RIETI Discussion Paper Series 22-E-107

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https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 22-E-107

November 2022

Inequalities in Student Learning and Screen Time due to COVID-19: Evidence from Japan[1]

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Abstract

We examine the impact of COVID-19-related school closures on student learning and screen time. We find that between January 2020 (pre-COVID-19) and May 2020, as the length of a COVID-19-related school closure increased, there was a decrease in learning time and an increase in screen time. These adverse effects tend to be more pronounced for students in low-income households, low academic achievers, and elementary school students living in single-parent households. Moreover, the increase in screen time may have persisted until January 2021 for elementary school students in single-parent households. On average, while live online classes mitigated the effects of decreased learning time for junior high school students, that effect is not found for low academic achievers.

Keywords: COVID-19, educational inequalities, learning time, screen time
JEL classification: I24, I28, J24

[1] This study is conducted as a part of the projects "Research and Analysis about COVID-19 and Child Poverty," undertaken at the Nippon Foundation and Mitsubishi UFJ Research and Consulting Co., Ltd. and "Implementing Evidence-Based Policy Making in Japan," undertaken at the Research Institute of Economy, Trade and Industry (RIETI). We are grateful to Michihito Ando, Daiji Kawaguchi, Koyo Miyoshi, Masayuki Morikawa, Daigo Nakata, Fumio Ohtake, and Yasuyuki Sawada for their helpful comments. The findings and conclusions expressed here are those of the authors. We are solely responsible for any remaining errors.

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1. Introduction

The spread of COVID-19 caused school closures in most countries. At the peak of these closures, more than 80% of the total number of enrolled learners were affected.[1] Previous studies have examined the impact of reduced class time resulting from teacher strikes (Baker, 2013; Jaume and Willén, 2019), inclement weather (Marcotte, 2007), and school system reforms (Pischke, 2007; Kawaguchi, 2016) and find that the loss of learning opportunities has various negative impacts on children. Separately, studies note the importance of schooling in equalizing gaps in education (Downey et al. 2004; Alexander et al. 2007). Based on the literature addressing both of these topics, we expect school closures due to COVID-19 to negatively affect children, and also expect the effects to be heterogeneous based on family background or the child's characteristics. Furthermore, the prolonged pandemic may influence how children's study habits are formed over the middle or long term through the pandemic's impacts on their parents' jobs or family lifestyle. However, few studies examine the effect of the COVID-19 pandemic on children's education or study habits due to a lack of data that would capture changes in learning conditions during the relevant period. Understanding who has been affected by COVID-19-related school closures and how those effects were manifested is essential for policymakers. Moreover, verifying the effectiveness of countermeasures against the effects of these school closures can provide hints on how to prepare for future pandemics.

With these considerations in mind, we investigate the heterogeneous effects of school closure due to COVID-19 on children in Japan using an online survey. Specifically, we examine changes in how school-aged children used their time, including learning time and screen time,[2] before the pandemic, during school closures, and after schools reopened, categorizing the students by household income, academic achievement, and household type. We also investigate

[1] Source: UNESCO map on school closures (https://en.unesco.org/covid19/educationresponse) and UIS, March 2022 (http://data.uis.unesco.org) (accessed July 22, 2022).
[2] Screen time includes time spent watching TV, playing video games, using the Internet, and using a smartphone.

the changes in learning time based on learning resources provided by schools or municipalities during the period when schools were closed. Our findings should help us to understand which learning resources were most effective during school closures.

To gather data for these analyses, we conducted an online survey of 4,000 households that include children who attend elementary, junior high, or high school. The survey asked for estimates of how the children spent their time during three monthly periods, January 2020, May 2020, and January 2021. In Japan, COVID-19 was not widespread in January 2020. Then, the number of infected people gradually increased and the government recommended nationwide school closures on March 02, 2020. Many schools were closed for several months; therefore many children were out of school during May 2020. In January 2021, although the number of COVID-19 infections again rose, schools were not closed nationwide. Thus, we can capture learning conditions before the pandemic, during school closures, and after schools reopened using this survey data. This study contributes to the literature by examining the heterogeneous changes in learning conditions by household and student characteristics and the persistence of those changes. By focusing on time use, we explore one of the mechanisms through which school closures affect students' test scores or achievement. Importantly, the survey captures learning time; including learning that takes place outside of school and is not limited to specific learning services.

Comparing students learning and screen time for January 2020 and May 2020, we find that the longer the COVID-19 school closure, the greater the decline in learning time and the greater the increase in screen time. These adverse effects tend to be most notable for students in low-income households, low achievers, and elementary school students in single-parent households. Because students' learning and screen time are correlated with academic achievement, these school closures may cause their level of academic achievement to decline over the middle or long term. Moreover, the increase in screen time may have persisted through January 2021 for elementary students in single-parent households. Finally, we find that, on average, while live online classes mitigated the decline in learning time for junior high school students, that effect is not found for low achievers.

The remainder of this study is organized as follows. In Section 2, we provide an overview of the relevant literature. Section 3 describes the details of our survey and data set, Section 4 provides our empirical framework, and Section 5 investigates the short-term effects of school closures on learning time and screen time. Section 6 examines the persistence of the effects of school closures. Finally, Section 7 discusses our main findings and presents our conclusions.

2. Related Literature

Many studies have investigated the effects of school closures on children using teacher strikes, inclement weather, and the like. For example, Baker (2013) shows that teacher strikes during the fifth and sixth grades reduce test score growth in Canada. Jaume and Willén (2019) examine the long-run effects of teacher strikes in Argentina. They find that exposure to teacher strikes in primary school reduces annual earnings when those students are 30–40 years old by 3.2% for males and 1.9% for females. Marcotte (2007) identifies the effect of reduced time in school based on a reduction in the number of school days due to heavy snowfall. He finds that test scores of students who took the Maryland School Performance Assessment Program exams in years with heavy snowfall are lower than those of students in the same school who took the exams in other years. However, few studies examine the impact of COVID-19 on children's education due to a lack of data that captures changes in learning conditions during the pandemic.

Some empirical studies that examine changes in learning conditions during COVID-19 are based on user logs of online learning resources, internet search data, and surveys. Bacher-Hicks et al. (2021) use Google search data and find that nationwide search intensity in the U.S. for online learning resources roughly doubled relative to the pre-COVID-19 level. Chetty et al. (2020) find that the number of lessons completed via an online learning service used as part of the math curriculum in the U.S. fell sharply during COVID-19. In particular, they find that the negative effects are strongest in low-income areas. Ikeda and Yamaguchi (2021) examine user logs of an online learning service used as a source of supplementary educational materials. They find that time spent using the online learning service increased during school closures; however, user logs regarding a specific service and internet search intensity cannot capture the other study time, such as self-study.

Aucejo et al. (2020), Andrew et al. (2020), and Grewenig et al. (2021) use survey data. Aucejo et al. (2020) asked 1,500 students at Arizona State University about counterfactual outcomes had the pandemic not occurred and recovered its subjective effects on students' current and expected outcomes. They find that COVID-19 caused large negative impacts across many dimensions, including education and employment, and that these effects are heterogeneous across socioeconomic factors. Andrew et al. (2020) and Grewenig et al. (2021) investigate whether educational inequalities expanded during the pandemic using time-use surveys in the U.K. and Germany, respectively. Andrew et al. (2020) find that inequalities in learning time between low-income and better-off students widened. In addition, they indicate that inequalities in the types of learning resources provided by schools compound the inequalities in learning time. Grewenig et al. (2021) find that the reduction in learning time for low-achieving students is larger than for high-achieving students.

A few studies analyze the impact of COVID-19 using test scores of academic achievement. Jack et al. (2022) estimate the effect of schooling mode (in-person, hybrid, or virtual learning) on students' pass rates on tests across 11 states in the U.S. They find that although pass rates declined during the pandemic, the decline was smaller for students engaged in in-person learning. The effect of in-person learning was larger in school districts with larger populations of black students. Asakawa and Ohtake (2022) examine the impacts of COVID-19 school closures on academic achievement in math for elementary school students. They show that although math scores declined in the short term, they recovered significantly six months after the school closure ended. They also indicate that math scores and motivation and attitude toward math declined for students in disadvantaged households.

Our study is closely related to Andrew et al. (2020) and Grewenig et al. (2021) in terms of relying on a time-use survey. There are two major differences between our study and those two studies. First, while Andrew et al. (2020) and Grewenig et al. (2021) compare students' time use before and during the pandemic, we investigate whether the effect of school closures continues after schools reopen, as we also asked survey participants to report time use after schools reopened. Second, we also investigate the heterogeneity of the impacts of learning resources provided by schools or municipalities. Bettinger et al. (2017) and Cacault et al. (2021) indicate that online lectures lower achievement for low-achieving students, which supports the hypothesis that the effects of learning resources are heterogeneous.

