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The Effects of Absenteeism on Cognitive and Social-Emotional Outcomes: Lessons for COVID-19

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In March 2020, most schools in the United States closed their doors and transitioned to distance learning in an effort to contain COVID-19. During the transition a significant number of students did not fully engage in these learning opportunities due to resource or other constraints. An urgent question for schools around the nation is how much did the pandemic impact student academic and social-emotional development. This paper uses administrative panel data from California to approximate the impact of the pandemic by analyzing how absenteeism affects student outcomes. We show wide variation in absenteeism impacts on academic and social-emotional outcomes by grade and subgroup, as well as the cumulative effect of different degrees of absence. Student outcomes generally suffer more from absenteeism in mathematics than in ELA. Negative effects are larger in middle school. Absences negatively affect social emotional development, particularly in middle school, with slight differences across constructs. Our results add to the emerging literature on the impact of COVID-19 and highlight the need for student academic and socialemotional support to make up for lost time.

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The Effects of Absenteeism on Cognitive and Social-Emotional Outcomes: Lessons for COVID-19[1]

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ABSTRACT

In March 2020, most schools in the United States closed their doors and transitioned to distance learning in an effort to contain COVID-19. During the transition a significant number of students did not fully engage in these learning opportunities due to resource or other constraints. An urgent question for schools around the nation is how much did the pandemic impact student academic and social-emotional development. This paper uses administrative panel data from California to approximate the impact of the pandemic by analyzing how absenteeism affects student outcomes. We show wide variation in absenteeism impacts on academic and social-emotional outcomes by grade and subgroup, as well as the cumulative effect of different degrees of absence. Student outcomes generally suffer more from absenteeism in mathematics than in ELA. Negative effects are larger in middle school. Absences negatively affect social-emotional development, particularly in middle school, with slight differences across constructs. Our results add to the emerging literature on the impact of COVID-19 and highlight the need for student academic and social-emotional support to make up for lost time.

[1] We are grateful to the six CORE districts who provided data for this study through the PACE/CORE Research Partnership. Our deep thanks go to Heather Hough and Joe Witte at PACE for facilitating the data needed and answering our multiple questions throughout the duration of this research and for their continued support of this work. Dave Calhoun at CORE facilitated interactions with districts that helped improve this study. Thank you to Libby Pier at Education Analytics and Jose Felipe Martinez for answering questions related to SEL and test scores. We are grateful to Clemence Darriet for research assistance. All errors remain our own. Corresponding author: lsantibanez@ucla.edu.

Introduction

In March 2020, the COVID-19 pandemic forced schools around the nation to close physical campuses and shift to distance learning. The pandemic exposed deep cracks in our education system, with low-poverty schools and students transitioning to online participation quickly and students of color in high poverty schools and English Learners lagging behind (Burke, 2020; Hamilton et al., 2020; Umansky, 2020). A nationally representative survey of teachers conducted by the EdWeek Research Center found that in May 2020, 23 percent of students were considered "truant" (i.e., not logging into any online work, not making contact with teacher, etc.) and close to 45 percent of teachers reported students had "much lower" levels of engagement with schoolwork than before the pandemic.[2] A report by the Los Angeles Unified School District, the 2nd largest district in the country, found that participation in online learning of middle and high school students between March 16 and May 22, 2020 never reached 100 percent and was lower for students in particular subgroups such as low income, English Learners, students with disabilities, and homeless and foster youth (Besecker, Thomas & Daley, 2020).

When schools closed in March 2020, it is safe to assume students were mostly absent at least in the first week or two immediately following the closures (Kuhfeld et al., 2020). This would put most students above average absenteeism levels for regular school years. Students who were consistently absent from March through June, would have missed 10 weeks of school (50 days) putting them at the far end of the normal absenteeism spectrum. The analysis presented here gives some indication of the negative impact absences would have on both academic and social-emotional learning outcomes. These estimates shed further light on the potential learning

[2] EdWeek Research Center Survey. Last update: June 2, 2020. Available: https://www.edweek.org/ew/articles/2020/04/27/survey-tracker-k-12-coronavirus-response.html

and social-emotional costs if students continue to be absent from school for long periods in 2020/21 due to the challenging circumstances posed by the COVID-19 pandemic.

Given the deep inequalities present in our school systems, an increasingly urgent question for schools around the nation is how much learning has been lost due to the COVID-19 pandemic? And how are different student subgroups affected by this? Are students in the earlier grades losing more ground than students in middle and high school? And, also importantly, how is the social-emotional development of students affected by their absence from school?

Although no data currently exist that can directly answer these questions, we can learn from recent past experience with absenteeism to gauge what the impact will be. Our study uses administrative panel data from six large school districts in California to analyze the effects of absenteeism in the recent past. We use data from 2014/15 to 2107/18 for students in grades 3-12 to understand (1) the average patterns of absenteeism occurring during regular school years for all students and by subgroup? And (2) the impact on test scores and social-emotional learning outcomes of being away from school for all students and by subgroup.

Our paper makes several key contributions beyond prior literature on this topic. First, we investigate the impact of absenteeism on both academic and social-emotional outcomes. Second, we estimate results for a large span of grades, allowing us to see how patterns related to absenteeism change across K-12 experience. Third, we drill down to results for four vulnerable student subgroups who may experience the effects of the pandemic in different ways: English Learners, students with disabilities, low-income students, and homeless/foster youth. Fourth, we have data from six of the largest, most diverse districts in the most populous US state. Last, our four-year student-level panel allows us to control for unobserved attributes of students that could bias the relationship between absenteeism and outcomes.

Our findings indicate that absenteeism hurts both academic and social-emotional outcomes with variation by grade and subgroup, as well as in the cumulative effect of different degrees of absence. Students generally suffer more from absenteeism in mathematics than in English Language Arts (ELA), and experience larger negative effects on academic outcomes in middle school than in elementary grades. With regard to social-emotional development, absenteeism appears to have the greatest negative impact on social awareness and self-efficacy, and the negative impact is most pronounced in middle school.

Previous Literature

Effects of Absenteeism on Test Scores

It is well established in the literature that absenteeism negatively impacts academic outcomes. Using data from elementary students in North Carolina, Aucejo and Romano (2016) find that being absent for 10 days from school would reduce test scores by about 0.03 SD in ELA and 0.06 SD in mathematics. The negative impact is greater in upper elementary grades (4th and 5th) than in 3rd grade and larger for low-performing versus high-performing students. In mathematics, the detrimental effects of absences in one school year can persist into subsequent grades, suggesting that absences today can have lasting consequences. Other studies have also found that absences impact mathematics more than ELA (Gottfried 2009; Gottfried, 2011; Gottfried, 2014) and later grades more than earlier grades (Gershenson, Jacknowitz & Brannegan, 2017). Liu, Lee and Gershenson (2020) use a high school student panel covering 2002/03 to 2012/13 in one large California school district and find that missing 10 mathematics classes in the spring semester reduces mathematics test scores by about 0.07 SD, math course grades by 0.19 SD, and the probability of on-time graduation by 0.08 SD. Results are similar for ELA outcomes. To account for time-varying classroom influences that could bias the relationship between absenteeism and outcomes, they use class period-level absences and control for absences in another subject (i.e., ELA or mathematics). The coefficient on spring semester absences in their student fixed effects model change only slightly when absences in another subject (class period) are added as a control. Importantly, they find that teacher and subject preferences are relatively stable across years and do not significantly bias the relationship between attendance and student outcomes.

Kuhfeld et al. (2020) estimate typical summer learning loss to project the impact of COVID-19 using a national sample of students in grades 3-7 who took MAP Growth assessments between 2017/18 and 2018/19. Assuming that students lost the three months (about 60 instructional days) immediately following school closures in March, the authors project students could lose 32-27 percent of the expected yearly learning gains in ELA and 63-50 percent in mathematics when they come back in the fall of 2020. Effects vary across student proficiency categories, with the most significant losses concentrated among students at low proficiency levels. One advantage of our study over studies like this is that we use absences during the school year to predict academic losses. When students are absent for extended periods during the year, teachers provide homework and supplemental lesson materials. While these instructional efforts may not be as intensive as those that have been exerted during the pandemic, they do mitigate learning losses due to absence in ways that are more relevant to the current COVID-19 situation than summer learning loss.

