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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 cognitive 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 and high school. Absences also negatively affect social-emotional development, 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 gains.

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

[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.

quickly, with 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]

The struggle to transition to online instruction was compounded by the demands placed on teachers and administrators in high poverty schools, which turned almost overnight into de facto social service providers: feeding students and families, helping students and families cope with mental and other health challenges, or fundraising to help the neediest cases. Children in these districts struggled with basic access to digital devices and internet connections – let alone access to safe and quiet spaces at home to focus and learn. Concerns about providing an equitable education to all students were cited as a major limitation for the provision of distance learning for over one-third of principals surveyed in a nationally representative survey conducted during May 2020 (Hamilton et al., 2020).

Given the considerable disruption caused by COVID-19 and 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? Are students in vulnerable groups such as English Learners and students with disabilities missing out on key learning opportunities which may affect their learning and

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[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

subsequent re-designation from these programs? And, also importantly, how is the social-emotional development of students affected by their absence from school?

Although no data exist that can directly answer these questions about the impact of COVID-19 on student learning and development, 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 impact of absenteeism in the recent past. We use data from 2014/15 to 2107/18 for students in grades 3-12 to understand (1) what are the average patterns of absenteeism occurring during regular school years for all students and by subgroup? And (2) what is the impact on test scores and social-emotional learning outcomes of being away from school for all students and by subgroup? Answers to the first question help set guides for what constitutes normal absenteeism levels (so that any changes during the pandemic can be compared to these trends). Answers to the second question can help policymakers and school officials understand whether certain groups are more affected than others by not participating in school and predict the extent to which they may expect to see differential impacts resulting from the pandemic-related school closures.

Our results thus benchmark the impacts of absenteeism in recent pre-COVID times and add to an emerging literature on the impact of COVID-19 on schools in four key ways. First, we estimate results not only for all students on average but also 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. Second, we project the impact of absenteeism not only on academic outcomes but also on social-emotional skills and do so for various levels of absenteeism. Third, because we have four years of longitudinal data at the student level, we are able to track the impact of absenteeism on these outcomes while controlling for unobserved attributes of students that could bias the relationship between absenteeism and outcomes in regular school years. Fourth, our paper covers a wide span of grades.

We find wide variation in absenteeism impacts on cognitive and social-emotional outcomes by grade and subgroup, as well as the cumulative effect of different degrees of absence. Our findings indicate that absenteeism hurts both cognitive and social-emotional outcomes. The rate of loss is greatest among vulnerable subgroups of students. Students generally suffer more from absenteeism in mathematics than in ELA, and experience larger negative effects in secondary grades than in elementary grades. The negative impact of absenteeism also varies across different types of constructs related to social-emotional development.

Previous Literature

Effects of Absenteeism on Test Scores

Aucejo and Romano (2016) use data from students in grades 3-5 in North Carolina to estimate the effect of being absent from school on test scores. They find that each day absent from school to be about 0.0036 SD (standard deviations) in reading, and 0.0067 SD in mathematics. Being absent from school has a more detrimental effect in later grades (4th and 5th grade in their sample), than in lower grades (3rd grade). Absences are also more problematic for low-performing students than for high-performing students, suggesting that the costs of catching up are greater for the former (Aucejo & Romano, 2016). Lastly, they find that particularly in the case of 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 absences appear to impact mathematics more than reading (Gottfried 2009; Gottfried, 2011; Gottfried, 2014), as well as to impact later grades more than earlier grades and low-income students more than high-achieving students (Gershenson, Jacknowitz & Brannegan, 2017).

Kuhfeld et al. (2020) use estimates from the literature and analyses of typical summer learning loss to project COVID-19 learning loss among a national sample of grades 3-7 students 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 between 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 (based on average test score growth during the school year). These effects varied across student proficiency categories, with the most significant losses concentrated among students with low proficiency levels. Their results do not consider any home schooling or online learning that students may have been involved with. Some student subgroups such as high achieving students, may experience much lower learning losses since typically, these groups return from the summer break with higher literacy scores (Kuhfeld et al., 2020).

Effects of Absenteeism on Social-Emotional Learning Outcomes

Social-emotional (SEL) skills have been found in the literature to be correlated with academic outcomes as well as adult outcomes (Heckman & Rubenstein, 2001; West et al., 2018a). For example, a greater sense of self-efficacy has been linked with better outcomes in mathematics (Pajares, 2005; Richardson, Abraham, & Bond, 2012; Usher & Pajares, 2009;). Having greater self-management, i.e., a better ability to regulate one's emotion and behaviors, including self-motivation, is also predictive of better academic outcomes (West et al., 2018b). Lastly, having a growth mindset has been linked to higher achievement, especially for low-income students (Claro, Paunesku & Dweck, 2016).

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 days from school and also experience more out-of-school suspensions. They find the strongest negative associations with absences are for self-management and self-efficacy.

Data and Methods

This study uses rich longitudinal student-level and school-level data from the CORE districts—a group of large districts in California. As an organization, CORE was founded in 2010, to engage districts in cooperative efforts to implement new academic standards, improve training for teachers and administrators, and pool data.[3] We use CORE data from a subset of six large districts. We use four years of data from 2014/15 through 2017-18.

Outcome Data

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 the survey items using a generalized partial credit model (GPCM)[4] 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

[3] See http://coredistricts.org/about-us/, accessed on 6/24/20.
[4] 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).

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[5] (Meyer, Wang & Rice, 2018). 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.[6] Table A1 in the 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: grade attended, days attended, days enrolled, race/ethnicity, gender, English Learner (EL) designation, disability status (SWD), whether student is a homeless or foster youth (HLFS), income proxied by free and reduced-price lunch (FRPL), and behaviors (i.e., suspensions or expulsions during the school year).