3. Data

3.1 Data Details

We conducted an online survey of 4,000 households that had children in elementary, junior high, or high school in March 2021. The survey respondent was a parent in the household. We use the quota sampling method so that the distribution of household income and composition matches the Comprehensive Survey of Living Conditions conducted by the Japanese Ministry of Health, Labour and Welfare. The survey asked about annual household income, household composition, grade level of the youngest school-aged child in the household, the duration of the school closure caused by COVID-19 between February and June 2020, learning resources provided by schools or municipalities during the closure, the student's academic achievement, and related questions. We also asked about the average amount of time spent daily on the following eight activities: sleeping, learning while in school, learning while not in school, extracurricular activities, enrichment lessons, screen time, outdoor activities, and others, during the months of January 2020, May 2020, and January 2021. As shown in Figure 1, COVID-19 was not widespread in January 2020, but the number of infected people gradually increased and the government requested nationwide school closures on March 02, 2020. Many schools remained closed for several months, and therefore many children were out of school in May 2020. In January 2021, although COVID-19 infection numbers rebounded, schools did not close nationwide.[3] Thus, we are able to capture learning conditions and time spent on various activities before the pandemic, during the period of school closures, and after schools reopened using this survey.

Responses for which the number of hours spent sleeping, learning in school in January 2020, or other activities, including mealtime, etc., was reported as zero were treated as missing values because these are likely to be wrong answers. Students in grades 1, 7, and 10 were likely to change the amount of learning time for reasons other than COVID-19 because some students have experienced studying for entrance exams by April 2020.[4] Therefore, we do not use the data for students in grades 1, 7, and 10 in the analysis.

3.2 Descriptive Statistics

Table 1 presents summary statistics for the key variables. The amount of time used in a given category is presented in hours. The mean of the total learning time in January 2020 is 7.594 hours, which had declined by 1.281 hours by May 2020, when many schools were closed due to COVID-19. Conversely, the mean screen time increased by 0.889 hours from January 2020 to May 2020. While two-thirds of students experienced one or more months of school closures between February and June 2020, 7.7% did not experience any school closures. The mean level reported for every type of achievement is approximately 4.5 on a seven-point scale, as many respondents stated that their children's level of achievement is above average. Low achievers and households whose income in 2019 was less than 4,000,000 JPY represent 17.2% and 17.7%

[3] To compensate for learning loss, schools shortened the summer vacation or reduced school events after schools reopened.
[4] In Japan, the school year runs from April to March next year.

of all respondents, respectively.[5] Students living in single-parent households are 5.2% of the total, and 68.0% of single-parent households have an annual household income below 4,000,000 JPY.

Figure 2 shows the distribution of time uses. As reported in Table 1, total learning time decreased between January 2020 and May 2020, and screen time increased. However, the distribution of time spent on most activities, other than extracurricular activities, is similar when comparing January 2020 and January 2021. These results imply that while COVID-19 school closures affected learning time and screen time temporarily, its impact on extracurricular activities may have persisted for a year or more.[6]

4. Empirical Framework

We begin this section by estimating the impact of school closures due to COVID-19 on student outcomes. First, Equation (1) is estimated by ordinary least squares (OLS) as follows:

$$\Delta T_i = \beta_0 + \boldsymbol{Closure}_i'\boldsymbol{\beta_1} + \boldsymbol{X}_i'\boldsymbol{\beta_2} + \varepsilon_i, \tag{1}$$

where ΔT_i denotes the difference in the average number of hours spent on learning or screen time in January 2020 versus May 2020;[7] $\boldsymbol{Closure_i}$ denotes a vector of dummy variables representing the duration of school closures for the period from February 2020 through June 2020 that includes "no closure," "less than one month," "one through two months," and "two or more months"; $\boldsymbol{X_i}$ denotes a control-variable vector that contains household income in

[5] The "low-achievers," "middle-achievers," and "high-achievers" represent students with achievement levels 1–3, 4, and 5–7 on a seven-point scale, respectively.

[6] In related work, Inui and Okudaira (2022) find that parents increased their investment in children's cognitive skills to compensate for the damage, but decreased spending on children's non-cognitive skills after the Great East Japan Earthquake.

[7] In related work, Oikawa et al. (2022) find that the deleterious effects of class closures due to a flu epidemic on economically disadvantaged male students were driven by increased time spent watching TV and playing video games.

2019, overall academic achievement in School Year (SY) 2019, household type, grade fixed effects, and the employment status of respondents in May 2020 or January 2021;[8] and ε_i is an error term. The coefficient vector of interest is $\boldsymbol{\beta_1}$, which captures the effect of school closures on students' time use. The duration of school closures was determined by the number of COVID-19 cases in the specific region and is treated as exogenous.

Next, we consider the interaction between the impact of school closure and a student's or household's characteristics. Specifically, Equation (2) is estimated by OLS as follows:

$$\Delta T_i = \gamma_0 + \boldsymbol{Closure_i'}\boldsymbol{\gamma_1} + \sum_k \sum_l \gamma_{kl}(Closure_{ik} \times Chars_{il}) + \boldsymbol{X_i'}\boldsymbol{\gamma_3} + \varepsilon_i, \qquad (2)$$

where $Chars_{il}$ denotes a student's or household's characteristics such as household income, academic achievement, and household type, and γ_{kl} captures the difference in the effect of school closure by those characteristics.

Because our data contains time spent on various activities for three periods, namely January 2020, May 2020, and January 2021, we can investigate the persistence of the effect of school closures on students' time use using the difference between the average time spent on learning or screen time in January 2020 compared to January 2021 as ΔT_i.

5. The Short-term Effects of School Closures

5.1 Baseline Results

Table 2 shows the impact of school closures on the change in average total learning time for January 2020 versus May 2020. Columns (1), (3), (5), and (7) present results with no controls, and the results indicate that the longer the duration of school closures, the greater the decrease

[8] To address the possibility of systematic differences in responses depending on the amount of time the responding parent was in the home, we control for respondents' employment status (e.g., full-time, part-time, unemployed, etc.).

in learning time. The damage (decrease in learning time) is greatest among elementary school students. Columns (2), (4), (6), and (8) present the results of Equation (1). The estimates for the entire sample show that learning time decreased by 0.779 and 1.748 hours (with standard errors of 0.121 and 0.134) when schools were closed for one to two months, and two or more months, respectively, compared to the case of no closure. In contrast, the coefficient of -0.136 is statistically insignificant for school closures of less than one month. As in the estimates with no control variables, the negative impact is the greatest for elementary school students; however, learning time also decreases significantly in high-school students for school closure of one or more months. Additionally, the estimates differ minimally with or without controls, which implies that the duration of the school closure is plausibly exogenous.

Table 3 presents results that are similar to those in Table 2, but the dependent variable is replaced by the difference in learning time outside of school when comparing January 2020 to May 2020. The estimates suggest that when students experienced school closures for two or more months, they significantly increased learning time outside of school to partly compensate for the loss of in-school learning.

We report the effect of school closures on the change in average screen time during January 2020 versus May 2020 in Table 4. As in Table 2, Columns (1), (3), (5), and (7) present the estimates with no controls, and Columns (2), (4), (6), and (8) present the results of Equation (1). The results indicate that the longer the duration of school closures, the greater the increase in screen time. The coefficients for closures of two or more months are largest for elementary school students, while those for closures of one to two months are largest for high-school students.

One concern regarding the baseline results is that the estimates may not distinguish the effects of school closures due to COVID-19 from other regional factors when the duration of school closures could be due to something specific to its region other than the level of COVID infections. Thus, we report the estimates including prefectural dummies in Table 5. The results do not change much from Tables 2 and 4, implying that the baseline results are reasonable.

5.2 Heterogeneity by Household and Student Characteristics

Table 6 presents the results of Equation (2), which analyzes the interaction between school closures and household income. Columns (1), (3), (5), and (7) present the results when the dependent variable is the difference in average total learning time for January 2020 versus May 2020, and Columns (2), (4), (6), and (8) present the results when the dependent variable is the difference in average screen time for January 2020 and May 2020. Column (1) shows that the coefficients of the duration of school closure are negative and statistically significant for students whose household income is less than 4,000,000 JPY, using the entire sample. However, when the school closure is less than one month, the adverse effects are almost offset for students whose household income is 8,000,000 or more JPY. When the school closures lasted for two or more months, the higher the household income, the smaller the negative impact; however, it is not entirely offset. Column (2) shows that the increased screen time declines in high-income households, but the adverse effect remains when school closure is one or more months. The effect also varies by the grade level of the students: elementary school and high school students with a household income below 4,000,000 JPY were more negatively impacted by school closures than students in junior high school.

We report the heterogeneous effects of school closures by the level of academic achievement in Table 7. The estimates for low achievers indicate that the longer the school closure, the greater the decrease in learning time and the increase in screen time. In contrast, high-achieving high school students almost entirely avoided these adverse effects while even high-achieving elementary school students were negatively affected by school closures in terms of decreased learning time and increased screen time.

Table 8 presents the heterogeneity of results by household type. We did not find any notable heterogeneity among junior high and high school students by type of household. However, elementary students appear to have been affected differently based on household type. Specifically, elementary school students in two-parent households suffered less of a decline in learning time and a smaller increase in screen time for school closures of two or more months compared to single parents. However, this result may be a false-positive as Benjamini and Hochberg's (1995) false discovery rate (FDR) q-values are higher than the conventional level.

