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ASAKAWA, Shinsuke
Saga University

OHTAKE, Fumio
RIETI

Research Institute of Economy, Trade & Industry, IAA
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Impact of COVID-19 School Closures on the Cognitive and Non-cognitive Skills of Elementary School Students*†

Shinsuke ASAKAWA
Saga University

Fumio OHTAKE
Osaka University and Research Institute of Economy, Trade and Industry

Abstract

This study examines the dynamic effects of school closures caused by COVID-19 on the cognitive and non-cognitive skills of fourth and fifth-grade students in Nara City, Japan. We use triannual math tests and concurrent surveys about students' motivation to learn math. Using Event Study and Difference-in-Differences methods, we compare cohorts with and without the experience of school closure and find that it reduced cognitive skills (math scores) in the short term. But on average, the scores significantly recovered within six months of schools fully reopening. However, some students with disadvantaged living conditions during and after the closure, and some students in fourth grade, did not fully recover. We also find that non-cognitive skills (student attitudes toward proactive learning in math) were higher than in cohorts which did not experience school closure. Furthermore, the lower the students' achievements in math, the greater the impact of living conditions on students' mathematical cognitive and non-cognitive skills.

Keywords: COVID-19 school closure, Cognitive and non-cognitive skills, Elementary school students, Event study and DID, Living conditions

JEL classification: I21, I24, I28

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† Asakawa: Assistant Professor, Faculty of Economics, Saga University, 1 Honjo-machi, Saga, 840-8502, Japan. Email: asakawas@cc.saga-u.ac.jp. Ohtake: Specially Appointed Professor, Center for Infectious Disease Education and Research (CiDER), Osaka University. Email: ohtake@econ.osaka-u.ac.jp

1. Introduction

The ongoing COVID-19 pandemic triggered temporary school closures across 188 countries in March 2020, which deprived approximately 1.5 billion students of in-person public education (OECD, 2021a; UNESCO, 2021). After the initial closures, governments could either re-open schools, fully or partially, or keep the schools fully closed (OECD, 2021a). Fully open meant in-person classes would resume, and fully closed meant the initial closure would continue. The duration of school closure varied across countries (UNESCO, UNICEF, and World Bank, 2020a; UNESCO, 2021) and even between regions within the same country (UNESCO, UNICEF, and World Bank, 2020b).[1]

Many schools opted for a partial reopening to balance the recovery of education opportunities with social distancing — a necessary measure for COVID-19 prevention. The partial reopening of schools was carried out differently across and within countries. While only certain prefectures or school districts reopened schools completely, others used a hybrid model in which some students attended classes in person and other students within the same school had classes on-demand or using online methods (OECD, 2021a, 2021b).

One impact of the COVID-19 school closures was the decline in students' cognitive skills, regardless of country or region (Donnelly and Patrinos, 2021; Engzell et al., 2021;

[1] As of May 2020, 13 countries had officially reopened primary and secondary schools. According to Box 4 and Table 1 of UNESCO (2020), the breakdown is 8 countries in Asia and the Pacific (China, Cook Islands, Japan, Marshall Islands, Republic of Korea, Tonga, Vanuatu, and Vietnam), 4 countries in Europe (Denmark, Faroe Islands, Greenland, and Norway), and 1 country in Africa (Madagascar). After about one year of closure, an increasing number of countries have fully or partially opened their schools. For example, the percentage of OECD countries that completely reopened schools increased from approximately 30% and 40% for elementary and lower secondary schools on February 1, 2021, to approximately 65% and 60% on May 20, 2021, respectively. The percentage of these countries that partially reopened also increased from approximately 12% and 17% for elementary and lower secondary schools on February 1, 2021, to approximately 29% and 31% on May 20, 2021, respectively.

Gore et al., 2021; Kuhfeld et al., 2020; Maldonado and De Witte, 2022; Schult et al., 2021; Tomasik et al., 2021). These results are consistent with studies conducted before the COVID-19 pandemic. They showed that students' academic performance deteriorated due to school closures; reasons for closure included summer breaks (Atteberry and McEachin, 2021; Cooper et al., 1996; Downey et al., 2004; Kuhfeld, 2019; Kuhfeld and Tarasawa, 2020; von Hippel et al., 2018), natural disasters (Andrabi et al., 2020; Goodman, 2014; Hansen, 2011; Marcotte, 2007; Marcotte and Hemelt, 2008; Sacerdote, 2012; Thamtanajit, 2020), infectious diseases (Meyers and Thomasson, 2021; Oikawa et al., 2022), teachers' strikes (Belot and Webbink, 2010; Wills, 2014), students absence (Liu et al., 2021), and reduction in class days (Aucejo and Romano, 2016; Kawaguchi, 2016; Motegi and Oikawa, 2019). The other impact of the COVID-19 school closures was on non-cognitive skills. In Japan, Doi et al. (2021) showed that the closure of daycare centers due to the COVID-19 pandemic worsened the social-emotional skills of preschool children.

To further understand the long-term effects of fully closed schools on academic performance, several recent studies have examined the medium-to-long-term recovery of student performance for over six months after schools were fully reopened (Halloran et al., 2021; Schult et al., 2021). Halloran et al. (2021) found that temporary school closures lowered district-wide passing rates on statewide achievement tests. However, a longer in-person instruction period after complete school closure lowered this decline in academic performance. Schult et al. (2021) compared cohorts from previous years to fifth-grade students who experienced school closure in 2020, and found a decline in reading comprehension, operations, and numbers. They also noted that only the reading comprehension of low-achieving children remained at pre-closure levels. These results could be attributed to teachers finding ways to compensate for coordinated disruptions, like modifying instruction schedules to support the delays in education outcomes for struggling learners (Goodman, 2014). However, no studies have captured the dynamic changes that caused a short-term decline (less than six months) and medium-to-long-term recovery (more than six months) of cognitive and non-cognitive skills. This is due to the lack of high-frequency test data and the insufficient time elapsed after schools were reopened.

Japan was one of the first countries to resume regular classes. The Ministry of Education, Culture, Sports, Science, and Technology (MEXT) shows that after the closure, many schools in Japan shortened vacations and eliminated school events to recover students' learning losses (MEXT, 2020, pp. 5–6). It is important to understand if these measures contributed to arresting the decline in academic performance due to COVID-19-related school closures. Thus, the present study examined the dynamic effects of school closures on the short-term decline and medium-to-long-term recovery of cognitive and non-cognitive skills among fourth- and fifth-grade elementary school students.

To examine the effects of school closures on cognitive skills, we use data from "Manabi Nara"—the tri-annual math test administered to all fourth- to sixth-grade elementary school students in Nara City, the prefectural capital of Nara Prefecture in Japan with a population of about 350,000. In Japan, the first term lasts from April to July, the second term from September to December, and the third term from January to March. However, during the COVID-19 pandemic, many schools pushed forward the spring break, which normally begins at the end of the third term (around March 25), and closed schools completely on March 2, 2020 (MEXT, 2020).[2] In Nara City, this closure was extended

[2] In Japan, the government temporarily closed elementary schools, junior high schools, high schools, and

with schools resuming regular classes from June 1, 2020. Thus, we use the test results for students in the grades that experienced the closure during elementary school (grades 4 and 5 in March 2020) — two tests before and four after the closure (from -2 term to +3 term from the closure).[3]

To estimate the treatment effect of COVID-19 school closures on cognitive skills, we must consider potential changes in the math test scores for the two years that involved the school closures. The math achievement test in Nara City was designed to be of the same difficulty level across grades and terms, allowing temporal comparisons among the same and between different cohorts. Therefore, we employ an event study methodology and compare the test results between cohorts who experienced the closure (grades 4 and 5 in March 2020) and those who did not (grade 6 and students about to graduate from primary school in March 2020).[4] To examine the heterogeneity in the effects of school closures, we also use the results of the "Living Conditions Survey" conducted by Nara City in May (during the closure) and June (after reopening) of 2020. Under the event study framework, we estimate the marginal average treatment effects (MATE) to test if and to what extent differences in living conditions during and after the closure generated heterogeneity in the effects on cognitive skills.

We also examine the effect of school closures on non-cognitive skills. For primary school teachers, the MEXT established the "Courses of Study," which have three

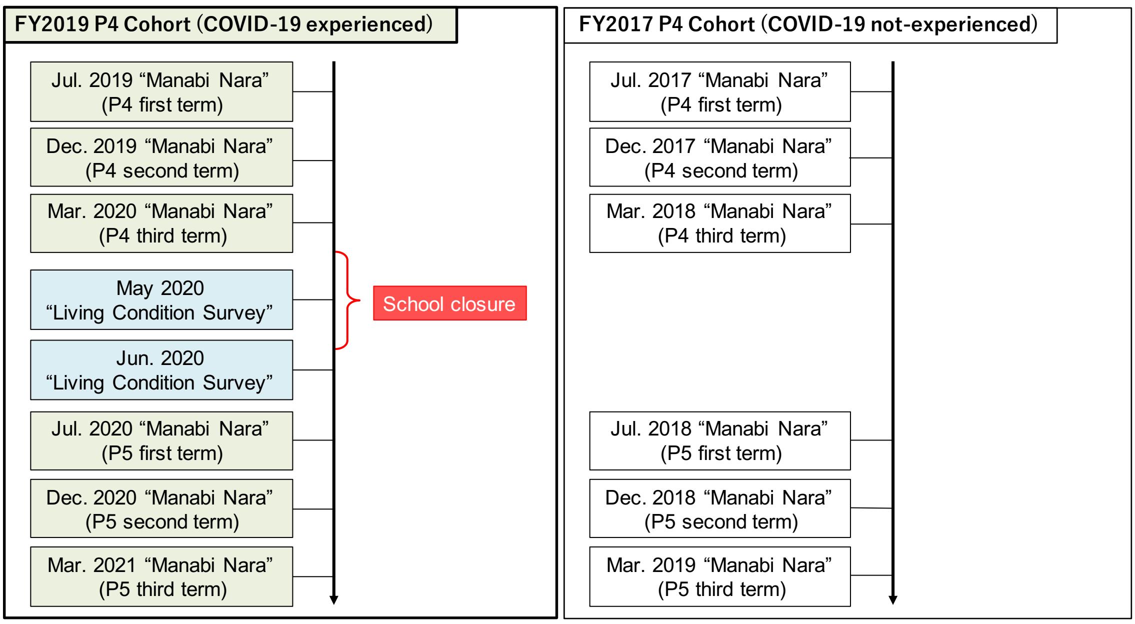
special-needs schools from March 2, 2020, to arrest the spread of the COVID-19 epidemic. As of March 5, 2020, 18,923 of the 19,161 elementary schools in Japan were closed (The Japan Times, 2020).

[3] When the COVID-19-related temporary school closures occurred in March 2020, the FY2019 P4-P5 cohort was at the end of the third term of grades 4 and 5, and the FY2019 P6 cohort was at the end of the third term of grade 6. Therefore, we consider the period from the end of the third term of grade five (school closure) to the end of the third term of grade six (+3 term from the closure) as the post-treatment period of the COVID-19 school closure.

[4] Engzell et al. (2021) and Maldonado and De Witte (2022) also regard the cohort who did not experience COVID-19 school closure as a control group. They used DID to compare the test results between cohorts who experienced the closure and those who did not.

educational perspectives including “basic and fundamental knowledge and skills,” “ability to think, make judgments, and express themselves,” and “an attitude of proactive learning to develop individuality.” Academic achievement tests can measure the first two perspectives, but not the third. Therefore, we use the results of self-reported questionnaires that ask about attitudes toward proactive learning in math and compare the responses of students who experienced the closure (grade 5 in March 2020) with those who did not (grade 6 in March 2020). We use difference-in-differences (DID) to estimate the impact of school closures on non-cognitive skills because this survey is conducted once a year (in December) in conjunction with the math test in Nara City. Figure 1 illustrates the timing of the “Manabi Nara,” “Student Survey,” and “Living Condition Survey" by cohort.

A. FY2019 P4 cohort (COVID-19 experienced) and FY2017 P4 cohort (not-experienced)



B. FY2019 P5 cohort (COVID-19 experienced) and FY2018 P5 cohort (not-experienced)

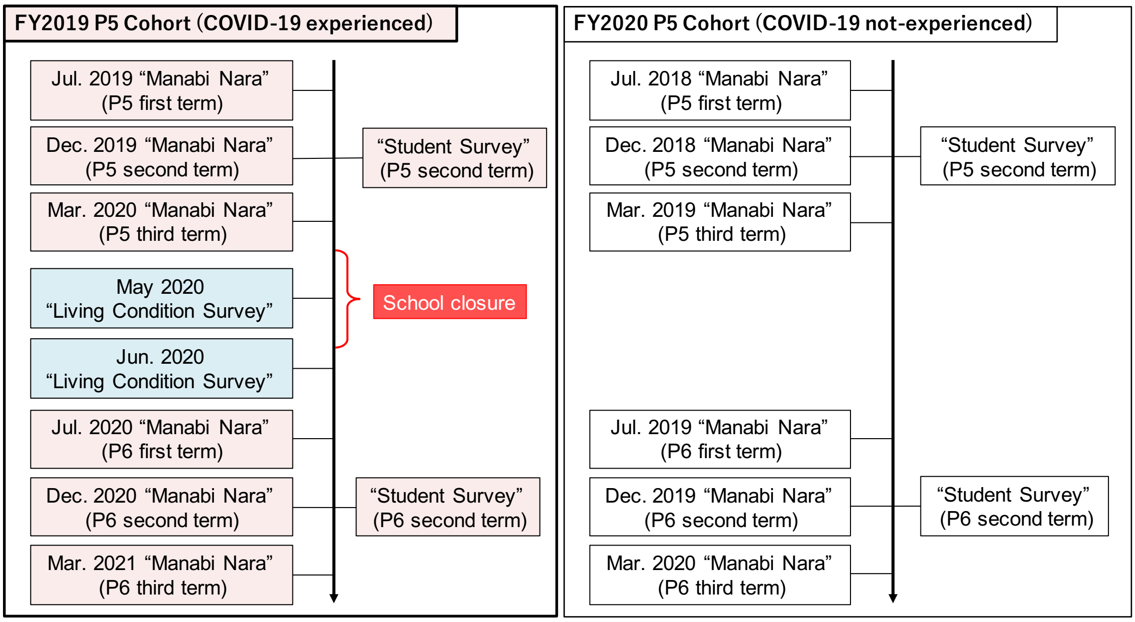


Figure 1. Timing of "Manabi Nara," "Student Survey," and "Living Condition Survey" by cohort

This study obtained four strands of evidence. First, the COVID-19 school closures led to a temporal decline in students' math achievement test scores, particularly those who were low-performing two terms prior to the closure. Second, on average, the test scores recovered six months after the closure ended (+1 term), but some students facing disadvantaged living conditions during and after the closure, or students in grade 4, did not fully recover. Consequently, only students in the lower (1st and 2nd) quantiles remained negatively affected by the +3 term. Third, non-cognitive skills, represented by their attitudes toward proactive learning in math, were higher than in the previous year's cohort. However, 18-34% of students showed worsened attitudes; as with the cognitive skills, the school closure's effects on non-cognitive skills also depended on their living conditions. Finally, the lower the quantile and younger the grade, the greater the impact of living conditions on students' cognitive and non-cognitive skills in math.

This study makes four contributions to the literature. First, we show that primary schools can adjust class schedules to compensate for students' learning losses caused by the COVID-19-related school closures. Previous studies have shown the decline in academic performance as a result of the COVID-19 school closures, but when and to what extent recovery occurred remains unclear. Therefore, we attempt to identify the timing and extent of recovery in math scores using tri-annual individual-level test results. Second, we present new evidence about the impact of the COVID-19 school closures by focusing on Nara City, where schools provided only take-home printed materials for students to engage in distance learning during the closure. In many countries, adequate online resources were not readily available during the closures, which is why this study can provide new evidence to these countries. Third, we reveal that the disadvantaged living conditions during and after the closures negatively affected the recovery of cognitive and non-cognitive skills, especially for the lowest performing group. Some studies have used school-level or residential-level data to show that students were more affected by the closures when their schools or residential areas were disadvantaged (Agostinelli et al., 2020; Gore et al., 2021; Schult et al., 2021). Moreover, Oikawa et al. (2022) shows that math achievement of students from economically disadvantaged households was adversely affected by class closures due to influenza. However, the differences in living conditions during the COVID-19 pandemic may also explain variations in the effects of school closures.[5] Thus, we use individual-level data to examine the heterogeneity within

[5] Some studies show that the quality and quantity of learning during the closure varied depending on students' educational ability, household income, Internet environment, and residential area (Andrew et al., 2020; Aucejo et al., 2020; Bacher-Hicks et al., 2021; Bansak and Starr, 2021; Bayrakdar and Guveli, 2020; Bonal and González, 2020; González and Bonal, 2021; Grätz and Lipps, 2021; Ikeda and Yamaguchi, 2021; Reimer et al., 2021; van der Velde et al., 2021).

Other studies show that living conditions deteriorated due to the pandemic. For example, COVID-19 reduced women's employment (Alon et al., 2020; Collins et al, 2021; Craig and Churchill, 2021; Heggeness, the same school or residential area, based on living conditions during and after the closures. Finally, our study is the first to estimate the causal effects of the COVID-19 school closure in Japan using rich data. Several reports focusing on Japan have tried to verify the effect of school closures on academic performance, but none were able to identify a causal relationship between COVID-19 school closure and students' cognitive and non-cognitive skills.[6] Hence, we use panel data to take into account the pre-closure differences across cohorts.

The remainder of the paper is organized as follows. Section 2 describes the changes in elementary school schedules in Nara City during and after the COVID-19 school closure. Section 3 presents the school closure's effects on cognitive skills. Section 4 discusses the school closure's effects on non-cognitive skills. Finally, Section 5 summarizes the study.

2. School closure and compensation for teaching hours in Nara City

Nara City implemented school closures for approximately three months, beginning on March 2, 2020. As a result, students enrolled in elementary schools, junior high schools,

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2020), and increased mothers' additional parenting time (Del Boca et al., 2020; Farré et al., 2020; Yamamura and Tsutsui, 2021b; Zamarro and Prados, 2021). The pandemic also worsened parents' mental health and well-being (Cheng et al., 2021; Huebener et al., 2021; Takaku and Yokoyama, 2021; Yamamura and Tsutsui, 2021a) and increased domestic violence (Baron et al., 2020; Hsu and Henke, 2021; Pereda and Díaz-Faes, 2020).

[6] For example, the MEXT announced that no school-level correlation was observed between the duration of closures and the test scores for all sixth- and ninth-grade students in the subjects of Japanese and math (MEXT, 2021a, p. 19; The Japan Times, 2021). This report uses only cross-sectional and school-based aggregate data from the 2021 National Assessment of Academic Ability (NAAA) in Japan and calculates correlation coefficients between school closure length and school-level test scores using only cross-sectional data for 2021 (correlation coefficients: Japanese language - 0.001; math - 0.009). Hence, it cannot identify if school closures narrowed the gap in test scores between schools with long and short closures, or if the duration of the closures did not really generate a difference in test scores.

Furthermore, the National Institute for Education Policy Research (NIER) shows that the means and variances of NAAA's scores in Japanese and math for the fiscal years (FY) 2016 and 2021 (COVID-19 not-experienced and experienced) did not change after the closure (MEXT, 2022). However, the NIER's report did not control the test scores before the closure and, therefore, cannot accurately compare the two cohorts (FY2016 and FY2021).

high schools, and special-needs schools in FY2019–FY2020, lost 23 class days in the third term of FY2019 and 54 class days in the first term of FY2020.[7] After the closure, Nara City shortened the summer break by 20 days to compensate for the fewer class days. Nara City also implemented many interventions to secure class time, such as reducing school events after the temporary closure. The following sections provide an overview of each policy.

