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The impact of increased absenteeism on post-pandemic test scores: A mediation analysis

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The impact of increased absenteeism on post-pandemic test scores: A mediation analysis

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Abstract

This study explores the relationship between rising student absenteeism and changes in student achievement since the beginning of the COVID-19 pandemic. We conduct a mediation analysis using detailed administrative data on middle school students in North Carolina to estimate how increased post-pandemic absenteeism has affected test scores. In 2021-22, math achievement remained 0.24-0.27 standard deviations (SDs) below pre-pandemic levels, while absence rates were 2.8 percentage points higher. We find that this increase in absences accounts for a 0.04-0.06 SD decline in achievement, explaining 16-23% of the total change in test scores. Further, increased absenteeism may have also widened racial/ethnic and socioeconomic achievement gaps. These results suggest attendance recovery efforts can play a key role in learning recovery.

Keywords: COVID-19; attendance; achievement; mediation analysis

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Introduction

In this brief, we estimate the extent to which post-pandemic absenteeism may be slowing the pace of K-12 academic recovery. This work is motivated by three existing findings. First, due to the COVID-19 pandemic, student test scores dropped markedly in 2020-21 and have since recovered only partially, with recovery potentially stagnating in 2022-23 (Kuhfeld & Lewis, 2023). Second, post-pandemic absenteeism is a growing concern. Between 2018-19 and 2021-22, the chronic absenteeism rate doubled nationally from 14.8% to 28.3% (Dee, 2023). Finally, absenteeism has modest but significant adverse effects on achievement (e.g., Gershenson et al., 2017; Gottfried, 2009; Gottfried & Kirksey, 2017; Liu et al., 2021). For example, research in North Carolina found that each additional day absent led to a 0.007 standard deviation (SD) decline in elementary students' math scores (Gershenson et al., 2017). Absenteeism can also have spillover effects within classrooms, as students' scores also decrease when their classmates miss more school (e.g., Gottfried, 2019).

These findings highlight the important role that attendance may play in learning recovery. However, there is little work quantifying the impact of post-pandemic absenteeism on achievement. One report shows that rising absenteeism may explain 16% to 27% of the decline in NAEP math scores (NCES, 2023). This finding is based on students' self-reported attendance in the month prior to the exam and adjusts for student demographic characteristics.

The current study extends this work by using granular student-level administrative data on multiple cohorts of students from North Carolina to examine the extent to which changes in average math test scores from pre- to post-pandemic can be explained by increased post-pandemic absenteeism. Specifically, we conduct a mediation analysis (Pearl, 2014; Valeri & VanderWeele, 2013; VanderWeele, 2016) using data on repeated cross-sections of 6th and 7th

graders in three pre-pandemic cohorts (2016-17 through 2018-19) and one post-pandemic cohort (2021-22). We consider the mediating impact of changes in absences at both the individual and classroom level on changes in test scores.

To preview, we find that average math scores decreased by 0.24-0.27 SDs between pre-pandemic and 2021-22, while absence rates increased by 2.8 percentage points, or about one additional week of school per student. Across a range of specifications, we estimate this increase in absenteeism accounts for a 0.04-0.06 SD reduction in test scores, such that increased absenteeism explains 16-23% of the total decrease in achievement between pre-pandemic and 2021-22. We also find that rising absenteeism may be contributing to growing achievement gaps between racial/ethnic and socioeconomic subgroups, though this result is somewhat sensitive to specification. These results suggest that efforts to return attendance to pre-pandemic norms may meaningfully increase the pace of recovery.

Data & Method

We use individual-level administrative data from the North Carolina Department of Public Instruction, including demographics, attendance, classroom rosters, and state test scores. We focus on cross-sectional cohorts of 6th and 7th graders in three pre-pandemic years (2016-17 through 2018-19) and one post-pandemic year (2021-22). Our outcome is a student's end-of-grade math test score. We standardized test scores in pre-pandemic cohorts within year and grade to have a mean of 0 and standard deviation of 1. We anchored scale scores from 2021-22 to their standardized equivalent from 2018-19. For example, a score of 548 in 6th grade math equaled a standardized score of -0.016 in 2018-19; we therefore also assigned it a standardized score of -0.016 in 2021-22. Our "treatment" variable is an indicator equal to one for those in the post-pandemic cohort. Our mediators include a student's own absence rate and the average absence rate of peers in their math class. We restrict our sample to students with at least 90 days enrolled and less than 50% of days absent to reduce skew due to outliers or errors. In addition, while national research shows that effects of the pandemic were most extreme at the bottom of the achievement distribution (Lewis et al., 2022), we observed weaker impacts on students whose pre-COVID achievement was in the bottom quintile, which may be due to floor effects on these exams. Therefore, our primary sample excludes these students. Appendix A provides further details on the data, including descriptive statistics in Appendix Table A1.