5.3 The Effectiveness of Countermeasures

Thus far, we have presented evidence that school closures due to COVID-19 caused a decline in students' learning time. In this subsection, we examine whether countermeasures provided by schools or municipalities mitigated the decline. We regress the difference in the number of hours of learning time for January 2020 versus May 2020 on three dummy variables, each of which takes a value of 1 if the school or municipality provided live online classes, on-demand classes, and home-learning packs, respectively, in May 2020. Figure 3 shows a Directed Acyclic Graph (DAG) for these countermeasures. We are interested in the effects of these countermeasures provided by schools or municipalities, but whether or not they were offered depended on the duration of the school closure, the school type, and household characteristics. In other words, we need to address potential confounds related to the possibility that the countermeasures provided by the school or municipality were determined by the number of infected people in the region, or that the school's resources affected both the availability of countermeasures and the student learning time. Furthermore, household characteristics could affect both the availability of countermeasures through school choice and learning conditions. Moreover, each household may decide to compensate for the loss of learning time by using a tutoring school or home-based tutor, based on the countermeasures taken by the school. Therefore, we control for the duration of school closure, school type (public, national, or private), and stopping or starting to use a tutoring school or home tutor in May 2020, to deal with this potential endogeneity.

Table 9 presents the impact of countermeasures taken to offset the impact of COVID-19 school closures on the difference in learning time for January 2020 compared to May 2020. Column (1) shows that live online classes increased learning time, mitigating the decline in learning time due to school closure. However, the effectiveness of live online classes is heterogeneous by educational stage. Live online classes increased learning time for junior high school students significantly, whereas the coefficient for elementary school students is close to zero. Moreover, tutoring schools or home tutors seem to better compensate for the decline in learning time than live online classes for high-school students. The coefficient of home-learning packs is negative in all columns.

We report the heterogeneity of the impact of these countermeasures by the students' level of academic achievement in Table 10. Column (3) implies that live online classes did not increase learning time for low-achieving junior high school students, but did mitigate the decline in learning time for mid-level or high achievers. However, it should be noted that Benjamini and Hochberg's (1995) FDR *q*-values are greater than 0.1, suggesting this result may be a false-positive.

6. The Persistence of the Effects of School Closures

6.1 The Effects on Learning and Screen Time

Thus far, we have shown that school closures due to COVID-19 decreased students' learning time and increased screen time in May 2020 compared to January 2020. Here, we verify the persistence of these adverse effects using data on students' time use in January 2021. Table 11 presents the impact of COVID-19 school closures on the change in average learning time and screen time in January 2021 compared to January 2020. On average, all of the estimates are statistically insignificant, suggesting that the adverse effects of the school closures did not persist until January 2021.

Table 12 presents results that are similar to those in Table 11, but the dependent variable is replaced by the difference in learning time outside of school for January 2020 compared to January 2021. Interestingly, in schools that were closed for two or more months, high-school students significantly increased their learning time outside of school in January 2021 compared to January 2020. While it should be noted that this pattern may be a false-positive, the results may also suggest one of the mechanisms of recovering from the learning loss imposed by the pandemic.

Next, Table 13 reports the heterogeneous persistence of the impacts of school closures by household type. Compared to January 2020, elementary school students in single-parent households still showed an increase in their screen time in January 2021 which is significant at the 10% level. Although it should be noted that the FDR q-values are more than 0.1, these results may indicate that parental supervision is crucial in forming elementary school students' daily habits and that once established, those habits are not easily improved for young students.

6.2 The Relationships Between Time Use and Achievement

Finally, having found evidence that school closures due to COVID-19 affected students' learning time and screen time, we examine the relationship between students' time use and academic achievement. Table 14 presents the results of the OLS regression of academic achievement in SY2020 (evaluated in March 2021) on students' time use in May 2020, during the pandemic. Columns (1) and (2) provide the estimates where overall achievement (based on a seven-point scale) is the dependent variable, Columns (3) and (4) indicate the results for language achievement as the dependent variable, and Columns (5) and (6) present the estimates for math achievement as the dependent variable. Columns (1), (3), and (5) show the results with no control variables, and Columns (2), (4), and (6) include dummy variables for household income, household type, and grade fixed effects and achievement for each subject in SY2019 (using a seven-point scale). The coefficients for learning time outside of school are positive and statistically significant, and those for screen time are negative and significant. The absolute values of the coefficients range from 0.009 to 0.014 in Columns (2), (4), and (6). Because the level of a student's achievement recorded in the survey is relative and subjective, and the experience of a school closure appears to be equivalent for students in the same school, the estimates for learning time (in school) are not positive. Nevertheless, the coefficients of learning time (not in school) and screen time are statistically significant, which suggests that school closures may affect students' academic achievement through the effect on their time use.

7. Discussion and Concluding Remarks

This study investigates the impact of school closure due to COVID-19 on students' time use in Japan. The main findings are as follows. First, the longer the school closure, the greater the decline in learning time and the greater the increase in screen time in May 2020, when many schools were closed due to the pandemic. Second, these adverse effects are heterogeneous by household and student characteristics. In particular, students in low-income households, low academic achievers, and elementary school students in single-parent households were more severely affected by school closures in terms of their learning time and screen time. When school closures were prolonged, household income appeared to play an important role in compensating for learning loss, and even high-achieving students in elementary school may not have been able to offset the learning loss. Since learning time (screen time) during the pandemic is positively (negatively) correlated with students' academic achievement in SY2020, these heterogeneities suggest that schools play a role as an equalizer for educational inequality, and this inequality may have expanded due to pandemic-related school closures. Third, on average, while live online classes mitigated the decline in learning time for junior high school students, we did not find evidence that other types of learning resources mitigated the decline in learning time. This implies that a real-time commitment may be essential to preserve learning habits in light of hyperbolic discounting.[9] Interestingly, such effects are not seen for low achievers. For these students, the ability to repeat and review might be more crucial. Finally, most of these negative impacts did not persist until January 2021. However, elementary school students in single-parent households showed an increase in screen time even in January 2021 when compared to 2020, which implies that parental caretaking is crucial for young children in forming their daily habits.

Our findings suggest that the COVID-19 school closures affected students' time use heterogeneously and may have temporarily increased educational inequality. Although live online classes mitigated some of the negative impacts of COVID-19, heterogeneity in the validity of the countermeasures also exists. In particular, the adverse effects are larger for students with lower levels of academic achievement, and those living in low-income and single-parent households. Given that 68.0% of single-parent households have an annual household income of less than 4,000,000 JPY they would need additional support to offset the negative effects of school closures. It should also be noted that while learning time in January 2021 had returned to the previous year's levels, time spent on extracurricular activities did not recover to pre-COVID-19 levels, which may damage non-cognitive skills over the medium or long term.

This study has some limitations. First, as we conducted the survey in March 2021, time-use questions were asked retrospectively and may contain measurement errors. Another limitation is that because we could not obtain the test score data, a student's academic achievement was based on subjective parental evaluations. Further work is needed to address these limitations.

[9] In related work, Kono et al. (2016) conducted a DVD-based distance-learning program targeting students aiming to take university entrance exams in Bangladesh. They find that the effect of the DVD-based distance-learning program depends on non-cognitive attributes and indicates the importance of commitment imposed through the program.

References

Alexander, K. L., Entwisle, D. R., and Olson, L. S. (2007). "Lasting Consequences of the Summer Learning Gap," *American Sociological Review*, 72(2), 167–180.

Andrew, A., Cattan, S., Costa Dias, M., Farquharson, C., Kraftman, L., Krutikova, S., Phimister, A., and Sevilla, A. (2020). "Inequalities in Children's Experiences of Home Learning during the COVID-19 Lockdown in England," *Fiscal Studies*, 41(3), 653–683.

Asakawa, S. and Ohtake, F. (2022) "Impact of COVID-19 School Closures on the Cognitive and Non-cognitive Skills of Elementary School Students," RIETI Discussion Paper Series 22-E-075.

Aucejo, E. M., French, J., Araya, M. P. U., and Zafar, B. (2020). "The Impact of COVID-19 on Student Experiences and Expectations: Evidence from a Survey," *Journal of Public Economics*, 191, 104271.

Bacher-Hicks, A., Goodman, J., and Mulhern, C. (2021). "Inequality in Household Adaptation to Schooling Shocks: Covid-Induced Online Learning Engagement in Real Time," *Journal of Public Economics*, 193, 104345.

Baker, M. (2013). "Industrial Actions in Schools: Strikes and Student Achievement," *Canadian Journal of Economics*, 46(3), 1014–1036.

Benjamini, Y. and Hochberg, Y. (1995) "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing," *Journal of Royal Statistical Society: Series B*, 57(1), 289–300.

Bettinger, E. P., Fox, L., Loeb, S., and Taylor, E. S. (2017). "Virtual Classrooms: How Online College Courses Affect Student Success," *American Economic Review*, 107(9), 2855–2875.

