Learning Loss and Learning Mode during the Pandemic: Evidence from Connecticut Public Schools

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Abstract

We examine decisions to offer in-person learning, student enrollment responses to these options, and the impact of in-person learning on attendance and student test scores during the 2020-21 school year in Connecticut Public Schools. Providing hybrid or in person leaning at the beginning of the year and offering a higher share of days in person were less likely in schools that had a large share of high need students and less likely in choice schools. Further, student take up of in person options was lower in schools with larger high need shares. Using difference-in-differences approaches that incorporate propensity scores for balance, we find minimal impact of in person options on fall enrollment, but substantial evidence that in person opportunities reduces pandemic associated declines in attendance and test scores. Unlike other recent studies, we do not find evidence that in person opportunities have greater positive effects for students in high need schools, potentially due to the lower rate of take-up in such schools.

Introduction

The 2020-21 school year was a challenge for states, school districts, teachers and students as many districts started the school year with either hybrid or entirely remote education. These states had only a few months to prepare between the end of school in fully remote mode, mostly asynchronous education, in spring 2020 and the start of the next school year. Research has documented significant declines in enrollment, especially in kindergarten and elementary school (Musadiqq et al. 2021; Bassok and Shapiro 2021; Chatterji and Li 2021). Several studies have also documented significant learning losses during the pandemic by interviewing teachers (Bailey et al. 2021), using parental survey responses on number of lessons received and hours

spent on school work (Major et al. 2021), and examining test scores that were administered before and after school closures in spring 2020 (Engzell et al. 2021). More recently, two studies (Halloran et al. 2021; Goldhaber et al. 2022) examine student test scores during the 2020-21 school year documenting worse performance compared to pre-pandemic levels and higher learning loss when students had less in person instruction. Further, many of the studies above document larger negative effects for disadvantaged student populations, including in the case of Halloran et al. (2021) and Goldhaber et al. (2022) larger negative effects of remote instruction.

For the State of Connecticut public school system, we examine the pattern of Local Education Agency's (LEA) decisions to offer in-person learning opportunities, student enrollment responses to those options, and the impact of in-person learning on attendance and student test scores during the 2020-21 school year. We examine whether these outcomes vary across school level student composition following state guidance to use the share of high needs students, which are defined as the fraction of students in a school who are classified as either free and reduced price lunch students, students with disabilities, and/or English Language Learners. We focus on school composition in order to compare more homogeneous institutions, as opposed to comparing large public school districts to individual endowed or charter schools that comprise their own LEA.

Decisions concerning remote learning were made at varying administrative levels: public school districts including regional school districts, individual or consolidated groups of charter schools, individual endowed schools, Regional Educational Service Centers (RESC) including their associated magnet school systems, the Connecticut Technical Education and Career System

(CTECS) and individual approved special education schools. [1] These learning mode decisions were reported weekly to the State of Connecticut, and these records are used to characterize the learning modes offered in the associated schools. Learning mode was characterized by reporting districts and schools as remote, hybrid or in-person following guidance from the State Department of Education to classify the learning mode as hybrid if the mode implied that between 25 and 75% of weekly school time was to be spent in person. This state collected data on learning mode is the same source of data collected and utilized by Halloran et al. (2021) in their study of district level test scores for several states, but differs from the data used by Goldhaber et al (2022), which was collected by web scraping district and school websites and applying machine learning algorithms to determine school re-opening dates.

We first estimate simple cross-sectional models of school and district decisions on providing a hybrid and/or fully in person learning opportunity. Given the dramatic heterogeneity across LEA's, these models are estimated based on school share of high need students to assess the likelihood that a school of a given student composition belonged to an LEA that provided in person learning opportunities. Both providing some in person learning at the beginning of the year and offering a higher share of days in person throughout the year were less likely among schools that had a large share of high need students and less likely in choice schools. For example, provision of an initial hybrid or in person option is available to 95-99% of students in traditional public schools with 25% share of high need students (25^{th} percentile), but falls to between 80 and 90% when schools are 60-70% high needs (75^{th} percentile) with higher shares in elementary school grades. Less than 10% of students in such high needs schools on average had

[1] All analyses presented exclude the approved special education schools because these schools are typically very small and quite specialized, but estimates including the students in these schools are very similar to the results presented below.

access to an early in person learning opportunity in the RESCs, charters and CTECS. Similarly, traditional public schools with low high need shares had 78, 70 and 60% of days in person for elementary, middle and high school, but for large shares of high need students the share of days was 72, 61, and 55%, respectively. Further, take-up of in-person options was also lower in schools with a large share of high need students between October and March with take-up rates of 76, 71 and 65% for elementary, middle and high school grades at the lower share of high need students, and rates of 52, 51 and 45%, respectively, for higher high need share schools.

We use student level difference-in-differences analyses to examine enrollment, attendance and test scores comparing changes within schools during the pandemic between schools belonging to LEA's that provided more in person opportunities compared to schools that provided less in person learning. The provision of in person or hybrid learning in September has minimal impact on fall enrollment decisions. However, for both attendance and test scores, we observe substantial declines in both outcomes during the 2020-21 school year, and find that these declines are smaller when students have more in person options, especially in elementary and middle school. Comparing schools in LEA's that provided the highest and lowest shares of days in person (100% elementary, 95% middle and 82% high school as compared to less than 50% on the low end – 90^{th} and 10^{th} percentiles), we find 2 percentage point declines in attendance for schools with less in person opportunities and those losses fall to no losses, one percentage point, but only to one and one half points in higher in person opportunity elementary, middle and high schools, respectively. For test scores, the losses range from 17% to 26% of a standard deviation in ELA and 33% to 44% for MATH when in person options are low with larger losses in lower grades, and these losses fall to between 11% and 15% for ELA and 27% and 31% for MATH for high in person opportunities. We can also look at SAT tests in English and Math that are

administered statewide in 11th grade using a three year lagged 8th grade Smarter Balance test scores, but we find no effect of in person learning in those models.

Finally, we find minimal evidence of differences in the positive effects of in person learning between schools that have a large share of high need students and those that do not, even though typically the losses in attendance and test scores were bigger for those schools with a large share of high needs students. Notably, simple difference-in-differences analyses provided some evidence of smaller attendance and test score declines when students had more in person opportunities, but this evidence of heterogeneous effects was not robust to the use of propensity score approaches to control for imbalance in the types of schools that provided a higher share of days in person. Learning losses were larger in schools with a large share of high need students, and these schools were much less likely to belong to LEA's that were aggressive in returning to in person learning. At the same time, students in schools with a larger share of high need students were less likely to take up the in person option, suggesting that the equal effects could be the result of larger benefits that are offset because less students took advantage of in person learning.[2]

These results complement the findings of Halloran et al. (2021) and Goldhaber et al. (2022) that providing students with in person learning opportunities reduced learning loss during the pandemic including in our case also showing improvements in attendance rates. Further, unlike these papers, we can also examine effects in high school and find little evidence of beneficial effects of in person learning opportunities. Our paper combines several advantages of each of those papers. Unlike Goldhaber et al., we are similar to Halloran et al. in obtaining

[2] Notably, Oster et al (2021) estimate models that include year fixed effects interacted with district demographic composition, which should in principle control for imbalance in remote learning on observables, and yet they find robust evidence of larger positive effects of in person learning for more disadvantaged districts.

documented weekly learning model information that was provided by the responsible LEA, allowing us to estimate with relative accuracy the share of days offered in person at each school and compare changes within schools during the pandemic. Also, unlike Halloran et al. (2021), we are similar to Goldhaber et al. in our ability to follow students over time conditioning on pre-pandemic outcomes and so avoiding bias that might arise from changes in district enrollment and in the composition of students taking standardized tests.[3] Further, our paper provides direct evidence of the lower rates of in person learning provision in schools that had a large share of high need students and to our knowledge is the first to document lower take-up of those in person options in such schools. Finally, unlike Halloran et al. (2021) and Goldhaber et al. (2022), we do not find evidence of higher returns to providing in person learning opportunities to high needs students, potentially because we address the clear imbalance in student composition between schools that offered a high level of in person opportunities and those that did not.

Data and Samples

The Connecticut State Department of Education provided administrative data covering academic years from the 2014-15 to the 2020-21. These include 1. fall enrollment files identifying each student's school and district as of October 1st along with their status on key indicators of whether the student qualifies for free or reduced price lunch (FRPL), whether the student is classified as disabled (SWD), i.e. has an individualized education plan, and whether the student is classified as an English Language Learner (ELL); 2. end of year enrollment file identifying end of year school and district, as well as the total number of days enrolled and attended at this final school; monthly data by student for number of days enrolled in-person and remote and number of days attended in-person and remote for the last school in which the

[3] Alternatively, they model test score growth rather than controlling for lagged test scores.

student was observed that month; and scale test scores on spring Smarter Balanced English Language Arts (ELA) and Mathematics (MATH) tests for 3rd through 8th grade students, except in the 2019-20 school year when no tests were administered.[4]

During the 2020-21 school year, the state collected weekly data from Local Education Agencies (LEA's) on the learning mode for each week. Each LEA reports whether the learning mode is remote, hybrid, or in-person where LEA's were given guidance that hybrid should be considered to be between 25 and 75% of time in-person. LEA's included town based public school districts, regional school districts that combine multiple small towns in order to deliver education at higher grades either providing high school or both middle and high school education, Regional Education Service Centers (RESC's) that primarily act as administrator for public magnet schools that operate separately from city and town based school districts, individual charter schools or small systems of charter schools, individual endowed schools that historically operated within a single district providing an alternative option in middle or high school, the Connecticut Technical Education and Career System (CTECS) that manages stand-alone technical education high schools throughout the state, and finally Approved Private Special Education Schools (APSES) that are primarily very small schools, servicing students with specific disabilities. All samples described below exclude the approved special education schools because these schools are typically very small and quite specialized, but estimates including the students in these schools are very similar to the results presented below.

