2,036
R-squared	0.004	0.096	0.001	0.000	0.002	0.005	0.007	0.014	0.005	0.003	0.005	0.000	0.002
Number of personid	1,039	1,039	1,022	1,005	1,023	1,008	1,004	1,031	1,034	1,032	1,025	1,021	1,018

Notes. All dependent variables are standardized to have mean zero and standard deviation one within grade and year, except for study hours. The unit of study hours is hours. The explanatory variable is a dummy indicating whether or not an individual has experienced calculation classes. Panels A and B report estimates based on the observations of females who were low- and high-performing in Japanese in the previous year, respectively. Panels C and D report estimates based on the observations of males who were low- and high-performing in Japanese in the previous year, respectively. The low-performing children are those who scored below the median. The symbols ***, **, * indicate that the coefficients are statistically significant at the 1, 5, and 10 % level, respectively. Standard errors are allowed for clustering at the school level.

Panel A. Preface of Textbook



はしがき

＊ この本は、珠算検定試験の練習用に作られました。
問題は試験規則により作られておりますので、いつも制限時間内に合格点がとれるまでくり返し練習し、無事検定試験に合格されることをお祈りします。

練習上の注意

1. 制限時間は、20分です。
2. そろばんを使用しないで、暗算で計算してもよい。ただし、電卓は使用しないこと。
3. そろばん上達の早道は、少しでも毎日集中して練習することです。
4. そろばんでは、速さよりも正確さが大切です。
5. 声をだして数を読んだり、九九の呼び声をだして計算してはいけません。
6. 制限時間内に計算が終った時は、必ず検算をしましょう。

答の書き方と直し方

1. 答は定められた答の欄の中にはっきり、ていねいに書くこと。
2. 答は縦に書いたり、2段に書かないこと。
3. 答を2つ以上書いたり、答の一部をなぞったりしないこと。
4. 答を書き直すときは、その答の全部を横線で消し書き直すこと。答の書き直しで定められた答の欄に書けないときは、欄外に書いてもとの欄と矢印でむすぶか、答の前に問題番号を書くこと。

Preface

* This book is designed for practice for the Abacus Certificate Examination. The questions are designed according to the rules of the exam, so please always practice repeatedly until you get a passing score within the time limit, and we hope you will pass the exam successfully.

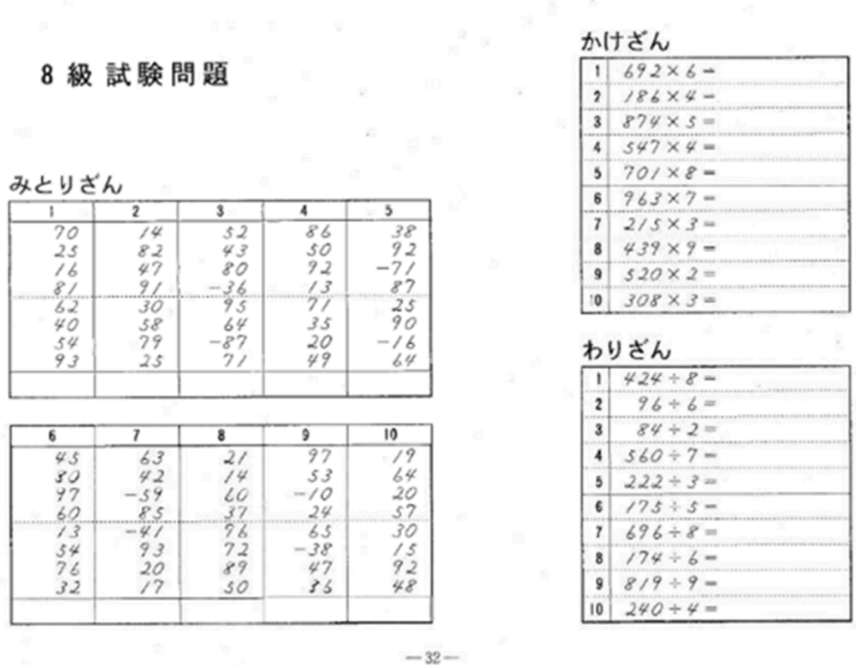
Notes on practice.

1. The time limit is 20 minutes.
2. You may calculate by mental arithmetic without using the abacus. However, calculators must not be used.
3. The fastest way to improve your abacus is to practice intensively every day as much as possible.
4. On the abacus, accuracy is more important than speed.
5. Do not read numbers aloud or calculate by calling out multiplication tables.
6. When you finish calculations within the time limit, be sure to check the accuracy of them.

How to write and rewrite answers.

1. Answers should be written clearly and carefully in the answer boxes provided.
2. Do not write answers vertically or in two lines.
3. Do not write more than one answer or trace over part of an answer.
4. When rewriting an answer, cross out the entire answer and rewrite it. If you cannot write the answer in the box, write the answer outside the box and connect it to the original box with an arrow, or write the question number at the beginning of the answer.

Panel B. Examples of Problem Sets



8級試験問題

みとりざん

1	2	3	4	5
70	14	52	86	38
25	82	43	50	92
16	47	80	92	−71
81	91	−36	13	87
62	30	95	71	25
40	58	64	35	90
54	79	−87	20	−16
93	25	71	49	64

6	7	8	9	10
45	63	21	97	19
80	42	14	53	64
97	−59	60	−10	20
60	85	37	24	57
13	−41	96	65	30
54	93	72	−38	15
76	20	89	47	92
32	17	50	36	48

—32—

かけざん

1	692 × 6 =
2	186 × 4 =
3	874 × 5 =
4	547 × 4 =
5	701 × 8 =
6	963 × 7 =
7	215 × 3 =
8	439 × 9 =
9	520 × 2 =
10	308 × 3 =

わりざん

1	424 ÷ 8 =
2	96 ÷ 6 =
3	84 ÷ 2 =
4	560 ÷ 7 =
5	222 ÷ 3 =
6	175 ÷ 5 =
7	696 ÷ 8 =
8	174 ÷ 6 =
9	819 ÷ 9 =
10	240 ÷ 4 =

Fig. A1. Actual class materials used in the calculation class.
Notes. Panel A. Preface of textbook, and Panel B. Examples of problem sets notes. Panel A. English translation of the preface of textbook is provided on the right side. Panel B. Left: addition and subtraction. Upper right: multiplication. Lower right: division.

Data availability

The data that has been used is confidential.

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