Cacault, M. P., Hildebrand, C. A., Laurent-Lucchetti, J., and Pellizzari, M. (2021). "Distance Learning in Higher Education: Evidence from a Randomized Field Experiment," *Journal* *of the European Economic Association*, 19(4), 2322–2372.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., and the Opportunity Insights Team. (2020). “How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-time Economic Tracker Based on Private Sector Data,” NBER Working Paper Series, w27431.

Downey, D. B., Von Hippel, P. T., and Broh, B. A. (2004). “Are Schools the Great Equalizer? Cognitive Inequality during the Summer Months and the School Year,” *American Sociological Review*, 69(5), 613–635.

Grewenig, E., Lergetporer, P., Werner, K., Woessmann, L., and Zierow, L. (2021). “COVID-19 and Educational Inequality: How School Closures Affect Low- and High-achieving Students,” *European Economic Review*, 140, 103920.

Ikeda, M. and Yamaguchi, S. (2021). “Online Learning during School Closure Due to COVID-19,” *Japanese Economic Review*, 72(3), 471–507.

Inui, T. and Okudaira, H. (2022) “Parental Investment after Adverse Event: Evidence from the Great East Japan Earthquake,” RIETI Discussion Paper Series 22-E-049.

Jack, R., Halloran, C., Okun, J., and Oster, E. (2022) “Pandemic Schooling Mode and Student Test Scores: Evidence from U.S. School Districts,” *American Economic Review: Insights.*

Jaume, D., and Willén, A. (2019). “The Long-Run Effects of Teacher Strikes: Evidence from Argentina,” *Journal of Labor Economics*, 37(4), 1097–1139.

Kawaguchi, D. (2016). “Fewer School Days, More Inequality,” *Journal of the Japanese and International Economies*, 39, 35–52.

Kono, H., Sawada, Y., and Shonchoy, A. S. (2016) “DVD-Based Distance-Learning Program for University Entrance Exams: RCT Experiments in Rural Bangladesh,” IDE Discussion Paper No. 580.

Marcotte, D. E. (2007). “Schooling and Test Scores: A Mother-Natural Experiment,” *Economics of Education Review*, 26(5), 629–640.

Oikawa, M., Tanaka, R., Bessho, S., Kawamura, A., and Noguchi, H. (2022) “Do Class Closures Affect Students’ Achievements? Heterogeneous Effects of Students’ Socioeconomic Backgrounds,” RIETI Discussion Paper Series 22-E-042.

Pischke, J. S. (2007). “The Impact of Length of the School Year on Student Performance and Earnings: Evidence from the German Short School Years,” *Economic Journal*, 117(523), 1216–1242.

Figure 1: Timing of the survey and major events related to COVID-19

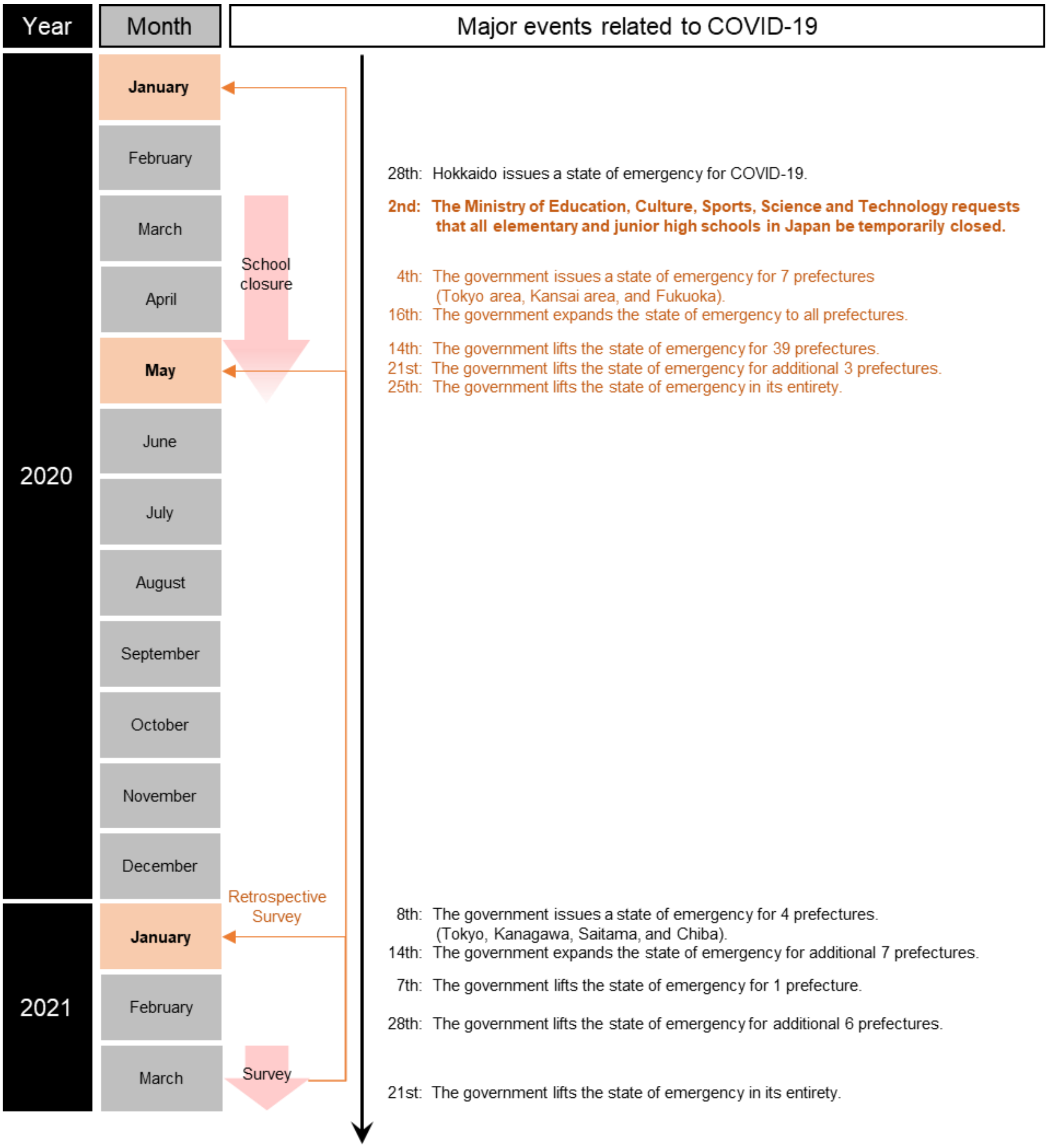
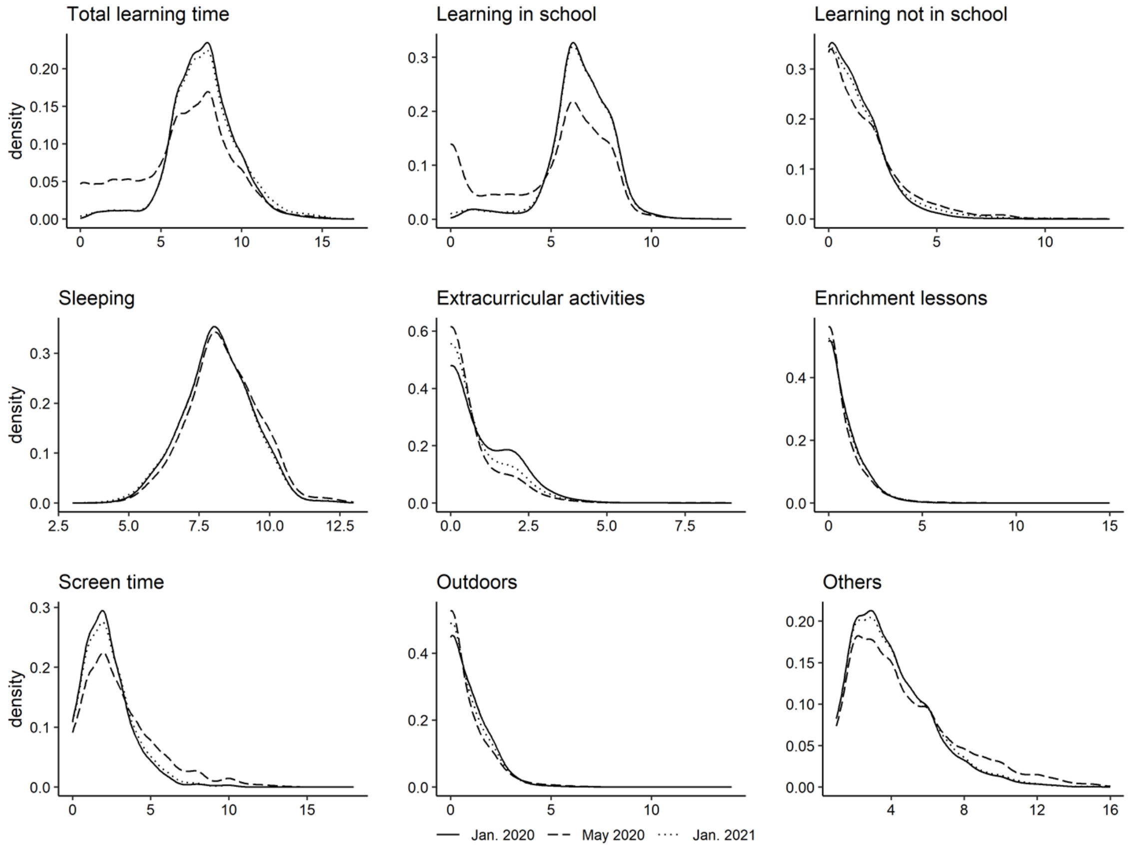


Figure 2: Kernel density estimates of time use



Notes: The figure shows the kernel density of the average time spent on each activity in January 2020, May 2020, and January 2021. All lines are smoothed using Gaussian kernels with the bandwidth = 0.5.