We create three variables on remote learning. Given that all students had the right to select all remote learning, we characterize LEA's based on whether they provided students with a hybrid or predominantly (>75%) in person option. We define our first variable as providing a

[4] During the 2020-21 school year, some schools opted for remote testing while others opted for in-person testing.

learning model involving in person education in September, coded as a 1 if at least two weeks of September were reported as hybrid or in person. We then define two additional variables: the approximate share of days offered in person through April for examining test score outcomes and through the end of the school year for examining attendance outcomes. For this variable, we count all days in a week as in person if the LEA learning mode for the week is as classified as in person, half the days in a week as in person if the week is classified as hybrid, and zero days as in person for remote.

We construct several samples for conducting our analyses depending upon the outcome considered. We construct cross-sectional samples of students for examining the likelihood of a school belonging to an LEA that provided an in-person option in September, exposure of a school to share of days in person, student take-up rates over time of in-person options, and the distribution of kindergarten student fall enrollment across schools that offered an in-person option in September. In the case of school exposure to in person learning, we use a student sample because these estimates will be used for developing propensity scores to support the later student level difference-in-differences analyses, and this sample essentially weights models by the enrollment size of the school. In the future, we intend to estimate these models at the school level and directly weight by school enrollment.

The first sample contains all students observed in the statewide fall enrollment file for 2019-20. We use this sample to examine both whether a school based on its LEA provides an in person option in September and share of days offered in person over the entire school year. By conditioning on school enrollment pre-pandemic, we avoid capturing effects of the September learning model option on pandemic year enrollment. The next sample is a cross-section of all students observed in the same school in the fall and end of year enrollment files for the 2020-21

school year, which is used to study student take-up of the in person option using the monthly data that reports attendance and enrollment separately by in person and remote in 2020-21. The final sample includes all kindergarten students observed in the fall enrollment files in years 2014-15 to 2020-21, and is used to examine changes in initial school enrollment during 2020-21 given that we do not observe previous year enrollment for kindergarten students.

We also construct longitudinal student samples for the school years of 2017-18 through 2020-21 pooling the cross-sections of students across these years. The use of longitudinal data allows us to control for lagged outcomes minimizing concerns of bias from selective attrition from the sample during this pandemic year. For continued enrollment for grades 1-12, we include any student observed in the previous year in the statewide spring enrollment file in grades K-11, and test whether we observe these students in the statewide fall enrollment file for the subject year, e.g. 2016-17 end of year enrollment sample and with fall enrollment outcome based on being observed in 2017-18. For attendance, we restrict this sample to observing each student in the spring enrollment of the previous year and observed in the same school in both the fall and end of year enrollment files for the current year. These restrictions assure that we observe attendance rates for both the current year and the previous year and that students are exposed for the entire year to the calculated treatment of share of days offered in person. Attendance rates in 2019-20 are based only on attendance through March because attendance data became unreliable after the onset of the pandemic in spring 2020. We also create an alternative attendance sample starting in 2016-17 (omitting 2019-20) that append two year lagged attendance rates for students who are observed in the spring enrollment file two years earlier than the subject year. Finally, we create subsamples of the two year lagged attendance rate sample for ELA and MATH test scores where students are only included in this sample if we

observe an ELA or MATH test score in both the subject year and two years earlier. The two year restriction is imposed because tests were not administered in 2019-20, and this restriction implies that our ELA and MATH test score samples are restricted to 5th, 6th, 7th and 8th grades.

In terms of distinguishing between schools with advantaged and disadvantaged student populations, we focus on a single measure recommended by the State of Connecticut in order to mitigate concerns about type 1 error. We define a measure of share of high need students as the fraction of students in a school that are classified as either Free and Reduced Price Lunch (FRPL) students, Students with Disabilities (SWD) and/or English Language Learners (ELL). Individual measures of share FRPL, ELL, Hispanic students, and African-American students are all very highly correlated with share high needs. For the 2020-21 cross-sectional samples and the longitudinal samples, we base the school share of high needs students on the three pre-pandemic cohorts of fall enrollment data in 2017-18 to 2019-20 to average out year to year variation in composition. For the enrollment composition sample running from 2014-15 to 2020-21, we based this measure on an average of all fall enrolled students across all pre-pandemic years from 2014-15 to 2019-20.

Methods

We first estimate a model of the likelihood that a student's (*i*) school (*s*) belongs to an LEA or district (*d*) that provides an in person option either hybrid or fully in person in September (*I*) as a function of both the school share of high needs students (Z_{sd}) and the type of LEA (T_d). We estimate simple probit models of this likelihood that follows the standard form.

$$I_{isd} = \begin{cases} 1 & if \;\; I^*_{isd} > 0 \\ 0 & otherwise \end{cases} \tag{1}$$

where

$$I^*_{isd} = \alpha_1 + \alpha_2 \, Z_{sd} + \alpha_3 T_d + \alpha_4 T_d \, Z_{sd} + \varepsilon_{isd} \tag{2}$$

We also estimate similar models for a two sided Tobit on share of days offered in person (*S*) since this share is truncated at zero and one.

$$S_{isd} = \begin{cases} 1 & if\ S^*_{isd} \geq 1 \\ S^*_{isd} & if\ 1 > S^*_{isd} > 0 \\ 0 & if\ S^*_{isd} \leq 0 \end{cases} \quad (3)$$

where

$$S^*_{isd} = \varphi_1 + \varphi_2\, Z_{sd} + \varphi_3 \boldsymbol{T}_d + \varphi_4 \boldsymbol{T}_d\, Z_{sd} + \varepsilon_{isd} \quad (4)$$

With the notable change that LEA type is specified as a vector of indicators because the continuous share of days variables allows for a more disaggregate classification of LEA's. Standard errors in both models are clustered at the district level. In the future, we plan to rerun these models using a school level sample weighted by school enrollment.

For examining student take up, we regress each student's fraction of days enrolled in person relative to the total days enrolled each month (F_{isdt}) on our calculated share of days available in person each month based on weekly learning modes relative to the total days of school each month (S_{sdt}).

$$F_{isdt} = \alpha + \beta S_{dt} + \varepsilon_{isdt} \quad (5)$$

We also estimate an interactive model based on each school's share of high needs students

$$F_{isdt} = \alpha + \beta_1 S_{dt} + \beta_2 Z_{sdt} + \beta_3 S_{dt} Z_{sdt} + \varepsilon_{isdt} \quad (6)$$

Standard errors are clustered at the district level.

For examining initial enrollment of kindergarteners, we only observe students who actually enrolled in kindergarten, and so we cannot know how many students would have enrolled if the pandemic had not occurred. Therefore, we reverse the regression, similar to many studies of discrimination in police stops where those at risk of stop are unobserved (Kalinowski et al. 2021; Grogger and Ridgeway 2006), and regress whether the school belongs to an LEA that

provided a September in person option (*I*) on a linear trend (*T*) and a dummy for the pandemic year (*P*) using a linear probability model.

$$I_{isdt} = \alpha + \beta T_t + \gamma P_t + \varepsilon_{isdt} \quad (7)$$

The trend allows enrollment to change over time away from or towards schools that will offer an in person option in 2020-21, and the pandemic dummy tests for a trend break associated with enrollment responses to an in person option. Again, we expand this model allowing effects to differ between schools with high and low shares of high needs students.

$$I_{idt} = \alpha_1 + \beta_1 T_t + \gamma_1 P_t + \alpha_2 Z_d + \gamma_2 P_t Z_d + \varepsilon_{idt} \quad (8)$$

Again, standard errors are clustered at the district level.

While we observe large declines in kindergarten enrollment, a significant share of that decline is eliminated by the end of the school year because students enroll in kindergarten midway through the school year. We have received the October enrollment files for 2021-22. Using first grade enrollments, we plan to estimate a month by month model of the likelihood of observing 2021-22 first graders enrolled in kindergarten (*E*) during the 2020-21 school year in order to test whether in person opportunities (share days in person) increases the likelihood of mid-year enrollment among those future first graders who have not yet enrolled.

$$E_{isdt} = \alpha + \beta S_{dt} + \varepsilon_{isdt} \quad (9)$$

$$E_{isdt} = \alpha + \beta_1 S_{dt} + \beta_2 Z_{sdt} + \beta_3 S_{dt} Z_{sdt} + \varepsilon_{isdt} \quad (10)$$

Next, we exploit longitudinal information on students starting with enrollment in fall 2020-21 (*E*) if the student was observed in public education in the previous year. Continued enrollment is estimated using a difference-in-differences model, comparing changes in the likelihood of continuing enrollment the next year pre/post pandemic and estimating differences in those differences between schools with an in person option in September and those without.

$$E_{isdt} = \alpha_{sd} + \gamma_1 P_t + \gamma_2 P_t\, I_d + \varepsilon_{isdt} \quad for \;\; E_{isdt} \quad = 1 \tag{11}$$

$$E_{isdt} = \alpha_{sd} + \gamma_1 P_t + \gamma_2 P_t I_d + \gamma_3 P_t\, Z_{sd} + \gamma_4 P_t\, I_d Z_{sd} + \varepsilon_{isdt} \;\; for \;\; E_{isdt-1} = 1 \tag{12}$$

where α_{sd} are school fixed effects.

Estimates of equations (2) and (4) will show that high needs districts are less likely to provide in person learning and traditional public schools are more likely to provide in person learning than choice schools like magnet or charter schools. Therefore, we use the propensity score estimates from equation (2) to develop overlap weights (Li et al. 2018), and re-estimate equations (11) and (12) using weighted regressions. Overlap weights, like inverse propensity score weights, restore sample balance, but do so by targeting the product of the probability of treatment and the probability of not receiving treatment, which places more weight on propensity scores near zero where the data provides equal support over treatment and non-treatment. Specifically, we define overlap weights as

$$W_{isd} = \begin{cases} \left(1 - F(\hat{\alpha}_1 + \hat{\alpha}_2\, Z_{sd} + \hat{\alpha}_3 T_d \; + \hat{\alpha}_4 T_d\, Z_{sd})\right) & if \; NR^*_{isd} = 1 \\ F(\hat{\alpha}_1 + \hat{\alpha}_2\, Z_{sd} + \hat{\alpha}_3 T_d \; + \hat{\alpha}_4 T_d\, Z_{sd}) & if \; NR^*_{isd} = 0 \end{cases} \tag{13}$$

based on estimates arising from equation (2).