Effects of Absenteeism on Social-Emotional Learning Outcomes

Social-emotional learning (SEL) skills, such as self-efficacy, self-management, and growth mindset, have been found in the literature to be correlated with academic outcomes (e.g., Claro, Paunesku & Dweck, 2016; Usher & Pajares, 2009; West et al., 2018b). Recent work using

Project CORE data suggests that when social-emotional learning outcomes improve, so do test scores and behavioral outcomes—this is true across student subgroups and regardless of the baseline level of social-emotional learning (Kanopka et al., 2020).

Only a handful of quantitative studies have tried to estimate the effect of being absent from school on social-emotional learning outcomes. Gottfried (2014) finds that chronic absenteeism reduces educational and social engagement for kindergartners. West et al. (2018a), using two years of survey data from CORE districts find that students in grades 4-12 with low ratings on growth management, self-awareness, self-efficacy and self-management miss more school. They find the strongest negative associations with absences for self-management and self-efficacy.

Data and Methods

This study uses rich longitudinal student-level data from the CORE districts—a group of the largest districts in California who formed a collaborative organization in 2010 to cooperate in efforts to implement new academic standards, improve training for teachers and administrators, and pool data.[3] We use CORE data from six districts to estimate the impact of absenteeism on academic outcomes and four districts to estimate the impact on social-emotional outcomes.[4] The total number of student-year observations in our analyses is over 1.3 million, representing close to 600,000 individual students. We use four years of data from 2014/15 through 2017/18.

Outcome Data

[3] See http://coredistricts.org/about-us/, accessed on 9/18/20.
[4] Two of the six districts used in the academic outcome analysis did not collect SEL data over the period of our study.

The achievement variables are composed of vertically-scaled test scores on the Smarter Balanced Assessments (SBAC) in ELA and mathematics. These tests are available for grades 3-8 and grade 11. Grades earlier than 3rd grade and grades 9, 10, and 12 are not tested.

Social-emotional data come from CORE surveys of students. The data provide scale scores generated from survey items using a generalized partial credit model (GPCM)[5] measuring the following constructs: (1) *Self-management*, the ability to regulate one's emotions, thoughts, and behaviors effectively in different situations, (2) *Growth mindset*, the belief that one's intelligence is malleable and can grow with effort, (3) *Self-efficacy*, the belief in one's own ability to succeed in achieving an outcome or reaching a goal, and (4) *Social awareness*, the ability to take the perspective of and empathize with others from diverse backgrounds and cultures, to understand social and ethical norms for behavior, and to recognize family, school, and community resources and support (Hough, Kalogrides & Loeb, 2017). A validation study found the CORE-generated SEL constructs to have high structural validity, and high reliability in most of the factors (Meyer, Wang & Rice, 2018).[6] Scaled SEL scores range from 5.5 to 4.6 depending on the construct, but we standardize all scaled scores to a mean of zero and standard deviation of 1 by school year and by construct.[7] Table A1 in the online appendix contains descriptive statistics on all variables used in our analyses.

Student Characteristics / Designations / Behaviors

Data available for each student for every school year include: days attended, days enrolled, grade attended, race/ethnicity, gender, English Learner (EL) designation, disability

[5] The construct developers at Education Analytics recommend using the GPCM scale scores provided for the type of analyses we conduct (Education Analytics, 2018; Meyer, Wang & Rice, 2018).
[6] The sole exception was the Growth Mindset factor, which had low reliability in grade 4.
[7] Loeb et al., (2019) and West et al. (2018a) standardize the scale scores for ease of interpretability, thus we follow this procedure.

status (SWD), whether student is a homeless or foster youth (HL/FST), income proxied by free and reduced-price lunch (FRPL), behaviors (i.e., suspensions or expulsions during the school year), and enrollment patterns related to school changes.

Methods

Studying the impact of absenteeism on student outcomes is challenging because of unobserved factors that could be associated with both absenteeism and student outcomes. If not accounted for, these unobserved factors could bias estimates of the impact of absenteeism on outcomes. To mitigate this potential source of bias, we use a student fixed effect model that essentially uses each student as their own control.[8] Such models control for time invariant qualities of individuals–fixed traits or some persistent degree of ability–that could be important sources of bias. Our independent variable of interest—days absent—varies almost yearly within students in the panel, making fixed effects ideally suited to the analysis. A limitation to student fixed effects is that they do not control for *time-varying* unobserved nonrandom student-specific variation that may contribute to both the outcome variables and absenteeism simultaneously. For example, students might have family problems during a given year, causing absenteeism to go up and outcomes to go down. If students dislike a particular teacher or subject, this would reveal a time-varying influence on absenteeism that is difficult to observe. This latter potential source of bias seems less of a threat since, as mentioned earlier, Liu, Lee and Gershenson (2020) did not find evidence of teacher- or subject-specific unobserved effects on absenteeism.

Our data allow us to control for several time-varying factors that could be potential time-varying sources of bias. We include the number of suspensions and expulsions a student has in a given year, which both controls for some involuntary sources of absenteeism and indicates

[8] This is equivalent to adding an indicator variable for each student.

problems that manifest in disciplinary behaviors. We also include an indicator for whether or not the student experienced a change of schools during the course of the year or in the prior summer, which allows us to control for absences due to adjustment issues or potential underlying factors that caused the school move (e.g., a change in residence, family divorce). We also include program designations such as EL or SWD that vary over time.

Equation (1) presents the basic model we estimate in this paper.

$$Y_{it} = Abs_{it}\beta_1 + Abs_{it}^2\beta_2 + Enr_{it}\beta_3 + X_{it} + G_{it} + \tau_t + \gamma_i + \varepsilon_{it} \qquad \text{(Eq. 1).}$$

In this model, Abs_{it} are the number of days student *i* was absent at time (year) *t*. We allow a squared term to pick up nonlinear relationships with absenteeism at different levels. Enr_{it} are the number of days student *i* was enrolled at time (year) *t*. X_{it} are time-varying student-level characteristics (i.e., number of suspensions or expulsions, whether the student changed schools that year, and program designations). G_{it} is a grade-level indicator. τ_t is a time (year-level) indicator. The student fixed effect is denoted by γ_i. To understand the effects of days absent by grade, we include two-way interactions (e.g., 5th grade * days absent). To estimate the effects of days absent from school by grade and program designation (e.g., EL status) we allow further nonlinearities in certain specifications and use three-way interactions (e.g., 5th grade * EL * days absent). Our findings lend themselves to graphical displays, which we provide. All models are estimated with robust standard errors to account for the possibility of arbitrary serial correlation and heteroskedasticity.

To check our model against other specifications, we ran models that did not include student fixed effects but did include all observable time-invariant student characteristics, time-varying variables, lagged achievement in one or both subjects, [9] and school-level fixed effects. The absenteeism coefficients from these approaches differ from those in the student fixed effects model, suggesting that the student fixed effects go one step further in eliminating sources of bias (see Table A2 in the online appendix). We are confident that the estimates from the models we present closely approximate the causal parameters. [10]

Findings

Table 1 displays descriptive patterns of absenteeism. Panel A shows that on average, students in grades K-12 are absent from school 7.4 days in a regular school year. Absences vary considerably by grade: elementary and middle school students spend about seven days away from school in a regular school year, whereas middle school and high school students are absent six and nine days on average every school year, respectively. Absences are highest for kindergarten and grades 10 through 12, with 12th graders absent an average of 10.8 days. Absenteeism rates also vary considerably by student subgroup. African-American students and those classified as SWDs, ELs, and HL/FST youth are much more likely than all students on average to be absent from school.

[Table 1 HERE]

Panel B shows that 14 percent of students are absent zero days, 65 percent are absent 1 to 10 days, 13 percent are absent 11 to 18 days per year, and 8 percent are absent 18 days or more – the level at which absenteeism is considered chronic. Chronic absence is more prevalent in

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[9] It should be noted that there is virtually no difference in the estimated effects of absenteeism when a lagged dependent variable (in one or both subjects) is included in the fixed effects model. This is because the student fixed effects model essentially takes a differencing or averaging type of approach, whereas models without student fixed effects necessitate the inclusion of lagged outcome variables. The lagged test scores convey little information beyond what is accounted for in the fixed effects.

[10] In all studies of the relationship of absenteeism to outcomes there's a potential threat of bias due to missing outcome data that is correlated with absenteeism. In this study, however, because we have a 4-year panel we have score data for the vast majority of students: 99% have at least 2 or more SBAC scores and 96% have at least 2 or more SEL scores.

grades 9-12 than in the earlier grades. About seven percent of students are absent from school 30 days or more in any given year, indicating that most chronically absent students are absent for longer periods than 18 days.