2.1. Learning during temporary school closure (elementary school)

During the COVID-19 school closure, elementary school students in Nara City were required to study at home.[8] The students studied by themselves using paper-based handouts. The teachers collected and graded the students' filled-in printouts and checked their understanding of the material.[9]

Given that all elementary schools in Nara City were closed temporarily at the same time and in the same manner for home-based learning, this study considers the temporary closure of elementary schools as the first policy intervention and examines its effects.

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[7] In response to a government request, Nara City temporarily closed the city's elementary, junior high, and senior high schools from March 2 to April 5, 2020 (with a spring break from March 25 to April 5). As a result, the third term of the 2019 school year was shortened by 23 days (from March 2 to March 24, including weekends and holidays) compared to the previous year. In addition, after the school opening ceremony and explanation of the school closure schedule on April 6, the school was closed again for one month, from April 7 to May 7. During this period, due to the nationwide COVID-19 pandemic and the declaration of a state of emergency on April 16, Nara City decided on April 28 to extend the re-opening deadline to May 31. As a result, the first term of the 2020 school year was shortened by only 54 days (April 8 to May 31, 2020, including weekends and holidays) compared to the previous year.

[8] Children (grades 1-6) who were unable to stay at home due to their parents' employment or other reasons, could attend elementary school during regular class hours from Monday to Friday. During this time the teachers did not conduct classes, and the students who attended school engaged in self-study. Students with any type of fever or cold symptoms were not allowed to attend school.

[9] Since May, Nara City has been lending school-based tablets and Wi-Fi routers to junior high school students from households that do not own tablets and/or have an internet connection. Junior high and elementary students were also given tablets, which allowed elementary school students to study at home using handouts during most of the temporary school closure. As a result, the distribution and collection of assignments and teachers' study guides were also able to be completed online.

2.2. Shortened summer break and reduction in school events

After the COVID-19 school closures, Nara City implemented two different policy interventions to compensate for the learning loss caused by the closures. First, the summer break in Nara City was drastically shortened from 36 days (July 20 to August 25, in FY2019) to 16 days (August 8 to August 24, in FY2020). Second, elementary schools in Nara City reduced or eliminated school events. Although the number of additional class days and hours varied across schools, on average, the class time was increased by nearly 50 hours (about eight days with six class hours per day). However, these school event cancellations were not accurately ascertained. The shortening of summer vacation and the reduction of school events may have contributed to the recovery of students' academic performance after the school closure. Therefore, we use these new initiatives implemented by schools to interpret the impact of the COVID-19 school closures.

3. Cognitive skills: Math Achievement Test

3.1. Hypotheses

To examine the impact of the COVID-19 school closure on students' cognitive skills, this study tests three hypotheses. The first hypothesis is that the COVID-19 school closure caused a temporary decline in math scores of elementary school students in Japan. Studies from other countries where school closures lasted about 8-10 weeks, similar to Japan, recorded a decline in math achievement (Engzell et al., 2021; Maldonado and De Witte, 2022; Schult et al., 2021). We aim to ascertain whether COVID-19 school closures worsened students' math test scores in Nara City, and to analyze changes in the math test results for the term when the school closure began and one term after the closure.

The second hypothesis is that students recovered their math scores in the medium- and long-term after the end of school closures. Nara city implemented various policies to compensate for the loss of face-to-face learning time, such as shortening summer breaks and canceling school events. By checking the math test's scores from the term after schools reopened, we would like to verify if these measures helped students recover their math scores in the medium-to-long-term after the closure.

The third hypothesis is that the living conditions of students during and after the COVID-19 school closures caused a large disparity in their academic performance after schools reopened. For example, Agostinelli et al. (2020), Gore et al. (2021), and Schult et al. (2021) show that COVID-19 school closures had larger effects on students in schools or residential areas that are disadvantaged in terms of parental socioeconomic status (SES) and school educational resources. Even within the same school and residential area, the living conditions (i.e. mental health and home environment) of students and their families differed during and after the COVID-19 school closure.[10] In Japan, Yamamura and Tsutsui (2021b) find that COVID-19 school closures aggravated the mental health of mothers with elementary school-aged children and low educational background. Ikeda and Yamaguchi (2021) show that students who already used online learning services at home and those in high-quality schools spent more time studying during the COVID-19 school closures than other students. Therefore, we use the results of the questionnaire on students' living conditions during and after the COVID-19 school closure to determine whether living conditions affected the improvement in math test scores after the school closure.

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[10] See the following studies: parental employment (Alon et al., 2020; Collins et al., 2021; Craig and Churchill, 2021; Heggeness, 2020), parenting time (Del Boca et al., 2020; Farré et al., 2020; Yamamura and Tsutsui, 2021a; Zamarro and Prados, 2021), parental mental health and well-being (Cheng et al., 2021; Huebener et al., 2021; Takaku and Yokoyama, 2021; Yamamura and Tsutsui, 2021b), domestic violence (Baron et al., 2020; Hsu and Henke, 2021; Pereda and Díaz-Faes, 2020).

3.2. Data

We use the panel data collected from the "Manabi Nara," which tracked math test scores at the end of each term for over three years (from grades 4–6) for all elementary school children in Nara City (43 elementary schools and approximately 2,700 students per grade). We focus on three cohorts of students: two cohorts who experienced the COVID-19 school closures (FY2019 P4 and P5 cohorts) and one cohort that did not experience them (FY2019 P6 cohort).

3.2.1. Outcome variable: math test scores

We examine changes in students' cognitive skills by using two years of math achievement test scores and six terms of data, starting from two terms before until three terms after the closure. The cohort and the test timing are shown in Figure 2.

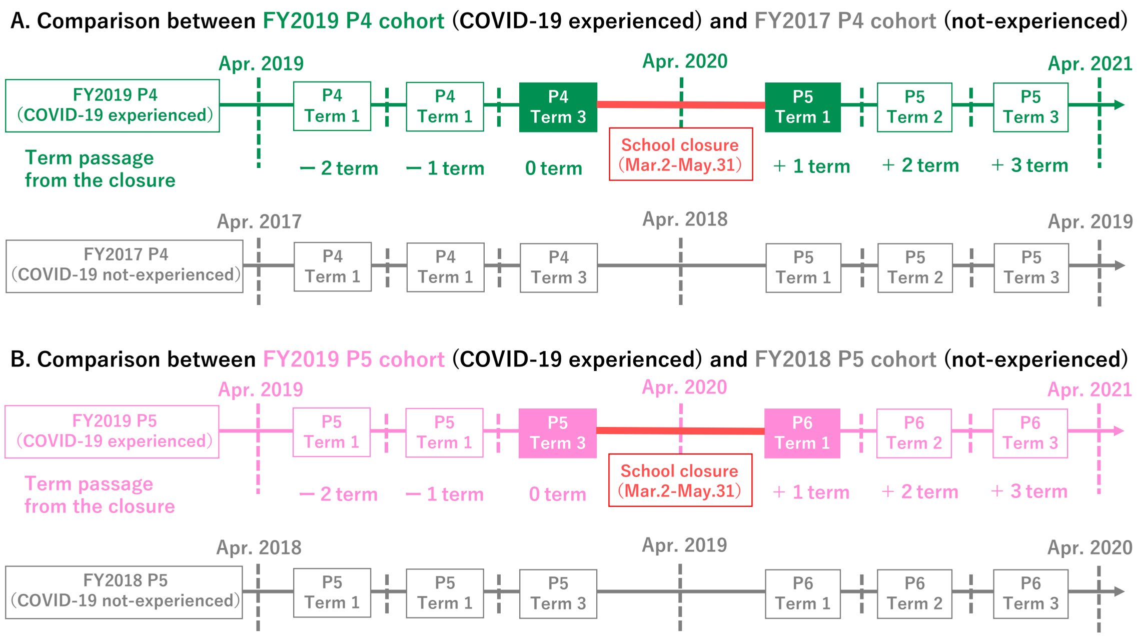

Figure 2. Cohort and timing of COVID-19 school closure

These data have four advantages. First, all students in the same grade take the city-wide math test at the end of each term (three times a year: July, December, and March). Second, we could obtain information on the students who experienced the COVID-19 school closure (FY2019 P4 and P5 cohorts) and compare it with those who did not experience the COVID-19 school closure in grades four and five (FY2019 P6 cohort). Third, the test is implemented three times per year. The high frequency of test results across the two grades provides a significant advantage. Finally, the difficulty level of the test remains the same for the same grade and term because similar problems are posed every year. Furthermore, the test is designed to ensure the same level of difficulty across all tests for the same cohort. Thus, the test scores can be compared across cohorts and terms.

Table 1 shows the descriptive statistics and indices of disparity for math test scores by treatment status and cohorts.

1-A. P4 cohort	FY2019 P4 cohort (COVID-19 experienced)					FY2017 P4 cohort (COVID-19 not-experienced)				
Terms	Obs.	Mean	S.D.	q90-q10	Gini coef.	Obs.	Mean	S.D.	q90-q10	Gini coef.
-1 term from closure	2197	66.54	22.30	59.00	0.19	2556	63.82	21.84	57.00	0.19
School closure	399	69.51	20.33	53.00	0.16	2538	68.44	20.69	57.00	0.17
+1 term from closure	2122	64.39	21.98	56.00	0.19	2570	64.65	22.82	60.10	0.20
+2 term from closure	1933	66.89	22.35	58.00	0.19	2531	63.06	22.10	59.00	0.20
+3 term from closure	2015	69.66	19.81	51.00	0.16	2474	64.02	21.03	54.00	0.19

1-B. P5 cohort	FY2019 P5 cohort (COVID-19 experienced)					FY2018 P5 cohort (COVID-19 not-experienced)				
Terms	Obs.	Mean	S.D.	q90-q10	Gini coef.	Obs.	Mean	S.D.	q90-q10	Gini coef.
-1 term from closure	2076	61.35	23.78	66.00	0.22	2477	63.03	22.03	58.00	0.20
School closure	276	60.56	23.70	62.50	0.22	2422	63.79	21.20	54.00	0.19
+1 term from closure	1981	68.68	21.93	57.00	0.18	2373	71.22	20.68	52.00	0.16
+2 term from closure	1949	76.09	19.79	50.00	0.14	2412	67.12	20.98	57.00	0.18
+3 term from closure	2037	78.57	17.92	43.00	0.12	1196	71.11	20.07	54.00	0.16

Note: "q90" and "q10" mean that the math test scores are just the top and bottom 10%, relatively. "Gini coef" means the Gini coefficients by cohorts and terms

Table 1. Summary statistics and indices of disparity for outcome variables (by treatment status and cohorts)

Indexes that capture gaps in math test scores—standard errors, the difference between the scores of just the top 10% and bottom 10%, and the Gini coefficient—suggest that the gap in math scores did not widen among students after the closure. We also see that the gap narrowed more for the FY2019 P5 cohort than for the FY2019 P4 cohort.

3.2.2. Treatment status and timing of COVID-19 school closure

We compare the students who experienced the COVID-19 school closure (FY2019 P4–P5 cohort) with those who did not (FY2019 P6 cohort). Thus, we create a COVID-19 experience dummy "COVID19" that takes a value of 1 for the FY2019 P4–P5 cohort and 0 for the FY2019 P6 cohort. This variable represents the treatment status of whether the cohort experienced the COVID-19 school closure.

Next, we explain the timing of the COVID-19 school closures. At the end of each term, Nara City conducts math achievement tests, known as the "Manabi Nara," after the entire content of each test has been taught in class. Thus, if the COVID-19 school closures were not implemented in 2020, the test would have been conducted at the end of March. However, due to the pandemic, the MEXT notified the prefectures and designated cities' education committees about the possibility of temporary school closures as of February 18. The government requested temporary school closures on February 27.[11] After the request, Nara City implemented the school closure from the middle of the third term on March 2.

Considering the possibility of the school closure, some elementary schools in Nara City moved up their examination schedule even though the class content had not been fully

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[11] This announcement can be found at: https://www.mext.go.jp/content/20200218-mxt_kouhou02-000004520_3.pdf.

taught.[12] Existing studies show that test scores declined when exogenous shocks led to an earlier examination date (Goodman, 2014; Marcotte, 2007; Marcotte and Hemelt, 2008). Therefore, students' academic performance may have also declined in the third term of FY2019 P4–P5, just before the temporary school closure. That is why this study defines the third term of FY2019 P4–P5 and terms after as the period affected by the COVID-19 school closure, and the previous terms as the period before the school closure.

3.2.3. Heterogeneity of living conditions

Most elementary school students in Nara City studied at home in the same manner (watching videos and learning through paper-based handouts) without any physical contact with teachers (see Section 2). However, the living conditions faced during and after the school closure are expected to vary widely among students. Schools provide equal educational opportunities to children and reduce the learning disparities due to living conditions (Downey, Von Hippel, & Broh 2004). If the school closure had not occurred, students would have received face-to-face instruction from teachers at school, and the disparities due to their living conditions would have been significantly mitigated. Consequently, the COVID-19 school closure may reveal the disparities due to the living environment that already existed among the students. Therefore, we examine whether the students' living conditions during and just after the school closure make a difference in each child's improvement in math achievement test scores after the school closure.[13]

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[12] In the third term of FY2019, many elementary schools in Nara City did not administer math exams due to the reduced school days as a result of the temporary school closures and failure to complete the test content. If the test scores of students who took the test in the third term of FY2019 P4–P5 are potentially higher those who did not, a self-selection problem would arise. Therefore, we tested for differences in the means and variances in each school average of test scores between in FY2019 Term 3 and in other terms. The results show that the mean and variances of both groups did not differ at the 5% significance level (see Appendix Table A-1). Therefore, this study also uses the third term of FY2019 P4–P5 for analysis.

[13] Video production skills and the speed at which the class is taught may differ among schools and classes. Therefore, this study deals with the unobservable heterogeneity of school and classroom units by

We use data from the "Survey of living conditions during the vacation (May, 2020)" and "Survey of living conditions after school re-opening (June, 2020)," which were conducted in conjunction with the "Manabi Nara." Specifically, we first create dummy variables for each of the two questionnaire results and assign a value of 1 if the respondent answered "quite applicable/applicable" to a disadvantaged living condition (DLC) or "not quite applicable/not applicable" to an advantaged living condition (ALC). In addition, we assign a value of 0 to both ALC and DLC for all periods of students who did not experience the school closure (FY2019 P6 cohort) and for pre-closure periods of those who experienced the closure (FY2019 P4 and P5 cohorts), since the students of these cohorts and periods attended classes in-person. Then, we take the average of the May and June questionnaire results and define these variables as living condition dummies.[14]

As many studies suggest, the COVID-19 epidemic may have affected the living conditions of the students themselves. However, we cannot confirm whether the students' living conditions changed before and after the COVID-19 school closure, because our data on the living conditions were observed only during and just after the school closure. Therefore, this study assumes the same change in living conditions before and after the school closure. In other words, we assume that the impact of COVID-19 on living conditions is equivalent for all households. Furthermore, no data on living conditions are available for the COVID-19 not-experienced cohort (FY2019 P6 cohort). Thus, we also assume the same change in living conditions for all households in the cohort. However,

---

controlling for school and class fixed effects, as described below.

[14] We create a variable equal to 1 if both May and June are equal to 1, 0.5 if one month equals 1, and 0 if both months are equal to 0. Thus, the two variables "studied using handouts from school (May)" and "sometimes have difficulty concentrating on studies (June)" are used in the analysis without averaging them as different variables. However, even if we assume that both variables mean "I can't concentrate on my studies" and use both averages as variables, the main results of the analysis remained the same. See Appendix Table A-2 for a detailed description of the disadvantaged living condition dummy and Appendix Figure A-1 for a histogram of the variables for the disadvantaged living conditions.

we would expect that even if the living conditions had changed, the impact on cognitive skills would have been mitigated, because the students attended school as usual during periods other than the COVID-19 school closure. Therefore, we do not consider these assumptions to dominate the results of our following analysis.

Table 2 shows the descriptive statistics for treatment status, summer dummy, and living conditions explained in Sections 3.1.2 and 3.1.3.

Variable	Cohorts	Observations	Min	Median	Mean	Max	St. Dev.	#NA
COVID19	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	8860	1	1	1.000	1	0.000	0
	FY2019 P4 cohort	9174	1	1	1.000	1	0.000	0
	Full sample	29605	0	1	0.609	1	0.488	0
Summer break (SB)	FY2019 P6 cohort	11571	0	0	0.450	1	0.498	0
	FY2019 P5 cohort	8860	0	0	0.484	1	0.500	0
	FY2019 P4 cohort	9174	0	0	0.475	1	0.499	0
	Full sample	29605	0	0	0.468	1	0.499	0
Lack food	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.115	1	0.269	866
	FY2019 P4 cohort	8507	0	0	0.100	1	0.254	667
	Full sample	28072	0	0	0.063	1	0.207	1533
Lack sleep	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.249	1	0.370	866
	FY2019 P4 cohort	8507	0	0	0.246	1	0.374	667
	Full sample	28072	0	0	0.146	1	0.310	1533
Lack print study (May)	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.086	1	0.280	866
	FY2019 P4 cohort	8507	0	0	0.089	1	0.285	667
	Full sample	28072	0	0	0.051	1	0.221	1533
Lack study (June)	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.253	1	0.435	866
	FY2019 P4 cohort	8507	0	0	0.221	1	0.415	667
	Full sample	28072	0	0	0.139	1	0.346	1533
Feel stressed	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.228	1	0.359	866
	FY2019 P4 cohort	8507	0	0	0.226	1	0.364	667
	Full sample	28072	0	0	0.134	1	0.299	1533

No passion	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.164	1	0.310	866
	FY2019 P4 cohort	8507	0	0	0.142	1	0.291	667
	Full sample	28072	0	0	0.090	1	0.242	1533
Bad health	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.184	1	0.322	866
	FY2019 P4 cohort	8507	0	0	0.170	1	0.317	667
	Full sample	28072	0	0	0.104	1	0.260	1533
No sport	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.207	1	0.345	866
	FY2019 P4 cohort	8507	0	0	0.162	1	0.307	667
	Full sample	28072	0	0	0.108	1	0.266	1533
Not fun	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.139	1	0.280	866
	FY2019 P4 cohort	8507	0	0	0.126	1	0.269	667
	Full sample	28072	0	0	0.078	1	0.220	1533
Feel unsafe	FY2019 P6 cohort	11571	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	7994	0	0	0.093	1	0.224	866
	FY2019 P4 cohort	8507	0	0	0.085	1	0.214	667
	Full sample	28072	0	0	0.052	1	0.174	1533

Table 2. Summary statistics of treatment status, summer dummy, and living conditions (by cohorts)

3.3. Estimation method

Table 1 indicated that the gap in math scores did not widen among students after the COVID-19 school closure. However, the school closure's effects on math test scores may be offset between students whose scores rose and fell due to their living conditions during and after the closure. Thus, this section tests the hypothesis that living conditions during and after school closure affected students' academic performance.

3.3.1. Baseline Event study

We test the first and second hypotheses using the following baseline dynamic event study methodology. We compare each of the FY2019 P4-P5 cohorts with the control group, the FY2019 P6 cohort.