Finally, we develop difference-in-differences models of attendance and test scores (Y) that include controls for lagged student outcomes. For these models, we control for the share of days offered in person over the relevant portion of the school year.

$$Y_{isdt} = \alpha_{sd} + \delta Y_{idt-s} + \gamma_1 P_t + \gamma_2 P_t\, S_{sd} + \varepsilon_{isdt} \tag{14}$$

$$Y_{isdt} = \alpha_{sd} + \delta Y_{idt-s} + \gamma_1 P_t + \gamma_2 P_t S_{sd} + \gamma_3 P_t\, Z_{sd} + \gamma_4 P_t\, S_d Z_{sd} + \varepsilon_{isdt} \tag{15}$$

where s represents the lag applied to the previous outcome control, which is one year for attendance in our primary models and two years for test scores.

As with September in person learning, we use the estimates from equation (4) to obtain a propensity score associated with each student's school's tendency to offer a higher share of days

in person based on the school's share of high need students and LEA. However, simple weighting approaches based on probabilities or densities are not available because the appropriate model for share of days involves a continuous variable with truncation. Since the weights are intended to avoid differences in trends created by imbalance in the sample over treatment, we instead address potential bias from such trends by adding an interaction of the propensity score with the pandemic control. The propensity score is defined as

$$\hat{S}_{sd} = \hat{\varphi}_1 + \hat{\varphi}_2 Z_{sd} + \hat{\varphi}_3 \boldsymbol{T}_d + \hat{\varphi}_4 \boldsymbol{T}_d Z_{sd} \quad (16)$$

Admittedly, the same effect could be accomplished by adding the controls in equation (16) interacted with the pandemic variable to equations (14) and (15). However, by using the propensity score, we can mean difference a single variable, propensity score, prior to inclusion in the model, and as a result the pandemic variable estimate represents the effect for the average school in terms of propensity to offer a high share of days in person. The resulting model is

$$Y_{isdt} = \alpha_{sd} + \delta Y_{idt} \quad + \gamma_1 P_t + \gamma_2 P_t S_{sd} + \gamma_3 P_t \left(\hat{S}_{sd} - \bar{S}\right) + \varepsilon_{isdt} \quad (17)$$

$$Y_{isdt} = \alpha_{sd} + \delta Y_{idt-s} + \gamma_1 P_t + \gamma_2 P_t S_{sd} + \gamma_3 P_t Z_{sd} + \gamma_4 P_t S_d Z_{sd}$$
$$+ \gamma_5 P_t \left(\hat{S}_{sd} - \bar{S}\right) + \varepsilon_{isdt} \quad (18)$$

Standard errors for all difference-in-differences models are clustered at the level of the fixed effects, i.e. the school.

For all difference-in-differences models, we estimate falsification tests where we treat an earlier year, 2018-19, as a fake pandemic year and use the years 2016-17 and earlier as the pre-event sample.

Results

Remote versus In-Person and Hybrid Learning

First, we examine variation in remote learning across schools and school districts within the state, as well as student take-up of hybrid and in-person learning opportunities. These analyses are cross-sectional relating educational learning options provided during the pandemic to school level student composition pre-pandemic, as of October 2019. Even though learning options were established at the district level for most schools, we can interpret these analyses as examining the likelihood that a school with a given student composition belonged to a district or was subject to an administrative decision maker that selected a specific learning mode. Given that all students had the option for remote learning, our analyses focuses provision of some or all in-person learning.

Table 1 presents the initial/September decision to offer hybrid or fully in-person learning as the primary learning mode. We divide the population of students into three subsamples by grade level: 1st-5th, 6th-8th, and 9th-12th following the most common grade configuration of elementary, middle and high schools in the state, but all results below are very similar if we analyze each grade separately.[5] The top panel presents the estimates showing that the likelihood of students having an in-person option in September falls with the share of high need students, and this relationship is even stronger for the subsample composed of students in charter schools and in schools managed by the RESCs and CTECS.[6] Turning to the Bottom panel, we present the fraction of students in the state that were provided with an in-person option in September for

[5] Districts do vary in grade composition so that some middle schools will be represented in 1st-5th or 9th-12th and some elementary schools in 6th-8th. The use of school fixed effects helps to address this issue. Further, as noted, this problem will not arise with analyses at the individual grade level and all results are robust

[6] We combine public and regional school districts because regional school districts are traditional public schools that are jointly under the supervision of and locally funded by a combination of towns. We also include endowed schools with town school districts because those endowed schools traditionally were affiliated with a specific town and received and in some cases still receive support from that town.

each of the three grade subsamples, as well as the 25th and 75th percentile school share of high need students within the state's student population. The share of students with an in-person option is 91% at the elementary school level, and 93% and 90% for middle and high school, respectively.

We then use these percentiles to predict the likelihood of a school providing an in-person option at a hypothetical school that was at the 25th and 75th percentiles of share of students with high needs. The 25th percentile is between 24% and 25% percent depending upon grade level, but the 75th percentile ranges more broadly between about 70% for elementary and middle school and 60% for high school. For traditional public schools, an in-person option in September was available to over 95% of students, 98% of elementary and middle school students, at the 25th percentile and available to 86% to 89% of students at the 75th percentile of share high needs. Looking at the RESCs, Charters and CTECS, percentages were relatively high at the 25th percentile ranging between 85% and 96%, but fall dramatically with share high needs in elementary and middle school with some in person being available to only 6% to 8% of students at the 75th percentile share.

Next, we examine the share of days that were offered in-person over the entire school year. Table 2 presents these results. Again, the estimates are shown in the top panel of the table. As in September, share of in person days available falls as the school share of high need students increases, although this effect weakens for higher grade levels. We cannot detect any differences between town based school districts and regional school districts, although estimates are very noisy at lower grade levels where regional school districts have minimal representation. The negative relationship between share high needs and having in person opportunities is even

stronger for the charter/RESC subsample in elementary and middle school grades, but the relationship is much weaker at endowed high schools.[7]

The bottom panel shows the average of share of days provided in-person: 78% for elementary, 70% for middle and 60% for high school grades and the expected share based on the 25th and 75th percentiles of share high need students separately for different types of schools. For traditional public schools, we observe approximately a 6 to 8 percentage point lower share of days provided in-person at the 75th percentile share high needs relative to the 25th percentile. These differences are even larger for RESCs and Charter schools: 35 percentage points for elementary, 26 points for middle and 13 points for high school grades. Endowed schools have on average substantially lower shares of in person days: 47% for middle school and 37% for high school at the 25th percentile, but for endowed high schools the share in person is unaffected by school share of high need students.

Finally, we examine rates at which students enroll in person as a function of the share of days offered in person. These results are shown in Table 3 separately for Oct-Dec, Jan-Mar and Apr-June in each column. The first panel presents the simple relationship between share enrolled and share available. The estimate ranges between 0.59 and 0.65 implying that if 10 additional days were available in person one would observe on average six to six and one half additional days of in-person enrollment per student. However, since virtually all districts required students to choose between all remote and the primary learning mode, a better interpretation of these estimates is that approximately six out of ten students enrolled in-person for all available days and four students continued with remote learning. The second panel estimates a model

[7] CTECS is one district with a single value for share of in person days and so the estimate on share high needs across the technical high schools is meaningless, opposite in sign and identical in magnitude to level estimate. Only one endowed middle exists in the state so the effect of share high needs for that school is unidentified.

interacting the share of days in person with the school share of high needs students. Estimates on these interactions are strongly negative for the fall and winter, and the level estimate on share in person increases to 0.92 and 0.85 for elementary and middle school grades, where an estimate of one would be consistent with perfect take-up.

The first two rows of the bottom panel present the average of the student share of enrollment days that are recorded as in person and the average share of days available in-person based on the weekly learning mode. As the year progressed, the share of days available in person and the share of days students enrolled in person education increased, but there was a steady gap of between 16 and 19 percentage points. The last two rows use the estimates from the second panel to predict the effect of share in-person provided for a hypothetical school at the 25th and 75th percentiles of share of students with high needs. For elementary and middle schools, we observe a sizable gap with 70% to 75% of students appearing to respond to a school offering more days in-person at the 25th percentile of share high needs, but just over 50% of students responding at the 75th percentile. In the spring, we observe less responsiveness overall to increases in in-person learning availability, but the influence of share high needs has declined with 57% of days in person at the 25th percentile of share high needs and 45% in person at the 75th percentile.

We also hypothesized that the students from schools with a larger share of high needs students might respond more slowly to the provision of more in person days, as opposed to simply having lower responsiveness overall. We did explore models that included lags to allow for such a delayed response to new in person offering, but we did not find evidence of such behavior. The data appears more consistent with simply a lower response rate among students in high needs schools to the provision of hybrid or in-person learning opportunities.

Remote Learning and Student Enrollment

In order to examine changes in fall enrollment, we first plotted total state enrollment year by year separately for public pre-school, kindergarten, 1st-5th grade, 6th-8th grade and 9th-12th grade initializing all enrollment by dividing by 2014 enrollment levels. In Figure 1, we show these trends for Alliance Opportunity districts, the 10 districts in the state that are lowest performing on standardized tests. While 1st-5th grade fall enrollment fell between 2019-20 and 2020-21, the decline in enrollment was very similar in magnitude to declines in the preceding years, and there is no evidence of a decline due to the pandemic. However, for publically provide pre-school and for kindergarten, enrollments drop dramatically between fall 2019-20 and 2020-21, declines much larger than the declines in previous years. In general, across all district types, we observe minimal deviation from trends in pandemic enrollment patterns, except in kindergarten and pre-school where we observe substantial declines. Figure 2 presents similar results for all non-Alliance districts and LEA's. Comparing Figures 1 and 2 shows that Alliance Opportunity districts experienced larger declines in kindergarten enrollment. Next, we examine kindergarten enrollment, which is relatively universal within the state, while we do not examine public pre-school which represents a much more selected population.