Figure 3: Directed acyclic graph for countermeasures

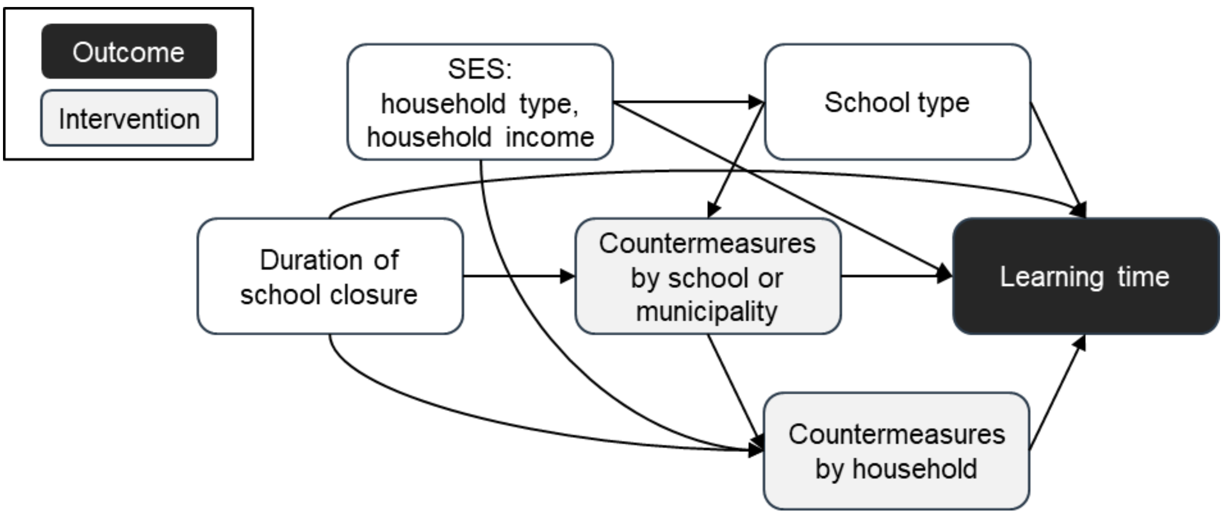


Table 1: Summary statistics

			January 2020		May 2020		January 2021	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Time use								
Total learning time	-	-	7.594	1.955	6.313	3.058	7.690	2.174
Sleeping	-	-	8.168	1.132	8.357	1.195	8.135	1.160
Learning (in school)	-	-	6.479	1.534	4.851	2.879	6.404	1.659
Extracurricular activiteis (in school)	-	-	0.761	1.051	0.437	0.934	0.562	0.957
Learning (not in school)	-	-	1.115	1.227	1.462	1.807	1.286	1.549
Enrichment lessons	-	-	0.591	0.906	0.539	1.004	0.594	0.981
Screen time	-	-	2.160	1.548	3.049	2.421	2.290	1.685
Outdoors	-	-	0.745	0.990	0.632	1.070	0.671	1.002
Others	-	-	3.980	2.200	4.672	2.894	4.059	2.268
Achievement in SY2019								
Overall	4.496	1.477	-	-	-	-	-	-
Language	4.480	1.499	-	-	-	-	-	-
Math	4.508	1.554	-	-	-	-	-	-
Achievement in SY2020								
Overall	4.518	1.486	-	-	-	-	-	-
Language	4.515	1.517	-	-	-	-	-	-
Math	4.524	1.559	-	-	-	-	-	-
Overall achievement in SY2019 (3 categories)								
Low achievers	0.172	-	-	-	-	-	-	-
Middle achievers	0.384	-	-	-	-	-	-	-
High achievers	0.445	-	-	-	-	-	-	-
School closure								
No closure	0.077	-	-	-	-	-	-	-
Less than 1 month	0.259	-	-	-	-	-	-	-
1–2 months	0.331	-	-	-	-	-	-	-
2+ months	0.332	-	-	-	-	-	-	-
Household income in 2019								
Less than 4,000,000 JPY	0.177	-	-	-	-	-	-	-
4,000,000–7,999,999 JPY	0.461	-	-	-	-	-	-	-
8,000,000+ JPY	0.363	-	-	-	-	-	-	-
Household type								
Single parent	0.052	-	-	-	-	-	-	-
Two parents	0.847	-	-	-	-	-	-	-
Three generation	0.100	-	-	-	-	-	-	-
Grade in SY2020								
2nd grade	0.142	-	-	-	-	-	-	-
3rd grade	0.117	-	-	-	-	-	-	-
4th grade	0.109	-	-	-	-	-	-	-
5th grade	0.102	-	-	-	-	-	-	-
6th grade	0.109	-	-	-	-	-	-	-
8th grade	0.121	-	-	-	-	-	-	-
9th grade	0.113	-	-	-	-	-	-	-
11th grade	0.102	-	-	-	-	-	-	-
12th grade	0.083	-	-	-	-	-	-	-
Observations = 2758								

Table 2: The effects of school closures on total learning time

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
School closure (Reference: No closure)								
Less than 1 month	-0.130	-0.136	-0.097	-0.107	-0.081	-0.105	-0.231	-0.279
	(0.110)	(0.109)	(0.166)	(0.165)	(0.220)	(0.221)	(0.189)	(0.204)
	[0.284]	[0.281]	[0.610]	[0.590]	[0.713]	[0.661]	[0.281]	[0.242]
1–2 months	-0.865***	-0.779***	-0.860***	-0.835***	-0.850***	-0.745***	-0.771***	-0.789***
	(0.121)	(0.121)	(0.173)	(0.172)	(0.252)	(0.255)	(0.231)	(0.243)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.005]	[0.002]	[0.002]
2+ months	-1.986***	-1.748***	-2.108***	-1.937***	-1.823***	-1.572***	-1.542***	-1.452***
	(0.130)	(0.134)	(0.183)	(0.186)	(0.276)	(0.289)	(0.271)	(0.280)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Household income (3 categories)		✓		✓		✓		✓
Overall achievement in SY2019 (3 categories)		✓		✓		✓		✓
Household type (3 categories)		✓		✓		✓		✓
Grade fixed effects		✓		✓		✓		✓
Employment status of respondents in May 2020		✓		✓		✓		✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.102	0.136	0.114	0.141	0.081	0.119	0.062	0.113

Notes: The dependent variable is the difference in total learning time for January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) false discovery rate (FDR) q-values, calculated using p-values of 24 hypothetical tests in this table, are in brackets. *** denotes significance at the 1% level.

Table 3: The effects of school closures on learning time outside school

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
School closure (Reference: No closure)								
Less than 1 month	0.077	0.062	0.103**	0.096*	-0.023	-0.003	0.177	0.129
	(0.054)	(0.055)	(0.052)	(0.055)	(0.136)	(0.139)	(0.110)	(0.140)
	[0.207]	[0.323]	[0.078]	[0.125]	[0.905]	[0.983]	[0.152]	[0.428]
1–2 months	0.246***	0.243***	0.266***	0.246***	0.065	0.074	0.525***	0.427**
	(0.060)	(0.062)	(0.055)	(0.056)	(0.149)	(0.152)	(0.166)	(0.185)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.724]	[0.717]	[0.004]	[0.043]
2+ months	0.457***	0.430***	0.458***	0.394***	0.384**	0.364**	0.692***	0.575***
	(0.066)	(0.070)	(0.064)	(0.068)	(0.175)	(0.180)	(0.175)	(0.186)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.053]	[0.076]	[0.000]	[0.005]
Household income (3 categories)		✓		✓		✓		✓
Overall achievement in SY2019 (3 categories)		✓		✓		✓		✓
Household type (3 categories)		✓		✓		✓		✓
Grade fixed effects		✓		✓		✓		✓
Employment status of respondents in May 2020		✓		✓		✓		✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.017	0.038	0.020	0.031	0.013	0.051	0.017	0.057

Notes: The dependent variable is the difference in learning time outside of school for January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 24 hypothetical tests in this table, are in brackets. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

Table 4: The effects of school closures on screen time

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
School closure (Reference: No closure)								
Less than 1 month	0.072	0.080	0.156	0.152	-0.172	-0.179	0.215	0.284
	(0.092)	(0.093)	(0.099)	(0.103)	(0.228)	(0.237)	(0.176)	(0.207)
	[0.452]	[0.451]	[0.188]	[0.215]	[0.452]	[0.452]	[0.281]	[0.227]
1–2 months	0.472***	0.469***	0.520***	0.544***	0.356	0.257	0.608***	0.644***
	(0.097)	(0.100)	(0.104)	(0.108)	(0.249)	(0.262)	(0.194)	(0.228)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.217]	[0.392]	[0.003]	[0.008]
2+ months	1.103***	1.016***	1.153***	1.109***	1.139***	0.907***	1.064***	1.005***
	(0.106)	(0.108)	(0.113)	(0.117)	(0.279)	(0.290)	(0.235)	(0.253)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]	[0.000]	[0.000]
Household income (3 categories)		✓		✓		✓		✓
Overall achievement in SY2019 (3 categories)		✓		✓		✓		✓
Household type (3 categories)		✓		✓		✓		✓
Grade fixed effects		✓		✓		✓		✓
Employment status of respondents in May 2020		✓		✓		✓		✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.061	0.089	0.068	0.090	0.063	0.087	0.041	0.116

Notes: The dependent variable is the difference in screen time for January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 24 hypothetical tests in this table, are in brackets. *** denotes significance at the 1% level.