Baseline event study

$$Y_{i,t} = \sum_{t=-1}^{3} \beta_t COVID19_i \times School\ close_t + \beta_4 Summer\ break_t + \mu_s + \mu_g + \mu_c + \epsilon_i \quad (1)$$

$Y_{i,t}$ is the difference between the math score of individual i in term t minus the mean score for each cohort just before the school closure ($t = -1$). We use this difference from the group mean just before the closure ($t = -1$) as the outcome to prevent students who did not take the test in period $t = -1$ from dropping out of the sample. $COVID19_i$ is a dummy variable that takes a value of 1 for the FY2019 P4–P5 cohort, and 0 for the FY2019 P6 cohort. $School\ close_t$ is a dummy variable that takes a value of 1 when the test period is t.[15] $Summer\ break_t$ is a dummy variable that takes a value of 1 if the test period is the end of the second term, after the summer break. μ_s, μ_g, and μ_c are the school (s), grade (g), and classroom (c) fixed effects, respectively. β_{-2} examines if the parallel trend assumption before the third term of FY2019 P4–P5 holds in the math scores between the treatment and control groups. β_0 and β_1 (β_2 and β_3) represent the short-term (medium- and long-term) effects of the school closure. β_4 helps determine that the summer break itself significantly affects math scores.

3.3.2. The effect of living conditions: An event study

To test the third hypothesis, we add dummy variables for living conditions to Equation (1). We first estimate the upper (lower) bound of the effects of the school closure on math achievement tests by controlling for disadvantaged (advantaged) living conditions.

[15] We define $School\ close_t = 0$ as the end of the third term of FY2019 P4–P5 when school closures began. For the correspondence between $School\ close_t$ and each grade and term, see Appendix Table A-3.

The upper bound of treatment effects

$$Y_{i,t} = \sum_{t=-1}^{3} \beta_t COVID19_i \times School\ close_t + \beta_4 Summer\ break_t$$

$$+ \sum_{t=-1}^{3} \sum_{j=1}^{10} \delta_{j,t} DLC_{i,j} \times School\ close_t + \mu_s + \mu_g + \mu_c + \epsilon_i \tag{2.1}$$

The lower bound of treatment effects

$$Y_{i,t} = \sum_{t=-1}^{3} \beta_t COVID19_i \times School\ close_t + \beta_4 Summer\ break_t$$

$$+ \sum_{t=-1}^{3} \sum_{j=1}^{10} \delta_{j,t} ALC_{i,j} \times School\ close_t + \mu_s + \mu_g + \mu_c + \epsilon_i \tag{2.2}$$

3.3.3. The impact of living conditions: Marginal average treatment effect (MATE)

Primary students in Nara City were unable to learn new content in person for nearly three months. They instead reviewed the content they had learned before the closure using paper-based handouts. Thus, the resultant temporary decline and subsequent recovery of students' academic performance may differ depending on the living conditions during and just after the closure. By adding living conditions indicators during the closure as treatment variables, we first estimate the impact of each living condition on the test scores. After this, the predicted values of these coefficients are used to estimate the marginal treatment effects conditioned on each combination of living conditions measured during and after the closure.

We compute the predicted values of the MATE, conditional on the effects of the living conditions, using the estimated coefficients on the living conditions during and after the

COVID-19 school closure.[16] Specifically, based on equation (2.1), we calculate the MATE using the following formula for each of the three terms from $t\ = 1$ (just after the school was re-opened) to $t\ = 3$,

Marginal average treatment effect (MATE)

$$MATE_{i,t}\ = \widehat{\boldsymbol{\beta_t}} COVID19_i \times School\ close_t + \sum_{j=1}^{10} \widehat{\delta_{j,t}}\ DLC_{i,j} \times School\ close_t \qquad (3)$$

$\widehat{\boldsymbol{\beta_t}}$ is the estimated average treatment effect (ATE) of all students in term t ($t \geq 1$). $\widehat{\delta_{j,t}}$ is the estimated effect of the school closure in period t ($t \geq 1$) for those with specific combinations of living conditions during and after the COVID-19 school closure. By fitting these estimated coefficients to each individual's circumstances, we can obtain the predicted MATE for each individual based on their living condition.

3.3.4. Subsample analysis

The effects of the COVID-19 school closure may depend on students' academic performance before the intervention. If so, the full sample analysis may offset the estimated effects if the effects are heterogeneous across student achievement quartiles.

Thus, to examine whether the school closure effects are heterogeneous across achievement quartiles, we calculate the quantiles for each treatment and control group based on the math scores one term prior to the period used in the analysis (i.e., the first term of grade 5) and divide the students into four subsamples.

[16] Abrevaya et al. (2015), Cattaneo (2010), and Grimmer et al. (2017) use MATE (or Marginal Average Treatment Effect) to separately estimate the causal effects of each of the multiple types of treatments. In this study, different combinations of living conditions can be considered as different treatments; thus we use MATE to estimate the causal effects of each combination of living conditions.

3.4. Results

3.4.1. Full sample results

We first present the results of the full sample in Figure 3 and Appendix Table A-4. The green lines and pink (and red) lines of Figure 3 show the results of the event study for FY2019 P4 and P5, respectively. From +1 term onward, we add the estimated coefficients in the figure to explicitly show that the heterogeneity of the school closure effects depends on the living conditions (LC) during and after the closure. We color the ATEs for FY2019 P4 and P5 obtained from Equation (1) with light pink and light green. The estimated results of Equations (2.1) and (2.2) represent the school closure effects on students in the most advantaged and disadvantaged LC, respectively. We show the upper bound of the effects for FY2019 P4 and P5 in pink and green lines, while we show the lower bounds in dark pink and dark green lines.[17]

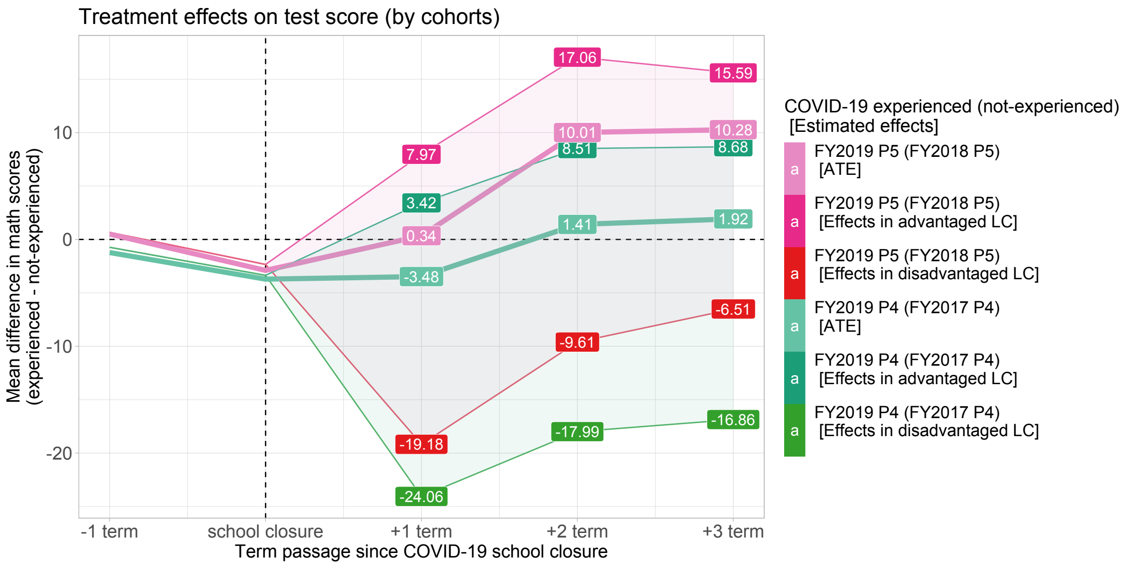

Figure 3. Treatment effects on math test scores (Event study, full sample)

[17] Since our sample is not balanced panel data and some students or schools do not take the test in some terms, the estimated coefficients of the -1 term are not equal to zero. However, since all estimated -1 term coefficients are not statistically significant, we do not consider that the unbalanced panel data causes significant bias on the results.

From the estimated ATEs, we find that the COVID-19 school closure decreased the math test scores by about 2.3 points in the term beginning with the closure, regardless of the grade. However, in the term immediately after the closure (+1 term), the negative impact of the closure disappeared on average (0.34 points) for the FY2019 P5 grades, while the FY2019 P4 grades still had an average negative effect of 3.48 points. Furthermore, by dividing the estimated ATEs by the mean of the standard deviation (SD) before and after school closure, which could be calculated from Table 1, the standardized mean difference from -1 term (d-index) was about -0.1 and -0.15 for FY2019 P4 cohort, and about -0.1 and -0.01 for FY2019 P5. [18] Taking into consideration Cooper et al (1996), who conducted a meta-analysis and find the decline in math achievement due to summer vacation, we showed that the d-index of the difference in scores from spring term to fall term divided by the SD of the two periods was -0.09. We concluded that the short-term negative impact of the COVID-19 school closure was almost equivalent to the impact of the summer vacation.

Moreover, in the +2 and +3 terms, both grades of FY2019 P4 and FY2019 P5 had higher scores compared to the cohorts who did not experience the closure. However, the lower the grade, the lower the increase in scores (FY2019 P4: 1.41–1.92, FY2019 P5: 10.01–10.28). From these results, we conclude that the negative impact of the school closure turned positive by the +2 term (six months after the closure); however, the lower grades (i.e., FY2019 P4) were more negatively affected by the closure.

Next, we explain the heterogeneity of the effects based on the LC. The students in the most advantaged LC, regardless of grade, turned their math scores positive within +1 term after the closures (FY2019 P4: 3.42–8.68, FY2019 P5: 7.97–17.06). On the contrary, the

[18] Average of SD was 21.31 for -1 term and School closure and 22.14 for -1 term and +1 term in FY2019 P4, and 23.74 for -1 term and School closure and 22.8 for -1 term and +1 term in FY2019 P5.

students in the most disadvantaged LC did not turn their math scores positive even at the end of +3 term after the closures (FY2019 P4: -6.51– -19.18, FY2019 P5: -16.66 – -24.06). We also confirm that the estimated coefficients were lower in FY2019 P4.

Finally, we estimate the MATE of FY2019 P4 and P5 for three terms after the closure (from +1 term to +3 term). We show their distributions in Panels A and B of Figure 4.

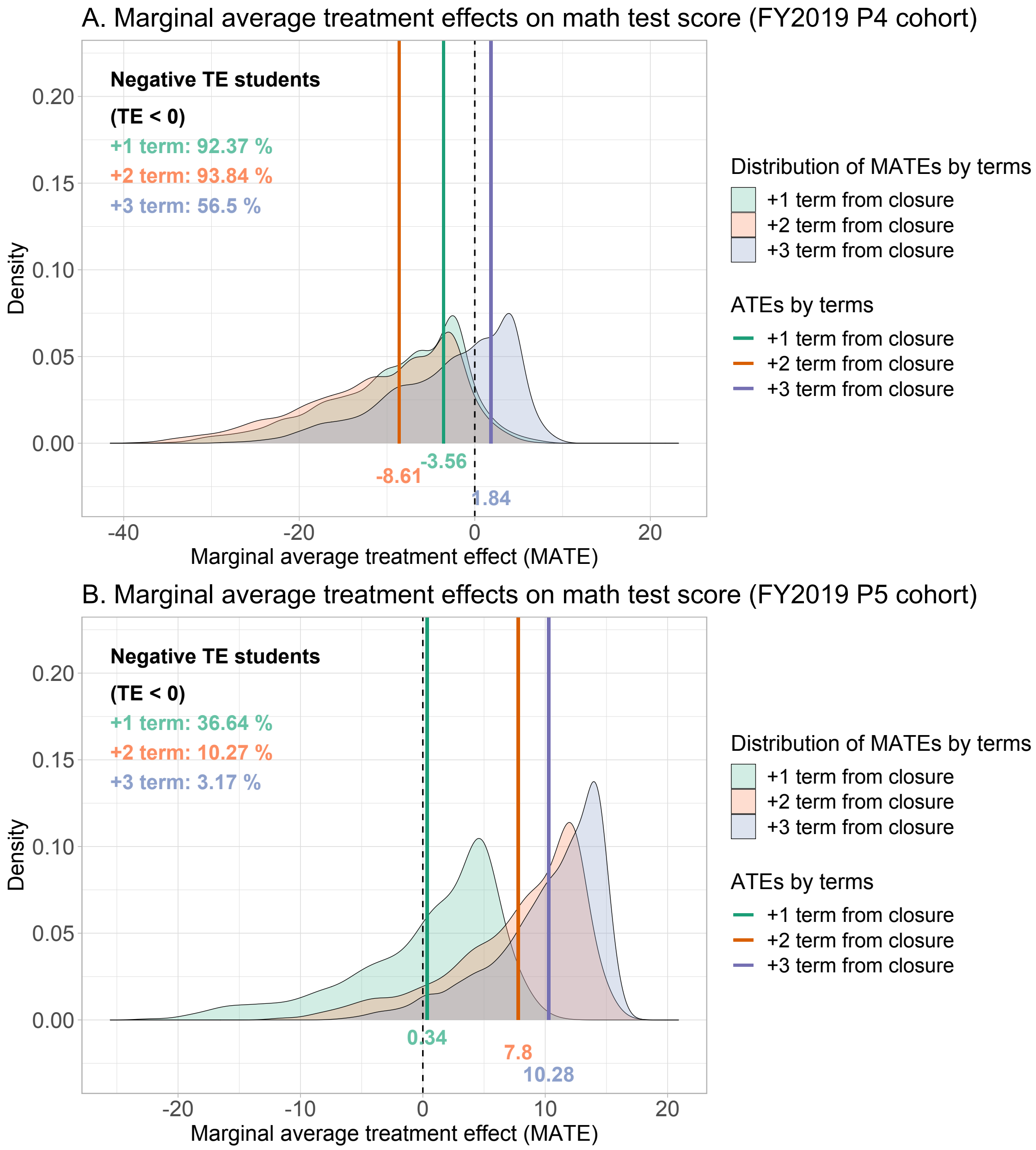

Figure 4. ATE and MATE on math test score (full sample)

This figure shows that as the terms progressed after the closure, the mean values of MATE increased in both cohorts. However, similar to Figure 3, the FY2019 P4 cohort recovered their scores more slowly and had smaller coefficients than the FY2019 P5 cohorts across all terms (FY2019 P4: from -3.48 in +1 term to 1.92 in +3 terms, FY2019 P5: from 0.34 in +1 term to 10.28 in +3 terms). Simultaneously, the percentage of students with negative MATE decreased from +1 term to +3 term, but the percentages remained larger in the FY2019 P4 cohort (FY2019 P4: from 57.9% to 30.6%, FY2019 P4: from 36.54% to 3.17%).

Both figures show that while the resumption of regular classes and shortening of some school events have helped many students recover their math scores, the scores of about 30.6% [3.17%] of the FY2019 P4 cohorts [FY2019 P5 cohort] still have not returned to the pre-closure levels. Based on these results, we conclude that students with more disadvantaged living conditions during and after the closure, or those in fourth grade, face lasting negative effects of the closure, persisting even after one year.

3.4.2. Subsample analysis

To test if the effects of the closure differed by the pre-closure math performance level, we next conducted a subsample analysis. As described in Section 3.2.4, we divided the students by quartiles of their math scores from the third term of grade 4, before the closure. Figure 5 and Appendix Tables A-5 to A-7 show the estimated results for the quartiles, using the same event study estimation as in Figure 3 and Appendix Tables A-4, respectively. For FY2019 P4 and P5, we represent the ATE and effects on students with the most advantaged and disadvantaged LC.

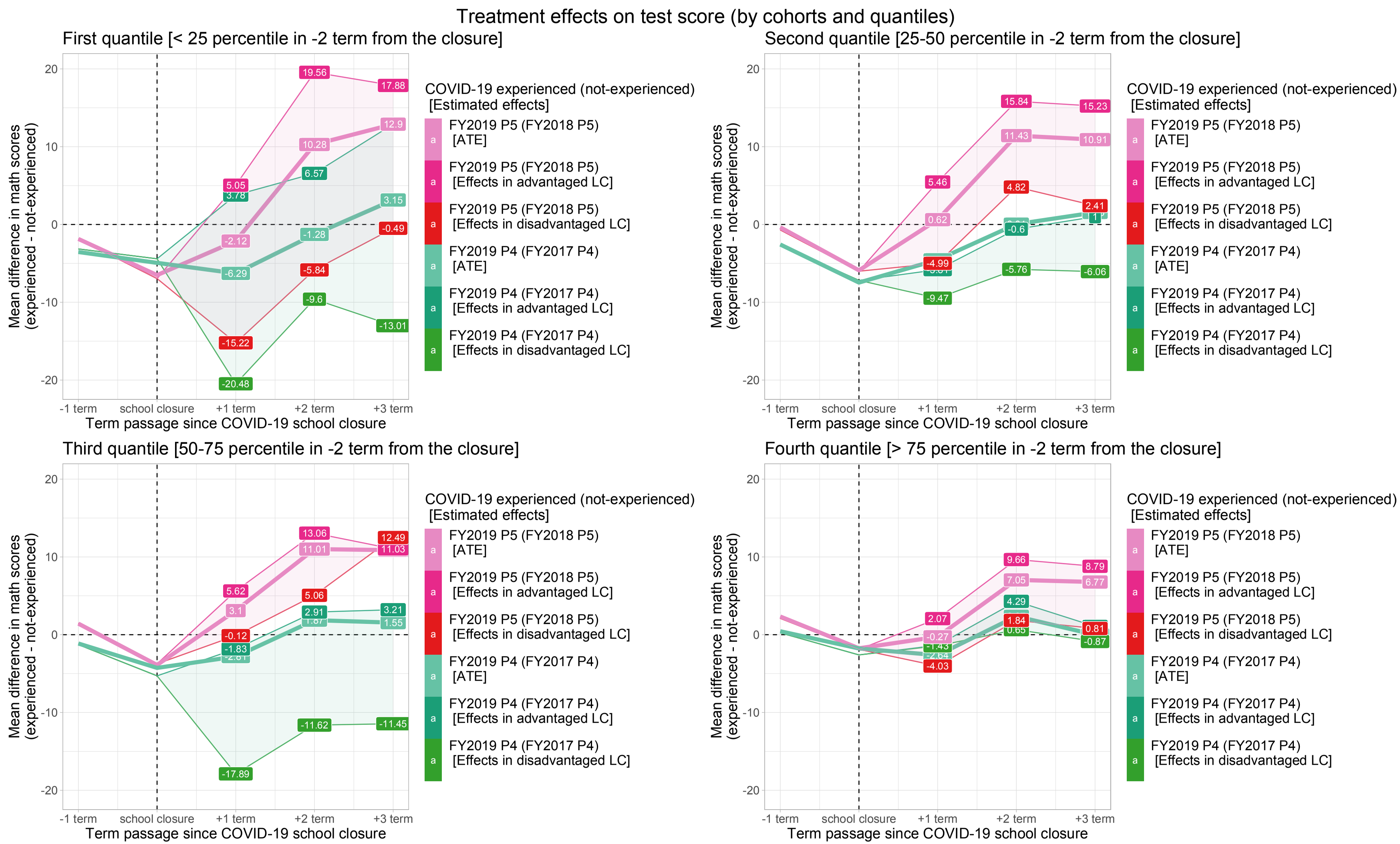

Figure 5. Treatment effects on test score (Event study, subsample)

Figure 5 shows that the scores of both cohorts turned positive across all quantiles by the +3 term. The increase in scores was higher in FY2019 P5, as shown in Figure 3. Furthermore, we compared the impact on the students with the most advantaged and disadvantaged LC. We found that while the students with the most advantaged LC recovered their scores in all quantiles, even by +3 term, those with the most disadvantaged LC had not returned to their original levels, across all quantiles for FY2019 P4 and P5, except the first quantile for FY2019 P5.