For kindergarten, we do not observe the full population of students eligible to enroll in kindergarten, and instead we use whether the school provided an in person option in September as a dependent variable in a student sample to capture changes in enrollment patterns. Table 4 shows these results for kindergarten, as well as 1st and 2nd grade for comparability. Panel one presents results for the pandemic effect on the composition of students between schools that provided an in-person option in September of 2020 and those that did not. Estimates suggest a small decline of approximately ½ of one percentage point in kindergarten enrollment loss,

significant at the 10% level, with no significant effects for 1st or 2nd grade. This effect is quite small given the 10 percentage point or more declines in October 2020 kindergarten enrollment. Further, the noisily estimated effect on the interaction of the pandemic variable with share high needs students is negative. Therefore, at the 75th percentile share of high needs students, our best estimate is that there is no improvement in October enrollment, even though kindergarten enrollment losses were stronger for more disadvantaged schools.

Next, Table 5 presents estimates of our difference-in-differences model of continued enrollment separately by column for 1st through 5th, 6th through 8th, and 9th and 12th grades. The top panel presents the unweighted results and the second panel presents results using the overlap propensity score weights based on the estimates presented in Table 1. The interaction term estimates in the top panel suggest that the in person option minimizes pandemic year enrollment loss by over a percentage point in elementary and by about two-thirds of a percentage point for middle school, but these effects are eroded substantially (especially in elementary school) by the use of overlap weights. These findings suggest that the effect of providing an in person option on enrollment in panel 1 was spurious and likely driven by differences between schools that offered a September in person option and those that did not. Table 6 presents continued enrollment estimates after including interactions with share of high need students. Most estimates are insignificant, and we do not observe any systematic relationship between an in person option and continued enrollment.

Remote Learning and Attendance

Table 7 presents estimates of the effect of in person learning availability on attendance using similar models to enrollment except including a student level control for past attendance rates. The top panel presents the results without the interaction between propensity score and the

pandemic variable, and the second panel presents the results after conditioning on this interaction. In both panels, we observe very large declines in attendance during the pandemic of between 2½ to 4½ percentage points with larger declines in earlier grades. Further, schools that provide a greater share of days in person experience less enrollment loss at all grade levels, especially in elementary and middle school. The inclusion of the propensity score leads to a reduction in the effect of in person share, and the high school estimates are substantially smaller and insignificant. However, pandemic effect estimates also erode in magnitude so that providing an in person option ameliorates a similar share of the learning loss in elementary and middle school whether or not models include the propensity score. The bottom panel presents predicted attendance rates at the 10th and 90th percentiles of share of in person using the propensity score model: 46% vs. 100% in person for elementary, 44% vs. 94% for middle and 41% vs. 82% for high school. In elementary, a school at the 90th percentile of in person share is predicted to have a 2 percentage point lower decline in attendance during the pandemic relative to the 10th percentile. Improvements are 1 percentage point for middle school and only half a point for high school.

Table 8 presents the results allowing effects to differ between schools with a low versus high share of high need students. In both models with and without propensity score, we observe that attendance outcomes during the pandemic are substantially worse in schools that have a larger share of high need students across all grade levels. Comparing attendance rates for the 25th and 75th percentiles of share high needs, the bottom panel shows 2 to 3 percentage point worse attendance rates for schools at the 75th percentile. However, the positive significant estimate on the interaction between share days in person and share high needs in panel 1, which is consistent with the previous findings of Halloran et al. (2021) and Goldhaber et al. (2022) for test scores, is

not robust to the inclusion of propensity score control (Panel 2). The estimate declines by 35 percent and is no longer significant. In the bottom panel for elementary school, we do observe a one percentage point difference based on remote versus in person learning at the 75th percentile that is not observed at the 25th percentile, and at the 75th percentile the estimate on the interaction between share in person and share in high needs is statistically significant,[8] but overall our propensity score models provide minimal evidence that in person learning has differential effects between schools based on the share of high needs students.

All models have been estimated grade by grade, and results for pooled elementary, middle and high school grades above are replicated at the individual grade level.

Remote Learning and Standardized Test Scores

Tables 9 and 10 present the results for English Language Arts (ELA) and Mathematics (MATH) Smarter Balance test scores, respectively, using similar models to attendance except including a two year lag of past test scores. For both ELA and Math tests, the pandemic has negative effects on test scores ranging from about 30% and 40% of a standard deviation decline for ELA and 40% and 60% for MATH for an entirely remote school with larger losses in the lower grades. As with attendance, a higher share of days in person leads to a significant reductions in these performance losses, with a modest erosion of these improvements in the model that includes the propensity score. Turning to the bottom panel, we use the estimates in panel 2 to compare the negative effects of the pandemic between schools at the 10th and 90th percentiles. At the 10th percentile, the losses range from 17% to 26% of a standard deviation for ELA and 34% to 44% for MATH again with larger losses in lower grades, and these losses fall to between 11% and 15% for ELA and 27% and 31% for MATH at the 90th percentile. We can

[8] Specifically, the coefficient on this interaction is significant in a model where the share high needs variable takes the value of zero at the 75th percentile, negative below and positive above.

also look at SAT tests in English and Math that are administered statewide in 11th grade including controls for the three year lagged 8th grade Smarter Balance test scores, but while we observe pandemic learning loss we find no effect of in person learning in those models, see Table 11.

Tables 12 and 13 present the share high needs interaction models for ELA and MATH, respectively. Table 12 shows substantially larger learning losses on the ELA test for schools with a larger share of high needs students, but the results are a little more unstable when we add the propensity score control. Nonetheless, the bottom panel of Table 12 shows substantial differences of 8 percent of a standard deviation larger decline in 5th and 6th grade ELA scores and 4 percent larger decline for 8th grade ELA at the 75th percentile of school share high needs compared to the 25th percentile, when measured at the 10th percentile of share of days in person. We do not find evidence of such differences between schools on the MATH test. Next, we look at the triple interaction of pandemic, share days in person and share high needs as a test of whether in person learning matters more for high needs schools. The estimates on this interaction are only significant for one grade for one test, 6th grade ELA, out of eight estimates, and so that estimate should likely be discounted given the risk of type one error. Further, even though Panel 1 for ELA shows sizable, noisy estimates on ELA for other grades in the same direction as the significant 6th grade estimate, these other estimates erode in magnitude substantially when the propensity score interaction is added and no clear pattern remains. Again, we find minimal evidence that the positive effects of share of days offered in person are greater in Connecticut schools with larger shares of high need students.

Falsification Tests

Table 13 presents falsification tests for attendance grade by grade with a two year lag. We present results from 2nd to 12th grade treating 2018-19 as the false treatment/pandemic year. Most estimates are small (all but two estimates are around one half a percentage point or less), and only two estimates out of 22 on pandemic and pandemic interacted with share of days are significant at the 10 percent level. While these models are estimated grade by grade with a two year lag model, we would expect similar results for elementary, middle and high school subsamples with a one year lag, given very similar results for the true pandemic year attendance models whether we use a one year lag and whether estimates are grade by grade or not.

Table 14 presents falsification tests for Smarter Balance ELA and Math test scores again using 2018-19 as a false pandemic year. The first panel presents estimates for ELA, and the second panel presents results for Math. The estimates on pandemic year imply a small trend in ELA and Math test scores, especially in ELA, but this trend is very small (less than 1/10th of a standard deviation) relative to the large pandemic test score losses documented in Table 9 and 10. Further, when we look at the impact on share of days in person during the false pandemic year, our estimates again are mostly quite small, less than 5% of a standard deviation from a change from all remote to all in person. Only one out of eight estimates exceed 5% in magnitude, and that estimate is only significant at the 10% level. All other estimates are insignificant.

Very similar results arise when falsification tests are estimated without the propensity score controls. This fact may appear surprising given that the inclusion of propensity score controls influences our results, especially related to whether in person learning has a larger positive effect for high needs schools. However, falsification tests of this type can only test for systematic trends over time, while the propensity score approaches can adjust estimates for the

possibility that the effects of the pandemic differed across schools and districts in ways that correlate with the use of hybrid and in-person modes.