Methods

We examine the impact on test scores and social-emotional learning outcomes of being away from school for all students and by subgroup, as well as average patterns of absenteeism for all groups. Studying the impact of absenteeism on test scores is challenging because of unobserved factors that could be associated with both absenteeism and student outcomes. To

[5] The sole exception was the Growth mindset factor, which had low reliability in the early grades (grade 4).
[6] Loeb et al., (2019) and West et al. (2018) standardize the scale scores for ease of interpretability, thus we follow this procedure.

account for unobserved factors, we use a student fixed effect model that essentially uses each student as their own control. These models are able to control for time invariant qualities of individuals –i.e., personality traits or some persistent degree of ability – that could be important sources of bias. These models are typically able to produce better causal estimates of the relationship between key variables and outcomes than models without them. 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, *Ab*s 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* 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). The student fixed effect is denoted by γ_i. G_{it} is a grade-level indicator. τ_t is a time (year-level) indicator. Because individual characteristics and program designations such as race, gender, EL-status, or FRPL are unlikely to change in the time frame covered by our data (4 years) they are largely absorbed by the student fixed effect. 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., English Learner 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.[7]

[7] Although this model is estimated in "levels" of the dependent variable, there is virtually no difference in the estimated effects of absenteeism when a lagged dependent variable is included. 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 fact that the specification with, say, lagged test

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 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 HLFS 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 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 much longer periods than 18 days.

Effects of Absences on Test Scores

Results from estimating Equation (1) with test scores as outcomes are presented in Figure 1 and Table A2 in the appendix. We only use grades 4-8 in the analysis since the panel for grades 3 and 11 is severely limited. Absences have a clear negative effect on test scores. In the graphical

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scores produces very similar results to that without indicates the lagged test score conveyed little information beyond what is accounted for in the student fixed effects. Also, models that include lagged test scores and student characteristics without student fixed effects produce similar patterns of results but with very slightly larger absenteeism effects.

display, what is important to note is the slope of the lines. The rate of loss due to absenteeism as it accumulates is steeper for 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. Note that 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.

[Figure 1 HERE]

Absences affect test scores differently depending on the student's grade level. Predicted effects by grade are found in Figure 2 (full results by grade can be found in the appendix). The slopes on the grade lines are steeper (downward trend) after 5th grade indicating that the bulk of the academic loss due to extended absences is borne more heavily by students in the secondary grades. In fact, while losses for students in elementary school are relatively small even when students are away from school for extended periods, the losses at the middle and high school grades are substantial. Figure 2 also shows how much steeper the decline is for mathematics versus ELA as absenteeism increases.

[Figure 2 HERE]

Impact of Absences on Test Scores by Student Subgroup

Absences hurt the academic achievement of vulnerable students more than they do other students. Overall predicted effects for students classified as EL, FRPL, SWD, and HLFS can be found in Figure 3 (full regression results in the appendix). For comparison we add a category of nonvulnerable students (NONVUL). The negative effects of absenteeism are large for all students, and are more pronounced among SWDs and HLFS. These findings are concerning, given that in our analytic sample, 77 percent of the student population is classified FRPL, 18 percent as ELs, 13 percent as SWDs, and 4 percent as HLFS, versus 19 percent non-vulnerable—these percentages closely mirror the proportions in the CORE student population.

[Figure 3 HERE]

We find variation in effects by subgroup by grade (results available in the appendix). In the case of FRPL students, absences appear to hurt mathematics more than ELA across grade levels, with a steeper rate of loss in 7^{th}-8^{th} grade. For ELs, absences from school hurt ELA more than mathematics for students in the elementary grades. In the case of SWDs, absences hurt mathematics more in 7^{th}-9^{th} grade. Absences hurt HLFS youth more in mathematics than ELA across grade levels, with the exception of 5^{th} grade. In contrast, the rate of loss by grade for non-vulnerable students is less severe.

Effects of Absences on Social-Emotional Outcomes

To estimate the effects of absenteeism on SEL outcomes in a normal school year, we estimate Equation (1) but instead of ELA and mathematics test scores as outcome measures, we use the SEL scale scores in each of the four constructs standardized by year—growth mindset (GM), social awareness (SA), self-efficacy (SE), and self-management (SM). SEL scores are available for grades 4-12 and all of those grades are included 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). This subsample represents 64 percent of the total sample of students with SEL questionnaire scores.

Predicted effects on SEL constructs of being absent at various absenteeism levels are shown in Figure 4 (regression coefficients are in Table A2 in the appendix). The coefficients on days absent for all four SEL constructs are negative and statistically significant, with very small positive coefficients on the squared term. As shown in Figure 4, being absent from school for 20 or more days, appears to harm all four SEL constructs, with slight variation across the constructs. Effects for most constructs flatten out after 40 to 50 days. However, for SA the decline is more or less linear suggesting a steeper rate of loss on this construct. These relationships are also evident for all four subgroups in our analysis: ELs, FRPL, SWD and HLFS (results available in the appendix).

[Figure 4 HERE]

The SEL constructs are affected differently by absenteeism across grades (see appendix). SA is most impacted in grades 6-9. SE is most affected by absenteeism in grades 6-9, but absences don't appear to hurt this construct in 11 and 12th grade. Absenteeism affects SM in all grades, except 11-12. Lastly, while GM is generally the least impacted construct, students in the middle grades will experience lower scores on the GM construct from prolonged absenteeism.