Effects of Absences on Test Scores

Results from estimating Equation (1) with test scores as outcomes are presented in Table 2 (columns 1 and 2) and Figure 1. We use only grades 3-8 in this analysis.[11] In the graphical display, what is important to note is the *slope* of the lines. The intercept for ELA and mathematics differs only because the vertically scaled SBAC scores and their means differ across the subjects—thus the distance *between* the lines is not due to a difference in absenteeism effects.

As the slopes reveal, absences have a clear negative effect on test scores. The rate of loss due to absenteeism as it accumulates is steeper for mathematics. Being away from school for 10 days results in a five percent of a standard deviation loss in ELA and an eight percent standard deviation loss in mathematics. The squared absence term is very small but statistically significant and positive and thus tends to lessen slightly the negative effect of additional days absent on test scores as absenteeism increases.

[Table 2 HERE]

[Figure 1 HERE]

Absences affect test scores differently depending on the student's grade level. Predicted effects by grade are found in Figure 2. The slopes on the grade lines are steeper (downward

[11] Eleventh grade is excluded from the analysis because in a four-year panel with no test score data between 8th and 11th grade, there are far fewer students with prior test score observations than in other grades, thus constraining the percentage of 11th grade students with longitudinal data. Moreover, there is evidence that the population of 11th graders taking the test was a more restrictive group, with higher rates of non-testing. According to Warren and Lafortune (2019), 6.2 percent of enrolled 11th grade students did not take the 2018 test compared to 2.5 percent of students in grades 3–8.

trend) in 6th, 7th and 8th grade, indicating that academic loss due to extended absences is borne more heavily by students in middle school. Effects for elementary students are noticeably flatter—indeed, even slightly positive for 3rd graders, suggesting that the ability of teachers and parents to compensate for lost schooling is greater in the early grades.

[Figure 2 HERE]

The impact of extended absences on academic achievement vary by student subgroup. Overall predicted effects for students classified as EL, FRPL, SWD, and HL/FST can be found in Figure 3. For comparison we add a category of non-vulnerable students (NONVUL) comprised of students who do not fall into any of these program designations. The negative effects of absenteeism are substantial for all students and are the most pronounced for students classified as FRPL, SWD, and HL/FST. These findings are concerning, given that in our analytic sample, 77 percent of the student population is classified as FRPL, 13 percent as SWD, and 4 percent as HL/FST.[12] ELs (18 percent of sample students) are an exception, as they are less affected even than non-vulnerable students (19 percent). It should be noted that this group includes students that are considered long-term ELs, newcomer ELs, and ELs at various points of English Language Development. More research is needed on variation within this subgroup to better understand these effects. For all subgroups, absences appear to have a more negative impact on test scores in the middle school grades relative to elementary grades (results by subgroup and grade available in the online appendix (Figure A1).

[Figure 3 HERE]

Effects of Absences on Social-Emotional Learning Outcomes

[12] These percentages closely mirror the proportions in the overall CORE student population.

To estimate the effects of absenteeism on SEL in a normal school year, we estimate Equation (1) using as outcomes the SEL scale scores in each of the four constructs standardized by year—social awareness (SA), self-efficacy (SE), self-management (SM), and growth mindset (GM). SEL scores are available for grades 4-12, and we include all of those grades in the analysis. As recommended by the construct developers and standard in this literature, we estimate this model on the subsample of students who answered at least 50 percent of the items used to generate each of the constructs (Education Analytics, 2018; West et al., 2018a).

Regression results are shown in Table 2 (columns 3-5). The coefficients on days absent for all four SEL constructs are negative and statistically significant, with very small (close to zero) positive coefficients on the squared term. As shown in Figure 4, being absent from school for 20 or more days, harms all four SEL constructs. Effects for most constructs flatten out after 40 days. However, for SA the decline is more or less linear suggesting a steeper rate of loss on this construct and the greater importance of schools in promoting social awareness.

[Figure 4 HERE]

Figure 5 shows that the SEL constructs are affected differently by absenteeism across grades. To facilitate viewing, we aggregate grades into school levels, but grade-specific results can be found in the online appendix (Figures A2-A5). All constructs are negatively affected by absenteeism. However, middle school is the level at which extended absence from school has the strongest negative impact on social-emotional development, with SE and SA having the steepest slopes. At the elementary level, the most affected constructs are SE and SM. At the high school level, the most affected construct is SA.

[Figure 5 HERE]

Absences are detrimental to all subgroups (see online appendix Figure A6). Absences harm SA and SE more or less equally across groups. Absences harm non-vulnerable students more than others in SM, and they harm non-vulnerable students and SWDs slightly more than others in GM.

Conclusion

After schools shut down in-person instruction in mid-March 2020, districts across the nation scrambled to provide various modes of distance instruction within weeks so students would lose as little learning as possible. In an effort to help assess the possible effects of being away from school during the pandemic, we estimated the impact of absenteeism on academic and social-emotional outcomes from recent pre-COVID experience. This study, using data from six large school districts in California, shows that average absenteeism is low in the regular school year: about seven days on average, although this is higher in secondary school and for certain subgroups such as homeless/foster youth and students with disabilities.

This paper adds important information to the growing evidence on the anticipated negative impact of COVID-19 on student development and its possible differential impacts by student subgroups. We show that absenteeism negatively affects student achievement, more so for mathematics than ELA and more so for middle school students than elementary students. Although all students experience the negative effects of absenteeism on academic outcomes, certain vulnerable subgroups of students—particularly low-income students, students with disabilities, and homeless and foster youth—are more subject to the negative impact than other students.

Being absent from school harms SEL skills, as well, particularly those related to social awareness, self-efficacy, and self-management and, again, more so for middle school students than others. Absences are detrimental to SEL for all subgroups, with some variation across groups.

Taken together with evidence that significant numbers of students were absent from virtual schooling opportunities for longer periods than normal during the COVID-19 pandemic (EdWeek Research Center, 2020; Hamilton et al., 2020) and that absenteeism was highest among students of color and disadvantaged groups (Besecker, Thomas & Daley, 2020), our results suggest that school disruptions brought on by the pandemic will negatively affect both the academic and social-emotional development of students, particularly for students in certain grades and vulnerable subgroups. It is increasingly evident that students will need both academic and social-emotional support to make up for lost time.

Our study raises some questions as to why these effects occur with different patterns for different groups and grades. For example, heterogeneity within certain groups such as ELs and SWDs across grades and sub-categorizations may be driving some of the differences we see. More research is needed with regard to the mechanisms by which absence from school affect students of all types so that the full effects of the pandemic or other such shocks to the school system can be better understood.

This study provides an overview of the effects of absenteeism on both academic and social-emotional development across a large span of grades and for several subgroups of students. As such, it enables districts to gauge the potential effects of absenteeism to better predict and proactively address the potential effects of COVID-19.

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Table 1. Average Days Absent per Year, By Subgroup

Panel A - Mean Days Absent by Subgroup

Grade	All	EL	FRPL	SWD	HL/FST	Latinx	White	African-American	Asian/P.I.
K	9.2	7.9	9.5	11.6	10.5	9.2	8.3	11.8	7.3
1	7.4	6.4	7.7	9.8	9.0	7.3	7.0	10.0	5.5
2	6.8	6.1	7.0	9.0	8.5	6.7	6.7	9.6	4.8
3	6.5	6.0	6.6	8.7	8.1	6.3	6.6	9.3	4.5
4	6.4	6.0	6.5	8.6	7.8	6.2	6.8	9.1	4.3
5	6.2	6.1	6.3	8.6	7.6	6.0	6.9	8.9	4.1
6	5.9	6.2	6.1	8.5	7.6	5.9	6.5	8.2	3.5
7	6.1	6.8	6.3	8.9	8.1	6.1	6.7	8.5	3.5
8	6.3	7.4	6.5	9.2	9.0	6.4	6.9	8.7	3.5
9	7.5	8.8	7.6	10.9	10.0	7.8	7.3	9.5	3.7
10	8.9	10.8	9.0	12.3	11.5	9.4	8.2	10.5	4.5
11	9.5	12.8	9.5	13.1	11.7	10.0	8.9	11.1	5.6
12	10.8	14.4	10.6	14.4	13.2	11.2	10.3	12.7	7.3
Mean	7.4	8.5	7.5	10.3	9.5	7.5	7.5	9.6	4.4
N	572,805	123,589	432,052	69,246	21,023	403,581	54,174	54,378	56,991
%		0.22	0.75	0.12	0.04	0.70	0.09	0.09	0.10