Summary and Conclusions

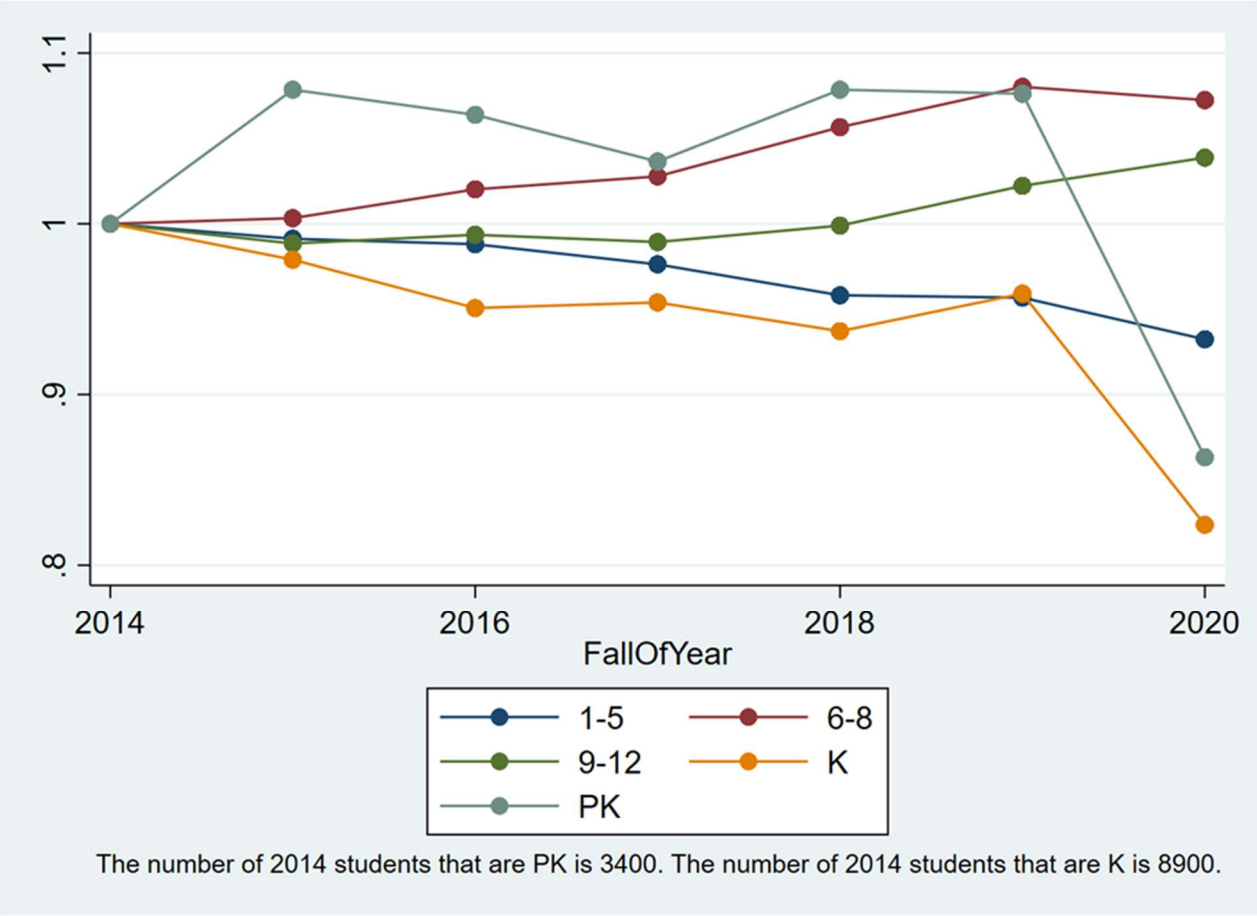
This study provides the first analysis of the effects of in person learning opportunities on educational outcomes using detailed longitudinal student data and regular administrative reports that identify the learning model used by each Local Education Agency. Further, our study is the first to look at the influence of in person learning opportunities on student enrollment decisions and attendance. Consistent with two other recent studies (Halloran et al. 2021; Goldhaber et al. 2022), we find that in person learning opportunities mitigated academic losses during the pandemic leading to smaller declines in both attendance and test scores, using a similar difference-in-differences design to those studies. However, we find no relationship between fall enrollment and whether schools provide in person learning at or near the beginning of the school year.

Similar to other studies (Parolin 2021; Camp and Zamarro 2021; Oster et al. 2021; Goldhaber et al. 2022), we find that in person learning opportunities were concentrated among more advantaged schools, schools with lower shares of high needs students. In what we believe is a new finding to the literature, we also demonstrate that student take-up of in person learning opportunities was lower in schools with the highest share of high need students, especially prior to April after which most schools began to transition towards fully in person. These low take-up rates might help explain why we find similar effects of in person learning opportunities in schools that have large and small shares of high need students. High need students experienced greater losses during the pandemic, but these students could only benefit from the offsetting

effect of in person learning if their parents chose to send them to school in person when those opportunity became available.

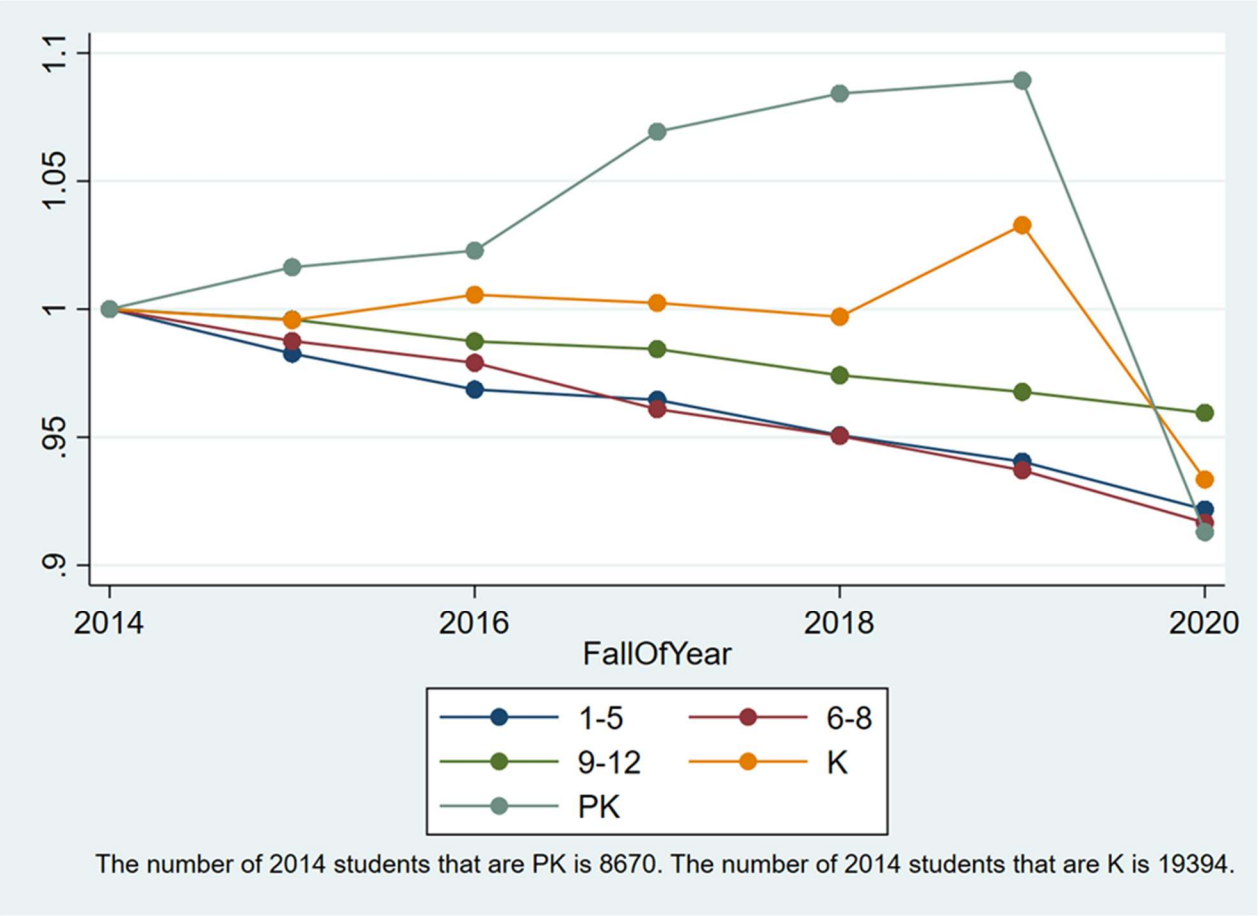
References

Figure 1. Enrollment Patterns for Alliance Opportunity Districts



The figure presents the average of enrollment in district and year as a fraction of district's 2014 enrollment. PK stands for public pre-school and K stands for kindergarten. All numbers on the legend refer to grades. Alliance opportunity districts are the 10 lowest scoring public school districts in the state.

Figure 2. Enrollment Patterns for Non-Alliance Districts



The figure presents the average of enrollment in district and year as a fraction of district's 2014 enrollment. PK stands for public pre-school and K stands for kindergarten. All numbers on the legend refer to grades. Non-Alliance districts represent all LEA's except for the 36 lowest test scoring public school districts.

Table 1. In-Person Option Available in September

Controls	(1) Grades 1st through 5th	(2) Grades 6th through 8th	(3) Grades 9th through 12th
Percent of students high needs: FRPL, SWD, or ELL	-1.845***	-2.426***	-1.705***
in school attended	(0.315)	(0.382)	(0.522)
District is a RESC, Charter or CTECS	2.340	2.708*	0.200
	(1.511)	(1.507)	(1.147)
District RESC/Charter/CTECS*Percent of students	-3.845*	-3.757*	-0.0568
high needs in school	(2.038)	(1.964)	(1.603)
Observations	547,165	353,048	477,837
Fraction of Students with Sept In person Option	0.914	0.925	0.902
25th Percentile Share High Need Students	0.251	0.247	0.238
75th Percentile Share High Needs Students	0.703	0.694	0.606
Estimated Probability of In-person Option			
Traditional Public (25th percentile high needs)	0.977	0.989	0.958
Traditional Public (75th percentile high needs)	0.876	0.887	0.864
RESC/Charter/CTECS (25th percentile high needs)	0.847	0.916	0.956
RESC/Charter/CTECS (75th percentile high needs)	0.061	0.081	0.856

The top panel shows the results of a probit model regressing in person/hybrid learning mode on school share of students who are high needs, whether the Local Education Agency represents a school choice option, and the interaction of these two variables. Columns 1 through 3 present results for elementary, middle and high school grades, respectively. The bottom panel presents the fraction of students with an in person/hybrid option in September, and the school share of high needs students at the 25th and 75th percentiles. The final rows in the bottom panel present the model based predicted likelihood of in person/hybrid option at the 25th and 75th percentiles of share high needs.

Table 2. Share of Days in Person Available Through End of School Year

Controls	(1) Grades 1st through 5th	(2) Grades 6th through 8th	(3) Grades 9th through 12th
Percent of students high needs: FRPL, SWD, or ELL	-0.315***	-0.236**	-0.182
in school attended	(0.105)	(0.118)	(0.119)
Regional School District	0.314	0.0865	-0.00766
	(0.241)	(0.131)	(0.0804)
Regional School District*Percent of students high needs	-1.078	0.0415	0.174
	(1.163)	(0.514)	(0.325)
Regional Education Service Centers or Charters	0.652***	0.706**	0.232
	(0.244)	(0.348)	(0.326)
Regional Education Service Centers or Charters*Percent of	-0.941***	-0.952**	-0.0858
students high needs	(0.304)	(0.402)	(0.392)
Endowed Schools		-0.215***	-0.282***
		(0.0432)	(0.0329)
Endowed Schools*Percent of students high needs			0.198*
			(0.119)
Connecticut Technical Education Career System			-0.230***
			(0.0329)
Observations	459,819	335,564	446,407
Average Share of Days with In Person Option	0.720	0.649	0.567
Estimated Share of Days with In Person Option			
Traditional Public (25th percentile high needs)	0.776	0.696	0.605
Traditional Public (75th percentile high needs)	0.717	0.613	0.549
RESC and Charter (25th percentile high needs)	0.982	0.981	0.889
RESC and Charter (75th percentile high needs)	0.633	0.719	0.762
Endowed School (25th percentile high needs)	*	0.474	0.369
Endowed School (75th percentile high needs)	*	0.389	0.377

The top panel shows the results of a tobit model regressing share of days in person offered for the entire school year on school share of students who are high needs, dummy variables for the type of Local Education Agency, and the interaction of these variables. Columns 1 through 3 present results for elementary, middle and high school grades, respectively. The bottom panel presents the average share of days in person. The rest of the rows in the bottom panel present model predicted share of days in person at the 25th and 75th percentiles of share high needs.