Conclusion

After schools shut down for 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. These efforts met with mixed success (EdWeek Research Center, 2020; Hamilton et al, 2020). Inequities present before COVID-19 were likely exacerbated due to differences in the quality of access to technology and instruction in the home for different subgroups of students. In an effort to help assess the possible effects of being away from school during the pandemic, we have estimated the impact of absenteeism on cognitive and non-cognitive 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. There is reason to believe, based on nationally representative teacher surveys that a significant number of students were absent from virtual schooling opportunities for extended periods and clearly longer periods than normal during the COVID-19 pandemic (EdWeek Research Center, 2020; Hamilton et al., 2020). It is also likely that absence from virtual schooling followed a similar pattern of variation by subgroup to that found in our data.

Our results suggest school disruptions brought on by COVID-19 pandemic will likely also affect social-emotional development as well as cognitive outcomes. Being absent from school harms SEL skills, particularly those related to self-efficacy, social awareness, and self-management.

This paper adds to the growing evidence on the negative impact of COVID-19 on student development and its possible differential impacts by student subgroups. It is increasingly evident that students will need both academic and social-emotional support to make up for lost gains. One advantage of our study over those that use summer learning loss (e.g., Kuhfeld et al, 2020) to predict COVID effects, is that we estimate the impact of absenteeism during the year to predict 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 the losses due to absence in ways that are more relevant to the current situation than predictions based on summer learning loss.

This paper provides an overview of the effects of absenteeism, and, as such, it raises many questions as to why these effects occur and show different patterns for different groups and grades. For example, heterogeneity within certain groups such as ELs and SWDs across grades and 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 so that the full effects of the COVID-19 pandemic can be better understood and addressed.

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Table 1. Average Days Absent per Year, By Subgroup

Panel A - Mean Days Absent by Subgroup

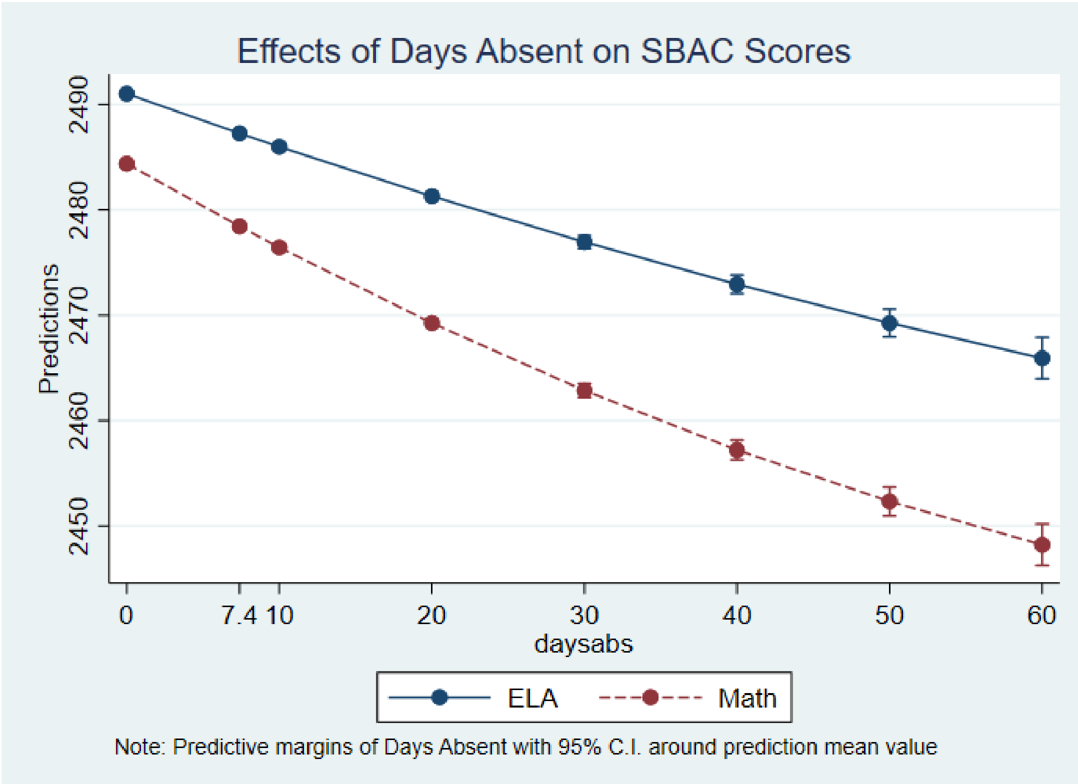
Grade	All	EL	FRPL	SWD	HL/FST	Latinx	White	Af. Am	As/P.I.
K	9.2	7.9	9.5	11.6	10.5	9.2	8.3	11.8	7.3
1	7.4	6.4	7.7	9.8	9.0	7.3	7.0	10.0	5.5
2	6.8	6.1	7.0	9.0	8.5	6.7	6.7	9.6	4.8
3	6.5	6.0	6.6	8.7	8.1	6.3	6.6	9.3	4.5
4	6.4	6.0	6.5	8.6	7.8	6.2	6.8	9.1	4.3
5	6.2	6.1	6.3	8.6	7.6	6.0	6.9	8.9	4.1
6	5.9	6.2	6.1	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
Average	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
Proportion		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
Average	0.14	0.65	0.13	0.08	0.07