We conduct a mediation analysis to estimate the indirect effect of changes in absenteeism on changes in test scores between pre-pandemic and 2021-22 (Pearl, 2014; Valeri & VanderWeele, 2013; VanderWeele, 2016). In cases where we examine only one mediator, we estimate this by multiplying the effect of absences on test scores by the effect of the pandemic on absences. Specifically, we estimate:

$$(1)\ Y = \theta_0 + \theta_1 a + \theta_2 m + \theta_3 a * m + \theta_4 c + \epsilon$$

$$(2)\ m = \beta_0 + \beta_1 a + \beta_2 c + \omega,$$

where *Y* refers to the outcome, a to treatment, *m* to the mediator, and *c* to covariates. In equation (1), θ_2 estimates the effect of absences on test scores pre-pandemic, while $\theta_2 + \theta_3$ estimates the post-pandemic impact. In equation (2), β_1 estimates the effect of the pandemic on absences.

Because we allow the effect of absences to vary across time, there are two possible estimates of the indirect effect, based either on the pre-pandemic or post-pandemic estimate of the impact of absences on test scores. Using the post-pandemic estimate calculates the "natural indirect effect" (NIE), defined as $\beta_1 * (\theta_2 + \theta_3)$ (we centered all covariates so that they zero out of these calculations). The remaining effect of the pandemic on test scores not due to the change in absences is then referred to as the "natural direct effect" (NDE), defined as $\theta_1 + (\theta_3 * \beta_0)$, while the total effect of the pandemic on test scores is the sum of the NIE and NDE. Using the pre-pandemic estimate calculates the "pure natural indirect effect" (PNIE), defined as $\beta_1 * \theta_2$. The direct effect is then the "total natural direct effect" (TNDE), defined as $\theta_1 + \theta_3 * (\beta_0 + \beta_1)$, and the total effect is again equal to the sum of the PNIE and TNDE. When we include own and peer absences as mediators, the NIE (PNIE) equals the sum of the NIE (PNIE) of each mediator from models that include both variables. For more detail, see Appendix A.

The PNIE and NIE offer complementary insights under different assumptions about why the impact of absenteeism may have changed over time. We suggest that any changes may be due to largely transient factors. For example, the greater need for remediation in the immediate aftermath of the pandemic as well as the higher rate of absenteeism may be causing teachers to slow their instructional pacing to cover less new content per day on average, leading each day absent to temporarily be less costly until recovery picks up. Therefore, the NIE provides insight into the immediate mediating impact of absenteeism given these temporary norms, while the PNIE provides insight into the impact of absenteeism as pre-pandemic norms return. We have a slight preference for the PNIE under the assumption that improving attendance rates would itself facilitate a return to pre-pandemic impacts of attendance. However, the NIE and PNIE offer a range of potential mediating impacts of increased absenteeism under different assumptions.

A key threat to identification is that our estimated impact of absences on test scores could be confounded (VanderWeele, 2016). We aim to generate an unbiased estimate using a robust set of covariates. This includes students' math test score from three years' prior (i.e., from 2018-19 for students in 2021-22), which explains 60 to 70 percent of the variance in outcomes. Other controls include student gender, race/ethnicity, economic disadvantage (ED), other educational classifications (e.g., disability), and school characteristics. We omit 16% of students who are missing data on any covariate, primarily students who were not observed three years' prior. For further discussion of covariates and conditions for causality, see Appendix A. We also show two sensitivity checks in Appendix B, first estimating the impact of absenteeism via longitudinal student fixed effects models and second using the Oster (2019) bounding method.

Finally, Appendix C provides results from three alternative specifications. First, we show results that include students from the bottom baseline achievement quintile. Second, we note that there was a change in the math test scale beginning in 2018-19 and a change in the structure of our absence data that resulted in slightly increased absence rates beginning in 2017-18. We show that using only the 2018-19 or 2017-18/2018-19 pre-pandemic cohorts does not substantively affect results. Third, we employ an alternative technique that allows us to interact our two mediators (VanderWeele & Vansteelandt, 2014). This also does not substantively affect results. However, these models suggest that absences are less costly in environments where peers are more absent, and accounting for this interaction reduces the extent to which the impact of absenteeism has changed over time in the full sample (though not in subgroup models), which may justify a slight preference for the PNIE over the NIE in the full-sample estimates.

Results

Main results

Table 1 presents key results from models without (Model 1) and with peer absence effects included (Model 2). In Model 1, we estimate a total decrease in test scores of 0.26 SDs from pre-pandemic to 2021-22 and a 2.8 percentage point increase in absence rates, or about one additional week of school missed per student. Each percentage point increase in absences led to a 0.019 SD reduction in achievement pre-pandemic and a 0.015 SD reduction in 2021-22 (or 0.010

and 0.008 SDs per day absent). Therefore, we estimate that the increase in absences accounts for decreases in achievement of 0.04 to 0.05 SDs, or 16% to 20% of the total change in test scores.