Panel B - Proportion of Students Absent, Various Levels of Absence

	Days Absent				
Grade	0	1-10	11-18	>18	>30
K	0.07	0.61	0.19	0.12	0.10
1	0.10	0.66	0.16	0.08	0.06
2	0.12	0.67	0.14	0.07	0.05
3	0.13	0.68	0.13	0.06	0.05
4	0.14	0.67	0.13	0.06	0.05
5	0.15	0.67	0.12	0.06	0.04
6	0.17	0.67	0.11	0.06	0.04
7	0.17	0.66	0.11	0.06	0.05
8	0.17	0.66	0.10	0.07	0.06
9	0.17	0.63	0.11	0.09	0.08
10	0.15	0.62	0.12	0.11	0.10
11	0.14	0.62	0.12	0.12	0.10
12	0.10	0.63	0.14	0.14	0.12
Mean	0.14	0.65	0.13	0.08	0.07

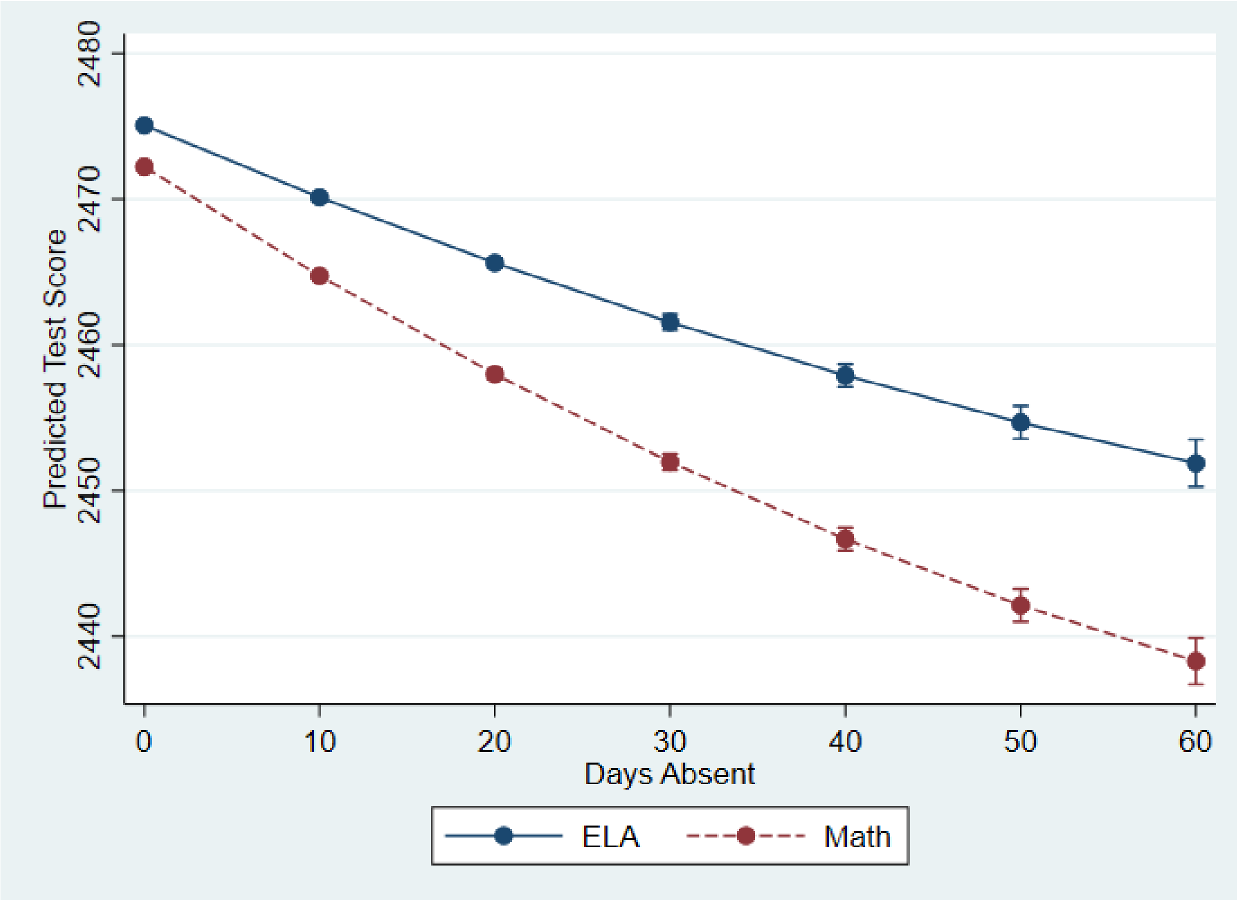
Note: Averages over 2014/15-2017/18 school years. Includes data from six CORE districts.

Table 2. Effects of Days Absent on Cognitive and Non-Cognitive Outcomes

	ELA	Math	GM	SA	SE	SM
	(1)	(2)	(3)	(4)	(5)	(6)
Days Absent	-0.515***	-0.786***	-0.003***	-0.004***	-0.005***	-0.004***
	(0.018)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)
Days Enrolled	0.047***	0.076***	0.000*	0.000***	0.000**	-0.000***
	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Days Absent Squared	0.002***	0.004***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	1,369,902	1,376,758	1,301,220	1,308,211	1,300,709	1,311,810
Num. Obs.	569,779	572,892	585,949	587,304	585,825	588,066

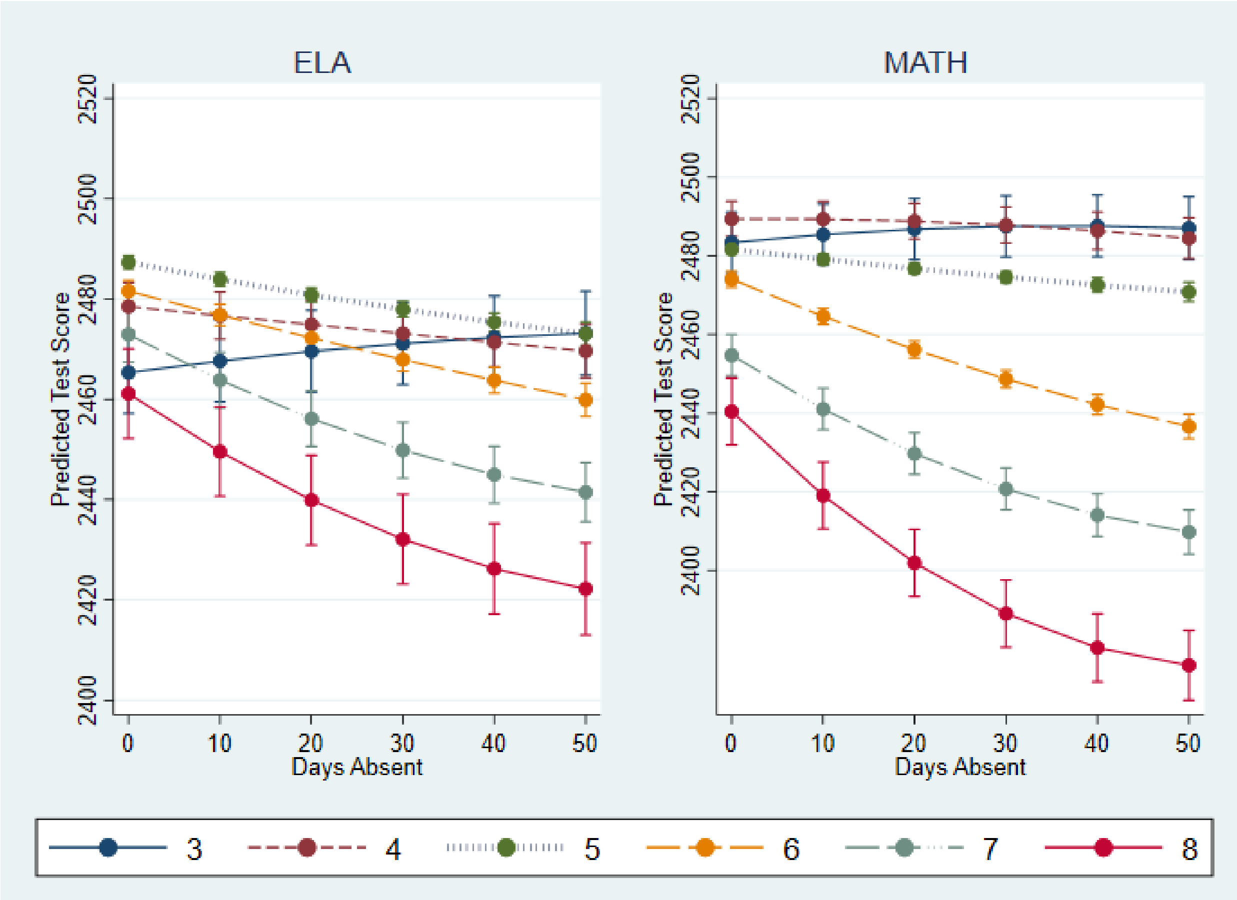
Note: Robust standard errors in parentheses. Models are estimated as shown in Equation (1). Data cover six CORE districts, for years 2014/15-2017/18.