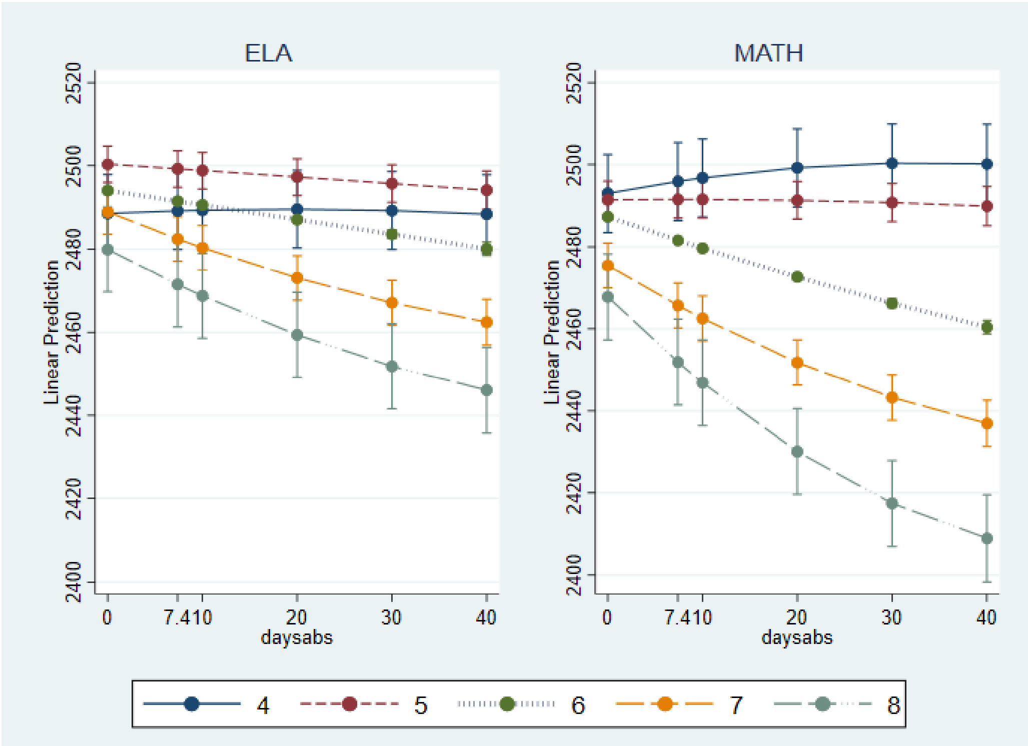
Note: Averages over 2014/15-2017/18 school years. Includes data from six CORE districts.

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



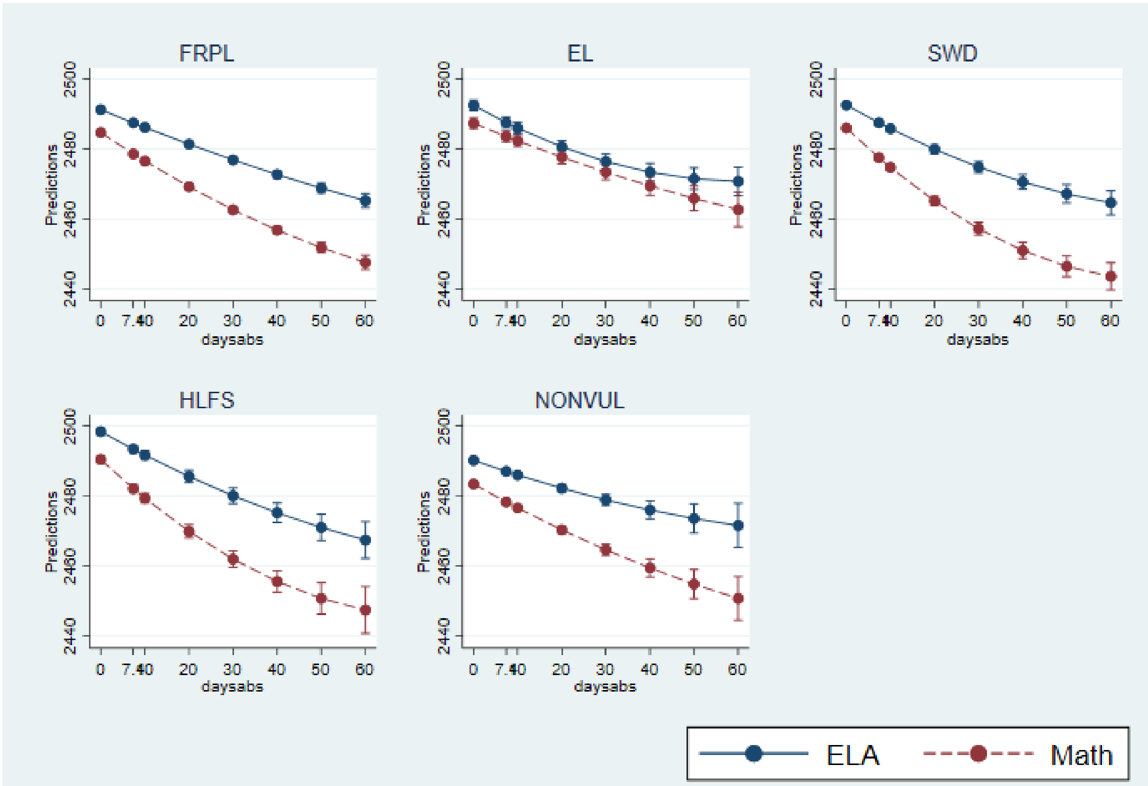
Note: Graph points represent the predicted probability on the outcome (test score) for a given value of days absent (0, 10, 20...) from the models estimated in Equation (1) with student fixed effects. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph.

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



Note: Graph points represent the predicted probability on the outcome (test score) for a given value of days absent (0, 10, 20...) from the models estimated in Equation (1) with student fixed effects. Confidence intervals of 95% around the prediction mean estimate.