Table 5: Robustness check

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
School closure (Reference: No closure)								
Less than 1 month	-0.153	0.100	-0.115	0.167	-0.175	-0.086	-0.215	0.304
	(0.115)	(0.097)	(0.177)	(0.114)	(0.277)	(0.278)	(0.258)	(0.261)
	[0.256]	[0.364]	[0.551]	[0.215]	[0.551]	[0.756]	[0.463]	[0.326]
1–2 months	-0.754***	0.456***	-0.778***	0.515***	-0.795***	0.331	-0.673**	0.614**
	(0.125)	(0.104)	(0.185)	(0.114)	(0.283)	(0.296)	(0.286)	(0.276)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.009]	[0.333]	[0.033]	[0.042]
2+ months	-1.709***	0.999***	-1.887***	1.088***	-1.604***	0.943***	-1.348***	1.004***
	(0.140)	(0.112)	(0.199)	(0.125)	(0.322)	(0.319)	(0.323)	(0.304)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]	[0.000]	[0.002]
Household income (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Employment status of respondents in May 2020	✓	✓	✓	✓	✓	✓	✓	✓
Prefectural dummies	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.137	0.094	0.130	0.091	0.139	0.089	0.105	0.126

Notes: The dependent variable is the difference in the average time spent on learning or screen time in January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 24 hypothetical tests in this table, are in brackets. *** and ** denote significance at the 1 and 5% levels, respectively.

Table 6: Heterogeneous effects of school closures by household income

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Less than 1 month (Reference: Less than 4,000,000 JPY)	-0.510**	0.512***	-0.200	0.304*	-0.870	0.579	-0.975**	1.297***
	(0.207)	(0.141)	(0.270)	(0.156)	(0.710)	(0.637)	(0.433)	(0.449)
	[0.050]	[0.002]	[0.541]	[0.117]	[0.331]	[0.459]	[0.074]	[0.018]
Less than 1 month × 4,000,000–7,999,999 JPY	0.425	-0.593***	0.060	-0.361	0.967	-0.778	0.862	-1.395**
	(0.262)	(0.189)	(0.353)	(0.227)	(0.776)	(0.683)	(0.572)	(0.574)
	[0.187]	[0.011]	[0.903]	[0.192]	[0.331]	[0.353]	[0.222]	[0.050]
Less than 1 month × 8,000,000+ JPY	0.572**	-0.503**	0.369	-0.025	0.819	-0.980	0.831	-1.069**
	(0.284)	(0.246)	(0.484)	(0.250)	(0.784)	(0.797)	(0.522)	(0.540)
	[0.110]	[0.110]	[0.541]	[0.948]	[0.403]	[0.331]	[0.192]	[0.116]
1–2 months (Reference: Less than 4,000,000 JPY)	-0.962***	0.776***	-0.914***	0.786***	-1.118	0.883	-1.360***	1.140***
	(0.240)	(0.162)	(0.313)	(0.193)	(0.809)	(0.766)	(0.486)	(0.372)
	[0.001]	[0.000]	[0.018]	[0.001]	[0.274]	[0.352]	[0.022]	[0.013]
1–2 months × 4,000,000–7,999,999 JPY	0.176	-0.475**	0.106	-0.464*	0.194	-0.578	0.817	-1.015*
	(0.300)	(0.214)	(0.396)	(0.267)	(0.886)	(0.806)	(0.652)	(0.545)
	[0.617]	[0.078]	[0.849]	[0.156]	[0.876]	[0.550]	[0.331]	[0.134]
1–2 months × 8,000,000+ JPY	0.374	-0.315	0.307	-0.168	0.664	-0.837	0.598	-0.237
	(0.317)	(0.260)	(0.517)	(0.266)	(0.894)	(0.908)	(0.591)	(0.480)
	[0.343]	[0.331]	[0.617]	[0.604]	[0.541]	[0.459]	[0.416]	[0.679]
2+ months (Reference: Less than 4,000,000 JPY)	-2.504***	1.620***	-2.638***	1.639***	-1.871**	1.276*	-2.794***	2.163***
	(0.269)	(0.195)	(0.345)	(0.227)	(0.765)	(0.710)	(0.698)	(0.692)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.050]	[0.149]	[0.001]	[0.011]
2+ months × 4,000,000–7,999,999 JPY	0.755**	-0.720***	0.826*	-0.795***	-0.057	-0.053	1.606*	-1.460*
	(0.328)	(0.249)	(0.422)	(0.293)	(0.873)	(0.801)	(0.838)	(0.816)
	[0.067]	[0.018]	[0.117]	[0.025]	[0.948]	[0.948]	[0.122]	[0.149]
2+ months × 8,000,000+ JPY	1.210***	-0.822***	1.125**	-0.547*	0.754	-0.798	1.581**	-1.296*
	(0.351)	(0.290)	(0.557)	(0.310)	(0.871)	(0.876)	(0.781)	(0.755)
	[0.004]	[0.020]	[0.110]	[0.151]	[0.481]	[0.459]	[0.110]	[0.160]
Household income (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Employment status of respondents in May 2020	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.138	0.090	0.142	0.090	0.118	0.084	0.109	0.120

Notes: The dependent variable is the difference between the average time spent on learning or screen time in January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 72 hypothetical tests in this table, are in brackets. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

Table 7: Heterogeneous effects of school closures by overall achievement in SY2019

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Less than 1 month (Reference: Low achievers)	-0.509**	0.413**	-0.501	0.236	-0.540	0.422	-0.468	1.033**
	(0.214)	(0.166)	(0.372)	(0.218)	(0.402)	(0.469)	(0.462)	(0.441)
	[0.052]	[0.042]	[0.294]	[0.418]	[0.294]	[0.501]	[0.449]	[0.054]
Less than 1 month × Middle achievers	0.380	-0.322	0.645	-0.258	0.320	-0.595	-0.378	-0.333
	(0.268)	(0.198)	(0.432)	(0.264)	(0.545)	(0.515)	(0.531)	(0.491)
	[0.268]	[0.199]	[0.246]	[0.462]	[0.657]	[0.381]	[0.603]	[0.618]
Less than 1 month × High achievers	0.634**	-0.567**	0.294	0.113	0.761	-0.855	1.012*	-1.657***
	(0.286)	(0.260)	(0.468)	(0.259)	(0.513)	(0.649)	(0.599)	(0.589)
	[0.071]	[0.075]	[0.641]	[0.766]	[0.246]	[0.301]	[0.178]	[0.023]
1–2 months (Reference: Low achievers)	-1.147***	0.862***	-0.842***	0.568***	-1.269**	1.021**	-1.707***	1.477***
	(0.228)	(0.174)	(0.320)	(0.209)	(0.492)	(0.520)	(0.552)	(0.419)
	[0.000]	[0.000]	[0.033]	[0.028]	[0.036]	[0.116]	[0.011]	[0.003]
1–2 months × Middle achievers	0.215	-0.316	-0.035	-0.093	0.204	-0.634	0.604	-0.444
	(0.294)	(0.214)	(0.408)	(0.265)	(0.679)	(0.610)	(0.627)	(0.509)
	[0.597]	[0.246]	[0.946]	[0.790]	[0.821]	[0.440]	[0.466]	[0.512]
1–2 months × High achievers	0.753**	-0.701***	0.052	0.100	1.016*	-1.182*	1.762**	-1.767***
	(0.302)	(0.267)	(0.432)	(0.253)	(0.596)	(0.684)	(0.709)	(0.583)
	[0.042]	[0.033]	[0.931]	[0.777]	[0.178]	[0.174]	[0.042]	[0.012]
2+ months (Reference: Low achievers)	-1.957***	1.583***	-1.698***	1.199***	-2.083***	1.815***	-2.353***	2.252***
	(0.247)	(0.208)	(0.374)	(0.262)	(0.532)	(0.580)	(0.517)	(0.505)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.010]	[0.000]	[0.000]
2+ months × Middle achievers	-0.061	-0.483*	-0.384	-0.134	-0.134	-0.460	0.817	-1.252**
	(0.319)	(0.255)	(0.459)	(0.315)	(0.712)	(0.738)	(0.672)	(0.596)
	[0.888]	[0.126]	[0.528]	[0.766]	[0.888]	[0.641]	[0.352]	[0.087]
2+ months × High achievers	0.624*	-0.951***	-0.184	-0.006	1.226*	-1.633**	1.626**	-2.095***
	(0.325)	(0.297)	(0.479)	(0.306)	(0.665)	(0.753)	(0.687)	(0.657)
	[0.123]	[0.009]	[0.777]	[0.984]	[0.139]	[0.076]	[0.053]	[0.009]
Household income (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Employment status of respondents in May 2020	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.136	0.089	0.141	0.088	0.118	0.090	0.116	0.127