Figure 1. Predicted Effects on Test Scores, by Different Values of Days Absent



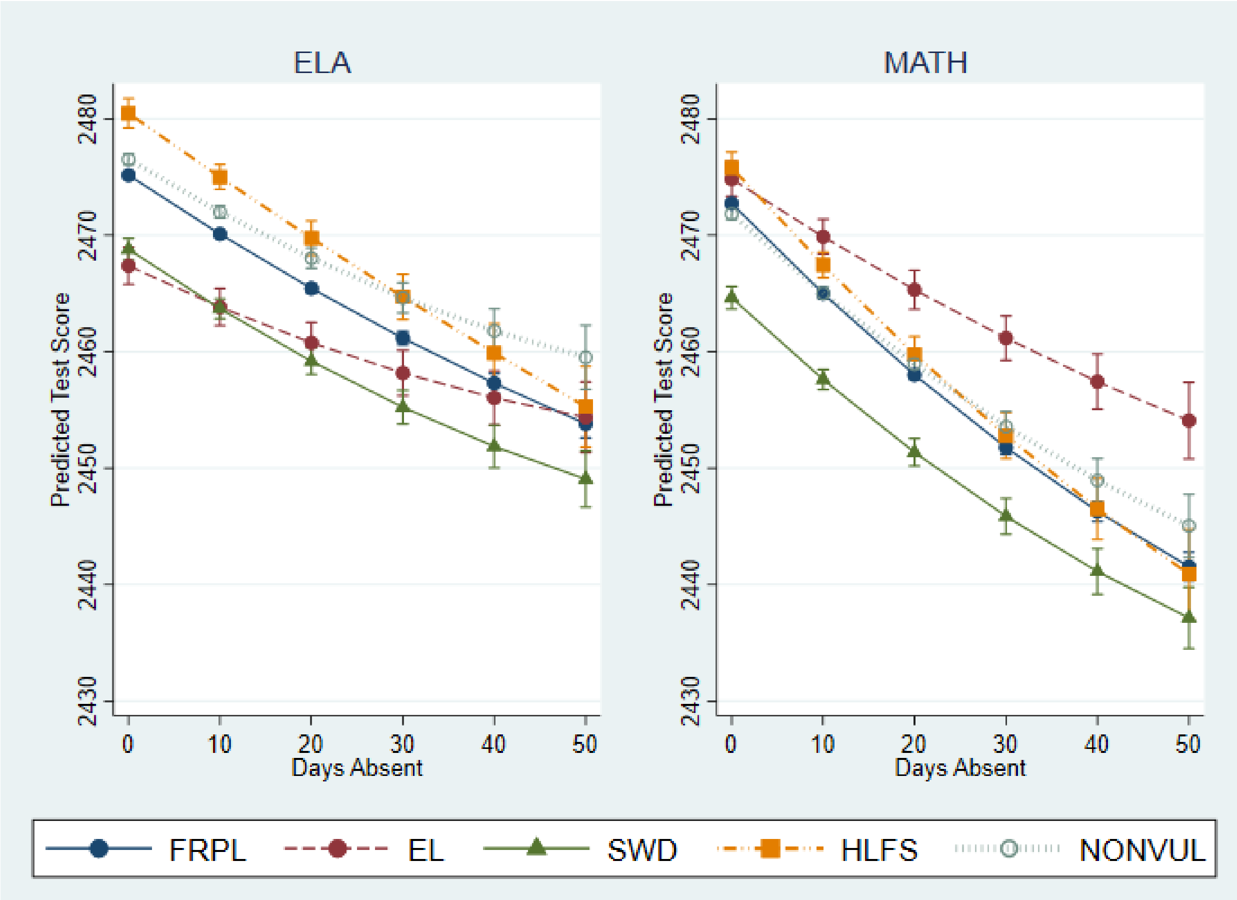
Note: Graph points represent the predicted outcome (test score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). Confidence intervals of 95% around prediction mean. Data cover six CORE districts, 2014/15-2017/18.

Figure 2. Predicted Effects of Absences on Test Scores, by Grade Level



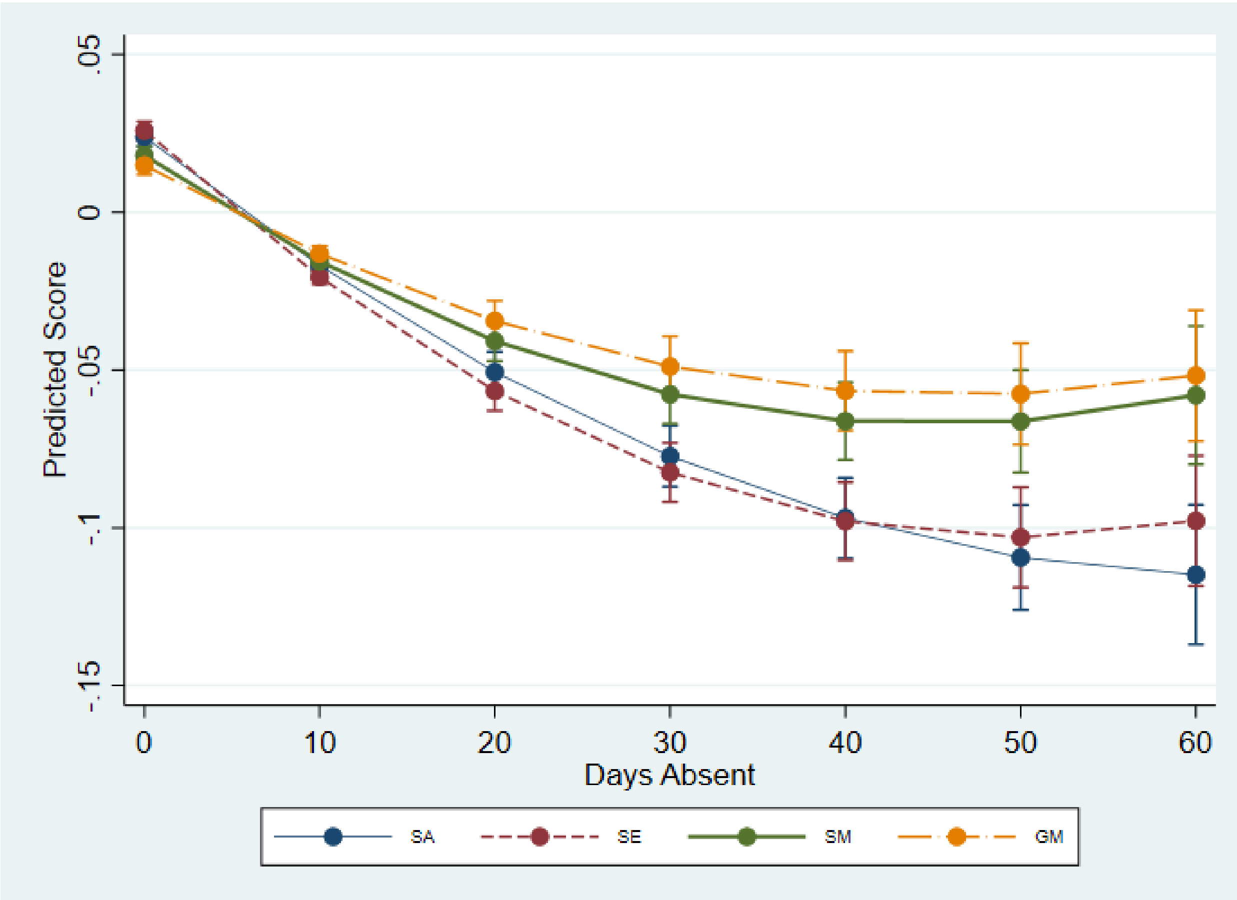
Note: Graph points represent the predicted outcome (test score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). Confidence intervals of 95% around prediction mean. Data cover six CORE districts, 2014/15-2017/18.