Next, we estimate the MATE for each term that elapsed after the closure. We show their distributions for FY2019 P4 and P5 in Figures 6 and 7, respectively. In Figure 6, we find that almost all students' scores were negatively affected at the +1 term, and 22.17%-40.51% of students still had negative scores in the +3 term. In Figure 7, while about half of the students' scores were negatively affected at the +1 term (share of negatively affected students: 20.67% to 54.77%), most students' scores turned positive by the +3 term (share of negatively affected students: 3.64% at maximum). In the lower quantile, we also find that the variance of MATE is larger for both the FY2019 P4 and P5 cohorts. Therefore, we conclude that in the lower quantiles and grades, the living conditions during and after the closure have a more significant impact on students' math achievement test scores.

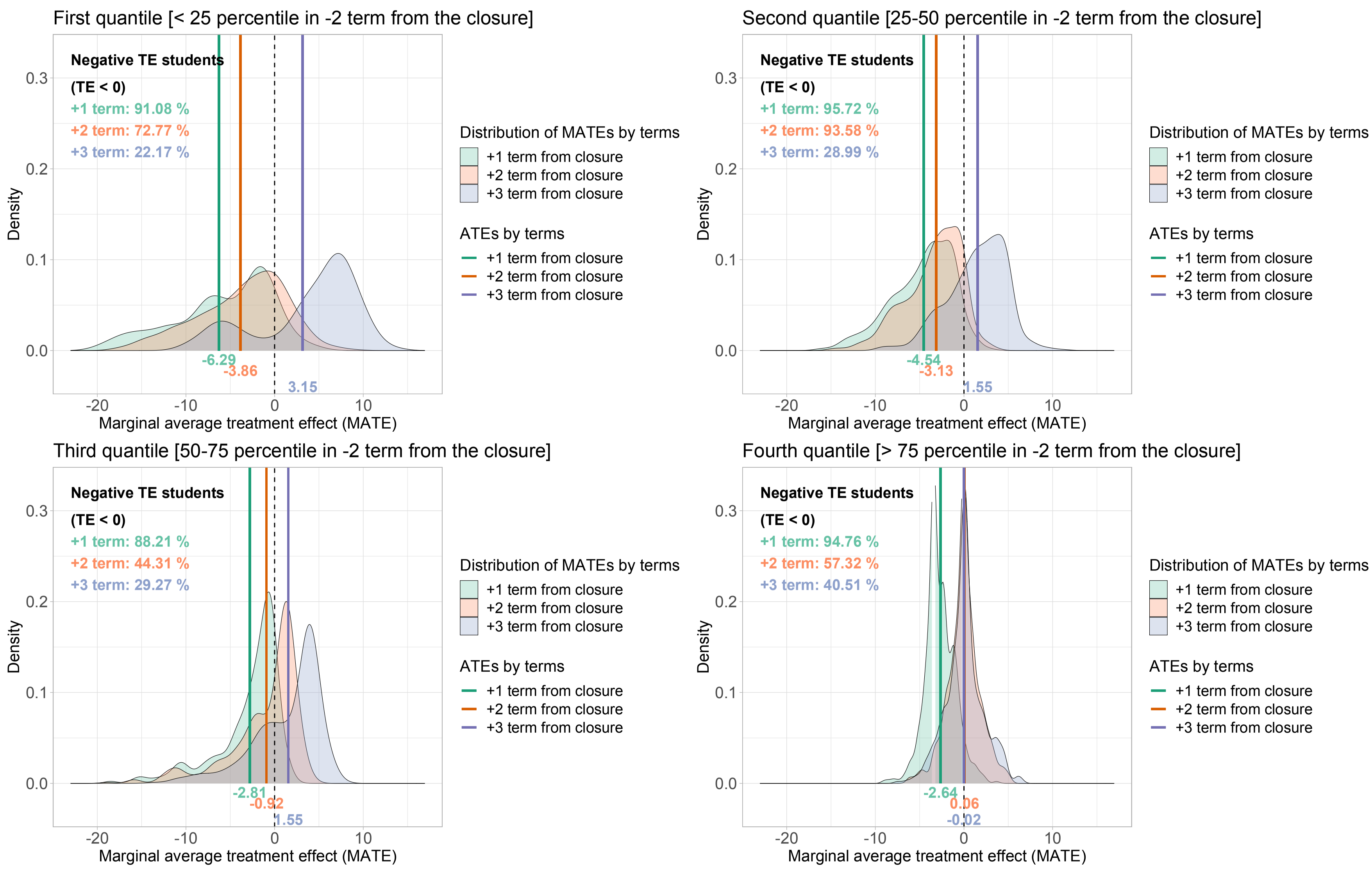

Figure 6. Marginal average treatment effects on math test score (FY2019 P4 cohort, subsample)

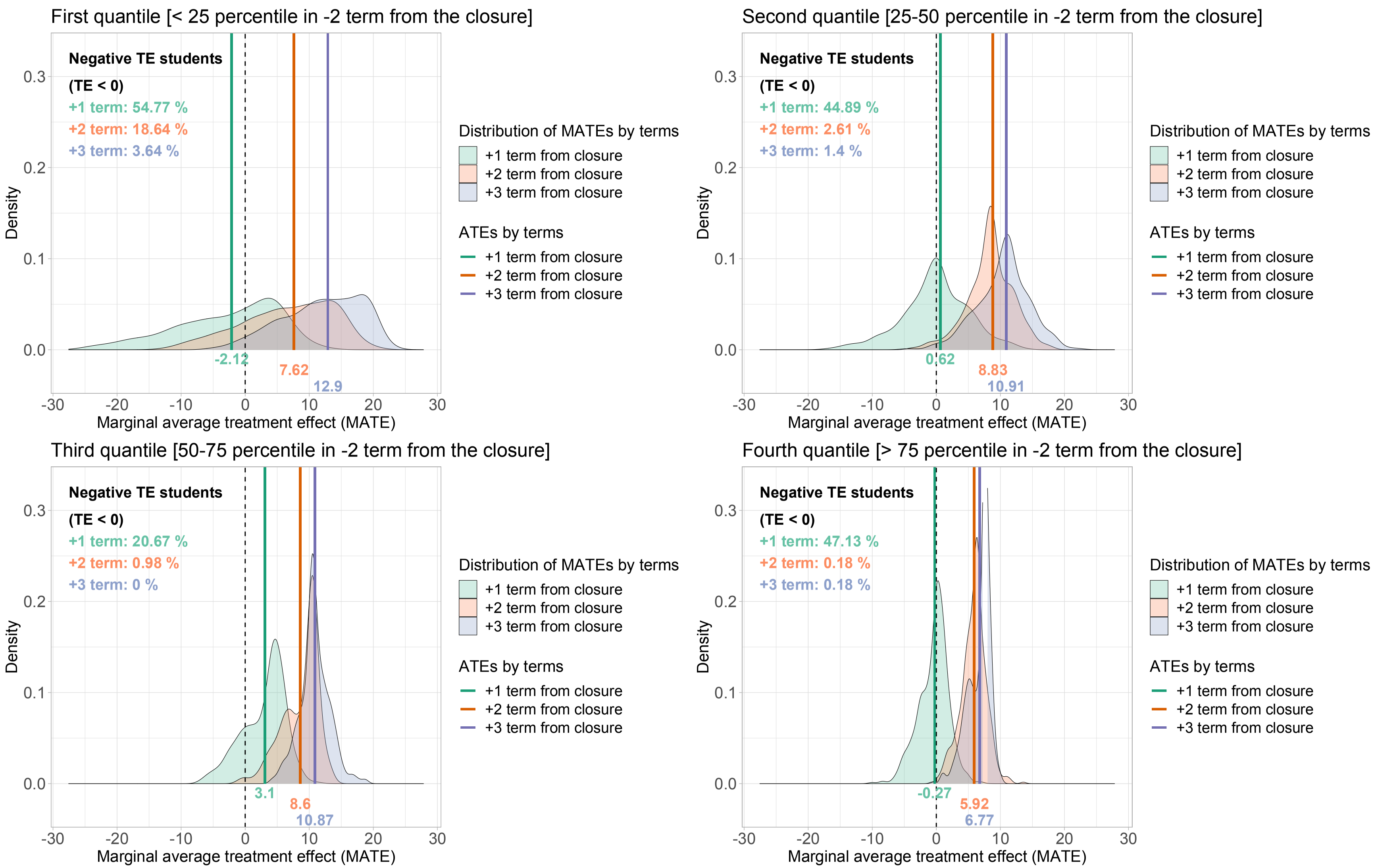

Figure 7. Marginal average treatment effects on math test score (FY2019 P5 cohort, subsample)

4. Effects on Non-cognitive Skills: Attitudes

Section 3 shows that math scores are significantly affected by COVID-19 school closures. However, both school and living environment affect not only cognitive but also non-cognitive skills. It is also possible that the effect of these closures on non-cognitive skills may vary depending on the students' living conditions. Therefore, to estimate the impact of school closures on the non-cognitive skills in math, we use the responses to the "Student Survey" questions regarding students' attitudes toward proactive math learning.

4.1. Data

To estimate the school closure's effects on attitude toward proactive mathematical learning, we use the "Student Survey," which was conducted in May and December in conjunction with the "Manabi Nara."[19] We use results from two serial years for two cohorts (COVID-19 experienced cohort [FY2019 P5]: Dec. 2019 and Dec. 2020, COVID-19 not-experienced cohort [FY2018 P5]: Dec. 2018 and Dec. 2019).

To identify if the survey period occurs after the closure, we create an "$After\ closure$" dummy that takes a value of 1 for December in P6 after the COVID-19 school closure (+2 term from the closure), and 0 for December in P5 (before the closure). We also create ten outcome variables common to all four surveys (2 time points × 2 cohorts), including the attitudes of students toward proactive learning for math.[20] For these questions, students choose one of the following four options: "Yes," "Partly Yes," "Partly No," and "No." Therefore, this study creates a dummy variable that takes a value of 1 if the student chooses "Yes" or "Partly Yes," and 0 otherwise, and uses them as the outcome variables.[21] The summary statistics of these variables are shown in Table 3.

[19] However, in May 2020, when schools were temporarily closed, this survey was not conducted. The living conditions survey introduced in Section 3.4 was conducted instead.
[20] See Appendix Table A-8 for details of each question and definitions of each of the outcome variables.
[21] See histogram of the attitude toward proactive learning for math for FY2019 P6 Cohort and FY2019 P5 Cohort in Appendix Figures A-2 and A-3, respectively.

Variable	Cohorts	Observations	Min	Median	Mean	Max	St. Dev.	#NA
Like math	FY2019 P6 cohort	4758	0	1	0.595	1	0.491	7
	FY2019 P5 cohort	3044	0	1	0.594	1	0.491	480
	Full sample	7802	0	1	0.595	1	0.491	487
Math is important	FY2019 P6 cohort	4758	0	1	0.954	1	0.210	7
	FY2019 P5 cohort	3013	0	1	0.952	1	0.214	511
	Full sample	7771	0	1	0.953	1	0.212	518
Understand math well	FY2019 P6 cohort	4755	0	1	0.889	1	0.314	10
	FY2019 P5 cohort	2947	0	1	0.901	1	0.298	577
	Full sample	7702	0	1	0.894	1	0.308	587
Math will be useful	FY2019 P6 cohort	4757	0	1	0.937	1	0.243	8
	FY2019 P5 cohort	3043	0	1	0.931	1	0.254	481
	Full sample	7800	0	1	0.935	1	0.247	489
Concentrate in math class	FY2019 P6 cohort	4758	0	1	0.931	1	0.254	7
	FY2019 P5 cohort	3058	0	1	0.940	1	0.238	466
	Full sample	7816	0	1	0.934	1	0.248	473
Ask questions in mass class	FY2019 P6 cohort	4752	0	1	0.521	1	0.500	13
	FY2019 P5 cohort	2986	0	1	0.553	1	0.497	538
	Full sample	7738	0	1	0.534	1	0.499	551
Complete math homework	FY2019 P6 cohort	4756	0	1	0.937	1	0.242	9
	FY2019 P5 cohort	2975	0	1	0.945	1	0.229	549
	Full sample	7731	0	1	0.940	1	0.237	558
Concern about test results	FY2019 P6 cohort	4758	0	1	0.844	1	0.363	7
	FY2019 P5 cohort	3062	0	1	0.837	1	0.370	462
	Full sample	7820	0	1	0.841	1	0.366	469
High motivation for Reco	FY2019 P6 cohort	4756	0	1	0.619	1	0.486	9
	FY2019 P5 cohort	3041	0	1	0.605	1	0.489	483
	Full sample	7797	0	1	0.614	1	0.487	492
Motivation for other Reco	FY2019 P6 cohort	4755	0	0	0.427	1	0.495	10
	FY2019 P5 cohort	3005	0	0	0.431	1	0.495	519
	Full sample	7760	0	0	0.428	1	0.495	529
COVID19	FY2019 P6 cohort	4765	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	3524	1	1	1.000	1	0.000	0
	Full sample	8289	0	0	0.425	1	0.494	0
After closure	FY2019 P6 cohort	4765	0	0	0.483	1	0.500	0
	FY2019 P5 cohort	3524	0	0	0.434	1	0.496	0
	Full sample	8289	0	0	0.462	1	0.499	0

Table 3. Summary statistics of attitude toward proactive learning of math (by cohorts)

4.2. Estimation method

Using only the COVID-19 experience group for pre- and post-closure comparison may not correctly estimate the effect of school closure, even though several outcomes change from 5th to 6th grade. Therefore, we use the following DID to test the effect of COVID-19 school closures on ten attitudes toward proactive learning for math:

$$
\begin{aligned}
Y_{i,t} &= \gamma_1\, COVID19_i \times After\ closure_{i,t} + \gamma_2\, COVID19_i + \gamma_3\, After\ closure_{i,t} \\
&\quad + \sum_{j=1}^{10} \delta_j DLC_{i,j} + \mu_s + \mu_c + \epsilon_i \qquad (4)
\end{aligned}
$$

$Y_{i,t}$ includes the ten outcome variables of individual i in term t, capturing the students' attitude toward proactive learning for math. $COVID19_i \times After\ closure_{i,t}$ takes a value of 1 if the student belongs to the FY2019 P5 cohort and the survey timing occurs after the closure. Hence, the parameter of interest — the coefficient γ_1 — captures the effects of COVID-19 school closures on students' attitudes toward proactive learning for math. $DLC_{i,t}$ includes the disadvantaged living conditions during and after temporal school closures. μ_s and μ_c are the school (s) and classroom (c) fixed effects.[22] Using the estimated coefficients, we predict the MATE from the following equation:

$$
MATE_{i,t} = \widehat{\gamma_1}\, COVID19_i \times After\ closure_{i,t} + \sum_{j=1}^{10} \widehat{\delta_j}\, DLC_{i,j} \qquad (5)
$$

[22] Here, only one survey is available for each cohort in each year, and thus, the year fixed effects are perfectly consistent. Therefore, we exclude this from the estimation in equation (4).

4.3. Results

In Figure 8, we present the distribution of MATE to examine the effects on students' attitudes toward proactive mathematical learning. In this figure, the distribution is colored blue [red] when MATE is negative [positive].

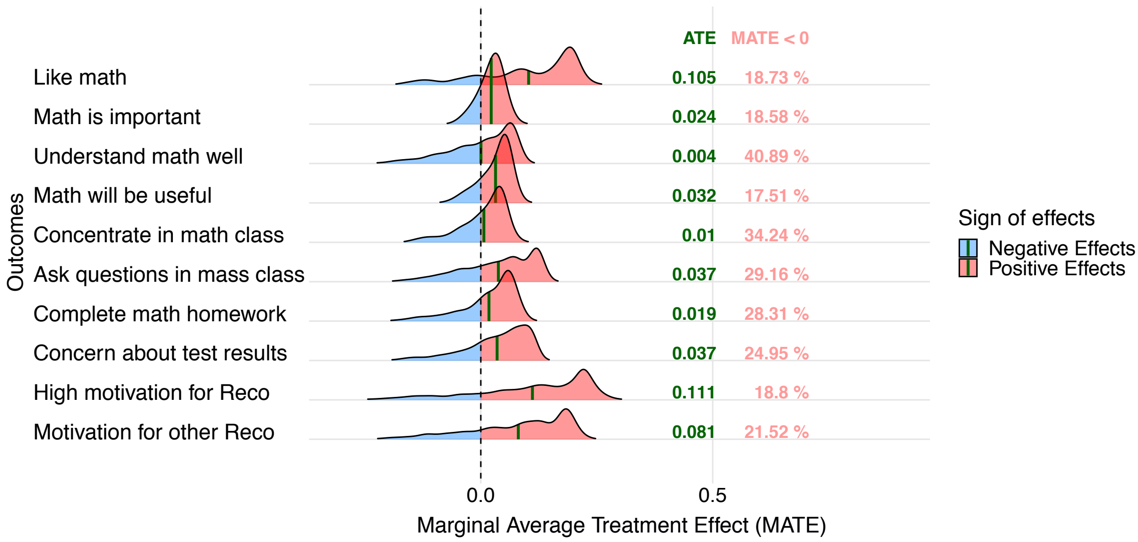

Figure 8. Treatment effects on non-cognitive skills (Full sample)

We find that the estimated coefficients for ATE ($\widehat{\gamma_1}$) are positive for all outcomes. These results mean that the cohort with an experience of COVID-19 school closures, improved their attitude toward proactively learning math, six months after the closure. First, the largest proportion of students [about 41%] was negatively affected under "Understand math well."

However, the MATE distribution shows that many students are still negatively affected regarding their attitude toward proactive learning for math. Considering the results in Figure 4, which show that 10.27% of the students had negative math scores at +2 terms from the closure, about 30% of the students had increased scores despite a decreased understanding. The results suggest that the temporary increase in school hours due to shortened summer breaks and reduced school events, only increased test scores, without an increase in understanding.

The other outcomes representing "attitude toward proactive learning," "Like math" [18.73%], "Math is important" [18.58%], "Math will be useful" [17.51%], “Concern about test results” [24.95%], "High motivation for Reco" [18.8%], "Motivation for other Reco" [21.52%], "Concentrate in math class" [34.24%], "Ask questions in math class" [29.16%], and "Complete math homework" [28.31%] indicate that about 18.58-34.24% of students were still negatively affected. Hence, we can conclude that the "attitude toward proactive learning" for math was negatively affected by the lack of face-to-face instruction due to school closures.

Next, we review the results of the subsample analysis in Figure 9. This figure shows that the dispersion of MATE is greater for students in the lower quantiles. Therefore, we conclude that in the lower quantiles, the living conditions during and after the closure have a significant impact on the students’ attitude toward proactive learning for math.