Notes: The dependent variable is the difference between the average time spent on learning or screen time in January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 72 hypothetical tests in this table, are in brackets. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

Table 8: Heterogeneous effects of school closures by household type

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Less than 1 month (Reference: Single parent)	-0.041	-0.158	-0.997*	0.667**	-0.618	0.420	0.555	-0.507
	(0.829)	(0.817)	(0.582)	(0.277)	(8.155)	(1.347)	(1.714)	(1.861)
	[0.991]	[0.991]	[0.624]	[0.231]	[0.991]	[0.991]	[0.991]	[0.991]
Less than 1 month × Two parents	-0.105	0.271	0.834	-0.438	0.661	-0.664	-0.848	0.771
	(0.835)	(0.822)	(0.602)	(0.292)	(8.158)	(1.372)	(1.732)	(1.872)
	[0.991]	[0.991]	[0.740]	[0.689]	[0.991]	[0.991]	[0.991]	[0.991]
Less than 1 month × Three generation	-0.124	0.131	1.385	-1.292	-0.144	-0.384	-1.276	1.629
	(0.907)	(0.877)	(1.115)	(0.787)	(8.175)	(1.412)	(1.830)	(2.029)
	[0.991]	[0.991]	[0.857]	[0.656]	[0.991]	[0.991]	[0.991]	[0.991]
1–2 months (Reference: Single parent)	-0.975	0.534	-1.841***	1.176***	-1.045	0.828	-2.035	1.540
	(0.893)	(0.870)	(0.685)	(0.324)	(8.193)	(1.578)	(1.864)	(2.093)
	[0.902]	[0.991]	[0.130]	[0.007]	[0.991]	[0.991]	[0.902]	[0.991]
1–2 months × Two parents	0.237	-0.079	0.989	-0.584*	0.441	-0.736	1.388	-0.990
	(0.900)	(0.874)	(0.702)	(0.338)	(8.198)	(1.604)	(1.873)	(2.096)
	[0.991]	[0.991]	[0.740]	[0.624]	[0.991]	[0.991]	[0.991]	[0.991]
1–2 months × Three generation	-0.036	0.011	1.397	-1.315	-0.418	0.271	0.464	-0.359
	(0.982)	(0.936)	(1.197)	(0.821)	(8.219)	(1.691)	(1.987)	(2.201)
	[0.991]	[0.991]	[0.876]	[0.656]	[0.991]	[0.991]	[0.991]	[0.991]
2+ months (Reference: Single parent)	-1.879**	1.179	-3.106***	2.000***	-2.107	1.824	-0.842	0.413
	(0.873)	(0.868)	(0.627)	(0.441)	(8.212)	(1.551)	(1.908)	(2.159)
	[0.377]	[0.740]	[0.000]	[0.000]	[0.991]	[0.876]	[0.991]	[0.991]
2+ months × Two parents	0.180	-0.179	1.226*	-0.870*	0.654	-1.081	-0.630	0.596
	(0.881)	(0.873)	(0.655)	(0.454)	(8.215)	(1.572)	(1.921)	(2.164)
	[0.991]	[0.991]	[0.553]	[0.553]	[0.991]	[0.991]	[0.991]	[0.991]
2+ months × Three generation	-0.269	-0.107	0.804	-1.427	0.145	-0.030	-0.865	1.003
	(0.983)	(0.952)	(1.201)	(0.914)	(8.251)	(1.837)	(2.027)	(2.224)
	[0.991]	[0.991]	[0.991]	[0.658]	[0.991]	[0.991]	[0.991]	[0.991]
Household income (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Employment status of respondents in May 2020	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.135	0.087	0.141	0.089	0.112	0.083	0.113	0.116

Notes: The dependent variable is the difference between the average time spent on learning or screen time in January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR *q*-values, calculated using *p*-values of 72 hypothetical tests in this table, are in brackets. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

Table 9: The effectiveness of countermeasures in May 2020

	Whole sample	Elementary school students	Junior high-school students	High-school students
	(1)	(2)	(3)	(4)
Live online classes	0.269*	-0.043	1.083***	0.008
	(0.145)	(0.267)	(0.258)	(0.234)
	[0.198]	[0.980]	[0.000]	[0.980]
On-demand classes	-0.190	-0.380	-0.119	0.008
	(0.170)	(0.243)	(0.357)	(0.339)
	[0.478]	[0.237]	[0.980]	[0.980]
Home-learning packs	-0.539***	-0.630***	-0.493**	-0.385*
	(0.103)	(0.142)	(0.215)	(0.223)
	[0.000]	[0.000]	[0.089]	[0.212]
Stopped using tutoring school or home tutor	-0.710	-0.960*	0.399	-0.667
	(0.450)	(0.529)	(1.501)	(1.088)
	[0.237]	[0.198]	[0.980]	[0.771]
Started using tutoring school or home tutor	0.260	0.022	0.374	5.188***
	(0.332)	(0.425)	(0.526)	(0.338)
	[0.721]	[0.980]	[0.734]	[0.000]
The duration of school closure	✓	✓	✓	✓
School type (public, national, or private)	✓	✓	✓	✓
Household income (3 categories)	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓
Employment status of respondents in May 2020	✓	✓	✓	✓
Observations	2758	1599	647	512
Adjusted R2	0.150	0.161	0.135	0.131

Notes: The dependent variable is the difference in total learning time in January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 20 hypothetical tests in this table, are in brackets. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

Table 10: Heterogeneous effectiveness of countermeasures by achievement in SY2019

	Whole sample	Elementary school students	Junior high-school students	High-school students
	(1)	(2)	(3)	(4)
Live online classes (Reference: Low achievers)	-0.317	-0.178	-0.504	0.325
	(0.386)	(0.776)	(0.779)	(0.534)
	[0.771]	[0.923]	[0.771]	[0.771]
Live online classes × Middle achievers	0.628	0.132	2.204***	-0.286
	(0.451)	(0.897)	(0.835)	(0.624)
	[0.551]	[0.948]	[0.124]	[0.889]
Live online classes × High achievers	0.705*	0.166	1.822**	-0.427
	(0.425)	(0.863)	(0.817)	(0.618)
	[0.516]	[0.932]	[0.230]	[0.771]
On-demand classes (Reference: Low achievers)	0.254	-0.196	0.849	-0.042
	(0.405)	(0.593)	(0.577)	(0.730)
	[0.771]	[0.905]	[0.518]	[0.970]
On-demand classes × Middle achievers	-0.768	-0.456	-1.092	-0.313
	(0.506)	(0.713)	(0.864)	(1.031)
	[0.516]	[0.771]	[0.605]	[0.905]
On-demand classes × High achievers	-0.299	0.026	-0.980	0.288
	(0.470)	(0.703)	(0.798)	(0.832)
	[0.771]	[0.970]	[0.605]	[0.905]
Home-learning packs (Reference: Low achievers)	-0.671**	-1.042***	-0.849*	0.173
	(0.265)	(0.395)	(0.497)	(0.540)
	[0.125]	[0.124]	[0.516]	[0.905]
Home-learning packs × Middle achievers	0.235	0.701	0.471	-0.885
	(0.317)	(0.455)	(0.643)	(0.652)
	[0.771]	[0.516]	[0.771]	[0.551]
Home-learning packs × High achievers	0.101	0.297	0.399	-0.518
	(0.299)	(0.436)	(0.577)	(0.636)
	[0.905]	[0.771]	[0.771]	[0.771]
Stopped using tutoring school or home tutor	-0.704	-0.983*	0.354	-0.660
	(0.452)	(0.530)	(1.542)	(0.973)
	[0.516]	[0.466]	[0.923]	[0.771]
Started using tutoring school or home tutor	0.277	0.022	0.425	4.983***
	(0.333)	(0.430)	(0.534)	(0.595)
	[0.771]	[0.970]	[0.771]	[0.000]
The duration of school closure	✓	✓	✓	✓
School type (public, national, or private)	✓	✓	✓	✓
Household income (3 categories)	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓
Employment status of respondents in May 2020	✓	✓	✓	✓
Observations	2758	1599	647	512
Adjusted R2	0.150	0.160	0.136	0.127

Notes: The dependent variable is the difference in total learning time in January 2020 versus May 2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 44 hypothetical tests in this table, are in brackets. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.