Figure 3. Predicted Effects of Absences on Test Scores, by Subgroup



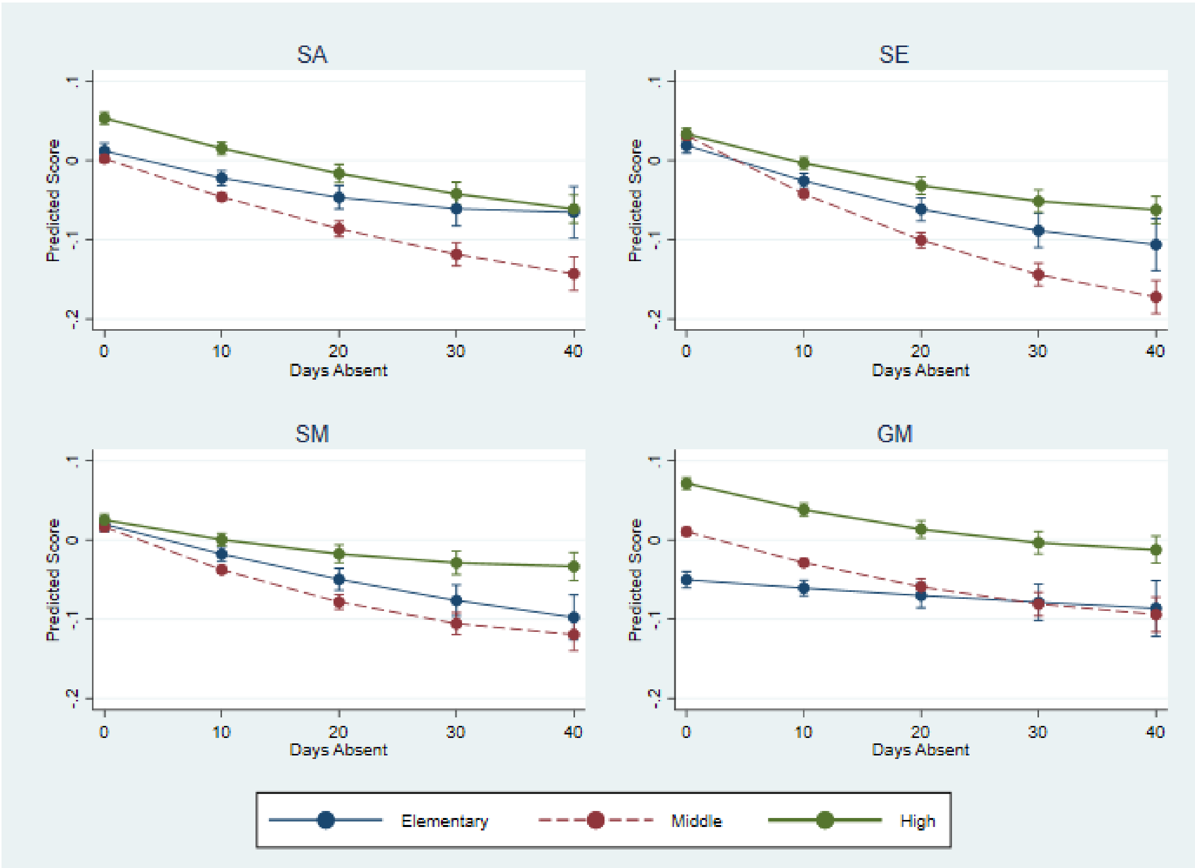
Note: Graph points represent the predicted outcome (test score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). Confidence intervals of 95% around prediction mean. Data cover six CORE districts, 2014/15-2017/18.

Figure 4. Predicted Effects on Social-Emotional Outcomes, by Different Values of Days Absent



Note: Graph points represent the predicted outcome (construct score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). Confidence intervals of 95% around prediction mean. Data cover four CORE districts, 2014/15-2017/18.

Figure 5. Predicted Effects on Social-Emotional Outcomes, by Different Values of Days Absent and School Level



Note: Graph points represent the predicted outcome (construct score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). Elementary grades include Grades 4–5. Middle grades include Grades 6–8. High school grades include Grades 9–12. Confidence intervals of 95% around prediction mean. Data cover four CORE districts, 2014/15-2017/18.

APPENDIX

Table A1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ELA Test Score (SBAC)	1,560,220	2483.84	112.45	2114	2795
Math Test Score (SBAC)	1,566,215	2475.91	108.47	2189	2862
Growth Mindset Score (std)	1,470,536	0.00	1.00	-3.6	2.5
Social Awareness Score (std)	1,477,334	0.00	1.00	-4.5	3.8
Self-Efficacy Score (std)	1,470,348	0.00	1.00	-3.6	2.1
Self Management Score (std)	1,482,136	0.00	1.00	-4.8	3.0
Student is female	3,153,310	0.49	0.50	0	1
Student receives free or reduced-price lunch (FRPL)	3,153,843	0.75	0.43	0	1
Student designated English Learner (EL)	3,059,130	0.23	0.42	0	1
Student is homeless/foster youth (HL/FST)	3,153,852	0.04	0.19	0	1
Student has a disability (SWD)	3,141,801	0.12	0.33	0	1
Student not in any vulnerability category (NONVUL)	3,197,591	0.02	0.40	0	1
Student's is Hispanic	3,153,846	0.70	0.46	0	1
Student's is African-American	3,153,846	0.09	0.29	0	1
Student's is Asian-American or Pacific-Islander American	3,153,846	0.10	0.30	0	1
Student's race is "Other"	3,153,846	0.00	0.06	0	1
Student's is White	3,153,846	0.10	0.29	0	1
Days Absent (total for school year)	3,153,852	7.41	11.09	0	182
Days Enrolled (total for school year)	3,153,852	169.45	32.27	0	200
Number of suspensions	3,153,852	0.04	0.53	0	76
Number of expulsions	3,153,852	0.00	0.09	0	20
Changed school mid-year	3,153,852	0.02	0.13	0	1
Changed school during the summer	3,153,852	0.12	0.33	0	1

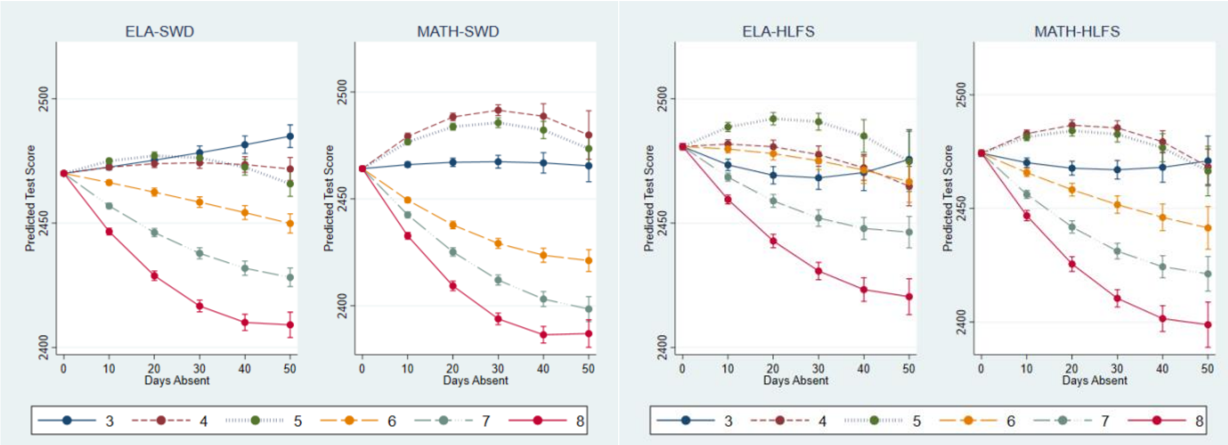
Note: Averages over 2014/15-2017/18 school years. Includes data from six CORE districts. Data are for grades 3-12.