In Model 2, we find that peer absences negatively impact a student's scores, but including this variable also weakens the estimated impact of one's own absences. In this model, a one percentage point increase in own absences led to a 0.017 SD reduction in achievement pre-pandemic and a 0.013 SD reduction in 2021-22, while a one percentage point increase in peer absences led to a 0.006 SD reduction pre-pandemic and a 0.003 SD reduction in 2021-22 (though note that the change in the impact of peer absences over time is not statistically significant). Therefore, we estimate that increased absences (own and peer) account for decreases in student achievement of 0.05 to 0.06 SDs, or 16% to 23% of the total change in test scores.

Figure 1 depicts what test scores might look like if attendance had returned to pre-pandemic levels in 2021-22 (taking initial pandemic impacts in 2020-21 as a given). The gray line indicates observed scores from 2017-18 through 2021-22. Descriptively, relative to pre-pandemic, test scores were 0.42 SDs lower in 2020-21 and 0.24 SDs lower in 2021-22. The dashed black line indicates predicted scores in 2021-22 based on our highest mediation estimate (23%). In this scenario, scores in 2021-22 would have been 0.19 SDs lower than pre-pandemic.

Subgroup results

We next examined results by student subgroups defined by race/ethnicity, prior achievement, and ED status. Table 2 shows key results (see Appendix D for full tables). We focus on discussing results by race/ethnicity, as other patterns are similar.

Black and Hispanic students' absence rates increased by 3.5 and 3.3 percentage points compared to White students' 2.3 points. In models that consider only own absences and using the PNIE, we estimate that increases in absences account for 20% of the decrease in Black students' test scores (0.062 of 0.31 SDs); 23% for Hispanic students (0.069 of 0.30 SDs); and 19% for White students (0.043 of 0.23 SDs). While the percent mediated is similar across subgroups, the absolute magnitude is larger for Black and Hispanic students, who experienced larger changes in absenteeism as well as larger changes in achievement. The total effect of the pandemic was 0.084 SDs greater for Black than White students, indicating a rising racial/ethnic achievement gap. As the difference in the PNIE between Black and White students is 0.019 SDs, this suggests that 23% of the increased achievement gap may be explained by indirect effects of changes in absences. For Hispanic students, 37% of the increased achievement gap may be due to indirect effects of absences.

As in the main results, estimates via the NIE are weaker and show less evidence of differences across subgroups. Further, in models with peer effects, the NIE is similar to the one-mediator model, but the PNIE is much stronger for Black and Hispanic students. This is because the negative impacts of peer absenteeism became much weaker in 2021-22 for these subgroups. Because the estimated impacts of peer absenteeism vary so substantively, we place less emphasis on interpreting these models. However, across models, our weakest estimates suggest that 10-15% of the total effect of the pandemic is mediated by increased absenteeism for all subgroups, while the strongest estimates suggest that absences mediate up to about 30% of the total change for certain subgroups.

Finally, we note that NIE and PNIE estimates are much more similar for students with high rather than low baseline achievement, and Appendix Tables D4 and D5 show that this also holds within racial/ethnic subgroups. Thus, changes in impacts of attendance over time are driven largely by lower-achieving students. This could be because these students are especially struggling to master grade-level material in the aftermath of the pandemic even when they are attending school at high rates.

Discussion

With student achievement remaining significantly below pre-pandemic levels, there are many questions about why student learning continues to lag and how to improve outcomes. Our results show that higher post-pandemic student absenteeism is a key mediator of changes in post-pandemic test scores, accounting for decreases of 0.04-0.06 SDs and explaining 16-23% of the total change in achievement between pre-pandemic and 2021-22. Impacts are about at least as large or larger for subgroups that experienced larger negative impacts on achievement and increases in absenteeism, including Black, Hispanic, ED, and low-performing students.

Our results are similar to estimates from NCES (2023), which found that 16% of the decline in 8th grade math and 27% of the decline in 4th grade math could be explained by rising rates of students' self-reported absenteeism in the month preceding the NAEP. Our study extends this work by using more detailed administrative data, considering impacts of both a student's own and their peers' absenteeism, and examining subgroup differences.

There are several limitations to this study. First, due to changes in the state's reading exam, we only examine impacts in math; however, NCES (2023) found that absences may mediate a larger portion of changes in reading. Additionally, we examine impacts only on 6th and 7th grade students, as all students in these grades take the same math exam and had pre-pandemic test scores for which we could control. However, future research should explore impacts on other grade levels. Finally, our results depend on the validity of our estimated impact of absenteeism on achievement. While we cannot know whether we produce an unbiased estimate, sensitivity analyses suggest that even large confounders would not alter qualitative conclusions.

This study complements research on learning recovery efforts. Our findings suggest that increased absenteeism may fully counteract the positive effects of some efforts. For example, post-pandemic summer school programs may increase math achievement by just 0.03 SDs (Callen et al., 2023). Another popular effort – high-dosage tutoring – can have large impacts on achievement (Nickow et al., 2020), but has proven difficult to reach students at scale (Robinson et al., 2022). Thus, attendance recovery might be just as impactful as other recovery efforts.

Overall, this study highlights that attendance recovery should be a key component of learning recovery efforts. Increasing attendance can meaningfully improve student achievement and may further complement other recovery efforts by providing students with greater access to programs that are provided during or after school. Education leaders should continue to pay close attention to the impact of the pandemic on student attendance and its impacts on student learning.

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Tables

Table 1

Overall mediation estimates

		(1)	(2)
TE		-0.264	-0.274
NIE		-0.042	-0.045
% NIE		16%	16%
PNIE		-0.054	-0.063
% PNIE		20%	23%
Eq. 1	COVID	-0.240***	-0.260***
(Y = test score)		(0.0117)	(0.0222)
	% Abs	-1.888***	-1.653***
		(0.0359)	(0.0243)
	Peer % Abs	.	-0.643**
			(0.2357)
	COVID x % Abs	0.405***	0.362***
		(0.0295)	(0.0380)
	COVID x Peer % Abs	.	0.302
			(0.2779)
Eq. 2	COVID	0.028***	0.027***
(Y = % Abs)		(0.0008)	(0.0008)
Eq. 3	COVID	.	0.029***
Y = Peer % Abs)		.	(0.0008)
N		611,644	611,644

Note. TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect. The NIE is calculated by multiplying the impact of the pandemic on absences (eq. 2/3) by the post-pandemic impact of absences on test scores (eq. 1), while the PNIE is calculated by multiplying the impact of the pandemic on absences by the pre-pandemic impact of absences on test scores. "% NIE" ("% PNIE)" obtained by dividing the NIE (PNIE) by the TE. Covariates in Model 1, not shown, include student demographics, educational classifications (e.g., disability status), and school characteristics, while Model 2 additionally controls for classroom averages of individual-level variables (see complete list in Appendix A). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was in the top 80 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. Standard errors, clustered by school-year, are shown in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 2

Mediation estimates by selected student subgroups

Subgroup	Mediator = own absences						Mediator = own and peer absences						
	Δ Abs	TE	NIE	% NIE	PNIE	% PNIE	Δ Abs	Δ Peer Abs	TE	NIE	% NIE	PNIE	% PNIE
Black	0.035	-0.313	-0.039	12%	-0.062	20%	0.034	0.035	-0.317	-0.032	10%	-0.090	28%
Hispanic	0.033	-0.301	-0.048	16%	-0.069	23%	0.032	0.032	-0.305	-0.039	13%	-0.098	32%
White	0.023	-0.229	-0.038	17%	-0.043	19%	0.023	0.026	-0.248	-0.038	15%	-0.044	18%
ED	0.040	-0.289	-0.047	16%	-0.071	25%	0.038	0.034	-0.301	-0.035	12%	-0.091	30%
Not ED	0.021	-0.247	-0.037	15%	-0.043	17%	0.021	0.026	-0.257	-0.042	16%	-0.047	18%
Quintile 2	0.037	-0.254	-0.036	14%	-0.064	25%	0.036	0.036	-0.265	-0.026	10%	-0.087	33%
Quintile 3	0.031	-0.299	-0.044	15%	-0.059	20%	0.029	0.032	-0.308	-0.045	15%	-0.078	25%
Quintile 4	0.025	-0.277	-0.047	17%	-0.051	18%	0.024	0.027	-0.294	-0.041	14%	-0.057	20%
Quintile 5	0.020	-0.222	-0.042	19%	-0.041	19%	0.019	0.021	-0.228	-0.051	22%	-0.037	16%

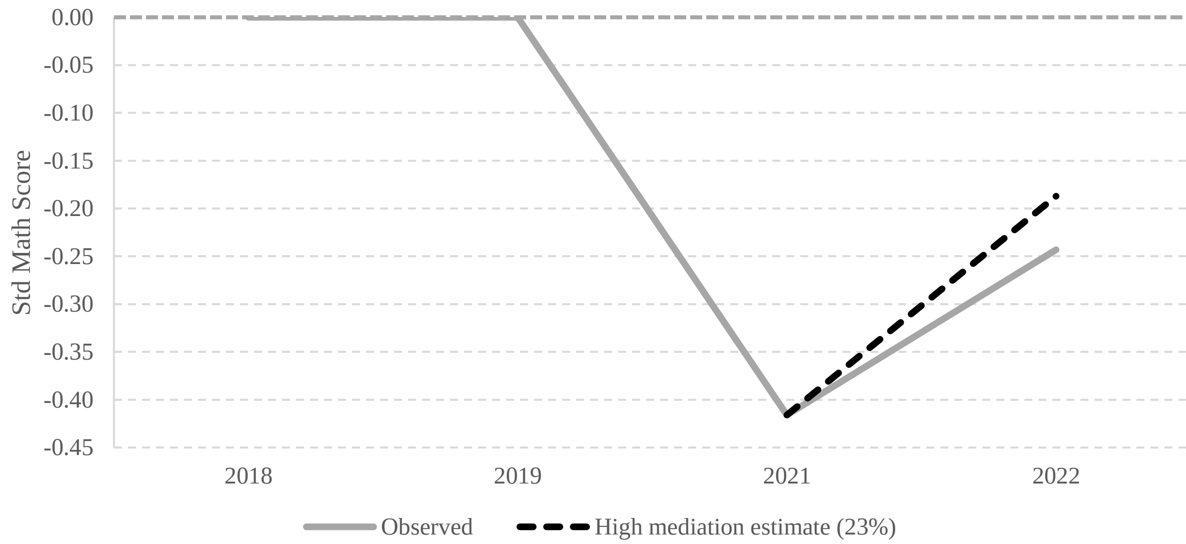
Note. Δ Abs = change in absence rates from pre- to post-pandemic, TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect, ED = economically disadvantaged, "quintile" refers to position in the baseline achievement quintile, with 5 being the highest. The NIE is calculated by multiplying the impact of the pandemic on absences (eq. 2/3) by the post-pandemic impact of absences on test scores (eq. 1), while the PNIE is calculated by multiplying the impact of the pandemic on absences by the pre-pandemic impact of absences on test scores. "% NIE" ("% PNIE)" obtained by dividing the NIE (PNIE) by the TE. Covariates, not shown, include student demographics, educational classifications (e.g., disability status), school characteristics, and (in peer effects models) classroom averages of individual-level variables (see complete list in Appendix A). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was in the top 80 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. Standard errors, clustered by school-year, are shown in parentheses. N's: Black = 126,247; Hispanic = 107,185; White = 322,424; ED = 250,303; Not ED = 361,341; Q2 = 159,802; Q3 = 158,211; Q4 = 143,908; Q5 = 149,723.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Figures

Figure 1

Observed test scores vs. predicted scores if absenteeism returned to pre-pandemic levels



Note. Gray line depicts students' standardized math test scores over time from 2017-18 through 2021-22. Black dashed line depicts potential math test scores if absences had returned to pre-pandemic levels in 2021-22, based on our highest estimate of the mediating impact of increased post-pandemic absenteeism on test scores (23%; Table 1, Model 2, PNIE). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was in the top 80 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent.

Online Appendix A. Additional Details on Data and Methods

Supplemental discussion of data and sample

This Appendix provides more detail on our data, sample, and methods. We begin by noting that we restrict our analysis to students in 6th and 7th grade because these students all take the same exam at the same time and had a pre-pandemic test score that we could include as a control. By contrast, students in grades 3 through 5 in the 2021-22 cohort do not have any pre-pandemic test scores, while 8th grade students take different exams depending on whether they are enrolled in regular 8th grade math or high school Math 1. Additionally, we focus on only math because the state reading test was rescaled between 2018-19 and 2021-22. While the math test was rescaled between 2017-18 and 2018-19, the content of the test remained comparable and the scale was consistent between 2018-19 and 2021-22, allowing us to anchor 2021-22 scale scores to the 2018-19 distribution. To address concerns that math test scores between 2017-18 and 2018-19 may not be comparable, we also produce an alternative specification in Appendix C using only the 2018-19 and 2021-22 cohorts, which yields similar results as the primary specification. Finally, we do not include other pandemic-affected years (2019-20 and 2020-21) because there were no exams in 2019-20 and because hybrid/remote instruction in these years may have altered the measurement of attendance.

Our data include a robust set of control variables, including: student-level gender, race/ethnicity, economic disadvantage status (eligibility for free or reduced-price lunch or auto-certified as disadvantaged by the rules of the Community Eligibility Provision), English Learner status, academically or intellectually gifted status, disability status, whether the student was suspended during the year, baseline achievement in math from three years' prior, and grade level; and school-level percent non-white, average prior math scores, and urbanicity. In peer effects models, we additionally control for variables describing the student's classroom peers including: the number of students in the class, average prior math scores, percent male, racial/ethnic percentages, percent economically disadvantaged, percent English Learners, percent academically/intellectually gifted, percent with a disability, and the percent who received a suspension. Descriptive statistics for all variables are shown in Appendix Table A1. In addition, we note that a change in the structure of our absence data in 2017-18 resulted in absences increasing by an average of close to 1 percentage point beginning in 2017-18. We therefore additionally included an indicator variable of whether an observation was in the 2016-17 cohort in all outcome analyses to adjust for this structural change.

Appendix Table A1. *Descriptive statistics*

	Pre-COVID	2021-22
Math Std Score	0.298 (0.888)	-0.003 (0.909)
% of days absent	0.045 (0.043)	0.074 (0.067)
Class: % of days absent	0.047 (0.017)	0.079 (0.032)
Male	50.6%	50.8%
Am. Indian	1.1%	1.1%
Asian	3.5%	3.9%
Black	20.4%	21.4%
Hispanic	16.9%	19.2%
Multi-racial	4.3%	5.1%
White	53.8%	49.4%
Economically Disadvantaged	42.8%	35.5%
Academically/Intellectually Gifted	22.1%	18.6%
Disability	9.3%	9.6%
English Learner	1.3%	5.1%
6^{th} grade	50.8%	49.7%
7^{th} grade	49.2%	50.3%
Suspended	15.3%	17.7%
Baseline math std score	0.374 (0.741)	0.358 (0.730)
School: Urban	38.5%	38.6%
School: Suburb	8.1%	7.9%
School: Town or Rural	53.4%	53.5%
School: % non-white	0.498 (0.242)	0.539 (0.241)
School: Baseline math avg	0.054 (0.369)	0.047 (0.362)
Class: # students	25.363 (7.985)	24.793 (7.268)
Class: Baseline math avg	0.167 (0.620)	0.141 (0.606)
Class: % male	0.504 (0.112)	0.507 (0.113)

Class: % Black	0.217 (0.213)	0.225 (0.215)
Class: % Hispanic	0.172 (0.150)	0.196 (0.161)
Class: % White	0.520 (0.276)	0.477 (0.276)
Class: % Economically Disadvantaged	0.444 (0.250)	0.367 (0.219)
Class: % English Learner	0.032 (0.065)	0.070 (0.105)
Class: % Gifted	0.206 (0.280)	0.173 (0.248)
Class: % Disability	0.111 (0.151)	0.117 (0.149)
Class: % suspended	0.166 (0.148)	0.191 (0.161)
N	457,122	154,522

Note. Standard deviations of continuous variables shown in parentheses. "Baseline" math scores refer to scores from three years' prior (i.e., 3rd grade scores of 6th graders and 4th grade scores of 7th graders). "Class" variables are calculated for peers in each student's math class (including students in the bottom quintile of baseline achievement). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 (pre-COVID) or 2021-22, whose baseline achievement from three years' prior was in the top 80 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. For 2021-22, students' math scale scores were assigned the standardized score equivalent from the 2018-19 distribution; for all other years, students' math scale score were standardized within year and grade – this defines "math std score."

Peer effects models

We identify classroom peers using roster data. We define classroom peers as students attending the same school and taking the same math class with the same teacher, class section, and class period. We omit classrooms with fewer than four students. Some classrooms may not be entirely separated by these variables, as a small number of cases show more than 50 students in a classroom, though at least some of these may be legitimate (e.g., virtual or hybrid classrooms). We include students in these larger classrooms under the assumption that at least some of these students are classroom-level peers and that, at minimum, all are school-level peers taking the same course with the same teacher in ways that could affect instruction. For each student, we identify the average absence rate of classroom peers as the average absence rate in the class excluding the focal student (we also define all other class-level variables this way).

To conduct peer effects models, we estimate the following three equations:

$$(1a)\ Y = \theta_1 a + \theta_2 m_1 + \theta_3 m_2 + \theta_4 a * m_1 + \theta_5 a * m_2 + \theta_6 c + \epsilon$$

$$(2a)\ m_1 = \beta_{01} + \beta_{11} a + \beta_{21} c + \omega_1$$

$$(3)\ m_2 = \beta_{02} + \beta_{12} a + \beta_{22} c + \omega_2$$

The NIE is then defined as $((\beta_{11} * \theta_2 + \beta_{11} * \theta_4) + (\beta_{12} * \theta_3 + \beta_2 * \theta_5))$. We highlight that this simply consists of two components that are a summative expansion of the one-mediator model: an estimate of the post-pandemic effect of own absences times the increase in own absences, and an estimate of the post-pandemic effect of peer absences times the increase in peer absences. The NDE is therefore defined as $(\theta_1 + \theta_4 * \beta_{01} + \theta_5 * \beta_{02})$. We expand the PNIE and TNDE similarly (VanderWeele & Vansteelandt, 2014).

Conditions for causality

There are four key criteria that must be satisfied to interpret results as causal: A) no confounding between treatment and the outcome; B) no confounding between treatment and the mediator; C) no confounding between the mediator and the outcome; and D) no mediator-outcome confounders are impacted by treatment (VanderWeele, 2016). We assume that there is no confounding between treatment (COVID-19 pandemic) and other variables given that the timing of the pandemic can be considered essentially random. While there were some changes in the composition of students who remained enrolled in public schools, these shifts are minor within the grade levels we examine and we account for these changes via demographic controls. These changes could constitute a violation of assumption D to the extent that demographics confound the relationship between absences and test scores, but changes to student composition induced by the pandemic are relatively minor.

Of more concern is identifying an accurate effect of absences on test scores (assumption C). We aim to do so using a robust set of covariates. The most important is students' standardized score in math from three years' prior (i.e., from 2018-19 for students in 2021-22), which explains 60% to 70% of the variance in our outcomes. However, as this assumption remains untestable, we conduct sensitivity checks in Appendix B to assess the credibility of our estimates.

Finally, there may be other violations of assumption D that are difficult to fully account for. For example, the pandemic may have affected student motivation levels, which could make them less likely to attend school and decrease their test scores. As these factors are unobservable, our results depend on the validity of the assumption that there are no such changes conditional on the covariates we include.

Online Appendix B. Sensitivity Checks

Fixed effects models

We conduct two sensitivity checks to assess the credibility of our estimates of the impact of absences. Our first check involves running student fixed effect models to estimate the impact of changes in days absent within students over time. To do so, we create an auxiliary sample consisting of students observed in grade 5 in 2016-17, grade 6 in 2017-18, and grade 7 in 2018-19. To approximate our primary models, we restrict to students with at least 90 days enrolled in each year, fewer than 50% of days absent in each year, and whose test scores were not in the bottom quintile in grade 5. We then ran a student fixed effects model of the form:

$$Y_{ig} = \alpha_i + \beta_1 \%Abs_{ig} + X_{ig} + \epsilon_{ig} \ ,$$

where α_i is an individual student indicator, Y_{ig} refers to a student's test score in grade g, $\%Abs_{ig}$ refers to the percent of days the student was absent in grade g, and X_{ig} refers to other time-varying student-level variables. The individual student indicator controls for all time-constant characteristics of the student (including observable and unobservable characteristics) that could affect their absence rate or test scores. This model thus relies on the weaker causal assumption that there are no unobserved time-varying confounders affecting the estimated impact of absences on test scores within the student. We include as time-varying covariates an indicator of having been suspended, school urbanicity, and school non-white percent in X_{ig}.

We show results of models with and without covariates in Table B1. While it is not expected that the models should exactly match the main estimates, the results here are just slightly weaker than the main pre-period treatment estimate – with no covariates, each one percentage point increase in days absent is associated with a 0.017 SD reduction in test scores instead of 0.019 SDs in Table 1 in the main results, while with time-varying covariates each percentage point increase in absences is associated with a 0.015 SD reduction.

Appendix Table B1. *Student fixed effects models*

	(1)	(2)
% Abs	-1.719***	-1.525***
	(0.036)	(0.036)
Covariates?	N	Y
N	228,102	228,102

Note. Time-varying covariates in Model 2, not shown, include whether the student received a suspension, school urbanicity, school percent non-white, and school average baseline math scores from three years' prior. Sample includes students enrolled in grade 5 in a traditional public school in North Carolina in 2016-17 who were observed in grade 6 in 2017-18 and grade 7 in 2018-19 and 2018-19, whose baseline achievement in grade 5 was in the top 80 percent of the achievement distribution and who always had at least 90 days in attendance and less than 50 percent days absent.
* p < .05, ** p < .01, *** p < .001.

If the true effect of a pre-pandemic absence was a 0.015 SD reduction in test scores, then we would estimate that the post-pandemic increase in absences (2.8 percentage points) would account for 0.042 SDs of the 0.264 SD reduction in post-pandemic test scores. This would suggest that the true PNIE would be 16% instead of 20%, or about 80% of its original strength. Thus, these models suggest that bias in the cross-sectional estimates due to unobservable time-constant student-level confounders does not likely substantially affect our estimates.

Oster (2019) sensitivity analysis

We next conducted a sensitivity analysis following the method of Oster (2019). Specifically, we assessed the impact of potential bias in our estimates of the effect of absences on test scores via the equation: $\beta^{*} = \beta^{\sim} - \delta(\beta^{0} - \beta^{\sim})\left(\frac{R_{max} - R^{\sim}}{R^{\sim} - R^{0}}\right)$, where β^{*} refers to the unobserved true effect, $\beta^{\sim}$ refers to the observed effect estimate and $R^{\sim}$ to the R^2 from this equation, β^0 refers to the effect estimate from a "short regression" with no covariates and R^0 to the R^2 from this equation, δ is a researcher-specified term that adds a weight for how important unobservables are relative to observables, and R_{max} is a researcher-specified term indicating the maximum possible value of R^2 that could be observed in a full equation with all observed and unobserved covariates.