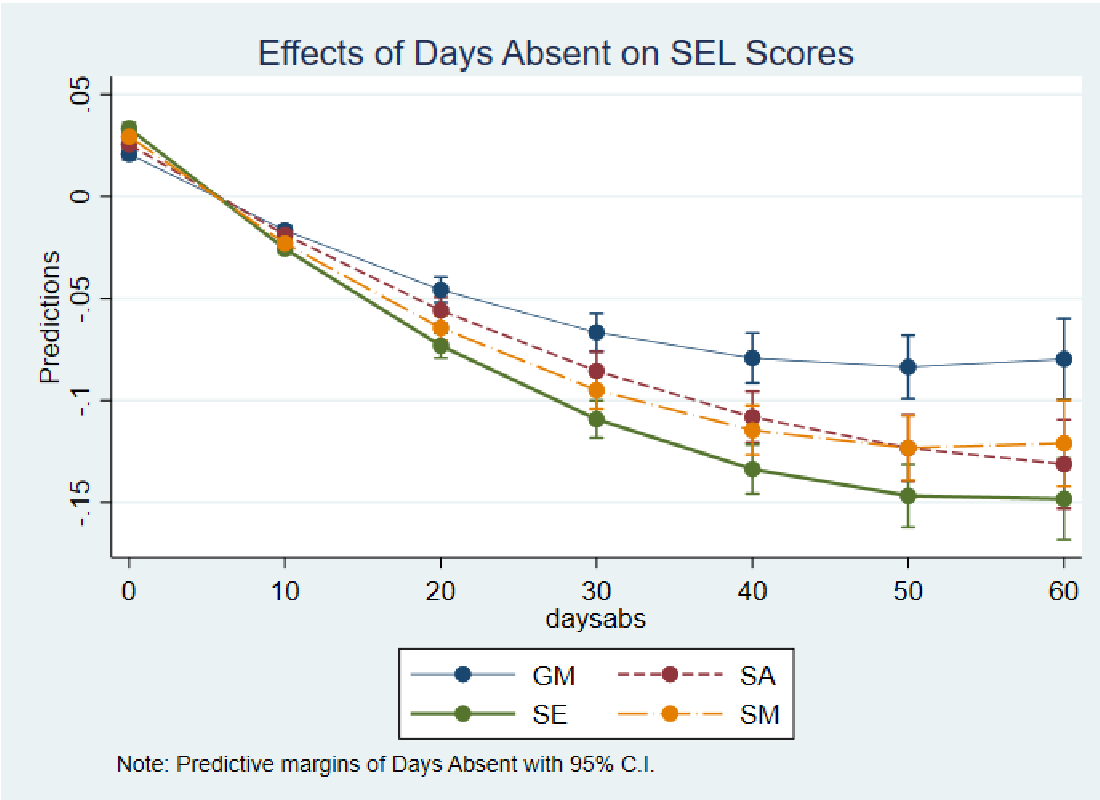
Figure 3. Predicted Effects of Absences on Test Scores, by Subgroup



Note: Predictive margins of Days Absent with 95% C.I. around prediction mean value

Note: Graph points represent the predicted probability on the outcome (test score) for a given value of days absent (0, 10, 20...) from the models estimated in Equation (1) with student fixed effects. Confidence intervals of 95% around the prediction mean estimate.

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



Note: Graph points represent the predicted probability on the outcome (social-emotional construct) for a given value of days absent (0, 10, 20...) from the models estimated in Equation (1) with student fixed effects. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph. Data covers six CORE districts. Years covered are 2014/15 - 2107/18.

Appendix

Table A1. Descriptive Statistics

Variable	Mean	SD	N
sbac_ELA	2488.06	103.58	1,136,429.00
sbac_MATH	2479.78	104.82	1,142,265.00
sel_GM_gpcm	-0.6290	1.098	1,332,633.00
sel_SA_gpcm	-0.0146	1.210	1,332,633.00
sel_SE_gpcm	-0.0206	1.008	1,332,633.00
sel_SM_gpcm	0.0002	1.121	1,332,633.00
female	0.49	0.50	1,230,893.00
FRPL	0.77	0.42	1,230,995.00
EL	0.18	0.39	1,201,413.00
HLFS	0.04	0.19	1,230,995.00
SWD	0.13	0.34	1,225,077.00
NONVUL	0.19	0.39	1,230,995.00
race_hi	0.71	0.46	1,230,994.00
race_aa	0.09	0.29	1,230,994.00
race_aspi	0.10	0.30	1,230,994.00
race_oth	0.00	0.06	1,230,994.00
daysabs	6.19	8.23	1,230,995.00
daysenr	171.54	29.20	1,230,995.00
stua_susp	0.06	0.68	1,230,995.00
stua_exp	0.00	0.11	1,230,995.00
gr4	0.22	0.41	1,230,995.00
gr5	0.21	0.41	1,230,995.00
gr6	0.19	0.39	1,230,995.00
gr7	0.19	0.39	1,230,995.00
gr8	0.19	0.39	1,230,995.00
yr15	0.26	0.44	1,230,995.00
yr16	0.25	0.43	1,230,995.00
yr17	0.25	0.43	1,230,995.00
yr18	0.24	0.43	1,230,995.00