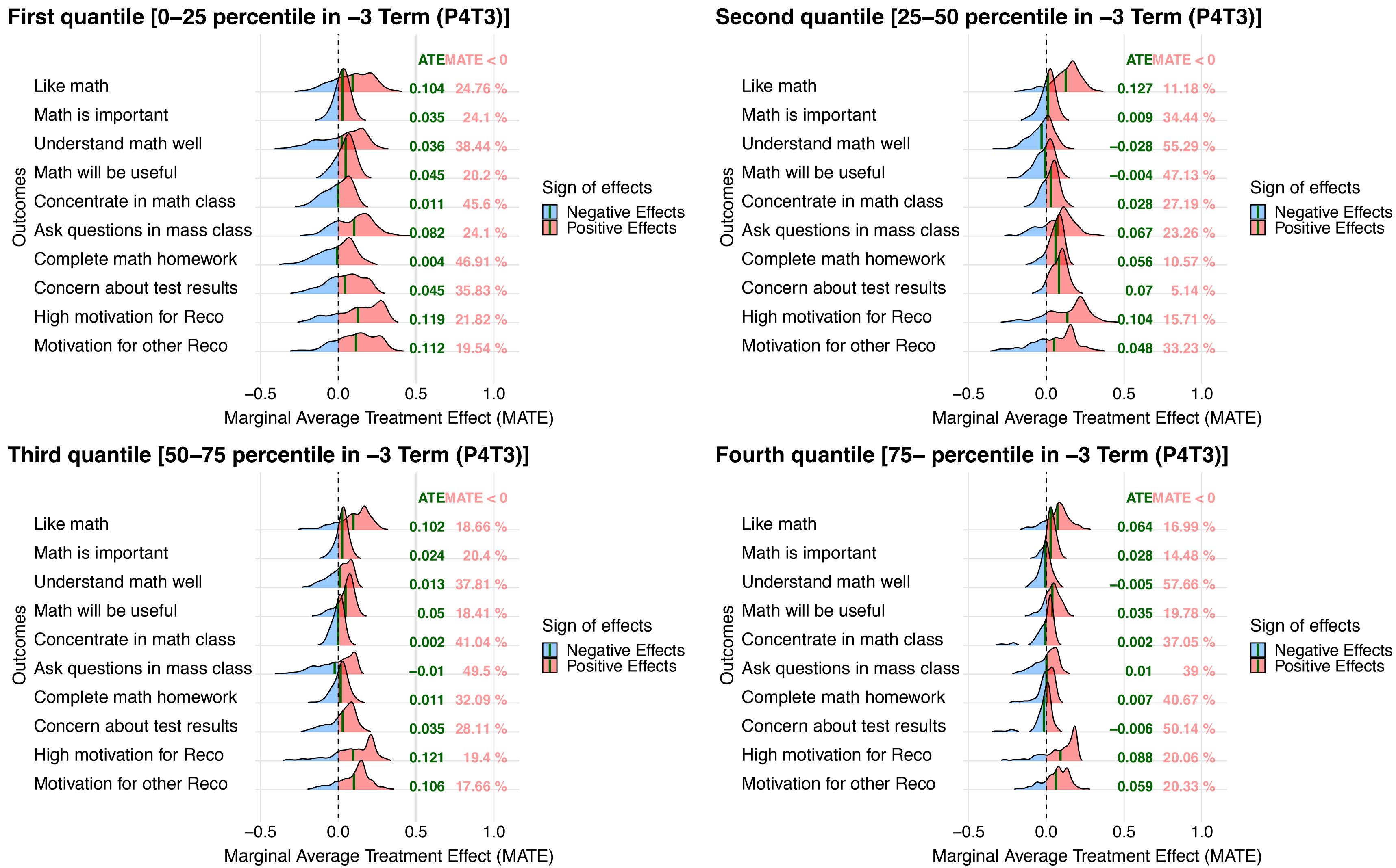

Figure 9. Treatment effects on non-cognitive skills (subsample)

5. Conclusion

This study examined the short- and medium-term dynamic effects of the COVID-19 temporary school closures and the subsequent policy interventions such as reducing summer break and eliminating school events.

We used data for three cohorts of children—those who experienced COVID-19 school closures (FY2019 P4 cohort and FY2019 P5 cohort) and those who did not (FY2019 P6 cohort) —from the "Manabi Nara," the math achievement test administered tri-annually to grades 4–6 in Nara City. The analysis defined the former cohort of children as the treatment group and the latter as the control group. We used the event study and DID methodology to examine whether the difference in cognitive and non-cognitive math skills between the two groups changed before and after the closure.

We present four main pieces of evidence. First, the COVID-19 school closures decreased students' math test scores, particularly of those who were not performing well before the estimation period. Second, on average, the math scores significantly recovered six months after the school closures, but some students who had disadvantaged living conditions during and after the closure, or who were in fourth grade, did not fully recover. Moreover, the variation was larger in the lower quantiles. Third, non-cognitive skills, represented by the attitudes toward proactive learning in math, were higher in the previous year's cohorts but they were negatively affected by the disadvantaged living conditions during and after the closure. Finally, the lower the quantile and younger the grade, the greater the impact of living conditions on students' math test scores and their attitude towards proactively learning math.

Additionally, experiencing school level differences in class changes and attending cram school/using a tutor may contribute to the recovery of students' cognitive and noncognitive skills. Thus, we also examine the school level differences of school closure’s effects and find that class changes and attending cram school/using a tutor had no more effect on cognitive and non-cognitive skills in math than the disadvantaged living conditions (see Appendix for details).

One policy implication of our findings is that the disadvantaged living conditions should be addressed and appropriately handled, especially for the lowest-achieving students. A related study by Carlana and La Ferrara (2021) suggests that online support for students from disadvantaged families during the COVID-19 temporary school closures improved their academic performance. However, our findings suggest that low-achieving students are vulnerable to unexpected shocks in public education, such as school closures, not only because of a deficient home learning environment, but also because of unfavorable living conditions. The households that experienced disadvantaged living conditions could not afford to recover their children's learning losses due to school closure by themselves because the COVID-19 pandemic also affected parents. Therefore, public education should investigate students’ living conditions during and after unexpected school closures and, if required, provide remedial classes to compensate for learning loss experienced by students.

We have two limitations with respect to data. One limitation is the lack of data for the COVID-19 experienced cohort on living conditions before the COVID-19 school closure. Because the impact of the COVID-19 epidemic on living conditions during and after the school closure may differ among students, our results may overestimate the impact of living conditions on the disparity in math achievement. Although changes in living conditions are still part of the impact of the COVID-19 epidemic, the possibility of overestimation can be addressed in a future study by using data from other municipalities that have information on living conditions before and after the closure. Another limitation is that the data we used is from one city in Japan, Nara City. While this data had the advantage of recording tests held three times per year, it also had the disadvantage of not representing the nationwide effect of the COVID-19 school closures. Therefore, a future study will be conducted to examine the effects of temporary school closures on the whole of Japan by using other nationwide surveys.

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Appendix

Sections 3-4 revealed that students who were forced to live in a disadvantaged living condition during and after the COVID-19 school closure showed slower recovery of cognitive and non-cognitive abilities. However, the disadvantaged living condition may not be the only factor that contributes to the recovery of students' cognitive and noncognitive skills. Thus, we examine the heterogeneity of school closure effects due to experiencing class changes and attending cram school/using a tutor, with variation across schools.

First, class changes may alter peer effects from classmates (Ammermueller and Pischke, 2009; Hoxby, 2000). In Nara City, class changes occur every April, but the COVID-19 school closure from March to May is interspersed with class changes. Therefore, the effects of the COVID-19 school closure may differ between schools with multiple classes and single classes. We therefore perform the same analysis as in equations (1)-(5) using only students in single-classroom schools without class changes. We show the summary statistics in Appendix Table A-9 and the results in Appendix Figures 4-10. These figures show that the school closure's effects only for schools without class changes did not differ significantly from the results for all schools (Figures 3-7).

Furthermore, the use of cram schools may contribute differentially to the school closure's effects, because Nara Prefecture has a higher rate of elementary school students attending cram schools/using tutors than the other prefectures in the country.[23] For example, Liu (2012) uses a representative sample of students in junior and senior high schools and 5-year vocational colleges in Taiwan and finds that attending cram schools

[23] According to the results of national survey of school performance and learning (MEXT, 2021b), the percentage of students who do not use cram schools or tutors was 42.8% in Nara Prefecture, compared to the national average of 52.6% in Japan. The data can be downloaded from the following URL (https://www.nier.go.jp/21chousakekkahoukoku/factsheet/prefecture-City.html)

has a significant positive effect on a student's math performance.

Therefore, we first calculate the average rate of attending a cram school/using a tutor for each school from the 2021 National Survey of Academic Achievement and show the summary statistics in Appendix Table A-10. Then, we divide the schools into three groups according to the magnitude of attending a cram school/using a tutor, and estimate equations (1)-(5) for each subgroup. The results show that schools with higher rates of attending a cram school/using a tutor can recover faster in cognitive and non-cognitive skills after COVID-19 school closure (See Appendix Figures 11-14). However, we find that the difference of COVID-19 school closure between the school group with the highest rates of attending a cram school/using a tutor (higher than 67.74%) and the group with the lowest rates (lower than 51.81%) do not differ as much as the ones produced by the disadvantaged living condition during and after the closure. Therefore, we conclude that the difference in the school closure's effect on attending a cram school/using a tutor is smaller than in the living condition.

It should be noted, however, that the rate of attending a cram school/using a tutor may have measurement errors because they are measured on a school level rather than on an individual level. In addition, we will analyze the effects of changing the rate of attending a cram school/using a tutor over time on cognitive and non-cognitive abilities in the future, since the 2021 National Survey of Academic Achievement for grade six primary school students is the only source for this information about these extracurricular learning activities.

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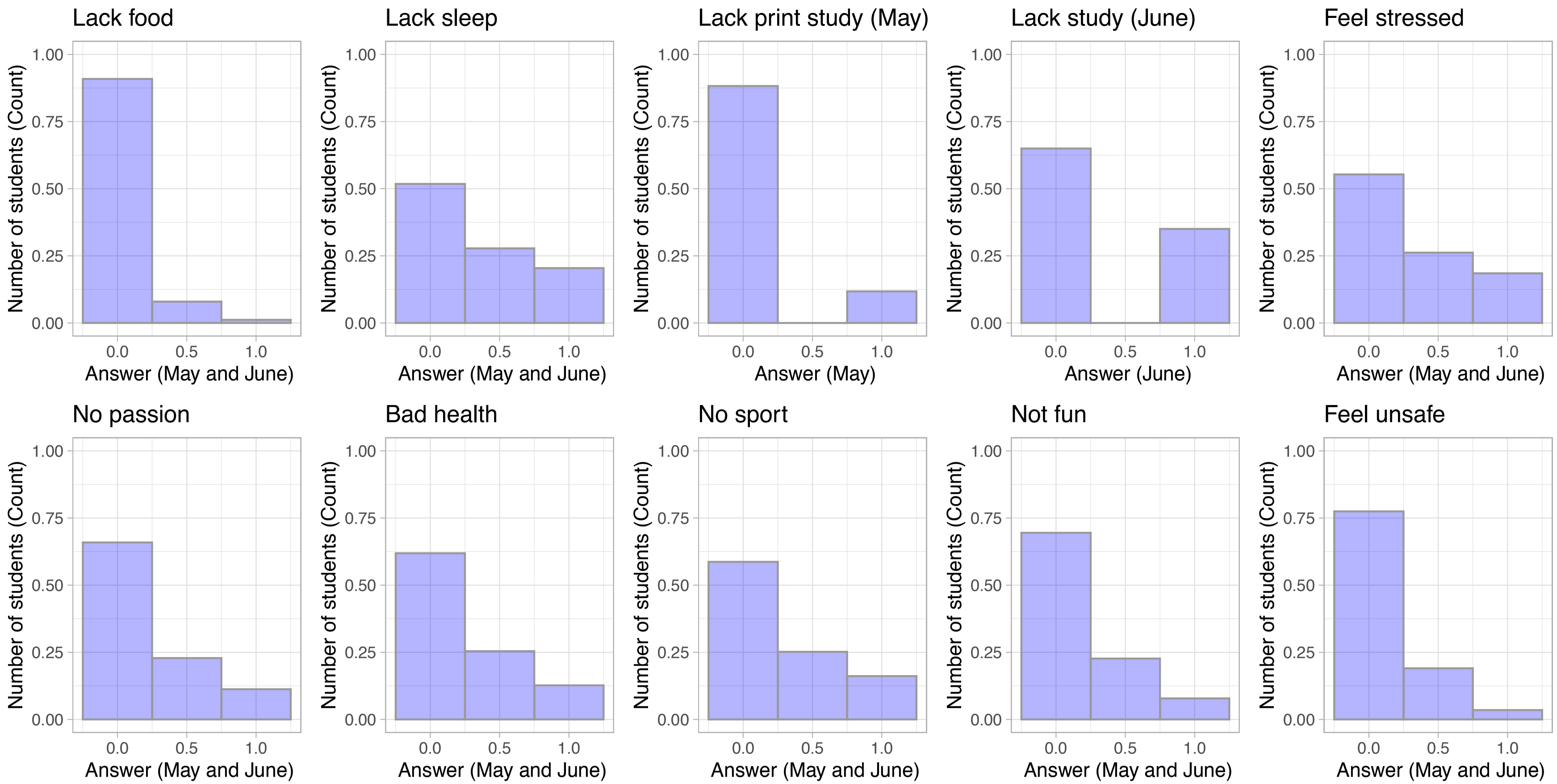
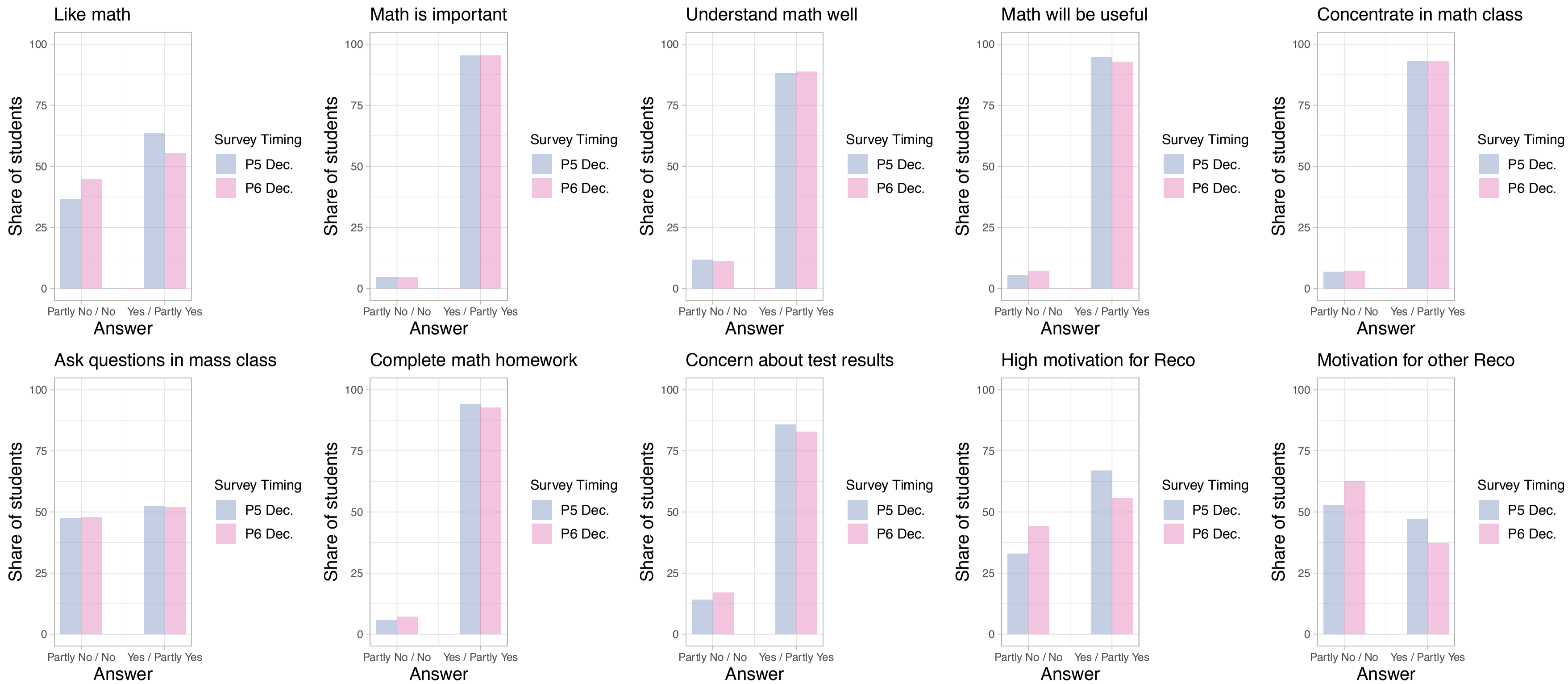
List of Appendix Figures

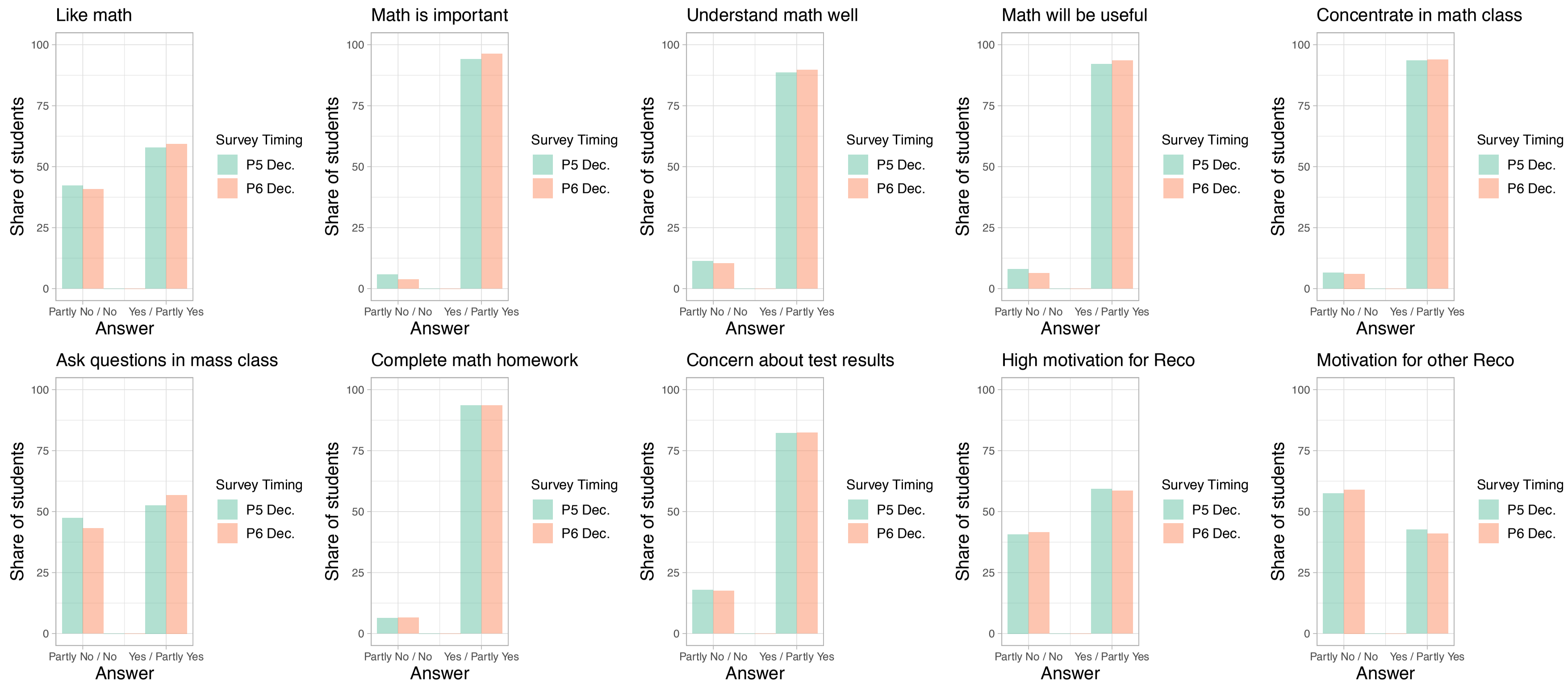
Appendix Figure A-1. Histogram of the disadvantaged living conditions