Table 2. Robustness to Alternative Specifications

	(1) ELA	(2) Math	(3) ELA	(4) Math	(5) ELA	(6) Math
Days Absent	-0.503***	-1.091***	-0.530***	-1.090***	**-0.515*****	**-0.786*****
	(0.017)	(0.018)	(0.017)	(0.017)	**(0.018)**	**(0.018)**
Lagged achievement	x	x	x	x		
School FE			x	x		
Student FE					x	x

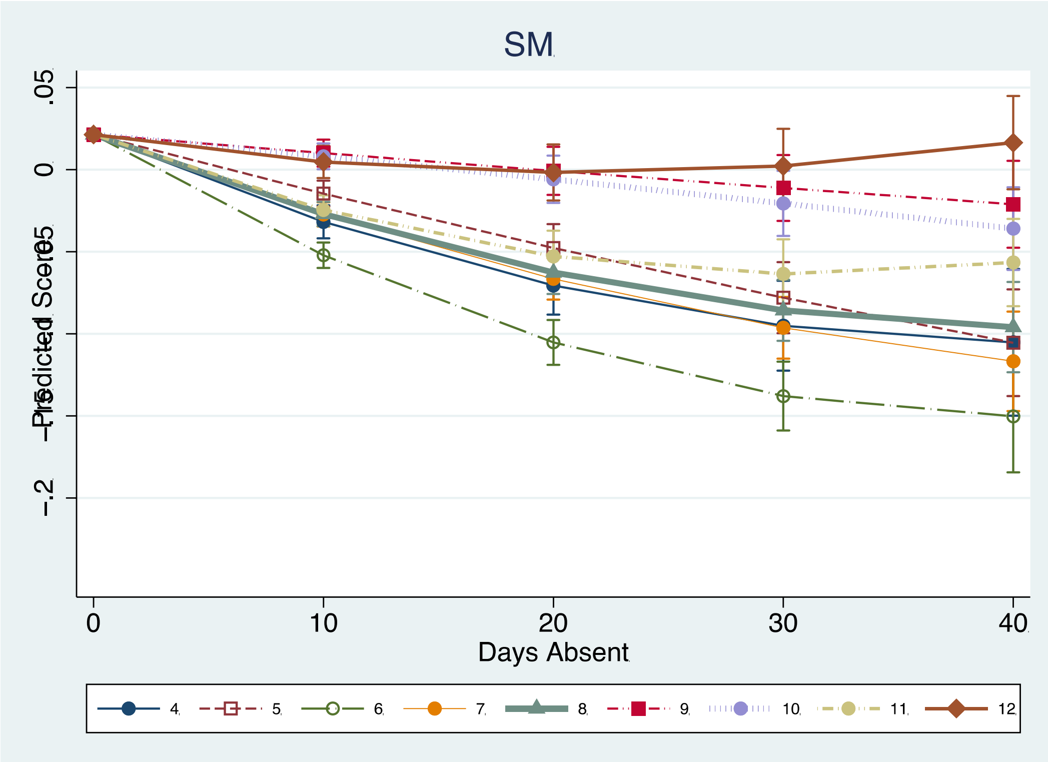
Note: Robust Standard errors in parentheses. Time varying controls include: suspensions, expulsions, change of school in mid-year or summer, and program designations (FRPL, EL, SWD, HL/FST). All models include grade dummies, year dummies, and fixed characteristics (gender, race/ethnicity). Models with lagged achievement include lags in ELA and Mathematics. Coefficients in bold represent main model – these are the coefficients reported in Table 2 of the main text.

Figure A1. Predicted Effects of Absences on Test Scores, by Subgroup and Grade



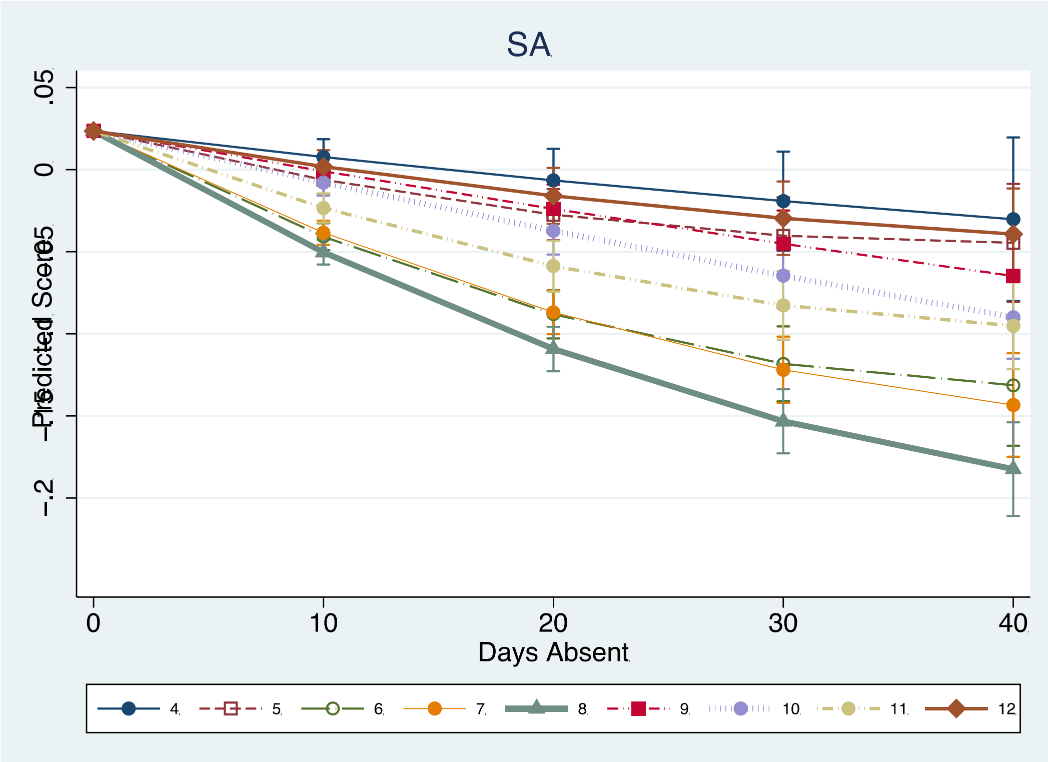
Note: Graph points represent the predicted outcome (test score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). All models include student fixed effects and a set of time-varying variables, grade- and year-dummies. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph. Data come from six CORE districts, 2013/14-2017/18.

Figure A2. Predicted Effects on Self-Management, by Grade



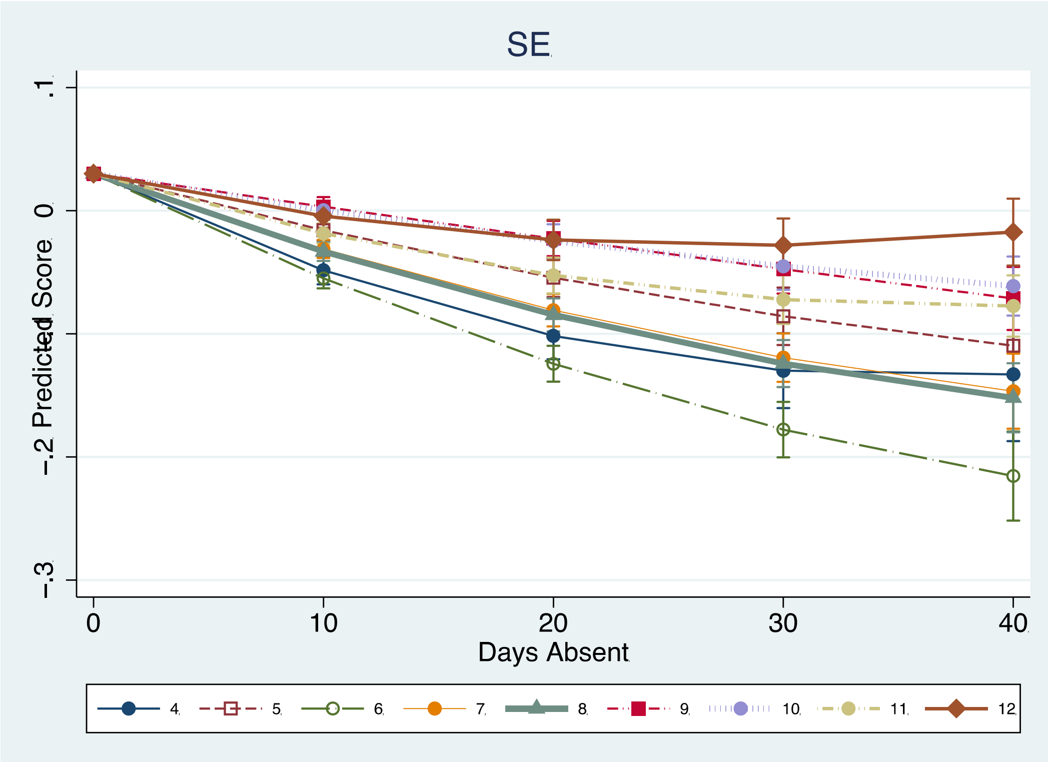
Note: Graph points represent the predicted outcome (construct score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). All models include student fixed effects and a set of time-varying variables, grade- and year-dummies. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph. Data come from four CORE districts, 2013/14-2017/18.