Table A2. Regression Results by Grade

	ELA (1)	Math (2)
daysabs	0.1035	0.4436
	(0.036)	(0.042)
daysenr	0.0512	0.0674
	(0.003)	(0.003)
c.daysabs#c.daysabs	-0.0027	-0.0066
	(0.001)	(0.001)
5.enrl_grade	11.8152	-1.5618
	(2.493)	(2.555)
6.enrl_grade	5.4817	-5.6712
	(4.975)	(5.100)
7.enrl_grade	0.3390	-17.5456
	(7.457)	(7.644)
8.enrl_grade	-8.6563	-25.2247
	(9.941)	(10.190)
4b.enrl_grade#co.daysabs	0.0000	0.0000
	(0.000)	(0.000)
5.enrl_grade#c.daysabs	-0.2564	-0.4174
	(0.036)	(0.040)
6.enrl_grade#c.daysabs	-0.4485	-1.2421
	(0.046)	(0.048)
7.enrl_grade#c.daysabs	-1.0276	-1.8470
	(0.044)	(0.049)
8.enrl_grade#c.daysabs	-1.3118	-2.7423
	(0.050)	(0.060)
4b.enrl_grade#co.daysabs#co.daysabs	0.0000	0.0000
	(0.000)	(0.000)
5.enrl_grade#c.daysabs#c.daysabs	0.0026	0.0050
	(0.001)	(0.001)
6.enrl_grade#c.daysabs#c.daysabs	0.0026	0.0097
	(0.001)	(0.001)
7.enrl_grade#c.daysabs#c.daysabs	0.0092	0.0176
	(0.001)	(0.001)
8.enrl_grade#c.daysabs#c.daysabs	0.0117	0.0273
	(0.001)	(0.002)
Constant	2,427.3277	2,434.3634
	(1.169)	(1.195)
N	1,136,429	1,142,265

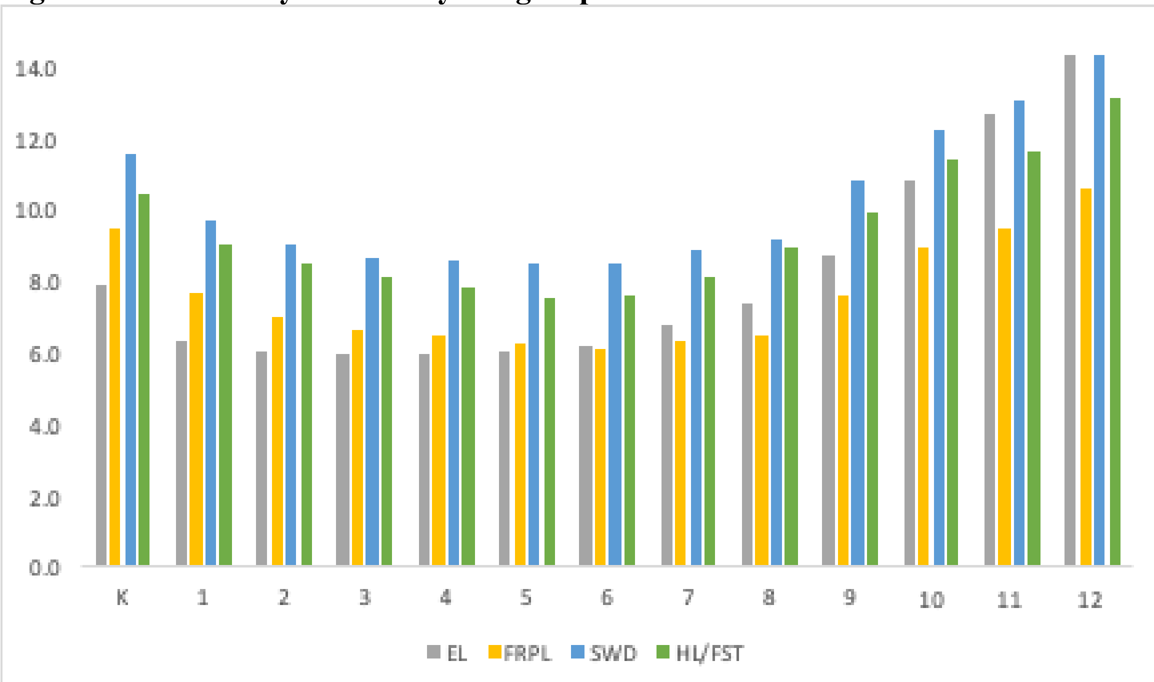
Note: Standard errors in parentheses. Controls include suspensions and expulsions, and year dummies. All models ran with student fixed effects.

Table A3. Regression Results by Grade and Subgroup

	ELA (1)	Math (2)	ELA (3)	Math (4)	ELA (5)	Math (6)	ELA (7)	Math (8)
daysabs	-0.4924	-0.7440	-0.4717	-0.9007	-0.4712	-0.7506	-0.5103	-0.8146
	(0.036)	(0.035)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)	(0.022)
daysenr	0.0549	0.0755	0.0547	0.0736	0.0550	0.0751	0.0550	0.0754
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
daysabs-sq	0.0028	0.0039	0.0006	0.0043	0.0011	0.0028	0.0017	0.0037
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
5.enrl_grade	10.0164	-4.3429	9.7324	-4.1821	9.9750	-4.7171	10.0206	-4.3237
	(2.492)	(2.568)	(2.497)	(2.579)	(2.512)	(2.586)	(2.492)	(2.567)
6.enrl_grade	2.0738	-13.5345	1.5252	-13.2310	1.9210	-14.3760	2.0697	-13.5180
	(4.979)	(5.129)	(4.988)	(5.151)	(5.018)	(5.165)	(4.978)	(5.127)
7.enrl_grade	-6.3171	-28.9609	-7.1135	-28.5478	-6.3310	-30.0084	-6.3172	-28.9263
	(7.464)	(7.689)	(7.478)	(7.722)	(7.523)	(7.743)	(7.464)	(7.687)
8.enrl_grade	-17.3768	-41.9381	-18.4293	-41.4105	-17.3903	-43.2523	-17.3699	-41.8784
	(9.951)	(10.250)	(9.970)	(10.294)	(10.029)	(10.322)	(9.950)	(10.247)
FRPL*daysabs	-0.0327	-0.1090						
	(0.036)	(0.035)						
FRPL* daysabs-sq	-0.0013	-0.0000						
	(0.001)	(0.001)						
EL*daysabs			-0.2392	0.3782				
			(0.041)	(0.049)				
EL*daysabs-sq			0.0052	-0.0025				
			(0.001)	(0.001)				
SWD*daysabs					-0.2472	-0.4628		
					(0.047)	(0.050)		
SWD*daysabs-sq					0.0031	0.0057		
					(0.001)	(0.001)		
HLFS*daysabs							-0.1957	-0.3670
							(0.059)	(0.069)
HLFS*daysabs-sq							0.0015	0.0041
							(0.001)	(0.002)
Constant	2,430.24	2,440.01	2,430.21	2,440.04	2,430.02	2,440.01	2,430.23	2,440.02
	(1.164)	(1.194)	(1.142)	(1.173)	(1.161)	(1.190)	(1.163)	(1.193)
N	1,136,429	1,142,265	1,129,367	1,135,154	1,130,817	1,136,675	1,136,429	1,142,265

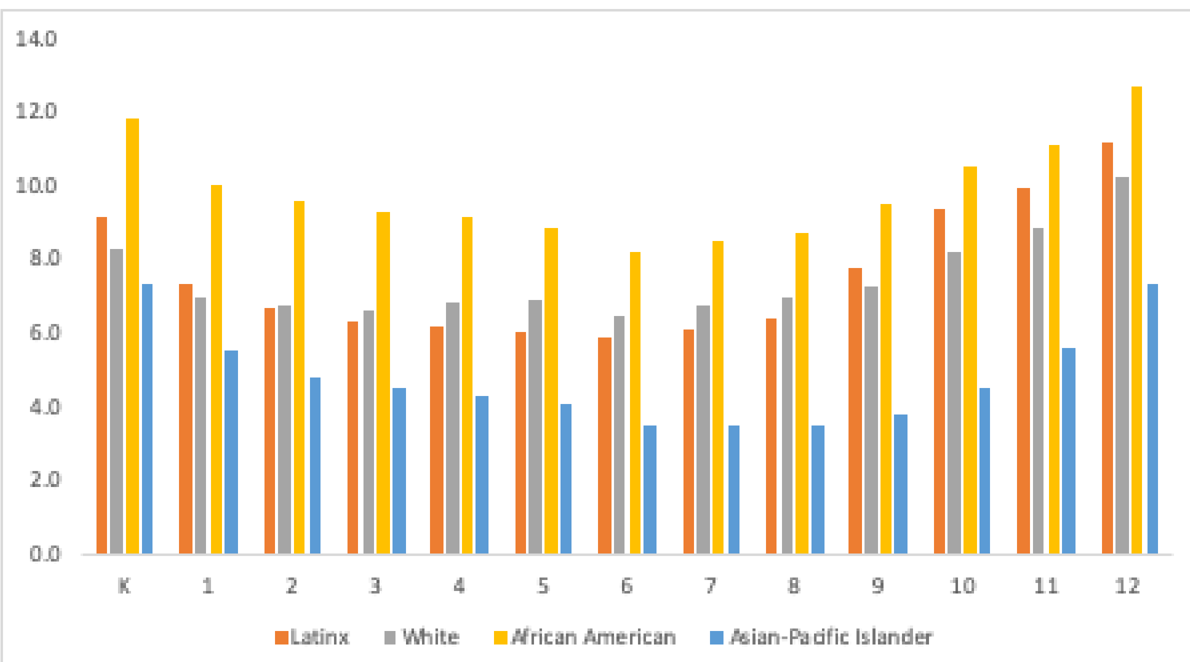
Note: Standard errors in parentheses. Controls include suspensions and expulsions, and year dummies.
All models ran with student fixed effects.

Figure A1. Mean Days Absent by Subgroup



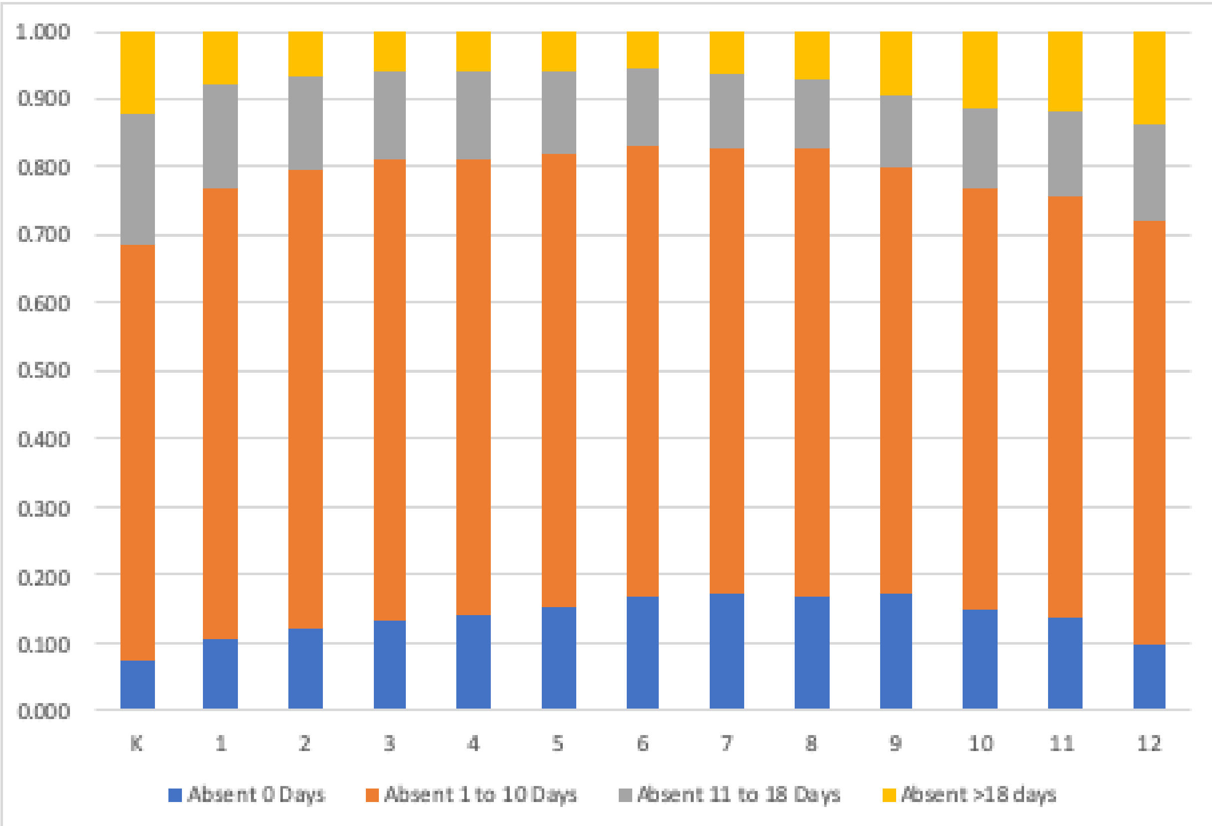
Note: Averages over 2014/15-2017/18. Includes data from six CORE districts: LAUSD, SAUSD, OUSD, LBUSD, and GGUSD.

Figure A2. Mean Days Absent by Race/Ethnicity



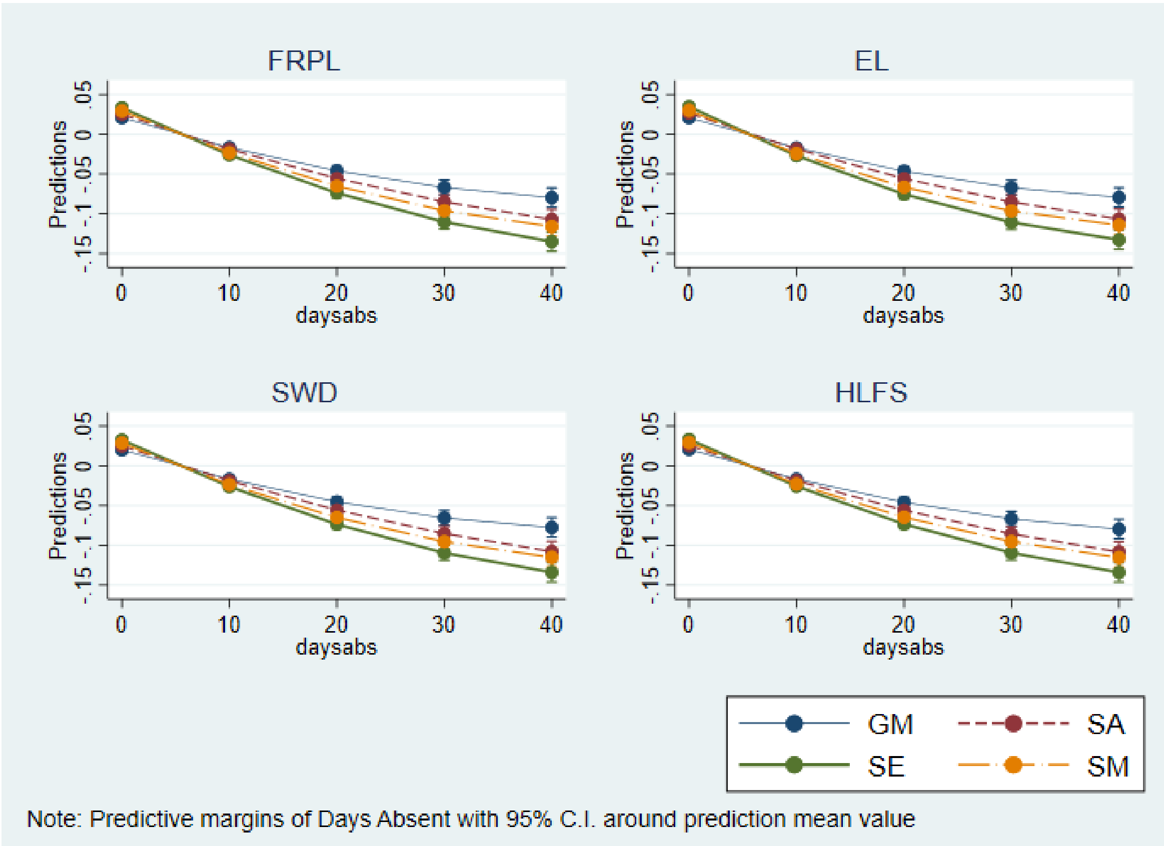
Note: Averages over 2014/15-2017/18. Includes data from six CORE districts: LAUSD, SAUSD, OUSD, LBUSD, and GGUSD.

Figure A3. Proportion of Students in Each Grade Absent for Different Lengths of Time



Note: Averages over 2014/15-2016/17. Includes data from six CORE districts: LAUSD, SAUSD, OUSD, LBUSD, and GGUSD.

Figure A4. Predicted Effects on Social-Emotional Outcomes, by Different Values of Days Absent and Student Subgroup



Note: Graph points represent the predicted probability on the outcome (social-emotional construct) for a given value of days absent (0, 10, 20...) from the models estimated in Equation (1) with student fixed effects. Confidence intervals of 95% around the prediction mean estimate can be seen on the graph.