Table 3. Monthly In-Person Enrollment Days as a Share of Total Enrollment Days

VARIABLES	(1) Oct_Dec	(2) Jan_Mar	(3) Apr_Jun
Share of Days Offered in Person for the Same Month	0.646***	0.651***	0.591***
	(0.0388)	(0.0316)	(0.0752)
Observations	1,401,411	1,388,433	1,279,065
R-squared	0.311	0.260	0.114
Share of Days Offered in Person for the Same Month	0.923***	0.849***	0.657***
	(0.0455)	(0.0537)	(0.141)
Percent of students high needs: FRPL, SWD, or ELL	0.0318	0.0413	-0.0804
	(0.0548)	(0.0796)	(0.280)
Share of Days in offered person* Percent of students high needs	-0.562***	-0.467***	-0.287
	(0.0900)	(0.0965)	(0.294)
Observations	1,398,156	1,385,238	1,276,179
R-squared	0.359	0.292	0.153
Average of Share Monthly In Person Enrollment Days	0.3741658	0.4145769	0.6823971
Average of Share of Days Offered in Person by Month	0.5316727	.6075055	0.8437183
Share days in person effect at 25th percentile high needs	0.756	0.710	0.572
Share days in person effect at 75th percentile high needs	0.519	0.514	0.451

The top panel shows the results from a linear regression of share of days a student is enrolled in person during a given month on the share of days offered in person by that school in the same month. The second panel presents estimates adding controls for the share of students who are high needs and the interaction of share high needs with share of days offered in person. Columns 1 through 3 present results for Oct-Dec, Jan-Mar and Apr-Jun, respectively. The bottom panel presents the average share of enrollment days in person, the average share of days offered in person, and the estimated effect of share days offered in person calculated at the 25th and 75th percentiles using the estimates from panel 2.

Table 4. In-Person Option in September as Dependent Variable

Controls	(2) Kindergarten	(3) Grade 1	(4) Grade 2
Pandemic year	0.00499*	-0.00106	0.000661
	(0.00262)	(0.00217)	(0.00238)
Observations	251,767	258,433	261,228
R-squared	0.000	0.000	0.000
Pandemic year	0.00990*	0.00248	0.00266
	(0.00558)	(0.00485)	(0.00499)
Pandemic year*Share of high need students	-0.0150	-0.00971	-0.00450
	(0.0123)	(0.00967)	(0.00980)
Observations	250,146	256,762	259,238
R-squared	0.038	0.059	0.065
2019-20 Mean School Enrollment in Districts w/ In Person Option	77.8	76.0	76.8
2020-21 Mean School Enrollment in Districts w/ In Person Option	69.6	75.2	74.9
2019-20 Mean School Enrollment in Districts w/out In Person Option	65.4	65.4	66.3
2020-21 Mean School Enrollment in Districts w/out In Person Option	55.9	64.5	64.6
25th Percentile High Needs			
Pandemic Effects on Relative Enrollment In-Person Option	0.00578**	-0.0002	0.0014
75th Percentile High Needs			
Pandemic Effects on Relative Enrollment In-Person Option	0.00004	-0.0046	-0.0007

The top panel shows the results of regressing in person/hybrid learning mode offered in September on a pandemic dummy variable and a linear trend. The columns present estimates for kindergarten, 1st and 2nd grades. The second panel presents results based on adding controls for the school share of students who are high needs, and the interaction of this variable with the pandemic dummy. The bottom panel presents mean enrollent in districts with and without a pandemic in person option both for periods prior to and during the pandemic. The final two rows in the bottom panel present the estimated effect of the pandemic based on the estimates in panel 2 measured at the 25th and 75th percentiles of share high need students.

Table 5. Fall Enrollment if Enrolled in the Previous Year

Controls	(1) Grades 1st through 5th	(2) Grades 6th through 8th	(3) Grades 9th through 12th
	Unweighted Model		
Pandemic year	-0.00288	0.00139	0.00315*
	(0.00221)	(0.00128)	(0.00172)
Pandemic year*In person learning option in Sept	-0.0125***	-0.00691***	-2.66e-06
	(0.00242)	(0.00150)	(0.00179)
Observations	726,758	468,726	636,613
R-squared	0.015	0.272	0.417
	Propensity Score Weights		
Pandemic year	-0.00367	0.00185	0.00397**
	(0.00251)	(0.00124)	(0.00155)
Pandemic year*In person learning option in Sept	-0.00249	-0.00479**	0.00127
	(0.00280)	(0.00225)	(0.00184)
Observations	726,758	468,726	636,613
R-squared	0.016	0.271	0.264
Fall Re-enrollment Rates 2017-2019 w/ In-Person Option	0.978	0.978	0.969
Fall Re-enrollment Rates 2017-2019 Remote Only	0.978	0.983	0.972
Fall Re-enrollment Rates 2020-2021 w/ In-Person Option	0.963	0.973	0.973
Fall Re-enrollment Rates 2020-2021 Remote Only	0.975	0.983	0.977

The top panel presents the estimates of regressing whether a student is observed enrolled in October of each year on a dummy variable for the pandemic year, the interaction of the pandemic dummy with a dummy variable for in person/hybrid option provided in September, and school fixed effects. Columns 1 through 3 present results for elementary, middle and high school grades, respectively. The second panel presents overlap propensity score weighted estimates based on the model presented in Table 1. The bottom panel presents student re-enrollment rates year to year seperately for schools with and without a pandemic in person/hybrid option both for the pre-pandemic period and during 2020-21.

Table 6. Fall Enrollment and Share High Need Students

Controls	(1) Grades 1st through 5th	(2) Grades 6th through 8th	(3) Grades 9th through 12th
	Unweighted Model		
Pandemic year*Share high need students	0.0201	-0.00260	0.0106*
	(0.0191)	(0.0168)	(0.00549)
Pandemic year*Share high need students*	0.0116	0.0134	-0.00254
In Person learning option	(0.0196)	(0.0171)	(0.00625)
Observations	726,758	468,726	636,613
R-squared	0.015	0.272	0.417
	Propensity Score Weights		
Pandemic year*Share high need students	0.0150	0.00550	0.00960*
	(0.0223)	(0.0184)	(0.00509)
Pandemic year*Share high need students*	0.0222	0.0108	0.00413
In Person learning option	(0.0228)	(0.0196)	(0.00682)
Observations	726,758	468,726	636,613
R-squared	0.016	0.271	0.264
25th Percentile High Needs			
Pandemic Effects Remote	-0.0098	-0.0007	0.0006
Pandemic Effects In-Person Option	-0.0205	-0.0102	0.0007
75th Percentile High Needs			
Pandemic Effects Remote	-0.0028	0.0017	0.0041
Pandemic Effects In-Person Option	-0.0030	-0.0029	0.0056

The top panel presents the estimates of regressing whether a student is observed enrolled in October of each year on a dummy variable for the pandemic year, the interaction of the pandemic dummy with a dummy variable for in person/hybrid option provided in September, the interaction of the pandemic dummy with school share of high needs students, the three way interaction between pandemic-in person/hybrid-share high needs, and school fixed effects. Columns 1 through 3 present results for elementary, middle and high school grades, respectively. The second panel presents overlap propensity score weighted estimates based on the model presented in Table 1. The bottom panel presents estimated effects of the pandemic on re-enrollment based on the estimates in panel 2, seperately for in-person/hybrid and fully remote at the 25th and 75th percentiles of school share of high needs students.

Table 7. Attendance conditional on previous year attendance

Controls	(1) Grades 1st through 5th	(2) Grades 6th through 8th	(3) Grades 9th through 12th
	No Propensity Score		
Lagged Attendance	0.404***	0.655***	0.660***
	(0.0302)	(0.0125)	(0.0197)
Pandemic year	-0.0468***	-0.0371***	-0.0276***
	(0.00372)	(0.00606)	(0.00986)
Pandemic year*Share of days in person	0.0487***	0.0318***	0.0198
	(0.00447)	(0.00825)	(0.0166)
Observations	584,085	444,062	592,910
R-squared	0.208	0.244	0.291
	Conditional on Centered Propensity Score		
Lagged Attendance	0.404***	0.655***	0.659***
	(0.0301)	(0.0125)	(0.0196)
Pandemic year	-0.0382***	-0.0325***	-0.0256***
	(0.00349)	(0.00581)	(0.00860)
Pandemic year*Share of days in person	0.0354***	0.0223***	0.0125
	(0.00422)	(0.00828)	(0.0139)
Pandemic year*Centered propensity score	0.0609***	0.0526***	0.342***
	(0.00854)	(0.0165)	(0.0607)
Observations	584,085	444,062	592,910
R-squared	0.215	0.248	0.297
Average Attendance Rates 2017-2018, 2018-2019, 2019-20	0.956	0.953	0.938
Average Attendance Rates 2020-21	0.944	0.934	0.919
10th Percentile Share of In Person Days Available	0.456	0.441	0.414
90th Percentile Share of In Person Days Available	1.000	0.943	0.818
Pandemic Effects at 10th Percentile Share In Person	-0.022	-0.023	-0.020
Pandemic Effects at 90th Percentile Share In Person	-0.003	-0.011	-0.015

The top panel presents the estimates of regressing student annual attendance rates on one year lagged student attendance rates, a dummy variable for the pandemic year, the interaction of the pandemic dummy with the share of days offered in person during the school year, and school fixed effects. Columns 1 through 3 present results for elementary, middle and high school grades, respectively. The second panel presents results of a model that also includes the propensity score from the estimates in Table 2 interacted with the pandemic dummy. The bottom panel presents average attendance rates pre-pandemic and during 2020-21. Share of days offered in person at the 10th and 90th percentiles, and estimates effects of the pandemic based on the estimates in panel 2 calculated at the 10th and 90th percentile share of days.