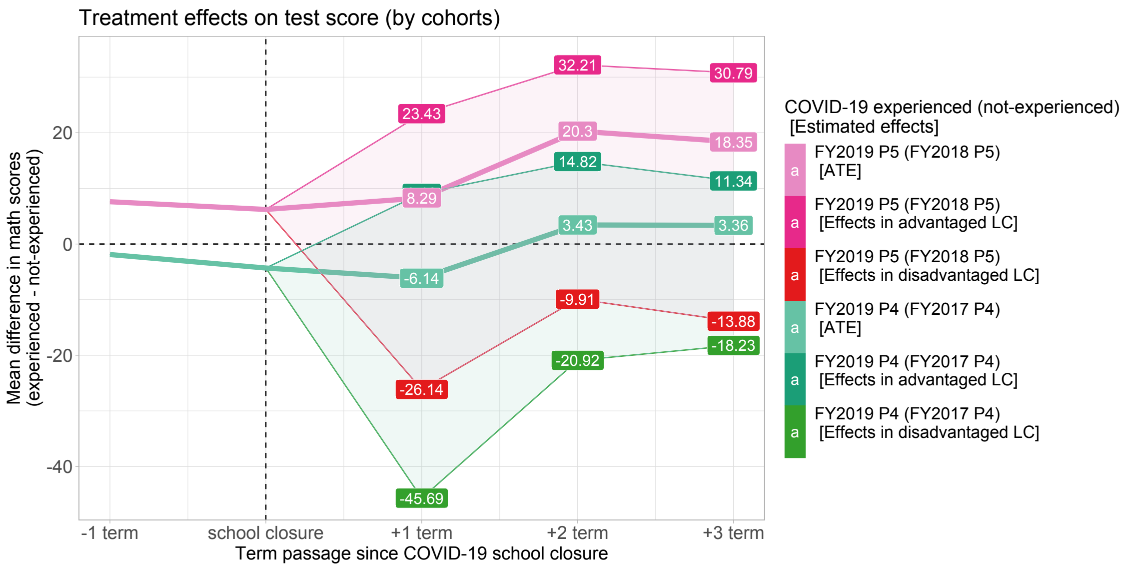
Appendix Figure A-2. Histogram of the attitudes toward proactive learning in math (FY2019 P6 Cohort)



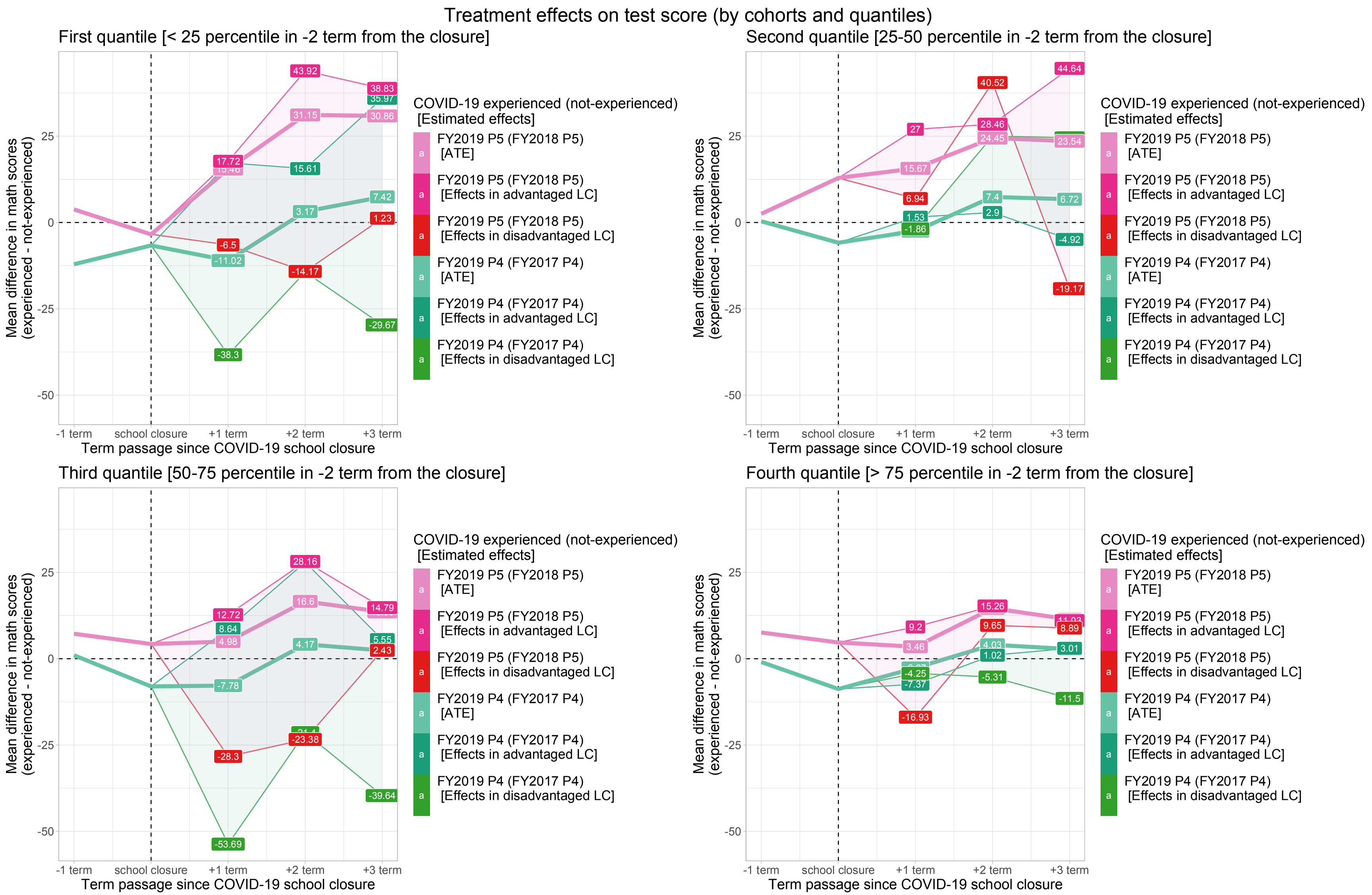
Appendix Figure A-3. Histogram of the attitudes toward proactive learning in math (FY2019 P5 Cohort)



Appendix Figure A-4. Treatment effects on math test score (Event study, Full sample of schools without class changes)

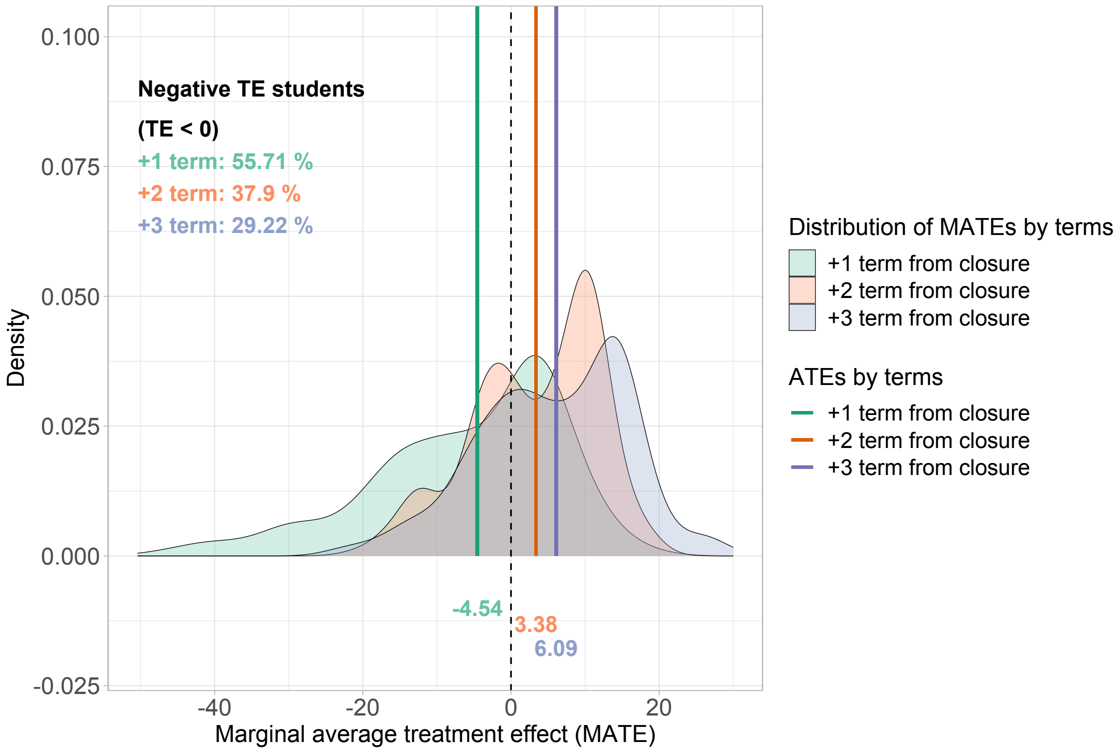


Appendix Figure A-5. ATE and MATE on math test score (Full sample of schools without class changes)

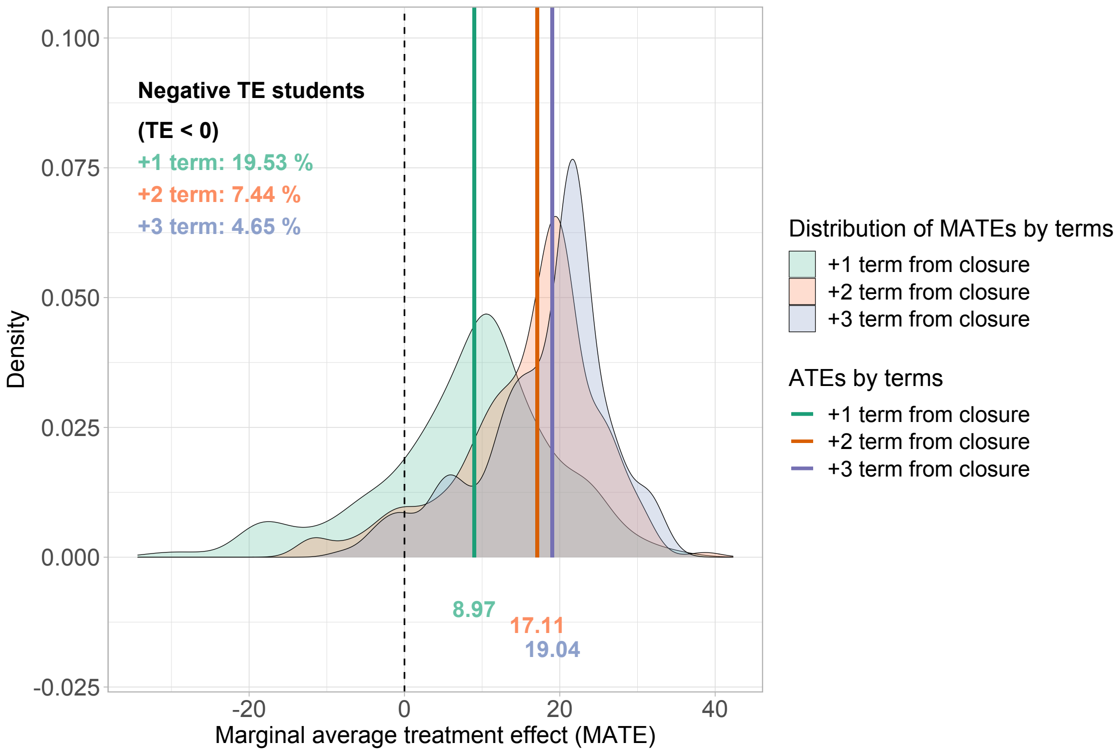


Appendix Figure A-6. Treatment effects on math test score (Event study, Subsample of schools without class changes)

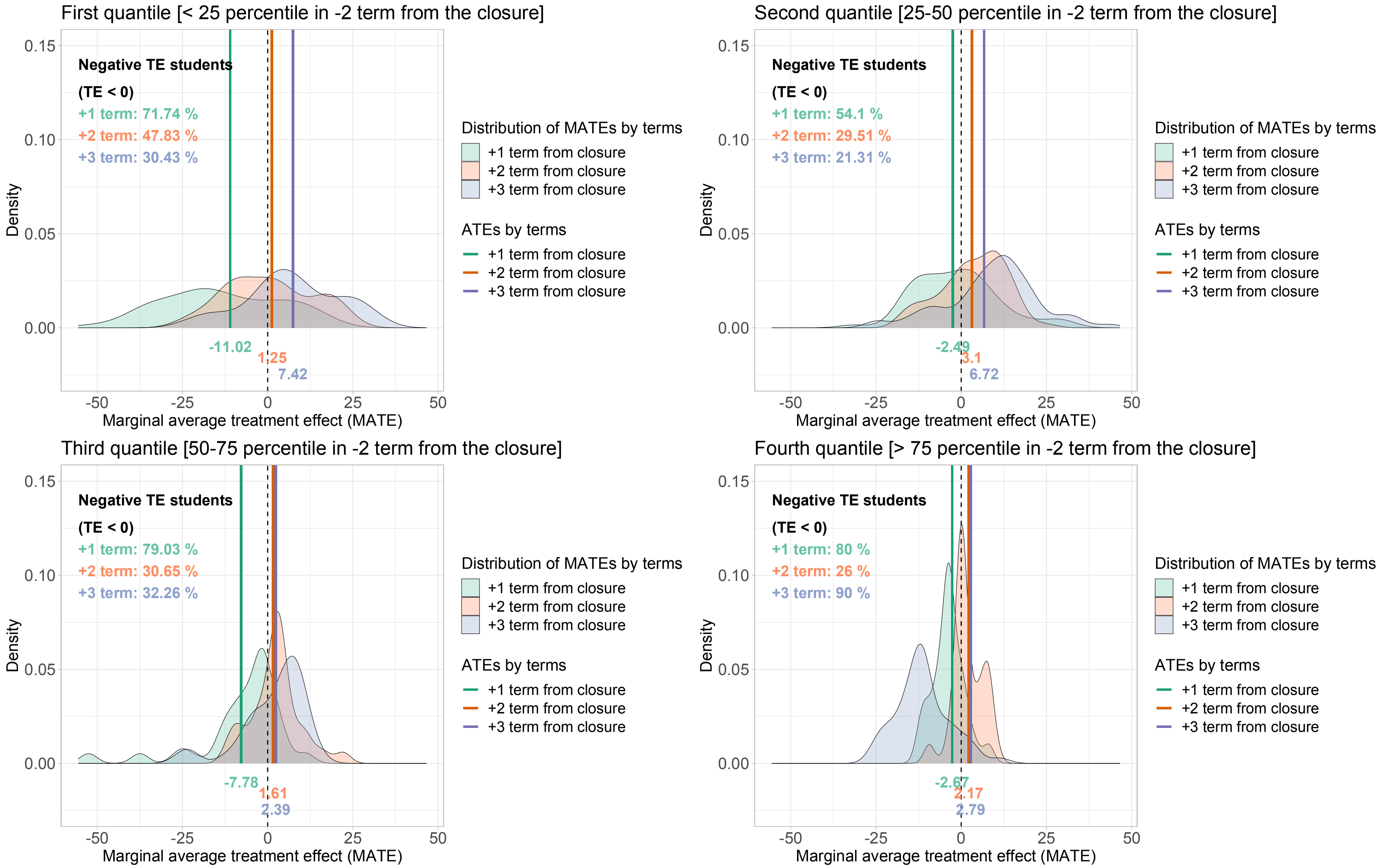
A. Marginal average treatment effects on math test score (FY2019 P4 cohort)



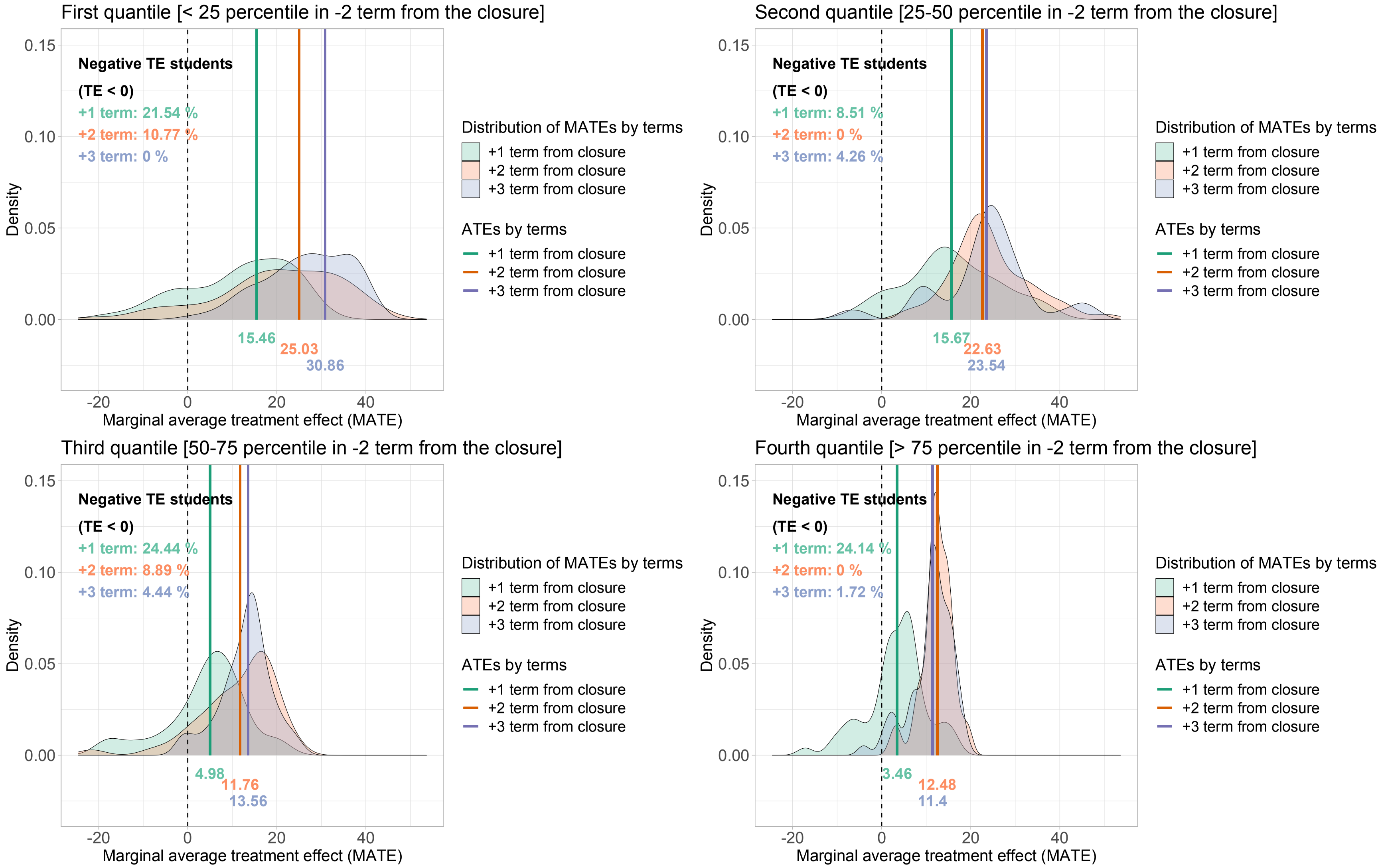
B. Marginal average treatment effects on math test score (FY2019 P5 cohort)