Table 11: Persistence of the effects of school closures

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
School closure (Reference: No closure)								
Less than 1 month	-0.020	0.005	0.004	-0.081	0.063	0.083	-0.087	0.075
	(0.065)	(0.052)	(0.057)	(0.057)	(0.162)	(0.126)	(0.163)	(0.127)
	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]
1–2 months	0.055	-0.001	0.017	-0.075	0.168	0.006	0.106	0.159
	(0.064)	(0.051)	(0.055)	(0.052)	(0.176)	(0.140)	(0.156)	(0.121)
	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]
2+ months	0.012	0.038	0.018	0.010	0.204	0.012	-0.159	0.015
	(0.068)	(0.054)	(0.057)	(0.058)	(0.187)	(0.149)	(0.188)	(0.113)
	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]	[0.982]
Household income (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Employment status of respondents in January 2021	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.039	0.000	-0.003	0.005	0.089	0.012	-0.001	-0.014

Notes: The dependent variable is the difference between the average time spent on learning or screen time in January 2020 versus January 2021. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 24 hypothetical tests in this table, are in brackets.

Table 12: Persistence of the effects of school closure on learning time outside school

	Whole sample	Elementary school students	Junior high-school students	High-school students
	(1)	(2)	(3)	(4)
School closure (Reference: No closure)				
Less than 1 month	0.013	0.025	0.062	-0.018
	(0.054)	(0.045)	(0.148)	(0.122)
	[0.879]	[0.772]	[0.810]	[0.885]
1–2 months	0.077	0.026	0.095	0.181
	(0.055)	(0.038)	(0.155)	(0.146)
	[0.519]	[0.772]	[0.772]	[0.519]
2+ months	0.133**	0.056	0.156	0.317**
	(0.056)	(0.043)	(0.158)	(0.153)
	[0.218]	[0.519]	[0.654]	[0.233]
Household income (3 categories)	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓
Employment status of respondents in January 2021	✓	✓	✓	✓
Observations	2758	1599	647	512
Adjusted R2	0.067	0.012	0.106	0.034

Notes: The dependent variable is the difference in learning time outside of school in January 2020 versus January 2021. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 12 hypothetical tests in this table, are in brackets. ** denotes significance at the 5% level.

Table 13: Heterogeneous persistence of the effects of school closures by household type

	Whole sample		Elementary school students		Junior high-school students		High-school students	
	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time	ΔLearning time	ΔScreen time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Less than 1 month (Reference: Single parent)	0.117	0.119	0.093	0.268*	0.321	-0.022	0.235	-0.057
	(0.129)	(0.096)	(0.107)	(0.146)	(6.751)	(3.903)	(0.384)	(0.270)
	[0.848]	[0.677]	[0.848]	[0.481]	[0.995]	[0.995]	[0.978]	[0.995]
Less than 1 month × Two parents	-0.150	-0.098	-0.072	-0.327**	-0.334	0.195	-0.278	0.046
	(0.147)	(0.109)	(0.122)	(0.155)	(6.753)	(3.905)	(0.433)	(0.289)
	[0.789]	[0.848]	[0.978]	[0.481]	[0.995]	[0.995]	[0.978]	[0.995]
Less than 1 month × Three generation	-0.100	-0.264	-0.324	-0.673**	0.060	-0.286	-1.053	1.147
	(0.250)	(0.232)	(0.246)	(0.342)	(6.759)	(3.916)	(0.977)	(0.990)
	[0.995]	[0.705]	[0.618]	[0.481]	[0.995]	[0.995]	[0.750]	[0.705]
1–2 months (Reference: Single parent)	0.043	0.326*	-0.041	0.328*	0.721	-0.115	-0.633	1.202
	(0.184)	(0.195)	(0.144)	(0.177)	(6.751)	(3.921)	(0.836)	(0.783)
	[0.995]	[0.489]	[0.995]	[0.481]	[0.995]	[0.995]	[0.922]	[0.502]
1–2 months × Two parents	-0.006	-0.322	0.074	-0.384**	-0.609	0.119	0.711	-1.075
	(0.196)	(0.201)	(0.153)	(0.182)	(6.754)	(3.924)	(0.854)	(0.795)
	[0.995]	[0.489]	[0.995]	[0.481]	[0.995]	[0.995]	[0.858]	[0.611]
1–2 months × Three generation	0.158	-0.477*	-0.098	-0.735**	-0.530	0.332	1.435	-1.339
	(0.261)	(0.272)	(0.208)	(0.348)	(6.762)	(3.941)	(0.987)	(0.833)
	[0.978]	[0.481]	[0.995]	[0.481]	[0.995]	[0.995]	[0.556]	[0.489]
2+ months (Reference: Single parent)	-0.184	0.314**	-0.057	0.269*	0.048	0.467	-0.240	-0.103
	(0.137)	(0.134)	(0.103)	(0.143)	(6.750)	(3.918)	(0.335)	(0.278)
	[0.611]	[0.481]	[0.987]	[0.481]	[0.995]	[0.995]	[0.922]	[0.995]
2+ months × Two parents	0.184	-0.254*	0.100	-0.237	0.055	-0.376	0.096	0.101
	(0.153)	(0.145)	(0.113)	(0.147)	(6.754)	(3.923)	(0.407)	(0.306)
	[0.685]	[0.481]	[0.848]	[0.489]	[0.995]	[0.995]	[0.995]	[0.995]
2+ months × Three generation	0.423*	-0.584**	-0.161	-0.537	1.186	-1.401	0.059	0.311
	(0.241)	(0.237)	(0.219)	(0.342)	(6.775)	(3.963)	(0.510)	(0.360)
	[0.481]	[0.481]	[0.922]	[0.494]	[0.995]	[0.995]	[0.995]	[0.848]
Household income (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Overall achievement in SY2019 (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Household type (3 categories)	✓	✓	✓	✓	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Employment status of respondents in January 2021	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2758	2758	1599	1599	647	647	512	512
Adjusted R2	0.039	0.000	-0.006	0.004	0.093	0.023	0.002	0.013

Notes: The dependent variable is the difference between the average time spent on learning or screen time in January 2020 versus January 2021. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR *q*-values, calculated using *p*-values of 72 hypothetical tests in this table, are in brackets. ** and * denote significance at the 5 and 10% levels, respectively.

Table 14: The relationships between achievement in SY2020 and time use in May 2020

	Overall		Language		Math	
	(1)	(2)	(3)	(4)	(5)	(6)
Time use in May 2020						
Sleeping	-0.001	-0.010	0.009	-0.005	0.013	-0.004
	(0.026)	(0.010)	(0.026)	(0.011)	(0.027)	(0.012)
	[0.977]	[0.469]	[0.876]	[0.831]	[0.820]	[0.876]
Learning in school	-0.020*	-0.004	-0.029**	-0.000	-0.025**	-0.007*
	(0.012)	(0.003)	(0.012)	(0.004)	(0.012)	(0.004)
	[0.185]	[0.396]	[0.072]	[0.977]	[0.131]	[0.142]
Extracurricular activities (in school)	0.002	0.001	0.000	0.016*	-0.002	0.016*
	(0.029)	(0.008)	(0.029)	(0.009)	(0.031)	(0.009)
	[0.977]	[0.977]	[0.989]	[0.185]	[0.977]	[0.185]
Learning (not in school)	0.147***	0.009*	0.136***	0.014***	0.138***	0.012**
	(0.016)	(0.005)	(0.018)	(0.005)	(0.017)	(0.005)
	[0.000]	[0.160]	[0.000]	[0.052]	[0.000]	[0.107]
Enrichment lessons	0.052*	0.009	0.048	0.014	0.049	0.006
	(0.030)	(0.007)	(0.030)	(0.008)	(0.031)	(0.009)
	[0.185]	[0.303]	[0.189]	[0.187]	[0.189]	[0.698]
Screen time	-0.102***	-0.009*	-0.107***	-0.011**	-0.107***	-0.014**
	(0.014)	(0.005)	(0.014)	(0.005)	(0.015)	(0.006)
	[0.000]	[0.185]	[0.000]	[0.115]	[0.000]	[0.072]
Outdoors	-0.063**	0.005	-0.065**	-0.007	-0.045	-0.002
	(0.025)	(0.008)	(0.026)	(0.010)	(0.028)	(0.010)
	[0.063]	[0.783]	[0.063]	[0.698]	[0.187]	[0.977]
Household income (3 categories)		✓		✓		✓
Overall achievement in SY2019 (3 categories)		✓		✓		✓
Household type (3 categories)		✓		✓		✓
Grade fixed effects		✓		✓		✓
Observations	2758	2758	2758	2758	2758	2758
Adjusted R2	0.067	0.773	0.061	0.667	0.058	0.660

Notes: The dependent variable is the achievement in SY2020. Robust standard errors are in parentheses. Benjamini and Hochberg's (1995) FDR q-values, calculated using p-values of 42 hypothetical tests in this table, are in brackets. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively.