Does instruction time improve student achievement and motivation? Evidence from Japan

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This paper examines how instruction time affects students' cognitive ability and motivation, using data from Japanese 4^{th} grade students from Trends in International Mathematics and Science Study. I estimate a fixed-effect model using within-student panel data in two subjects. To remove teacher fixed effects, I restrict the sample to classes taught by the same teacher. The results show that instruction time positively affects both score and motivation. Further, I find a positive heterogeneity effect on score for schools with an absence problem, while the magnitude of the effect on motivation is about twice as large in boys relative to girls.

Keywords: Instruction time, education policy, cognitive ability, motivation to learn, educational inequity.

1. Introduction

This study examines the impact of instruction time on students' cognitive ability and motivation to learn, using the change in instruction time by revision of Japanese education as a natural experiment.

Across the global landscape in 2020, many schools have had to close due to the COVID-19 pandemic. The UNESCO web page[1] reported that 84.3% of the world student population has been affected by school closures since April 1, 2020 due to the pandemic. Concerns are rising regarding the effect of this disruption in education on children's future. Beyond academic achievement, children's health condition, physical strength, and non-cognitive abilities, such as sociability, are all at risk of harm. Therefore, it is urgent to discuss in depth the issue of education in the context of the COVID-19 pandemic. One especially pressing issue is how to mitigate the education gaps caused by families' economic background. Due to the rapid expansion of online education, the global education system may change dramatically. With many students having to attend online lessons at home, children's learning environment is expected to be strongly influenced by their economic background. In this context, we have little evidence on the impact of school instruction time.

One key issue to consider is the importance of classroom teaching for students. Do in-person school lessons encourage cognitive ability and non-cognitive ability? An accurate examination of the effects of instruction time in school is necessary.

[1] https://en.unesco.org/covid19/educationresponse#schoolclosures (2021/5/5)

Education is greatly relevant to the development human capital (Schultz 1961; Becker 1962). In economics, studies of return to education have mainly focused on understanding the effect of extending one's education period (Acemoglu and Angrist 2000; Pischke 2007; Fischer et al. 2020). Recently, it has become important to design education policies based on evidence; the effects of particular policies on the education production function can be examined. Moreover, since Coleman et al.'s (1966) report, analysis of schools' education resources has become particularly important in shaping educational reform. Endogeneity must be excluded to estimate the pure causal effect of education resources on student performance.

School education is among the most important policy areas in most countries. Debate continues regarding how lessons can most effectively contribute to improving children's ability. Education policies under which instruction time is increased or instruction contents changed can easily gain support from many people because they do not need additional resources at the school level. In other words, such policies are generally expected to improve children's ability at a low cost. Therefore, changes to instruction at school play a key role in many countries' education reform. In this regard, it is important to discuss around effective instruction time and school days (Gromada and Shewbridge 2016).

Among other countries, Japan has been discussing instruction time and content for the past 30 years. Japanese children have equal access to compulsory education across Japan under the Basic Act on Education (*Kyoiku kihon ho*) and the School Education Act (*Gakko kihon ho*), based on the spirit of the Japanese Constitution. Furthermore, all public schools' curricula in Japan must follow the curriculum guidelines (*Gakushu shido yoryo*) notified by the Ministry of Education, Culture, Sports, Science and Technology (MEXT). The Japanese public education curricula, including instruction time and contents, are determined by these guidelines. Of course, these guidelines merely set the standards that schools should abide by, so some schools deviate from them. Further, the guidelines are revised every 10 years to keep pace with the latest developments. In 2002 the curriculum guidelines were substantially changed. Ahead of this change, from 1995 to 2002, all public schools gradually saw a shift to the five-day school week, having previously also attended school on Saturday. Furthermore, school instruction time and contents were substantially reduced. This education reform was controversial and many people, especially children's parents, were concerned about a decline in children's academic ability.

Generally, an increase in school instruction time is equated to increased input and, in turn, improved academic ability. Figure 1 shows Japanese 4th and 8th grade students' average test scores and their total standard instruction time in mathematics and science from 1995 to 2015. The lines illustrate changes in scores on the Trends in International Mathematics and Science Study (TIMSS), which is an international academic survey, while the bars indicate changes in the accumulated standard lesson times for students of each grade in the two subjects. There is no apparent simple correlation between TIMSS score and school instruction time in Figure 1.

<Please insert Figure 1 here>

This study examines whether increasing instruction time really improves students' academic ability. It is hard to estimate the pure effect of instruction time because that it encompasses not only the time but also the content of the lessons. Thus, I have tried to analyze only the effect of instruction time. In addition, to estimate the causal effect of instruction time, it is necessary to eliminate the individual fixed effects of students' ability and teachers' quality of teaching, as well as the characteristics of each school and class.

To estimate the causal effect, previous studies have conducted natural experiments using an exogenous change in schooldays due to weather or policy (Marcotte 2007; Bellei 2009; Aucejo and Romano 2016; Battistin and Meroni 2016). Some studies have used a fixed-effect model employing panel data for different academic subjects

(Lavy 2015; Rivkin and Schiman 2015; Cattaneo, Oggenfuss, and Wolter. 2017; Motegi and Oikawa 2019). These studies have shown that the effect of instruction time on students' academic ability is heterogeneous due to numerous factors Gromada and Shewbridge 2016). Furthermore, while instruction time's effect on children's cognitive ability has been examined, its effect on children's non-cognitive ability, which has an important role in human capital development (Heckman, Stixrud, and Urzua 2006), is still unknown.

To find the pure effect of instruction time, I estimated a between-subjects fixed-effect model using panel data comprising the scores of Japanese 4^{th} grade students on the TIMSS in 1995, 2003, and 2007. My estimation removed both student and teacher fixed effects that related closely to students' outcome. Moreover, in addition to the test score, I use students' motivation to learn as a second outcome variable. I confirmed the heterogeneity of the effects by analyzing the interaction terms.

The results show that increasing the instruction time leads to a significant rise in students' test scores and their motivation to learn. The value of the coefficient of test scores indicates roughly the same effect size as previous studies have reported. Additionally, I estimated the heterogeneity of the effects of instruction time by adding variable interactions. The results suggest that schools facing a high student absence rate see a positive effect on the test score with increasing instruction time, although the size of the effect on motivation is about twice as strong in boys as in girls. In addition, there is a positive effect on test scores and motivation for the combination of instruction time and students' study-time at home.

The contributions of this paper are threefold. First, I show the effect of instruction time on students' motivation to learn, which previous studies have not examined. Second, by considering instruction time for the whole year, the estimate of the real change generated by instruction time is likely more accurate than in previous studies focused on weekly instruction time. Third, I performed detailed estimations using a fixed-effect model to remove student and teacher fixed effects, using Japanese student data, which have a high average score.

The rest of this paper is organized as follows: Section 2 explains the Japanese education system and reforms. Section 3 summarizes the existing literature on the effect of instruction time and content of lessons. Section 4 presents the data and describes identification strategies. The results are reported and discussed in Section 5. Finally, Section 6 presents conclusions.

2. The Japanese education system and school instruction time

The TIMSS provides all the data for participating countries, but this study focuses especially on Japan to investigate the effect of instruction time in a society where schools have many resources and students achieve high test scores. The TIMSS data show that Japanese students in compulsory schools have high cognitive ability on average. Furthermore, Japanese public education provides equal standards of education nationwide, so there are only small gaps in student ability. I examine the effect of instruction time under such an environment.

Despite their high achievement, Japanese students have lower motivation to learn on average than their peers in other countries. It is thus important for Japanese education policy to raise students' motivation as well as their scores. The effect of the learning environment on students' motivation is an important area in which this study can provide valuable knowledge.

The Japanese compulsory education system comprises six years of elementary school education and three years of junior high school education, and is regulated by a law called the School Education Act (*Gakko kihon ho*). The school year begins in April and ends in March the following year. Generally, children attend elementary school from 6 to 12 years of age, and junior high school from 12 to 15 years of age.

Japan's National School Curriculum (*Gakusyu shido yoryo*) ensures that children can receive a consistent standard of education nationwide. Besides, the School Education Law (*Gakko kyoiku ho shiko kisoku*) sets the standards for instruction time and contents for all subjects, and each school makes its own curriculum in accordance with these standards. The National School Curriculum is revised about every 10 years to keep pace with the latest developments. The revision in 2002 greatly changed Japanese education policy, marking a shift from merely inputting knowledge toward fostering thinking and self-creation. Japanese public schools introduced the five-day school week in April 2002. As Saturdays ceased to be school days, the annual number of lessons for each grade dropped by about 70.[2] The 2002 revision also greatly reduced standard instruction time. As many discussions ensued regarding a possible decline in children's academic ability, the standard instruction time was raised in the following revision in 2011, but the five-day school week was retained and, from 2020, English was added as a new subject at elementary school.

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[2] This represents a 3,150-minute (52.5-hour) reduction because each lesson in the Japanese elementary school system lasts 45 minutes.

For all that the standard instruction time provides by school guidelines and that all schools are required to follow, the actual number of school days and the curriculum is decided by each school based on community and school conditions. Therefore, there might be a difference in instruction time between the standard number and the true number.

<Please insert Figure 2 and Figure 3 here>

Figure 2 shows differences between schools and changes across years in the instruction time of 4th grade students in public elementary schools. *Standard* indicates schools whose instruction time matched the curriculum guidelines, while *low* and *high* respectively indicate schools in which instruction time was lower and higher than the standard instruction time. I recognize that many schools had longer instruction time than the national standard. In addition, the difference between the school with the highest instruction time (1121 lessons) and the school with the lowest instruction time (944 lessons) is over 100 lessons. Figure 3 shows the distribution of total school days each year for all Japanese public elementary schools, and how this distribution changed between 2002 and 2008. Over 90% schools had 196–205 school days between 2002 and 2008; some schools had more than 206 days while a few schools had less than 195 days, so the difference could be over 10 days between schools.

Thus, during the period of time this study has focused on, many Japanese public schools had an instruction time over the standard time, and the amount of instruction time and school days varied by school and area. Consequently, I cannot treat the change to instruction time in the revision of the National School Curriculum as an exogenous variable in the analysis. Furthermore, the curriculum is determined by each school, so instruction time is influenced by characteristics of the school, teachers, students, and school area. To estimate the causal effects of instruction time, it is necessary to remove these endogenous factors as much as possible. In Japan, elementary schools have large class sizes (up to 40 students), and the teacher has significant responsibility and workload. Furthermore, an elementary school teacher needs to teach almost all the subjects, whereas a junior high school teacher focuses on a specific subject. The teacher has a strong influence on student performance, so I need to remove teacher fixed effects to estimate the impact of instruction time accurately.

3. Related literature

To identify how school education resources can be most effectively allocated, many studies have focused on how education reform affects instruction (Gromada and Shewbridge 2016). Their findings suggest that an increase in instruction time generally improves children's cognitive ability. However, there is a lack of data on whether instruction time and children's academic performance are positively correlated. Since the 2000s, many studies have tried to estimate detailed causal analyses using microdata since. These studies have used natural experiments to estimate the causal effects of instruction, using measures of instruction time or number of school days. The most common method is a difference-in-difference estimation following an area's education reform (or other policy change) that serves as a natural experiment.

Some studies have shown that instruction time positively affects students' cognitive ability. Several of these studies used the event of German education reform, which led to increased instruction time but a reduction in the high school year (Dahmanna 2017; Huebener, Kuger, and Marcus 2017; Huebener and Marcus 2017). Elsewhere, Bellei (2009) evaluated the impact of increasing instruction time as a result of the education reform in Chilean high schools, while Lavy (2020) used Israeli high school data.

One study reported a 0.05 standard deviation (SD) improvement in English test scores for students who engaged in a program delivering increased instruction time in low-scoring elementary schools and junior high schools in Florida (Figlio, Holden, and Ozek 2018). Thompson (2020) found that a one hour increase in weekly instruction time was associated with test-score improvements of 0.018 SD in mathematics and 0.006 SD in reading in 3rd through 8th grade students in Oregon. Furthermore, increased instruction time through supplementary lessons has been found to improve junior high school students' mathematics scores in the United States (Taylor 2014) and in south Italy (Meroni and Abbiati 2016). Conversely, Meyer and Klaveren (2013) found no effect of instruction time on mathematics and language achievement for Dutch elementary school students using instrumental variables (IV) estimation. Lengthening the school day has been found to positively impact on student test scores following a change in climatic conditions, such as heavy snow (Marcotte 2007; Aucejo and Romano 2016).

Besides natural experiments, some studies have adopted a within-student between-subject identification approach using a fixed-effect model (Lavy 2015; Rivkin and Schiman 2015; Cattaneo, Oggenfuss, and Wolter (2017)). They estimated the effect of instruction time with an international comparison using Programme for International Student Assessment (PISA) data, and found that instruction time has a significant positive effect on student test scores. In addition, Cattaneo, Oggenfuss, and Wolter (2017) found heterogeneity on instruction time; specifically, students with typically better academic results benefitted more. Lopez-Agudo and Marcenaro-Gutierrez (2019) analyzed PISA 2015 data for Spain and showed that the effect of instruction time differs between areas.

In Japan, Motegi and Oikawa (2019) found that the change in instruction time following education reform had heterogeneous effects on 8th grade students' TIMSS scores (1999 and 2003) due to differences in instruction quality. Likewise, the reduction of instruction time as a result of the education reform in Japan caused a decrease of 0.5 years for Japanese women's education period (Kikuchi 2014) and increased the gap in academic achievement between children from different socioeconomic backgrounds (Kawaguchi 2016). Meanwhile, Bessho et al. (2019) showed that supplementary lessons totaling 45 hours resulted in a 0.13 SD improvement on Japanese language art scores of 3rd and 4th grade students in Japan.

Other studies have focused on instruction contents (Machin and McNally 2008; Van Klaveren 2011; Schwerdt and Wuppermann 2011). Machin and McNally (2008) analyzed the effect of the Literacy Hour policy in the United Kingdom using a difference-in-difference approach; they found this policy to be particularly effective for children with weak ability to read and write, and also more cost-effective than other education policies. Van Klaveren (2011) concluded that the proportion of lesson time devoted by teachers to lecturing the class is unrelated to students' cognitive performance in the Netherlands. However, Schwerdt and Wuppermann (2011) indicate that traditional lecture-style teaching is associated with higher student achievement. In the United States, McMullen and Rouse (2012) estimated the effect of year-round schooling and confirmed that this did not affect average student performance.

The above studies used student test scores (indicating cognitive ability) as the student outcome measure. Improving cognitive ability is the main purpose of education because it is closely related to future productivity. However, following Heckman's studies (Heckman and Rubinstein 2001; Heckman, Stixrud and Urzua 2006; Cunha and Heckman 2007), non-cognitive ability, motivation, and behavior in school, are recognized as being of equal importance to cognitive ability. As for the analysis of education resources and non-cognitive factors, I consider the effect of class size (Dee and West 2011; Ito and Nakamuro and Yamaguchi 2020) and the effect of teacher and teaching (Blazar and Kraft 2017). Concerning the effect of instruction time, Lavy (2020) found that increasing the weekly instruction time has a positive effect on academic achievement with no behavioral cost, while Meroni and Abbiati (2016) used the students' attitudes and behaviors toward studying as the outcome index. However, little research has investigated the effect of instruction time on students' motivation.

4. Data

4.1. TIMSS

This study uses Japanese 4th grade data from TIMSS 1995, 2003, and 2007. TIMSS is an international comparative assessment aimed at improving teaching and learning in mathematics and science for students around the world. It is carried out every four years by the International Association for the Evaluation of Educational Achievement (IEA) to test the mathematics and science achievements of 4th and 8th grade students. Besides students' educational achievement data, it collects information on the teaching and learning of mathematics and science from students, teachers, and school principals. The number of participating countries grew from 46 in 1995 to 58 in 2019. TIMSS 1995, 1999, 2003, 2007, 2011, 2015, and 2019 data for each country are available from the IEA's webpage.[3]

In Japan, about 140–150 schools and 4,000–5,000 students have participated each year at both 4th and 8th grade levels. The survey data provide accurate estimates of national student populations with a two-stage sample design, but students registered at a

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[3] https://timssandpirls.bc.edu.

special needs school or attending associated classes are excluded at the sampling stage. Japanese investigations were carried out in February or March of each survey year. The Japanese academic year starts in April, so I consider that the results of estimations using TIMSS data show the effects of educational resources in that year. I can also control the influence of students' cognitive or non-cognitive abilities because TIMSS test scores of each student can be matched with the answers given by each student, their teacher and their school principal for each questionnaire about school resources and students' attitudes toward study and motivation.

There are two reasons why I use data from TIMSS 1995, 2003, and 2007. First, Japanese school instruction time was substantially changed between 1995 and 2007 because of revision to the National School Curriculum in 2002. Motegi and Oikawa (2019) captured the effect of this revision as an exogenous change and estimated the effect of instruction time using Japanese 8^{th} grade data from TIMSS 1999 and 2003. This study differs from them in that change of instruction time considering non-exogenous change. However, that great change of instruction time during 1995-2007 makes enough changes to catch the effect in the estimation.

Second, this study tries to control teacher fixed effects. Assuming that the teacher strongly affects students' performance through their lessons, I control for that effect by limiting the sample to classes taught by the same teacher in mathematics and science. After 2007, many Japanese elementary schools have two or more teachers in class, especially for mathematics. I thus decided to use TIMSS 1995, 2003, and 2007 data to enable estimations without restricting many samples that have two or more teachers in class.[4]

4.2. Empirical model

To estimate the causal effects of instruction time, I need to remove the effects of unobserved student and school factors that correlate with instruction time and student outcomes. I considered using IV estimation to remove endogeneity for instruction time, but were unable to find an appropriate instrumental variable in the TIMSS data. Furthermore, these data are cross-sectional, not panel data. Therefore, I created panel data using the difference in instruction time between subjects, following the approach of Lavy

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[4] We cannot identify whether a school is public, national, or private. There are three national or private schools in 2007.

(2015), Rivkin and Schiman (2015), and Motegi and Oikawa (2019). Then, I estimated the following equation as the production function of education using a fixed-effect model:

$$y_{istc} = \lambda H_{stc} + \boldsymbol{\beta} \boldsymbol{X}_{\boldsymbol{istc}} + \boldsymbol{\gamma} \boldsymbol{Z}_{\boldsymbol{stc}} + \mu_i + \theta_s + \phi_t + \eta_c + \omega_{ct} + \pi_{isc} + \varepsilon_{istc} \tag{1}$$

where subscripts *i, s, t,* and *c* indicate the *i* th student at the *s* th school at the *t* th time (t=1:1995; t=2:2003; t=3:2007) in the *c* th subject (c=1: mathematics; c=2: science). Variable y_{istc} is students' outcome variable, representing either the test score or learning motivation. H_{stc} is the total instruction time in one year, $\boldsymbol{X}_{\boldsymbol{istc}}$ is a vector of the characteristics of the student and their family, and $\boldsymbol{Z}_{\boldsymbol{stc}}$ is the vector of school characteristics. As control variables X, I use dummy variables of students' birth month and sex. Variable *Z* represents teachers' experience and sex.

Also in equation (1), variable μ_i is the student fixed effects, capturing unobserved student ability, family background, and constant non-cognitive skill. Variable θ_s is the school fixed effects, capturing unobserved school characteristics such as school quality and the environment of the school area. As we limited the sample to classes taught by the same teacher, θ_s also includes teacher fixed effects, such as teacher quality. I can remove these effects (μ_i, θ_s) by estimating a fixed-effect model. Furthermore, ϕ_t and, η_c

represent time and subject effects, while ω_{ct} shows the time effect for each subject and captures the influence of each subject by year. I control ϕ_t, η_c, and ω_{ct}, using subject dummies and time dummies. The variable π_{isc} captures individual-by-school-by-subject fixed effect. If this variable does not occur at random and affects student education achievement, the estimation would be biased. For example, if a student chooses a school that provides more instruction time for a specific subject in which that students wants order to improve their test score, this may result in upward bias in the estimates. However, elementary-level students in Japan generally attend the public school in their district. Nonetheless, it is necessary to pay attention to the results on the effect of instruction time. Finally, ε_{istc} is an error term.

In estimating model (1), I make two assumptions, namely that the effects of instruction time are equal for both subjects and include spillover between the two subjects.

This study's main purpose is to find the effect value of coefficient (λ) for instruction time (*H*). Our estimation uses the annual instruction time (*H*), as the unit used in education guidelines. This guideline determined the standard annual instruction time and lessons of 45 minutes at elementary schools. I consider this variable more suitable than other times (for example, hours, minutes per week) because I can check the consistency of TIMSS data with real school operations in each year, by checking whether instruction time changes along with the education guideline changes.

TIMSS does not enquire directly about annual school instruction time, so I created this variable through the following steps. First, I obtained the instruction time (minutes) per week from the question, 'How many minutes per week do you teach mathematics (science) to the students in the TIMSS class?' Second, I obtained the annual school instruction days[5] from the question, 'How many days per year is your school open for instructing students?' Third, I calculated the number of school weeks per year by dividing annual school instruction days by the number of school days per week (5 or 6 days). Finally, I calculated the annual instruction time as instruction time (minutes) per week times the number of school weeks per year, and then divide this by 45 minutes (the standard school instruction time in elementary school).

Table 1 shows the standard instruction time for mathematics and science by curriculum guidelines for each grade of elementary school in 1995, 2002, and 2007.

[5] We subtracted 10 days from the data provided by the school to account for days with no studying instruction, such as school events. The average of such days is about 10 as per MEXT investigation.

Figure 4.1 depicts a histogram of annual instruction time for 4th grade students in mathematics and science by year. It shows three peaks in 2003 and 2007, following the reduction in instruction time in the 2002 revision. Many schools' instruction times for 4th grade students exceed those of the guidelines (Table 1 shows mathematics, 150, science, 90), which is consistent with the results shown in Figure 2 and indicates that instruction time is an endogenous variable. Figure 4.2 combines all the data from the three years and shows the difference of instruction time for mathematics and science.