Table 8. Attendance conditional on previous year attendance

Controls	(1) Grades 1st through 5th	(2) Grades 6th through 8th	(3) Grades 9th through 12th
	No Propensity Score		
Lagged Attendance	0.404***	0.655***	0.659***
	(0.0301)	(0.0124)	(0.0196)
Pandemic year*Share high need students	-0.0994***	-0.0732***	-0.0376
	(0.0127)	(0.0216)	(0.0402)
Pandemic year*Share high need students*	0.0340**	-0.0260	-0.0848
In Person learning option	(0.0162)	(0.0321)	(0.0655)
Observations	584,085	444,062	592,910
R-squared	0.225	0.261	0.297
	Conditional on Centered Propensity Score		
Lagged Attendance	0.404***	0.655***	0.659***
	(0.0301)	(0.0124)	(0.0196)
Pandemic year*Share high need students	-0.0840***	-0.0808***	-0.00416
	(0.0131)	(0.0225)	(0.0369)
Pandemic year*Share high need students*	0.0224	-0.0203	-0.0868
In Person learning option	(0.0163)	(0.0306)	(0.0647)
Pandemic year*Centered propensity score	0.0170**	-0.00916	0.168***
	(0.00754)	(0.0194)	(0.0637)
Observations	584,085	444,062	592,910
R-squared	0.225	0.262	0.298
25th Percentile High Needs			
Pandemic Effects 10 Percentile In-Person	0.004	0.006	-0.011
Pandemic Effects 90th Percentile In-Person	0.0067	0.0057	-0.0011
In Person Option Interaction Significance			
75th Percentile High Needs			
Pandemic Effects 10 Percentile In-Person	-0.0310	-0.0336	-0.0252
Pandemic Effects 90th Percentile In-Person	-0.0222	-0.0383	-0.0283
In Person Option Interaction Significance	***		

The top panel presents the estimates of regressing student annual attendance rates on one year lagged student attendance rates, a dummy variable for the pandemic year, the interaction of the pandemic dummy with the the share of days offered in person during the school year, the interaction of the pandemic dummy with school share of high needs students, the three way interaction between pandemic-share of days in person-share high needs, and school fixed effects. Columns 1 through 3 present results for elementary, middle and high school grades, respectively. The second panel presents results of a model that also includes the propensity score from the estimates in Table 2 interacted with the pandemic dummy. The bottom panel presents estimated effects of the pandemic on attendance based on the estimates in panel 2, seperately for the 10th and 90th percentiles of share of days offered in person for both the 25th and 75th percentiles of school share of high needs students. The bottom rows under the 25th and 75th percentiles on share high needs represents the statistical significance of the share of days in person interaction with the pandemic dummy when share of high need students has been centered to take a value of zero at the 25th and 75th percentiles, respectively.

Table 9. English Language Arts Test Score Effects

Controls	(1) Grade 5	(2) Grade 6	(3) Grade 7	(4) Grade 8
	No Propensity Score			
Lagged Score	0.835***	0.784***	0.815***	0.822***
	(0.00286)	(0.00295)	(0.00317)	(0.00339)
Pandemic year	-39.95***	-28.48***	-27.07***	-24.31***
	(2.495)	(2.514)	(2.885)	(3.225)
Pandemic year*Share of days in person	28.70***	15.24***	14.79***	14.41***
	(3.480)	(3.816)	(4.720)	(5.153)
Observations	138,378	139,262	140,129	143,337
R-squared	0.686	0.674	0.671	0.663
	Conditional on Centered Propensity Score			
Lagged Score	0.835***	0.784***	0.815***	0.822***
	(0.00284)	(0.00294)	(0.00317)	(0.00338)
Pandemic year	-37.22***	-27.71***	-25.33***	-22.74***
	(2.412)	(2.408)	(2.795)	(3.035)
Pandemic year*Share of days in person	23.92***	13.84***	11.60**	11.41**
	(3.373)	(3.634)	(4.536)	(4.906)
Pandemic year*Centered propensity score	23.58***	8.907**	16.83***	19.65**
	(4.082)	(4.300)	(4.810)	(7.649)
Observations	138,378	139,262	140,129	143,337
R-squared	0.687	0.674	0.671	0.664
Average ELA Test Scores 2016-17, 2017-18, 2018-19	2519.2	2539.7	2561.7	2577.6
Standard Deviation of ELA Test Scores Control Years	97.0	96.6	101.3	100.8
Average ELA Test Scores 2020-21	2501.4	2522.5	2547.4	2565.7
Standard Deviation of ELA Test Scores 2020-21	103.5	99.5	104.8	106.1
10th Percentile Share In Person Days through April	0.414	0.397	0.414	0.414
90th Percentile Share In Person Days through April	1.000	0.964	0.933	0.933
Pandemic Effects at 10th Percentile Share In Person	-27.32	-22.17	-20.69	-18.18
Pandemic Effects at 90th Percentile Share In Person	-13.30	-14.80	-14.51	-12.09

The top panel presents the estimates of regressing Smarter Balance ELA scale test scores on two year lagged ELA scores, a dummy variable for the pandemic year, the interaction of the pandemic dummy with the share of days offered in person through April of the school year, and school fixed effects. Columns 1 through 4 present results for 5th, 6th, 7th and 8th grades, respectively. The second panel presents results of a model that also includes the propensity score from the estimates in Table 2 interacted with the pandemic dummy. The bottom panel present the average and standard deviation of ELA test scores both pre-pandemic and in 2020-21, the 10th and 90th percentiles of share of days offered in person through April, and estimates effects of the pandemic based on the estimates in panel 2 calculated at the 10th and 90th percentile share of days.

Table 10. Mathematics Test Score Effects

Controls	(1) Grade 5	(2) Grade 6	(3) Grade 7	(4) Grade 8
	No Propensity Score			
Lagged Score	0.888***	1.032***	0.996***	0.928***
	(0.00435)	(0.00422)	(0.00512)	(0.00711)
Pandemic year	-56.26***	-60.33***	-47.21***	-44.82***
	(2.941)	(3.279)	(3.318)	(4.028)
Pandemic year*Share of days in person	31.80***	28.63***	18.54***	12.91**
	(4.062)	(4.903)	(5.185)	(5.963)
Observations	137,887	138,486	138,971	141,927
R-squared	0.734	0.754	0.750	0.744
	Conditional on Centered Propensity Score			
Lagged Score	0.888***	1.032***	0.996***	0.928***
	(0.00433)	(0.00421)	(0.00512)	(0.00711)
Pandemic year	-53.49***	-59.25***	-46.41***	-43.50***
	(2.781)	(3.238)	(3.103)	(3.756)
Pandemic year*Share of days in person	26.92***	26.65***	17.04***	10.36*
	(3.855)	(4.757)	(4.916)	(5.554)
Pandemic year*Centered propensity score	24.37***	12.47***	7.825	16.19**
	(4.991)	(4.276)	(6.352)	(7.812)
Observations	137,887	138,486	138,971	141,927
R-squared	0.735	0.754	0.750	0.744
Average of Math Test Scores 2018-19	2512.3	2532.2	2547.7	2561.7
Standard Deviation of Math Test Scores 2018-19	91.7	105.2	111.4	119.6
Average of Math Test Scores 2020-21	2487.1	2504.1	2529.3	2539.7
Standard Deviation of Math Test Scores 2020-21	96.4	109.3	109.6	119.7
10th Percentile Share of In Person Days through April	0.414	0.400	0.414	0.414
90th Percentile Share of In Person Days through April	1.000	0.964	0.933	0.933
Pandemic Effects at 10th Percentile Share In Person	-42.35	-48.59	-39.59	-39.36
Pandemic Effects at 90th Percentile Share In Person	-26.57	-34.39	-30.51	-33.83

The top panel presents the estimates of regressing Smarter Balance Math scale test scores on two year lagged Math scores, a dummy variable for the pandemic year, the interaction of the pandemic dummy with the share of days offered in person through April of the school year, and school fixed effects. Columns 1 through 4 present results for 5th, 6th, 7th and 8th grades, respectively. The second panel presents results of a model that also includes the propensity score from the estimates in Table 2 interacted with the pandemic dummy. The bottom panel present the average and standard deviation of ELA test scores both pre-pandemic and in 2020-21, the 10th and 90th percentiles of share of days offered in person through April, and estimated effects of the pandemic based on the estimates in panel 2 calculated at the 10th and 90th percentile share of days.

Table 11. SAT Test Scores 11th Grade

	(1)	(2)	(3)	(4)
	w/out Score		w/ Score	
VARIABLES	ELA	Math	ELA	Math
Lagged Score	0.796***	0.759***	0.796***	0.759***
	(0.00719)	(0.0102)	(0.00719)	(0.0102)
Pandemic year	-15.47***	-24.72***	-15.70***	-24.89***
	(2.718)	(2.838)	(2.710)	(2.836)
Pandemic year*Share of days in person	-4.711	-2.925	-4.336	-2.653
	(5.036)	(5.327)	(5.031)	(5.325)
Pandemic year*Centered propensity score			16.87	13.23
			(11.00)	(10.90)
Observations	93,322	93,163	93,322	93,163
R-squared	0.661	0.717	0.661	0.717

Columns 1 and 2 present the estimates of regressing SAT ELA and Math scale test scores on three year lagged 8th grade Smarter Balance ELA and Math scale scores, a dummy variable for the pandemic year, the interaction of the pandemic dummy with the share of days offered in person through April of the school year, and school fixed effects. Columns 3 and 4 present these estimates after includinf the propensity score from the estimates in Table 2 interacted with the pandemic dummy.