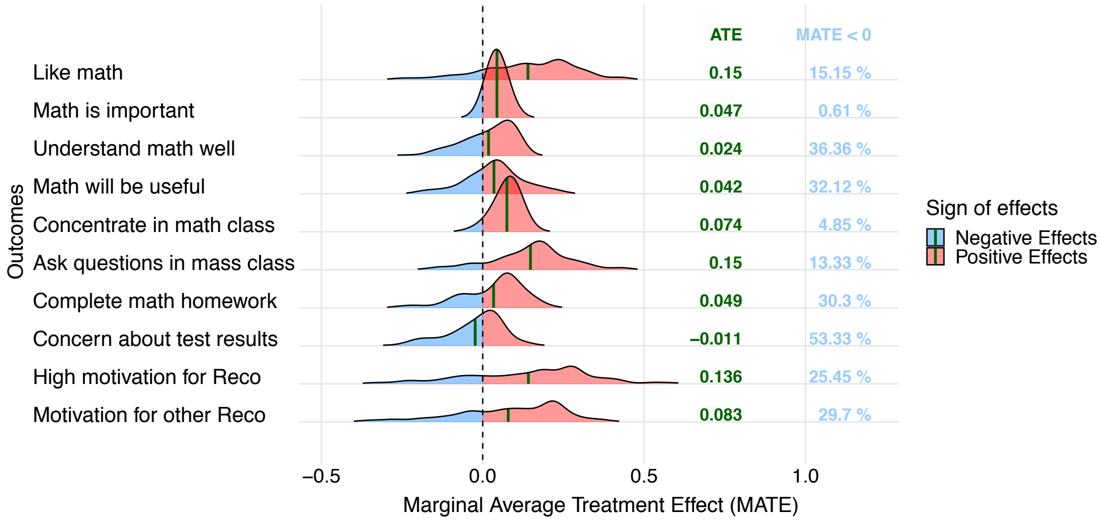
Appendix Figure A-7. Marginal average treatment effects on math test score (FY2019 P4 cohort, Subsample of schools without class changes)



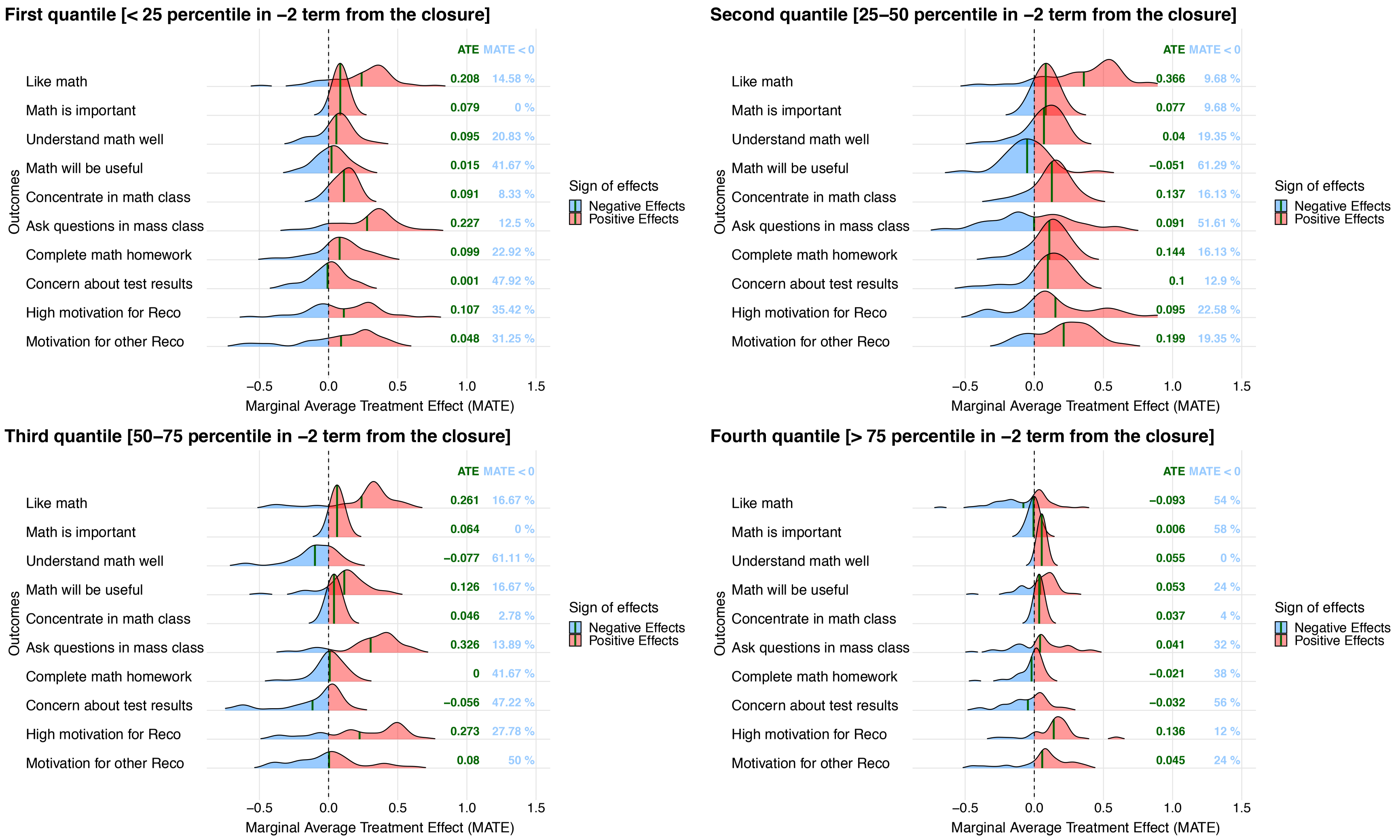
Appendix Figure A-8. Marginal average treatment effects on math test score (FY2019 P5 cohort, Subsample of schools without class changes)



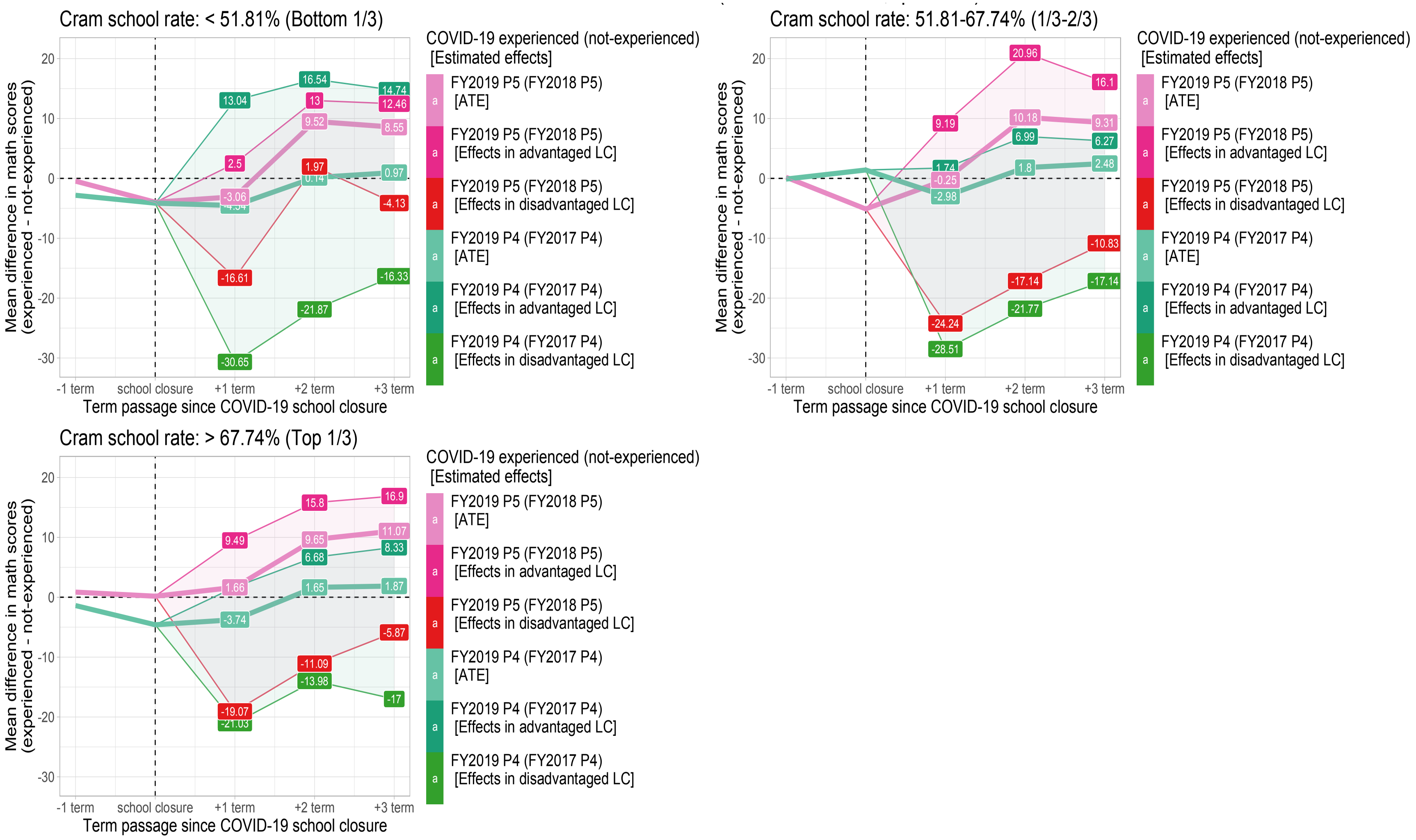
Appendix Figure A-9. Treatment effects on non-cognitive skills (Full sample of schools without class changes)



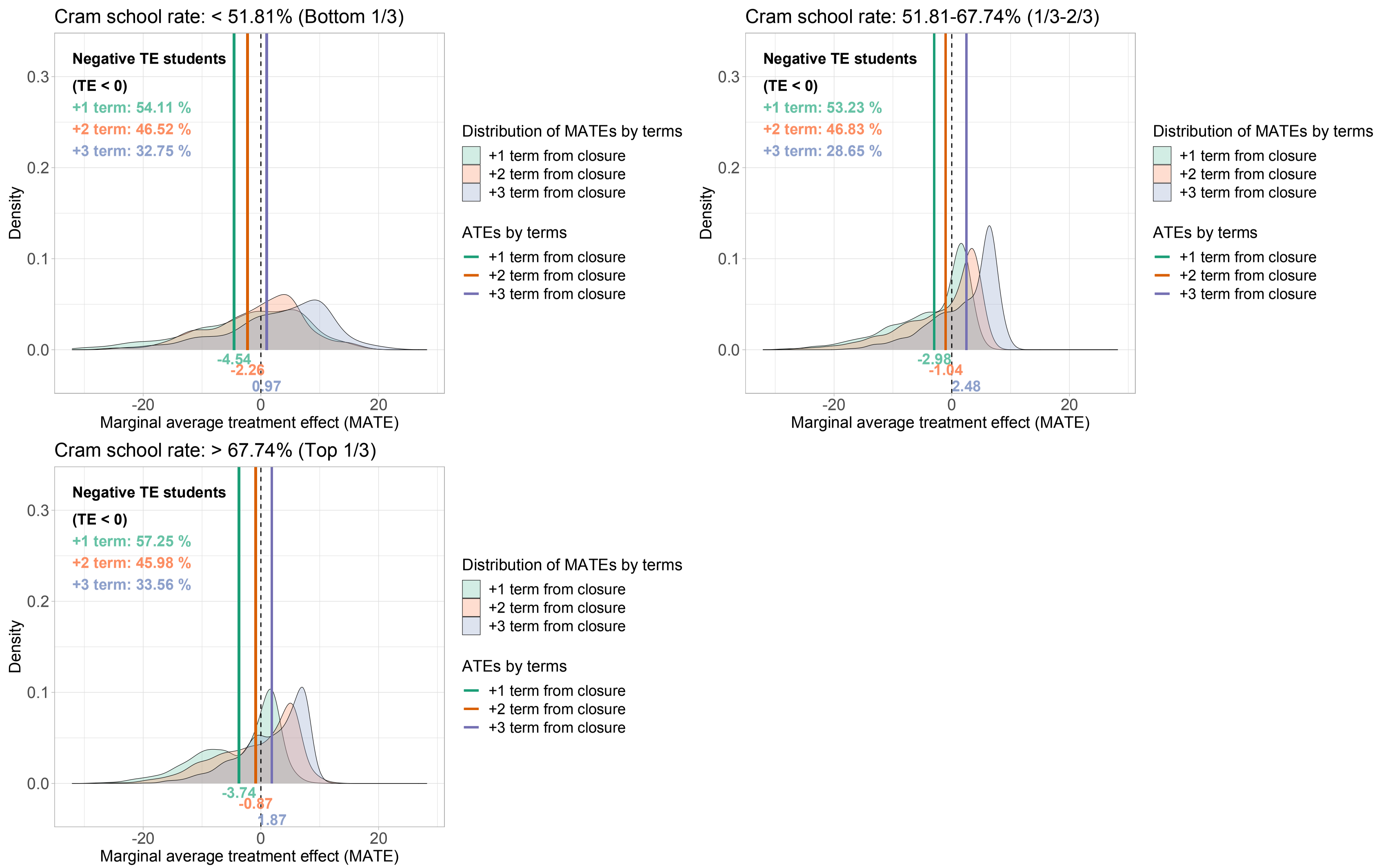
Appendix Figure A-10. Treatment effects on non-cognitive skills (Subsample of schools without class changes)



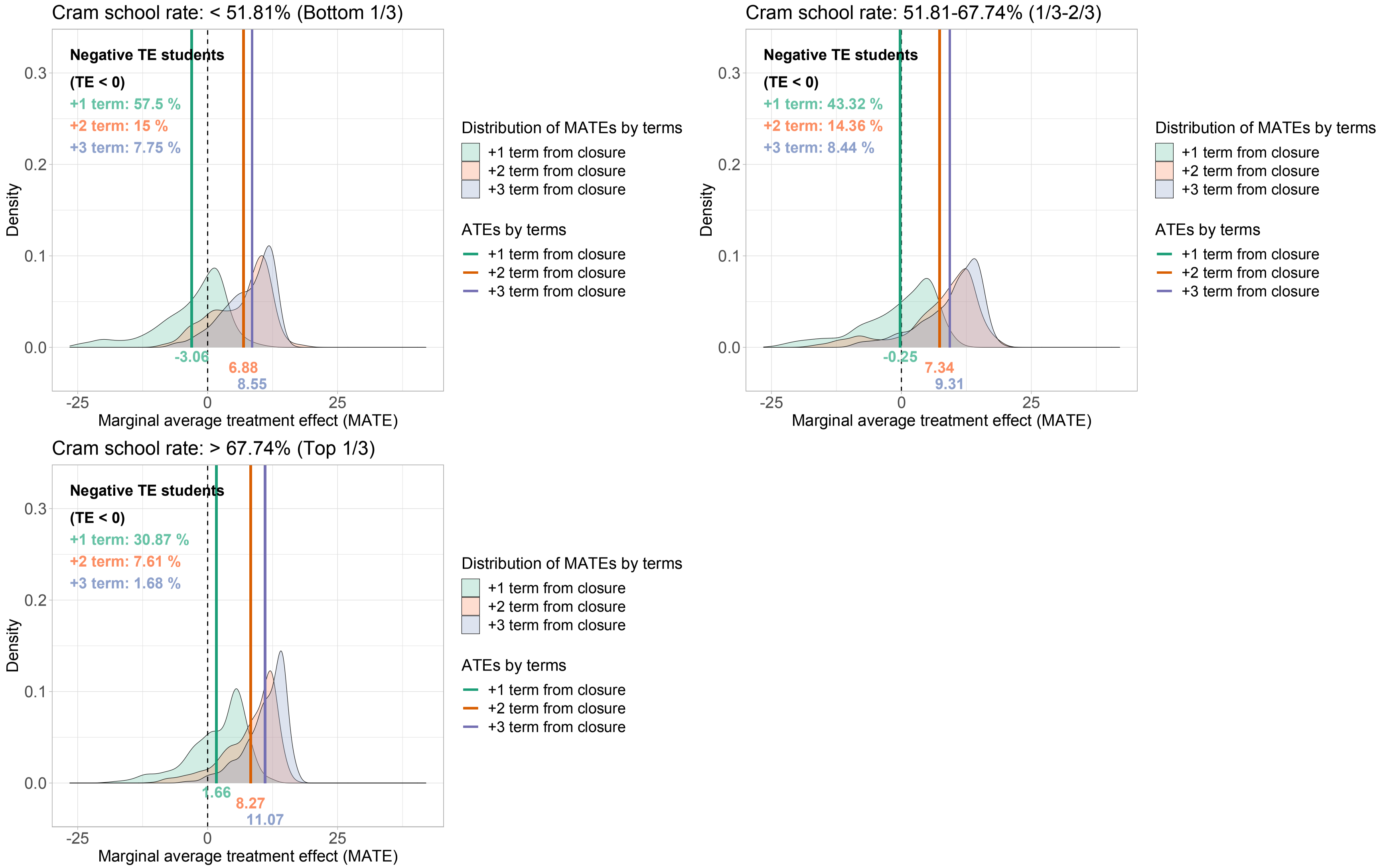
Appendix Figure A-11. Treatment effects on math test score (Event study, Subsample by the average rate of attending a cram school /using a tutor)