<Please insert Table1, Figure 4.1, and Figure 4.2 here>

I adopt three dependent variables (*y*) to measure the instruction time effects: the standardized test score (*score*) and two indexes of learning motivation (*joy* and *positive*). I use a TIMSS standardized raw score with a mean of 50 and a standard deviation of 10 within each country.[6] The motivation indexes *joy* and *positive* are calculated using responses from the student questionnaire. *Joy* is captured by responses on a 4-point scale

[6] TIMSS provides five scores called "plausible values" to enable inter-countries comparisons. Jerrim et al. (2017) pointed out that it is not appropriate to use this value in this fixed-effect model, so some studies created their own test scores. However, I decided to use the original standardized scores from TIMSS to avoid introducing other biases into the estimation.

(1=strongly disagree, 2=disagree, 3=agree, 4=strongly agree) to the statement ‘I enjoy learning mathematics (science)’. A higher number means greater motivation to study. *Positive* is the second index for student motivation to learn. I make it by principal component analysis using responses on a 4-point scale (1=strongly disagree, 2=disagree, 3=agree, 4=strongly agree) to three questions: ‘I enjoy learning mathematics (science)’; ‘I usually do well in mathematics (science)’; and ‘I learn things quickly in mathematics (science)’. I estimated and got the principal component scores from the first principal component of covariant variable. Table 2 reports the descriptive statistics for the variables for each TIMSS year and aggregated. It shows that the mean instruction times of mathematics is 186 in 1995, 173 in 2003, and 175 in 2007; for science, they are 111 in 1995, 102 in 2003, and 103 in 2007. Therefore, both subjects decreased instruction time after 2002, when the guidelines were revised.

<Please insert Table 2 here>

5. Results

5.1. Ordinary least squares

As the first step in my analysis, I checked the relationship between variables by ordinary least squares (OLS) using pooled data. Columns (1)–(6) of Table 3 report the coefficient estimates. Specifically, columns (1)–(2) shows the results for *score*, columns (3)–(4) show the results for *positive*, and columns (5)–(6) show the results for *joy*. Columns (7)–(8) then show the results for *joy* by ordered logistic estimation, which is used because *joy* is the variable made from the ordered number of answers. The coefficients on *instruction time* in columns (1)–(6) are all positive, but the only significant value is in column (1): the significance disappears when the control variables are added in column (2).

<Please insert Table 3 here>

Regarding the school control variables, *school size* is significantly positively related to *score* and *positive*, while *female teacher* is significantly positively related to *joy*. However, *teaching experience* is not significantly related to any of the dependent variables. Notably, the coefficient of the *girls* shows a significantly negative value for all dependent variables, indicating that 4th grade girls have a lower understanding of and motivation to learn mathematics and science than 4th grade boys.

I ran the estimation using *birth month 2, 3* and *birth month 4* dummies. These coefficients show the difference from the *birth month 1* dummy, which denoted students born in January, February, and March. As all Japanese public schools start in April, students born from January to March are the youngest among their class. With one exception, the coefficients on the *birth month 2-4* dummies are all significantly positive for *score* and *birth month 2,3* dummies are significantly positive for *positive,* and increase in magnitude for older children. These results suggest there is a clear effect of relative age. Conversely, all the *birth month* dummies show no significant correlations with *joy*. *Study time at home* is significantly positively related to *positive* and *joy,* but does not influence *score*. I cannot rule out the possibility of reverse causality: increasing study time at home may follow from increases in motivation and joy resulting from an increase in instruction time. Finally, the ordered logistic results in columns (7)–(8) do not greatly differ from the OLS results for *joy*. The only differences are that the coefficient on *instruction time* is negative (but still insignificant) and that the positive coefficient on *school size* becomes significant (at the 10% level).

These OLS estimation results explain some correlations between the variables, but it is difficult to control all variables related to instruction time, such as teacher quality and student ability, because of that these variables do not have observable data.

The instruction time changed greatly after the 2002 guidelines revision; this can be seen in Figure 4.1, but the size of the change differs between schools. This means that instruction time is an endogenous variable likely influenced by school characteristics, so I need to remove the endogeneity from the estimation. To estimate causal effects of instruction time, previous works clearly demonstrate the need to control for factors that may affect students' test scores and learning motivation, such as their individual ability, family background, and teacher quality.

5.2. Fixed-effect model

5.2.1 Basic estimation results

The extent of the change in instruction time in Japan was determined by the actual situation of students, teachers, and the school district environment. Therefore, I applied a fixed-effect model using a within-student between-subject identification approach to address endogeneity with respect to instruction time. This helps remove fixed effects of students, schools and teachers.

Table 4 reports the results of estimating equation (1) using the fixed-effect model. For all estimations I used robust standard errors clustered at the school level and controlled for year and subject fixed effects. Panel A shows the results of full-sample estimations with *score*, *positive*, and *joy* as dependent variables. The coefficients on *instruction time* are significantly positive for *score* and *joy* (5% level) and for *positive* (10% level). However, these coefficients have small magnitudes: if *instruction time* were to increase by 100 lessons (4,500 minutes), students' *score* is predicted to rise by only 0.85 and their motivation by only 0.18 for *positivity* and 0.15 for *joy.*

<Please insert Table 4 here>

To compare our findings with those of previous studies, I calculated my results for weekly instruction time adopting the methods used by previous studies and obtained a standard deviation value of 0.027 for score. This is very similar to the value of 0.02–0.03 reported by Rivkin and Schiman (2015), and quite close to the value of 0.05–006 reported by Lavy (2015). Bessho et al. (2019) found that remedial education programs for Japanese 3rd and 4th grade students had a positive effect of 0.13 SD on test score of Japanese language arts, but no effect on mathematics. These remedial programs comprise 45 hours of instruction time. I recalculated my effect for the same time of them, and it's 0.029SD, that is around 1/4th of the size of the effect reported by Bessho et al. (2019) result. However, they used the Japanese language arts test score (vs. mathematics and science in my study) and estimated the effect for remedial lessons (vs. normal school instruction time). These differences in their approach compared to mine at least partly explain the differences between their results and my findings.

Panel A of Table 4 shows that *instruction time* is positively related to both dimensions of learning motivation, i.e., *joy* and *positive.*[7] However, this study cannot provide sufficient evidence on whether instruction time directly affects student motivation, or what other variables affect student motivation. For example, when students receive more school lessons, their understanding should be enhanced, potentially leading to higher motivation. How students' learning motivation increases remains a matter for further discussion.

Panels B and C of Table 4 show the results of robustness tests for the above estimations. Specifically, both tests restricted the sample to consider π_{isc} as a non-exogenous variable. Although my estimation removed school fixed effects and student fixed effect, some students might move the school, which decide to increase the instruction time for special subject after the education revision in 2002, in order to learn more that subject at the school. This might affect the result of the estimation. Therefore, Panel B shows the results after limiting the sample to students taking 50–250 lessons. That number range represents standard hours ±100 in mathematics in Japan from 2003.

[7] We also ran a fixed effect ordered logistic estimation for *joy* and found no clear difference with the result from Table 4 (see Appendix A).

On the other hand, Panel C shows the results after limiting the sample to students in class sizes exceeding 30 students. The upper limit for class size in Japanese public elementary schools is 40 students. The difference in class size between schools is so large that it can affect student performance. Moreover, schools with large classes might focus on a special subject (mainly mathematics) thus, influencing the school curriculum. It is, therefore, possible that the effects of instruction time are seen in only small classes where teachers can devote significant attention to each student. The results in Panels B and C show that the positive association between instruction time and *positive* is no longer statistically significant, while the significance level of the coefficients on *score* and *joy* drops from 5% in the basic estimation to 10% in the robustness tests.

5.2.2 Heterogeneous effects

Next, I estimate the heterogeneous effects of instruction time. I interact *instruction time* with *female teacher*, *teacher experience*, schools having absence problems (*absence problem*), and female students (*girls*) along with the school instruction time. Motegi and Oikawa (2019) found that the effect of instruction time on Japanese 8th grade students' TIMSS scores was stronger in combination with teacher quality. Table 5 shows the results of my estimations of heterogeneous effects. I found significantly positive associations between *score* and the interaction of instruction time with *teacher experience*, *absence problem*, and *girls*. Conversely, *positive* was significantly positively associated with the interaction of *instruction time* and *female teacher* but significantly negatively related to the interaction of *instruction time* and *girls*. The variable *joy* was not significantly related to any of the variable interactions.

<Please insert Table 5 here>

I then applied the same restricted-sample robustness checks detailed above (50–250 lessons of instruction time, more than 30 students in a class); the results of these two tests are reported in Tables 6 and 7, respectively. In both restricted samples, *score* is significantly positively associated with the interaction of *instruction time* with *absence problem*. These findings indicate that increasing instruction time raises the score of students at schools with problematic student absence. Furthermore, in both restricted samples, the coefficients of *positive* with the interaction of *instruction time* with *girls* are significantly negative (at the 1% level where only classes of over 30 students are included in the estimation). These findings suggest that increasing instruction time extends the gender gap in students' motivation to study.

<Please insert Table 6 and Table 7 here>

For the interaction between *instruction time* and *teaching experience*, the coefficient for *score* in the baseline estimation is 0.0003, significant at the 5% level, but the significance disappears in the restricted sample of classes with more than 30 students. Comparing with the impact found by Motegi and Oikawa (2019), their effect of cross term (*instruction time(minutes)* × *teacher experience(years)*) indicates 0.001, and it changes to 0.045 for our measure, so the effect size in my baseline estimation is 1/150th of the effect size they found. The difference between my result and that of Motegi and Oikawa (2019) could be explained by our estimation removing teacher fixed effects, which form the core of teacher quality. The difference is also likely explained by the difference in class contents between elementary and secondary students. In addition, both positive significant signs for the coefficient of the interaction between instruction time and *female teacher* on *positive* and *girls* on *score* were not present in the restricted samples.

Finally, in Table 8, I estimate the effects of the interaction between *instruction time* and *study time at home*. All three coefficients for the dependent variables are significantly positive. These results clearly show that the time spent studying at home is critical to learning, especially as *instruction time* alone is not significantly associated with any of the dependent variables in the first row of Table 8. These effects indicate there may be reverse causality between instruction time and students' understanding and motivation, which should be considered when interpreting the relationships.

<Please insert Table 8 here>

If *study time at home*, which is tied to *instruction time*, influences students' *score* and motivation, then increasing instruction time could expand the gap between students of different family backgrounds. Kawaguchi (2016) found that a reduction in schooldays after the Japanese school guidelines revision in 2002 was likely to expand the gap between families from distinct backgrounds because of differences in the time spent studying at home. Thinking about education policy, increasing instruction time could decrease the gap between students with different family backgrounds.

6. Conclusion

Does school instruction time contribute to improving students' performance? This study analyzed the effects of instruction time on students' test score and learning motivation using Japanese 4th grade data from TIMSS 1995, 2003, and 2007. Within the study period, Japanese standard instruction time changed substantially as education policy was revised in 2002. That change reduced the instruction time of mathematics more than that of science. I thus formed panel data using within-student information between these subjects to investigate the causal effects of instruction time in a fixed-effect model that removes student and school fixed effects. The study also removed teacher fixed effects by limiting the sample to students taught both subjects by one teacher. This is a key contribution of the study to advancing understanding because the teacher has a great influence on lesson quality. I also estimated the interaction effects of instruction time with a female teacher dummy, years of teacher experience, a school absence problem dummy, a female students dummy, and students' study time at home, which served to check the heterogeneity of the effects of instruction time.

The estimation results show that *instruction time* is positively related to *score* and *joy*. The effect size for *score* is about the same as that reported by Rivkin and Schiman (2015). It is unclear whether the positive effect on *joy* result comes through students' improved score or a boost to their curiosity from expanding the lesson. This is one limitation of this study that future research should aim to address.

The interaction estimations reveal that instruction time positively affects *score* in absence-problem schools. This indicates that schools with student absence problems can improve students' test scores by increasing instruction time. Conversely, there is no effect of instruction time on score and motivation with female teachers and teacher experience. With regard to female students, the effect of instruction time on *positive* is half the size of the effect for male students, but there are no gender-based differences for the effects on *score* and *joy*. Moreover, an increase in study time at home raises the effect of school instruction time with regard to both *score* and motivation.

This study's results indicate that increasing instruction time can improve students' scores and *joy* for learning, but do not clearly reveal the mechanism for increasing motivation. Further research is required to reveal what factors affect motivation.

In addition, my results suggest that the effects of instruction time are not influenced by the teacher's gender or experience. The apparent absence of heterogeneity could be explained by my study controlling for teacher fixed effects. As Motegi and Oikawa (2019) point out, education policy on instruction time should be discussed to combine any additional instruction time with other school resources like teacher quality. Further investigations into the connection of teacher quality with instruction time and contents or instruction method would be of value in this field. Finally, I find clear evidence that the interaction of instruction time and study time at home influences student performance. This may suggest reverse causality, and suggests that increasing instruction time may expand the education gap between students with different family backgrounds. Many schools have been forced to close during the COVID-19 pandemic, creating the major challenge for the education sector of reduced instruction time, even with some lessons delivered online. We should think urgently about not only increasing instruction time but also implementing other measures, such as remedial lessons at home.

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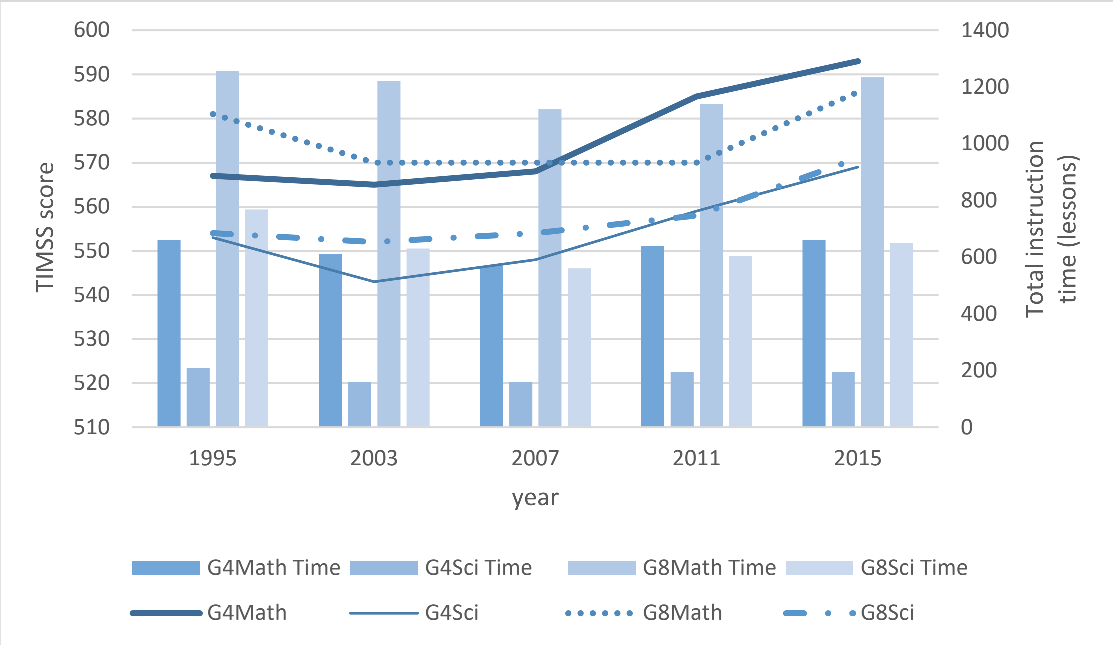
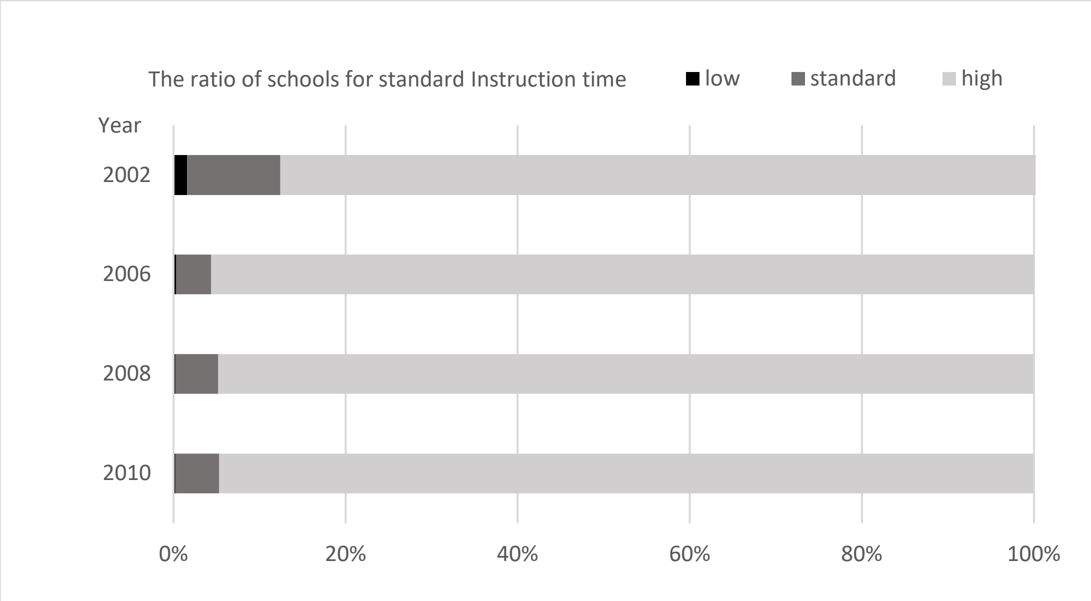
Figure 1. TIMSS score and total instruction time of Japanese 4th and 8th grade students.



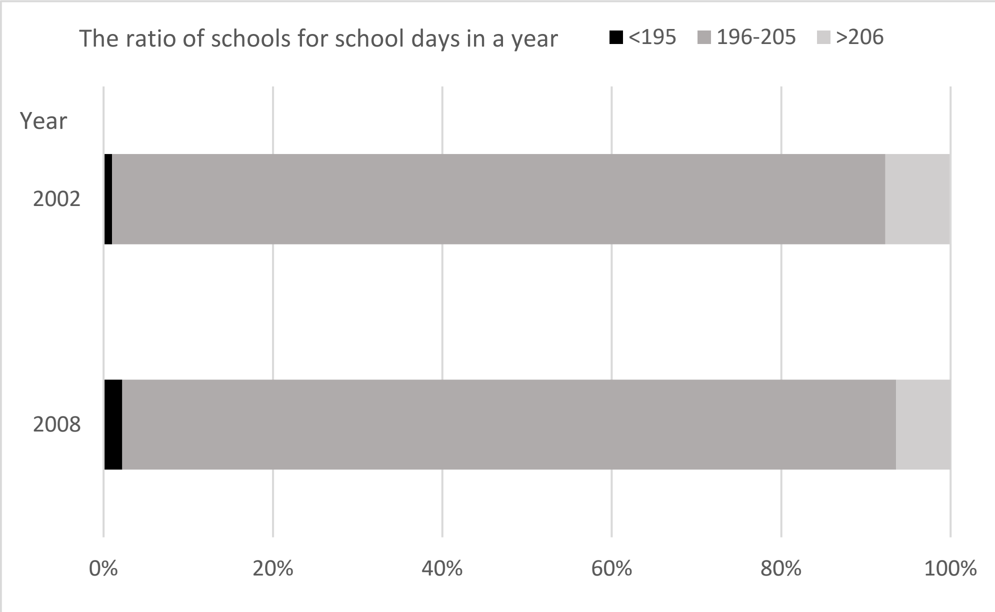
Notes: Total instruction time makes the aggregate number of each grade mathematics (or science) standard instruction time. G4, 4th grade; G8, 8th grade.

Figure 2. Annual instruction time for 4th grade students in Japanese public elementary schools, 2002–2010.



Notes: Standard represents the schools whose instruction time matches the curriculum guidelines, while low(high) represents the schools whose instruction time is lower(higher) than is stipulated in the curriculum guidelines.I made this graph from the data of “investigation for curriculum in elementary and junior high school (*kyouikukatei no hensei jisshi jyoukyou chousa*)“ by MEXT. https://www.mext.go.jp/a_menu/shotou/new-cs/1263169.htm

Figure 3. Comparative distributions of annual school days in Japanese public elementary schools in 2002 and 2008



Notes: It is the ratio of elementary schools in japan which have their school days in a year in 2002 and 2008. I made this graph from the data of "investigation for curriculum in elementary and junior high school (kyouikukatei no hensei jisshi jyoukyou chousa)"by MEXT.
https://www.mext.go.jp/a_menu/shotou/new-cs/1263169.htm

Figure 4.1. Total instruction time in mathematics and science for Japanese 4th grade students by year (TIMSS data).

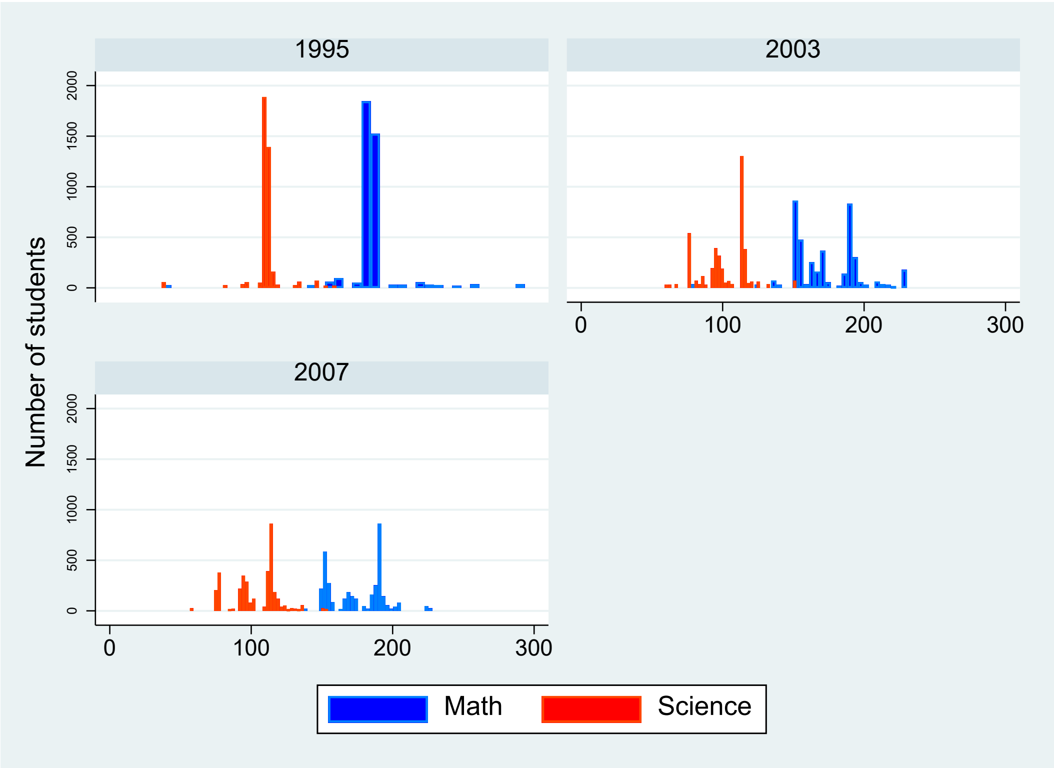


Figure 4.2. Total instruction time in mathematics and science for Japanese 4th grade students in all years (TIMSS data).

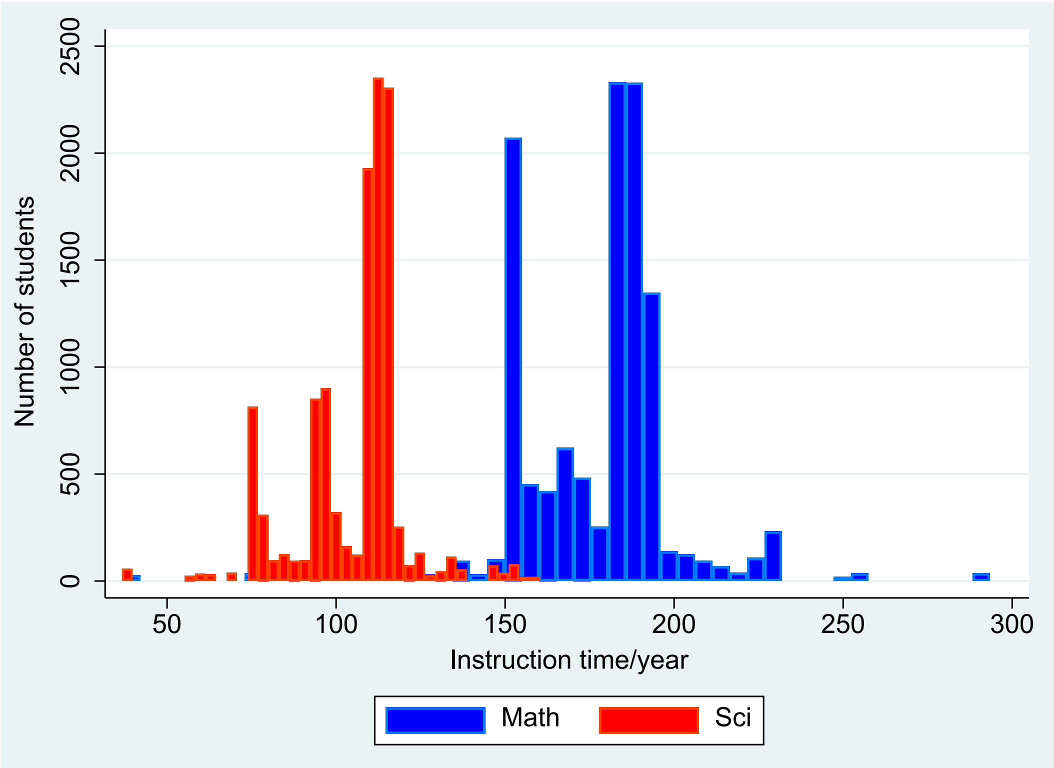


Table1 Japanese standard instruction time in 1995,2003,2007

	1995		2003/2007	
Grade	Math	Science	Math	Science
1st	136	0	114	0
2nd	175	0	155	0
3rd	175	105	150	70
4th	175	105	150	90
5th	175	105	150	95
6th	175	105	150	95

Table2 Summary statistics

Variable		All				1995		2003		2007	
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Istructuin time	Math	177.6	22.6	37	293	185.66	20.64	172.69	24.34	174.50	19.94
	Science	105.5	15.9	37	160	110.82	12.31	102.20	16.83	103.36	16.82
score	Math	51.03	9.87	7.06	68.93	53.03	9.24	49.97	10.04	50.06	10.01
	Science	51.00	9.82	-1.86	73.63	52.84	9.14	50.06	10.00	50.08	10.03
Positive	Math	4.66	1.10	1.71	6.85	4.59	0.94	4.63	1.15	4.78	1.20
	Science	5.01	1.05	1.72	6.88	4.97	0.92	4.93	1.10	5.12	1.10
Joy	Math	2.87	0.89	1	4	2.82	0.74	2.84	0.96	2.95	0.95
	Science	3.29	0.79	1	4	3.24	0.71	3.25	0.84	3.41	0.79
School											
school Size		560.98	262.59	40	1363	547.10	283.40	525.00	230.65	617.32	264.44
class Size		32.65	5.50	5	41	32.44	5.48	32.84	5.72	32.66	5.25
teacher experience (year)		17.69	9.34	1	39	15.89	7.41	18.40	9.48	18.84	10.68
female teacher		0.60	0.49	0	1	0.59	0.49	0.60	0.49	0.62	0.48
absence problem		0.21	0.40	0	1	0.27	0.45	0.16	0.37	0.18	0.39
Student											
girls		0.50	0.50	0	1	0.50	0.50	0.49	0.50	0.50	0.50
birth month1 (January-March)		0.24	0.43	0	1	0.24	0.43	0.23	0.42	0.24	0.43
birth month2 (April-June)		0.24	0.43	0	1	0.24	0.43	0.25	0.44	0.24	0.43
birth month3 (July-September)		0.27	0.45	0	1	0.27	0.45	0.27	0.45	0.27	0.44
birth month4 (October-December)		0.25	0.43	0	1	0.25	0.43	0.24	0.43	0.25	0.43
Study time at home (hours/day)		1.06	0.89	0	4.5	1.18	0.97	0.95	0.78	1.06	0.88
Number of students			11607			3907		4118		3582	

Table3 Results of OLS and Ordered Logistic estimation

	OLS						ordered logistic	
	Score		*Positive*		*Joy*		*Joy*	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
instruction time	0.0110*	0.0086	0.0001	0.0002	0.0001	0.0002	-0.00018	-0.0001
	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
instruction time	-0.0031	-0.0011	0.0003	0.0004	0.0000	0.0000	-0.0002	-0.0002
× *science dummy*	(0.0092)	(0.0091)	(0.0013)	(0.0013)	(0.0010)	(0.0010)	(0.0021)	(0.0021)
science dummy	0.912	0.492	0.349*	0.354*	0.424***	0.429***	0.884***	0.906***
	(1.321)	(1.312)	(0.185)	(0.189)	(0.152)	(0.154)	(0.308)	(0.314)
school size		0.0010**		0.00012**		0.0001		0.00015*
		(0.0004)		(0.0001)		(0.0000)		(0.0001)
female teacher		0.16		0.0311		0.0375*		0.0906*
		(0.24)		(0.028)		(0.0218)		(0.0466)
teacher experience		0.0232		-0.0019		-0.0019		-0.00401
		(0.0148)		(0.0015)		(0.0012)		(0.0027)
girls		-0.314*		-0.248***		-0.151***		-0.405***
		(0.1850)		(0.0178)		(0.0148)		(0.0322)
birth month 2		2.372***		0.0456**		0.000988		-0.014
		(0.24)		(0.0224)		(0.0171)		(0.0378)
birth month 3		1.898***		0.0390*		0.0055		-0.0023
		(0.2330)		(0.0224)		(0.0184)		(0.0401)
birth month 4		0.837***		0.0186		-0.00355		-0.0112
		(0.2350)		(0.0238)		(0.0184)		(0.0390)
study time at home		0.0807		0.115***		0.0830***		0.192***
		(0.1040)		(0.0101)		(0.0076)		(0.0182)
Observations	23,213	22,740	22,594	22,315	22,799	22,500	22,799	22,500
R-squared	0.023	0.034	0.031	0.053	0.066	0.082		
Pseudo-R^2							0.031	0.039

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table4 Results of fixed effect estimation

	Fixed effect		
	Score	*Positive*	*Joy*
VARIABLES	(1)	(2)	(3)
Panel A		All	
instruction time	0.0085**	0.0018*	0.0015**
	(0.0039)	(0.0009)	(0.0008)
Observations	23,213	22,594	22,799
R-squared	0.001	0.069	0.144
Panel B	drop lessons under 50& over 250		
instruction time	0.0082*	0.0016	0.0016*
	(0.0044)	(0.0011)	(0.0009)
Observations	23,055	22,437	22,642
R-squared	0.001	0.070	0.145
Panel C	over 30 students in a class		
instruction time	0.0095*	0.0009	0.0015*
	(0.005)	(0.0011)	(0.0009)
Observations	16,338	15,909	16,042
R-squared	0.001	0.071	0.148

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table5 Results of Fixed effect estimation for heterogeneous effect

	Fixed effect											
	Score	*Positive*	*Joy*	*Score*	*Positive*	*Joy*	*Score*	*Positive*	*Joy*	*Score*	*Positive*	*Joy*
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
instruction time	0.0076*	0.00115	0.00115	0.0041	0.0015	0.0012	0.0061	0.0015	0.0014*	0.0067	0.0022**	0.0014*
	(0.0042)	(0.001)	(0.0008)	(0.004)	(0.0011)	(0.0008)	(0.0042)	(0.001)	(0.0008)	(0.004)	(0.001)	(0.0008)
instruction time												
× *female teacher*	0.0013	0.0008*	0.0005									
	(0.0023)	(0.0004)	(0.0004)									
× *teacher experience*				0.0003**	0.0000	0.0000						
				(0.0001)	(0.0000)	(0.0000)						
× *absence problem*							0.0057*	0.0006	0.0003			
							(0.0031)	(0.0005)	(0.0005)			
× *girls*										0.00381*	-0.0009***	0.0002
										(0.0023)	(0.0003)	(0.0003)
Observations	23,213	22,594	22,799	23,213	22,594	22,799	23,213	22,594	22,799	23,213	22,594	22,799
R-squared	0.001	0.070	0.144	0.001	0.070	0.144	0.001	0.070	0.144	0.001	0.070	0.144

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table6 Results of Fixed effect estimation for heterogeneous effect (drop lessons under 50& over 250)

	Fixed effect (drop lessons under 50& over 250)											
	Score	*Positive*	*Joy*	*Score*	*Positive*	*Joy*	*Score*	*Positive*	*Joy*	*Score*	*Positive*	*Joy*
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
instruction time	0.0068	0.0010	0.0012	0.0035	0.0012	0.0011	0.0065	0.0015	0.0016*	0.0063	0.0021*	0.0015*
	(0.0047)	(0.0012)	(0.0009)	(0.0049)	(0.0012)	(0.0009)	(0.0045)	(0.0011)	(0.0009)	(0.0046)	(0.0011)	(0.0009)
instruction time												
× *female teacher*	0.0018	0.0008*	0.0005									
	(0.0024)	(0.0005)	(0.0004)									
× *teacher experience*				0.0002*	0.00002	0.00002						
				(0.0001)	(0.0000)	(0.0000)						
× *absence problem*							0.0067**	0.0004	0.0002			
							(0.0034)	(0.0005)	(0.0005)			
× *girls*										0.0039	-0.0008**	0.0003
										(0.0024)	(0.0003)	(0.0003)
Observations	23,055	22,437	22,642	23,055	22,437	22,642	23,055	22,437	22,642	23,055	22,437	22,642
R-squared	0.001	0.071	0.146	0.001	0.070	0.146	0.001	0.070	0.145	0.001	0.071	0.146

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table7 Results of Fixed effect estimation for heterogeneous effect (over 30 students in a class)

	Fixed effect (over 30 students in a class)											
VARIABLES	*Score*	*Positive*	*Joy*	*Score*	*Positive*	*Joy*	*Score*	*Positive*	*Joy*	*Score*	*Positive*	*Joy*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
instruction time	0.0096*	0.0007	0.0014	0.0052	0.0001	0.0010	0.0064	0.0007	0.0014	0.0082*	0.0015	0.0016*
	(0.0053)	(0.0012)	(0.0009)	(0.0054)	(0.0012)	(0.0009)	(0.0054)	(0.0012)	(0.0009)	(0.0049)	(0.0011)	(0.0009)
instruction time												
× *female teacher*	-0.0001	0.0003	0.0002									
	(0.0028)	(0.0006)	(0.0005)									
× *teacher experience*				0.0002	0.00005*	0.0000						
				(0.0001)	(0.0000)	(0.0000)						
× *absence problem*							0.0063*	0.0006	0.0003			
							(0.0036)	(0.0006)	(0.0005)			
× *girls*										0.0028	-0.0013***	-0.0002
										(0.0024)	(0.0004)	(0.0003)
Observations	16,338	15,909	16,042	16,338	15,909	16,042	16,338	15,909	16,042	16,338	15,909	16,042
R-squared	0.001	0.071	0.148	0.001	0.071	0.149	0.002	0.071	0.148	0.001	0.072	0.148

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table8 Results of Fixed effect estimation for heterogeneous effect of study time at home

	Fixed effect		
	Score	*Positive*	*Joy*
VARIABLES	(1)	(2)	(3)
instruction time	0.0051	0.0008	0.0007
	(0.0039)	(0.0010)	(0.0008)
instruction time			
× *study time at home*	0.0032**	0.0010***	0.0009***
	(0.0013)	(0.0002)	(0.0002)
Observations	22,898	22,461	22,650
R-squared	0.002	0.072	0.147

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix A Results of Fixed effect Ordered Logit estimation

	Joy					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
instruction time	0.0044***	0.0046***	0.0023	0.004***	0.0048***	0.0019
	(0.0014)	(0.0016)	(0.0016)	(0.0015)	(0.0015)	(0.0015)
instruction time						
× *female teacher*		0.0003				
		(0.0009)				
× *teacher experience*			0.0001**			
			(0.0000)			
× *absence problem*				0.0009		
				(0.0010)		
× *girls*					-0.0009	
					(0.0008)	
× *study time at home*						0.0025***
						(0.0005)
Observations	17,754	17,754	17,754	17,754	17,754	17,624
Pseudo-R^2	0.225	0.225	0.226	0.225	0.225	0.228

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1