Figure A3. Predicted Effects on Social Awareness, by Grade



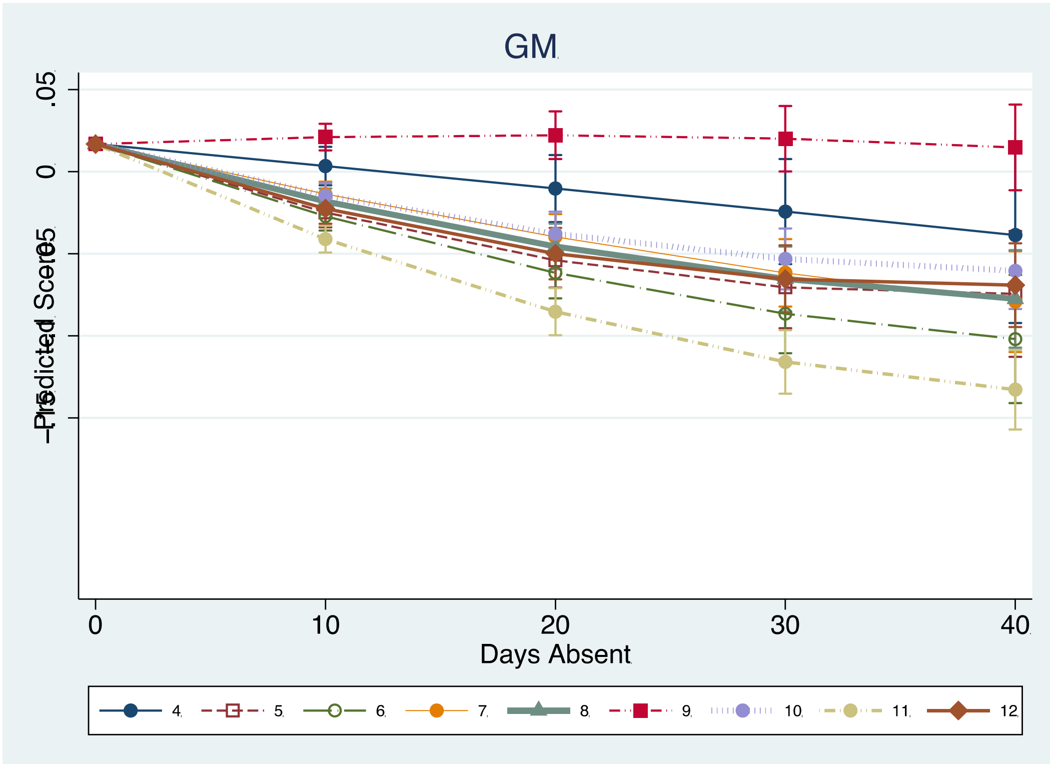
Note: Graph points represent the predicted outcome (construct score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). All models include student fixed effects and a set of time-varying variables, grade- and year-dummies. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph. Data come from four CORE districts, 2013/14-2017/18.

Figure A4. Predicted Effects on Self-Efficacy, by Grade



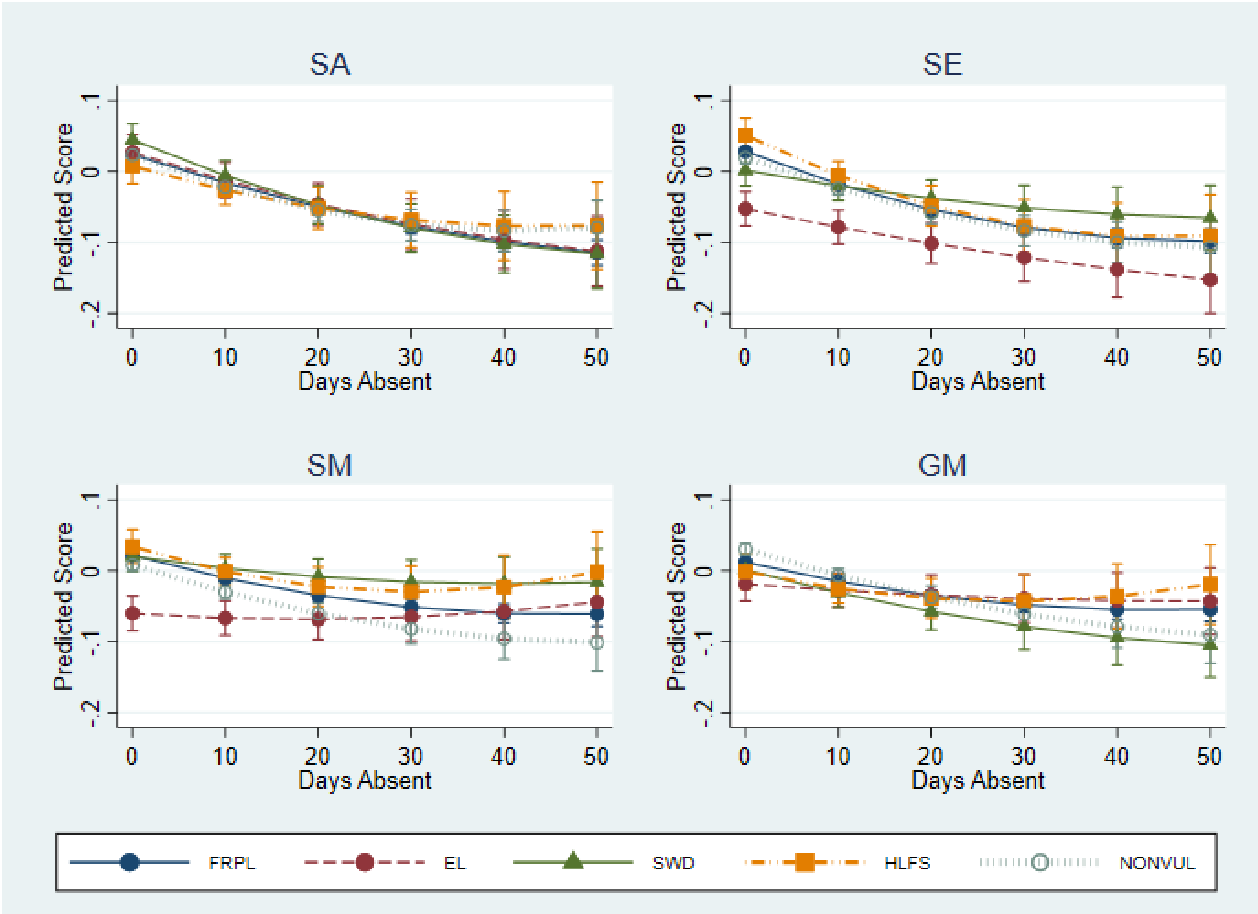
Note: Graph points represent the predicted outcome (construct score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). All models include student fixed effects and a set of time-varying variables, grade- and year-dummies. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph. Data come from four CORE districts, 2013/14-2017/18.

Figure A5. Predicted Effects on Growth Mindset, by Grade



Note: Graph points represent the predicted outcome (construct score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). All models include student fixed effects and a set of time-varying variables, grade- and year-dummies. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph. Data come from four CORE districts, 2013/14-2017/18.

Figure A6. Effects of Absenteeism on SEL Constructs by Subgroup



Note: Graph points represent the predicted outcome (construct score) for a given value of days absent (0, 10, 20, etc.) from the models estimated in Equation (1). All models include student fixed effects and a set of time-varying variables, grade- and year-dummies. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph. Data come from four CORE districts, 2013/14-2017/18.