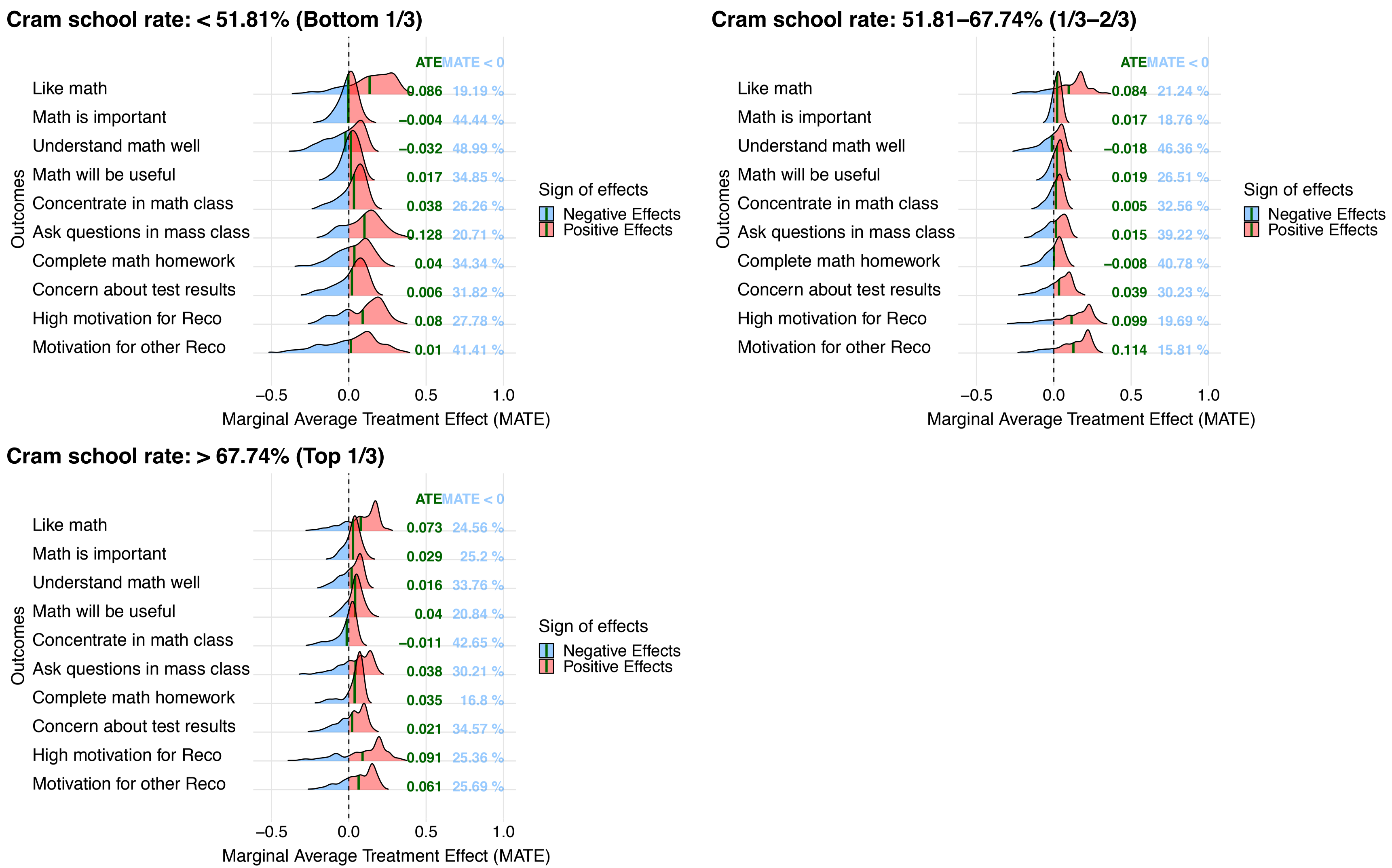
Appendix Figure A-12. MATE on math test score (FY2019 P4 cohort, Subsample by the average rate of attending a cram school /using a tutor)



Appendix Figure A-13. MATE on math test score (FY2019 P5 cohort, Subsample by the average rate of attending a cram school /using a tutor)



Appendix Figure A-14. Treatment effects on non-cognitive skills (Subsample by the average rate of attending a cram school /using a tutor)



List of Tables

Comparison:	FY2019 term 3 vs. Other terms							
Cohorts:	FY2019 P4				FY2019 P5			
Tests:	T-test		F-test		T-test		F-test	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Test score	3.77	0.104	0.720	0.654	−8.77	0.0776*	1.55	0.352

Note: *$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$*

Table A-1: Balance test of math test between school average for schools tested in FY2019 Term 3 and in other terms: T-test and F-test

Living Condition	Definition
Lack food	= 1 if the student answered, "not applicable" or "not really applicable" to the question "I eat breakfast and lunch every day," or 0 otherwise
Lack sleep	= 1 if the student answered, "applicable" or "mostly applicable" to the question "I sometimes have difficulty sleeping," or 0 otherwise
Lack print study (May)	= 1 if the student answered, "not applicable" or "not really applicable" to the question "I studied using handouts from school during the temporary primary school closure," or 0 otherwise
Lack study (June)	= 1 If the student answered, "applicable" or "mostly applicable" to the question "I sometimes have difficulty concentrating on studies," or 0 otherwise
Feel stressed	= 1 if the student answered, "applicable" or "mostly applicable" to the question "I get upset, frustrated, or angry," or 0 otherwise
No passion	= 1 if the student answered, "applicable" or "mostly applicable" to the question "I have no motivation to do anything," or 0 otherwise
Bad health	= 1 if the student answered, "applicable" or "mostly applicable" to the question "I sometimes have physical problems such as a headache or stomachache," or 0 otherwise
No sport	= 1 if the student answered, "not applicable" or "not really applicable" to the question "I exercise a lot," or 0 otherwise
Not fun	= 1 if the student answered, "not applicable" or "not really applicable" to the question "I enjoy every day," or 0 otherwise
Feel unsafe	= 1 if the student answered, "applicable" or "mostly applicable" to the question "I have felt anxious about something," or 0 otherwise

Table A-2: Definitions for disadvantaged living condition dummy

Fiscal Year	Term	Timing of school closure	Grade and Term		
			FY2019 P4	FY2019 P5	FY2019 P6 (COVID-19 not experienced)
	T1 (Apr.– Jul.)	-	-	-	P4T1
2017	T2 (Sep.– Dec.)	-	-	-	P4T2
	T3 (Jan.– Mar.)	-	-	-	P4T3
	T1 (Apr.– Jul.)	-	-	-	P5T1
2018	T2 (Sep.– Dec.)	-	-	-	P5T2
	T3 (Jan.– Mar.)	-	-	-	P5T3
	T1 (Apr.– Jul.)	−2 Term from closure	P4T1	P5T1	P6T1
2019	T2 (Sep.– Dec.)	−1 Term from closure	P4T2	P5T2	P6T2
	T3 (Jan.– Mar.)	School closure	P4T3	P5T3	P6T3
	T1 (Apr.– Jul.)	+1 Term from closure	P5T1	P6T1	-
2020	T2 (Sep.– Dec.)	+2 Term from closure	P5T2	P6T2	-
	T3 (Jan.– Mar.)	+3 Term from closure	P5T3	P6T3	-

Note: P4−P6 mean primary school grades (fourth−sixth). FY2019 P4−P6 represent each cohort. T1-T3 mean school terms 1-3.

Table A-3: Corresponding list: Fiscal year, term, school closure, cohort

Dependent Variable:	Score Difference					
Cohorts:	FY2019 P4 cohort			FY2019 P5 cohort		
	ATE	(1) + DLC [Upper bound]	(1) + ALC [Lower bound]	ATE	(4) + DLC [Upper bound]	(4) + ALC [Lower bound]
Model:	(1)	(2)	(3)	(4)	(5)	(6)
COVID19 × −1 term from closure	-1.229	-0.7387	-0.7387	0.5026	0.6566	0.6566
	(0.8090)	(0.8695)	(0.8695)	(0.9123)	(0.9056)	(0.9056)
COVID19 × School closure	-3.717^{**}	-3.362^{*}	-3.362^{*}	-2.900^{*}	-2.343	-2.343
	(1.562)	(1.904)	(1.904)	(1.728)	(1.834)	(1.834)
COVID19 × +1 term from closure	-3.477^{***}	3.420^{**}	-24.06^{***}	0.3436	7.969^{***}	-19.18^{***}
	(0.7233)	(1.733)	(3.087)	(0.8575)	(1.619)	(3.325)
COVID19 × +2 term from closure	1.406^{*}	8.506^{***}	-17.99^{***}	10.01^{***}	17.06^{***}	-9.608^{***}
	(0.7933)	(1.810)	(3.394)	(0.7652)	(1.495)	(2.958)
COVID19 × +3 term from closure	1.921^{***}	8.677^{***}	-16.86^{***}	10.28^{***}	15.59^{***}	-6.511^{**}
	(0.6699)	(1.618)	(2.911)	(0.7411)	(1.228)	(2.791)
Summer break (SB)	-2.668^{***}	-2.654^{***}	-2.654^{***}	-2.208^{***}	-2.202^{***}	-2.202^{***}
	(0.3235)	(0.3209)	(0.3209)	(0.3501)	(0.3533)	(0.3533)
DLC	No	Yes	No	No	Yes	No
ALC	No	No	Yes	No	No	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Grade FE	Yes	Yes	Yes	Yes	Yes	Yes
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,339	20,361	20,361	19,190	18,397	18,397

Note: Before the "School closure", there is no difference in the coefficients between [Upper bound] and [Lower bound] because the living conditions did not change before the closure. All coefficients for living conditions are omitted for simplicity. "Score Difference" means the difference between math score of an individual i in term t minus the mean just before the school closure (−1 term from closure) for each cohort. "COVID19" is a dummy variable taking one if the student belongs to the FY2019 P4 cohort or FY2019 P5 cohort. "DLC" (ALC) is a dummy variable that takes 1 when the respondent answered applicable/somewhat applicable to the disadvantaged (advantaged) living conditions during and after the closure. Standard errors in parentheses are clustered at the classroom level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A-4: Results of event study estimation (full sample)

Dependent Variable:	Score Difference							
Cohorts:	FY2019 P4 cohort				FY2019 P5 cohort			
Score QT:	1st QT	2nd QT	3rd QT	4th QT	1st QT	2nd QT	3rd QT	4th QT
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID19 × −1 term from closure	-3.537**	-2.572**	-1.132	0.4432	-1.857	-0.3623	1.423	2.339***
	(1.440)	(1.260)	(0.9602)	(0.7673)	(1.547)	(1.327)	(1.220)	(0.8816)
COVID19 × School closure	-4.934***	-7.467***	-4.267*	-1.773	-6.508**	-5.895*	-3.892	-1.746
	(1.597)	(1.646)	(2.275)	(1.620)	(2.841)	(3.059)	(3.411)	(1.742)
COVID19 × +1 term from closure	-6.286***	-4.538***	-2.808**	-2.636***	-2.125	0.6209	3.097***	-0.2672
	(1.486)	(1.200)	(1.192)	(0.7657)	(1.670)	(1.451)	(1.089)	(0.9119)
COVID19 × +2 term from closure	-1.277	0.0428	1.867	2.366**	10.28***	11.43***	11.01***	7.046***
	(1.640)	(1.284)	(1.184)	(0.9612)	(1.713)	(1.372)	(0.9794)	(0.7407)
COVID19 × +3 term from closure	3.150**	1.549	1.550	-0.0186	12.90***	10.91***	10.87***	6.772***
	(1.465)	(1.210)	(1.103)	(0.8551)	(1.531)	(1.411)	(1.171)	(0.6893)
Summer break (SB)	-2.582***	-3.175***	-2.790***	-2.310***	-2.662***	-2.600***	-2.411***	-1.128***
	(0.5756)	(0.4778)	(0.4312)	(0.3863)	(0.6012)	(0.5151)	(0.4972)	(0.3614)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,894	5,390	5,279	5,776	4,449	4,812	4,575	5,354

Note: "Score QT" is calculated by the test score in −2 term from closure. Standard errors in parentheses are clustered at the classroom level. **p<0.1; **p<0.05; ***p<0.01*

Table A-5: Results of event study estimation (by quantiles): ATE

Dependent Variable:	Score Difference							
Cohorts:	FY2019 P4 cohort				FY2019 P5 cohort			
Score QT:	1st QT	2nd QT	3rd QT	4th QT	1st QT	2nd QT	3rd QT	4th QT
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID19 × −1 term from closure	-3.142*	-2.628*	-1.277	0.2450	-1.844	-0.6971	1.481	2.101**
	(1.632)	(1.353)	(0.9678)	(0.7915)	(1.502)	(1.355)	(1.255)	(0.9058)
COVID19 × School closure	-4.409**	-7.184***	-5.289**	-2.599	-6.956***	-6.006*	-3.746	-1.887
	(2.110)	(1.666)	(2.357)	(1.774)	(2.624)	(3.078)	(3.362)	(1.755)
COVID19 × +1 term from closure	3.779	-5.805**	-1.832	-1.355	5.050*	5.463**	5.624***	2.066
	(3.263)	(2.698)	(2.364)	(2.068)	(2.947)	(2.603)	(2.160)	(1.583)
COVID19 × +2 term from closure	6.573*	-0.6015	2.909	4.288**	19.56***	15.84***	13.06***	9.663***
	(3.446)	(2.700)	(2.683)	(2.154)	(3.086)	(2.381)	(2.089)	(1.179)
COVID19 × +3 term from closure	12.90***	1.005	3.210	1.063	17.88***	15.23***	11.03***	8.795***
	(3.135)	(2.615)	(2.429)	(2.183)	(2.932)	(2.079)	(1.828)	(1.189)
Summer break (SB)	-2.587***	-3.176***	-2.753***	-2.302***	-2.664***	-2.593***	-2.454***	-1.137***
	(0.5733)	(0.4789)	(0.4315)	(0.3868)	(0.6150)	(0.5226)	(0.5043)	(0.3657)
DLC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,584	5,159	5,043	5,575	4,146	4,625	4,407	5,219

Note: "Score QT" is calculated by the test score in −2 term from closure. "DLC" is a dummy variable that takes 1 when the respondent answered applicable/somewhat applicable to the disadvantaged living conditions during and after the closure. Standard errors in parentheses are clustered at the classroom level. **p<0.1;* ***p<0.05;* ****p<0.01*

Table A-6: Results of event study estimation (by quantiles): Effect for students with the most advantaged living conditions (upper bound)

Dependent Variable:	Score Difference							
Cohorts:	FY2019 P4 cohort				FY2019 P5 cohort			
Score QT:	1st QT	2nd QT	3rd QT	4th QT	1st QT	2nd QT	3rd QT	4th QT
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID19 × −1 term from closure	-3.142*	-2.628*	-1.277	0.2450	-1.844	-0.6971	1.481	2.101**
	(1.632)	(1.353)	(0.9678)	(0.7915)	(1.502)	(1.355)	(1.255)	(0.9058)
COVID19 × School closure	-4.409**	-7.184***	-5.289**	-2.599	-6.956***	-6.006*	-3.746	-1.887
	(2.110)	(1.666)	(2.357)	(1.774)	(2.624)	(3.078)	(3.362)	(1.755)
COVID19 × +1 term from closure	-20.48***	-9.473**	-17.89***	-1.432	-15.22***	-4.992	-0.1210	-4.027
	(5.953)	(4.458)	(4.673)	(4.004)	(4.347)	(4.883)	(4.699)	(3.068)
COVID19 × +2 term from closure	-9.603	-5.763	-11.62**	0.6502	-5.839	4.817	5.064	1.843
	(6.335)	(5.294)	(5.027)	(3.501)	(4.553)	(4.990)	(4.848)	(3.569)
COVID19 × +3 term from closure	-13.01***	-6.058	-11.45**	-0.8712	-0.4875	2.413	12.49***	0.8059
	(4.455)	(5.281)	(4.606)	(3.623)	(4.815)	(4.610)	(3.863)	(2.828)
Summer break (SB)	-2.587***	-3.176***	-2.753***	-2.302***	-2.664***	-2.593***	-2.454***	-1.137***
	(0.5733)	(0.4789)	(0.4315)	(0.3868)	(0.6150)	(0.5226)	(0.5043)	(0.3657)
ALC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,584	5,159	5,043	5,575	4,146	4,625	4,407	5,219

Note: "Score QT" is calculated by the test score in −2 term from closure. "ALC" is a dummy variable that takes 1 when the respondent answered applicable/somewhat applicable to the advantaged living conditions during and after the closure. Standard errors in parentheses are clustered at the classroom level. **p<0.1; **p<0.05; ***p<0.01*

Table A-7: Results of event study estimation (by quantiles): Effect for students with the most disadvantaged living conditions (lower bound)

Outcome variables	Definition
Like math (Like math)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you like to study math?," or 0 otherwise
Math important (Math is important)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you think it is important to study math?," or 0 otherwise
Understand math well (Understand math)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you understand the content of the math class well?," or 0 otherwise
Math will be useful (Math useful)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you think that what you learned in math class will be useful in the future when you start working?," or 0 otherwise
Concentrate in math class (Math concentration)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you listen carefully to the teacher in math class?," or 0 otherwise
Ask questions in math class (Math question)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you ask questions to your teacher in math class if you don't understand something?," or 0 otherwise
Complete math homework (Math homework)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you complete your math homework regularly?," or 0 otherwise
Concern about test results (Math results)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you care about the results of the test?," or 0 otherwise
High motivation for Reco (Reco motivation)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "Do you have a high motivation to study using the Reco sheets (reflection study sheets)?," or 0 otherwise
Motivation for other Reco (Other Reco)	= 1 if the student answered, "applicable" or "mostly applicable" to the question "You receive 3 Reco-sheets each time. Do you want to try to work on the other numbered Reco-sheets besides your own?," or 0 otherwise

Note: Words in parentheses are abbreviations for the outcome variables used in the manuscript.

Table A-8: Definition of outcome variables for attitude toward proactive learning of math

Variable	Cohorts	Observations	Min	Median	Mean	Max	St. Dev.	#NA
Test score	FY2019 P6 cohort	937	0	70	65.894	100	22.388	0
	FY2019 P5 cohort	959	0	74	67.613	100	24.541	0
	FY2019 P4 cohort	639	0	68	64.501	100	21.715	0
	Full sample	2535	0	71	66.193	100	23.089	0
COVID19	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	959	1	1	1.000	1	0.000	0
	FY2019 P4 cohort	639	1	1	1.000	1	0.000	0
	Full sample	2535	0	1	0.630	1	0.483	0
Summer break (SB)	FY2019 P6 cohort	937	0	0	0.453	1	0.498	0
	FY2019 P5 cohort	959	0	0	0.447	1	0.497	0
	FY2019 P4 cohort	639	0	0	0.482	1	0.500	0
	Full sample	2535	0	0	0.458	1	0.498	0
Lack food	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.139	1	0.317	166
	FY2019 P4 cohort	446	0	0	0.120	1	0.284	193
	Full sample	2176	0	0	0.075	1	0.239	359
Lack sleep	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.242	1	0.376	166
	FY2019 P4 cohort	446	0	0	0.228	1	0.369	193
	Full sample	2176	0	0	0.135	1	0.305	359
Lack print study (May)	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.078	1	0.269	166
	FY2019 P4 cohort	446	0	0	0.101	1	0.302	193
	Full sample	2176	0	0	0.049	1	0.216	359
Lack study (June)	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.248	1	0.432	166
	FY2019 P4 cohort	446	0	0	0.235	1	0.425	193
	Full sample	2176	0	0	0.139	1	0.346	359
Feel stressed	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.239	1	0.375	166
	FY2019 P4 cohort	446	0	0	0.243	1	0.377	193
	Full sample	2176	0	0	0.137	1	0.308	359
No passion	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.164	1	0.308	166
	FY2019 P4 cohort	446	0	0	0.195	1	0.334	193
	Full sample	2176	0	0	0.100	1	0.255	359
Bad health	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.190	1	0.327	166
	FY2019 P4 cohort	446	0	0	0.200	1	0.351	193
	Full sample	2176	0	0	0.110	1	0.271	359
No sport	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.221	1	0.356	166
	FY2019 P4 cohort	446	0	0	0.163	1	0.303	193
	Full sample	2176	0	0	0.114	1	0.274	359
Not fun	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.136	1	0.285	166
	FY2019 P4 cohort	446	0	0	0.111	1	0.265	193
	Full sample	2176	0	0	0.072	1	0.219	359
Feel unsafe	FY2019 P6 cohort	937	0	0	0.000	0	0.000	0
	FY2019 P5 cohort	793	0	0	0.100	1	0.233	166
	FY2019 P4 cohort	446	0	0	0.127	1	0.260	193
	Full sample	2176	0	0	0.062	1	0.192	359

Table A-9: Summary statistics of the outcome variable and main variables (Single-classroom schools, by cohorts)

Statistic	N	Mean	St. Dev.	Min	Max
Average rate of attending a cram school / using a tutor for each school	43	0.584	0.148	0.250	0.833

Note: First, for each individual from the NSAA, we created an "attending a cram school / using a tutor dummy," which is 1 if the student answered "attending a cram school / supplementary school" or "using a tutor." Then, we averaged the dummy variables for each school and calculated the "Average rate of attending a cram school /using a tutor for each school."

Table A-10: Summary statistics of the average rate of attending a cram school/using a tutor from the 2021 NSAA