Table 12. English Language Arts Test Score Effects

Controls	(1) Grade 5	(2) Grade 6	(3) Grade 7	(4) Grade 8
	No Propensity Score			
Lagged Score	0.835***	0.784***	0.815***	0.822***
	(0.00286)	(0.00295)	(0.00317)	(0.00338)
Pandemic year*Share high need students	-30.36**	-37.46***	-18.91	-30.77**
	(11.80)	(11.32)	(11.61)	(15.15)
Pandemic year*Share high need students*	14.73	44.99***	17.05	28.78
In Person learning option	(16.02)	(16.40)	(18.65)	(22.71)
Observations	138,378	139,262	140,129	143,337
R-squared	0.687	0.674	0.671	0.664
	Conditional on Centered Propensity Score			
Lagged Score	0.835***	0.784***	0.815***	0.822***
	(0.00285)	(0.00294)	(0.00317)	(0.00338)
Pandemic year*Share high need students	-19.66*	-33.46***	-1.860	-18.31
	(11.87)	(10.58)	(12.76)	(15.03)
Pandemic year*Share high need students*	6.962	41.55***	2.425	18.78
In Person learning option	(15.52)	(15.33)	(18.61)	(21.68)
Pandemic year*Centered propensity score	12.89***	3.968	16.56***	14.82*
	(4.672)	(4.716)	(5.785)	(8.924)
Observations	138,378	139,262	140,129	143,337
R-squared	0.687	0.674	0.671	0.664
25th Percentile High Needs				
Pandemic Effects 10 Percentile In-Person	-21.68	-16.53	-20.40	-14.79
Pandemic Effects 90th Percentile In-Person	-11.46	-16.44	-14.62	-12.39
In Person Option Interaction Significance	***		*	
75th Percentile High Needs				
Pandemic Effects 10 Percentile In-Person	-30.00	-24.81	-20.80	-19.378
Pandemic Effects 90th Percentile In-Person	-17.76	-13.82	-14.44	-12.72
In Person Option Interaction Significance	***	***	**	**

The top panel presents the estimates of regressing Smarter Balance ELA scale test scores on two year lagged ELA scores, a dummy variable for the pandemic year, the interaction of the pandemic dummy with the share of days offered in person through April, the interaction of the pandemic dummy with school share of high needs students, the three way interaction between pandemic-share in person-share high needs, and school fixed effects. Columns 1 through 4 present results for 5th, 6th, 7th and 8th grades, respectively. The second panel presents results of a model that also includes the propensity score from the estimates in Table 2 interacted with the pandemic dummy. The bottom panel presents estimated effects of the pandemic on attendance based on the estimates in panel 2, seperately for the 10th and 90th percentiles of share of days offered in person for both the 25th and 75th percentiles of school share of high needs students. The bottom rows under 25th and 75th percentiles share high needs represents the statistical significance of the share of days interaction with the pandemic dummy when share high needs has been centered to take a value of zero at the 25th and 75th percentiles, respectively.

Table 13. English Language Arts Test Score Effects

Controls	(1) Grade 5	(2) Grade 6	(3) Grade 7	(4) Grade 8
	No Propensity Score			
Lagged Score	0.888***	1.032***	0.996***	0.928***
	(0.00435)	(0.00422)	(0.00513)	(0.00712)
Pandemic year*Share high need students	-6.163	-15.05	3.193	-15.64
	(15.10)	(13.92)	(16.23)	(20.12)
Pandemic year*Share high need students*	-14.05	14.57	9.914	36.90
In Person learning option	(20.44)	(19.97)	(25.86)	(29.50)
Observations	137,887	138,486	138,971	141,927
R-squared	0.735	0.754	0.750	0.744
	Conditional on Centered Propensity Score			
Lagged Score	0.887***	1.032***	0.996***	0.928***
	(0.00434)	(0.00421)	(0.00513)	(0.00712)
Pandemic year*Share high need students	10.70	-2.801	19.72	6.628
	(13.39)	(14.26)	(13.92)	(16.82)
Pandemic year*Share high need students*	-26.30	3.944	-4.301	18.83
In Person learning option	(17.90)	(19.50)	(22.81)	(25.14)
Pandemic year*Centered propensity score	20.30***	12.17**	16.06**	26.45***
	(6.110)	(4.850)	(6.926)	(8.119)
Observations	137,887	138,486	138,971	141,927
R-squared	0.735	0.754	0.750	0.744
25th Percentile High Needs				
Pandemic Effects 10 Percentile In-Person	-42.64	-48.16	-54.06	-43.17
Pandemic Effects 90th Percentile In-Person	-23.76	-34.58	-32.61	-37.86
	***	***	***	
75th Percentile High Needs				
Pandemic Effects 10 Percentile In-Person	-42.73	-48.77	-45.15	-37.14
Pandemic Effects 90th Percentile In-Person	-31.44	-34.15	-25.51	-27.55
In Person Option Interaction Significance	***	***	**	**

The top panel presents the estimates of regressing Smarter Balance Math scale test scores on two year lagged Math scores, a dummy variable for the pandemic year, the interaction of the pandemic dummy with the share of days offered in person through April, the interaction of the pandemic dummy with school share of high needs students, the three way interaction between pandemic-share in person-share high needs, and school fixed effects. Columns 1 through 4 present results for 5th, 6th, 7th and 8th grades, respectively. The second panel presents results of a model that also includes the propensity score from the estimates in Table 2 interacted with the pandemic dummy. The bottom panel presents estimated effects of the pandemic on attendance based on the estimates in panel 2, seperately for the 10th and 90th percentiles of share of days offered in person for both the 25th and 75th percentiles of school share of high needs students. The bottom rows under 25th and 75th percentiles shares high needs represents the statistical significance of the share of days in person with the pandemic dummy when share high needs has been centered to take a value of zero at the 25th and 75th percentiles, respectively.

Table 13. Falsification Tests for Attendance Two Year Lag

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Controls	2nd Grade	3rd Grade	4th Grade	5th Grade	6th Grade	7th Grade	8th Grade	9th Grade	10th Grade	11th Grade	12th Grade
Lagged Attendance	0.364***	0.461***	0.465***	0.494***	0.532***	0.609***	0.588***	0.663***	0.587***	0.611***	0.489***
	(0.0170)	(0.0120)	(0.0154)	(0.0145)	(0.0181)	(0.0167)	(0.0220)	(0.0262)	(0.0204)	(0.0224)	(0.0483)
Pandemic year	-0.00160	-0.000453	-0.00258*	5.85e-05	-0.00120	-0.00224	-0.00151	0.00580	0.00546	0.00343	0.00450
	(0.00148)	(0.00150)	(0.00149)	(0.00164)	(0.00172)	(0.00186)	(0.00221)	(0.00554)	(0.00378)	(0.00429)	(0.00481)
Pandemic year*Share of days	-0.000773	-0.00301	0.000516	-0.00200	-0.000834	0.000983	-0.000105	-0.0120	-0.0113*	-0.00651	-0.0118
in person	(0.00192)	(0.00200)	(0.00205)	(0.00222)	(0.00269)	(0.00263)	(0.00328)	(0.00994)	(0.00653)	(0.00663)	(0.00751)
Pandemic year*Centered	0.00304	0.00975***	0.00165	-0.00405	0.00195	0.00746**	0.00927*	0.0168	0.0468	0.0144	0.0399
propensity score	(0.00247)	(0.00288)	(0.00410)	(0.00424)	(0.00334)	(0.00362)	(0.00506)	(0.0218)	(0.0327)	(0.0219)	(0.0397)
Observations	66,937	69,156	71,713	72,100	73,885	74,074	76,164	74,989	75,504	74,989	73,482
R-squared	0.251	0.286	0.278	0.280	0.274	0.283	0.280	0.375	0.333	0.302	0.258

The table presents the estimates of regressing student annual attendance rates on two year lagged student attendance rates, a dummy variable for a false pandemic year associated with 2018-19, the interaction of the false pandemic dummy with the share of days offered in person during the actual pandemic school year, the propensity score from the estimates in Table 2 interacted with the pandemic dummy, and school fixed effects. The samples contains students from 2018-19 and 2014-15 through 2016-17. Columns present results seperately by grade from 2nd to 12th grade.

Table 15. Falsification Tests for Test Scores

Controls	(1) Grade 5	(2) Grade 6	(3) Grade 7	(4) Grade 8
	ELA Smarter Balance			
Lagged Score	0.843***	0.790***	0.822***	0.838***
	(0.00352)	(0.00343)	(0.00373)	(0.00413)
Pandemic year	5.824**	1.774	6.530**	9.203***
	(2.558)	(2.365)	(2.548)	(2.946)
Pandemic year*Share of days in person	3.935	4.424	0.595	-2.272
	(3.652)	(3.532)	(4.127)	(4.193)
Pandemic year*Centered propensity score	-14.38***	-2.357	-13.22***	-1.024
	(5.048)	(3.635)	(4.038)	(5.692)
Observations	69,817	71,439	71,369	72,855
R-squared	0.695	0.679	0.683	0.670
	Math Smarter Balance			
Lagged Score	0.900***	1.040***	1.011***	0.941***
	(0.00496)	(0.00507)	(0.00526)	(0.00753)
Pandemic year	-7.131**	-7.640**	-6.306**	-7.019*
	(3.106)	(3.424)	(2.886)	(3.712)
Pandemic year*Share of days in person	7.505*	-0.469	2.077	-1.322
	(4.258)	(5.173)	(4.317)	(5.562)
Pandemic year*Centered propensity score	-6.766	1.332	-2.562	-3.791
	(5.604)	(5.436)	(4.299)	(6.411)
Observations	69,831	71,368	71,191	72,620
R-squared	0.739	0.758	0.760	0.749

The table presents the estimates of regressing Smarter Balance ELA (Panel 1) and Math (Panel 2) scale test scores on two year lagged test scores, a dummy variable for a false pandemic year associated with 2018-19, the interaction of the false pandemic dummy with the share of days offered in person through April, the propensity score from the estimates in Table 2 interacted with the pandemic dummy and school fixed effects. The samples contains students from 2018-19 and 2014-15 through 2016-17. Columns present results seperately by grade from 5nd through 8th grade.