To fit the present application, we focus on equations with individual absences only (no peer effects); we include in our "short" regression the interaction of treatment with absences; and we use β values that refer to pre-pandemic effect estimates. Following Oster's recommendations, we initially set R_{max} to $R^{\sim} * 1.3$ (approximately equal to 0.9) and δ to 1. However, in our application these values are likely too strong – for example, it seems unlikely that unobservables are as important to a student's test score as the variables we control for. We therefore produce a table of results that vary δ from 0.25 to 1 and R_{max} from $R^{\sim} * 1.1$ to $R^{\sim} * 1.3$. We recalculate the PNIE and percent mediated based on these estimates of potential confounding.

Results are shown in Appendix Table B2. Under the strongest assumptions about bias ($R_{max} = R^{\sim} * 1.3, \delta = 1$), our observed estimates of the effect of absences would be about two times too strong. Even under this scenario, changes in absences would still mediate about 9% of the total change in test scores from pre- to post-pandemic.

Appendix Table B2. *Oster (2019) sensitivity analysis*

	$\delta = 1$	$\delta = 0.75$	$\delta = 0.5$	$\delta = 0.25$
$R_{max} = R^{\sim} * 1.10$	-1.544 (16%)	-1.631 (17%)	-1.716 (18%)	-1.802 (19%)
$R_{max} = R^{\sim} * 1.20$	-1.202 (13%)	-1.373 (15%)	-1.544 (16%)	-1.716 (18%)
$R_{max} = R^{\sim} * 1.30$	-0.858 (9%)	-1.116 (12%)	-1.373 (15%)	-1.631 (17%)

Note. Cells show impact estimate of absences on test scores, with calculation of percent mediated by change in absences shown in parentheses. Main estimate = -1.888, PNIE = 20%, TE = 0.264.

Online Appendix C. Alternative Specifications

This Appendix presents results from alternative specifications, including: A) results that include students in the bottom quintile of baseline achievement, which includes all students but may be affected by potential floor effects on the state exams; B) results using only one or two pre-pandemic cohorts instead of three, which reduces sample size but avoids complications that arise from changes in our data structure over time (i.e., that there were changes in the math test scale between 2017-18 and 2018-19 and slight changes in absence rates due to a change in the structure of absence data in 2017-18); and C) results from models that incorporate mediator-mediator interactions, which require use of an alternative mediation analysis technique.

Results pertaining to points A and B are shown in Table C1. The results are generally similar to the main estimates. Specifically, adding the bottom quintile widens the difference between the NIE and PNIE, ranging from 10% (for the NIE) to 25% (for the PNIE) in peer effects models as compared to the 16% and 23% in the main specification. Restricting to one or two pre-pandemic cohorts instead of three results in almost identical estimates as the main results when using only one mediator and modestly weaker estimates when using both mediators.

Appendix Table C1. *Alternative Specifications*

		W/bottom quintile		One pre-COVID cohort		Two pre-COVID cohorts	
		(1)	(2)	(3)	(4)	(5)	(6)
TE		-0.237	-0.251	-0.265	-0.279	-0.263	-0.275
NIE		-0.032	-0.025	-0.040	-0.037	-0.042	-0.041
% NIE		13%	10%	15%	13%	16%	15%
PNIE		-0.051	-0.063	-0.049	-0.057	-0.053	-0.059
% PNIE		21%	25%	19%	20%	20%	21%
Eq. 1	COVID	-0.235***	-0.287***	-0.242***	-0.277***	-0.240***	-0.265***
(Y = test score)		(0.0108)	(0.0200)	(0.0133)	(0.0262)	(0.0116)	(0.0231)
	% Abs	-1.589***	-1.407***	-1.793***	-1.554***	-1.859***	-1.629***
		(0.0299)	(0.0206)	(0.0604)	(0.0383)	(0.0420)	(0.0289)
	Peer % Abs		-0.641***		-0.561		-0.502
			(0.1890)		(0.3727)		(0.2821)
	COVID x % Abs	0.605***	0.488***	0.351***	0.267***	0.397***	0.342***
		(0.0520)	(0.0352)	(0.0749)	(0.0480)	(0.0611)	(0.0411)
	COVID x Peer % Abs	.	0.749**	.	0.438		0.309
		.	(0.2278)	.	(0.3823)		(0.3116)
Eq. 2	COVID	0.032***	0.031***	0.028***	0.026***	0.028***	0.027***
(Y = % Abs)		(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Eq. 3	COVID	.	0.031***	.	0.028***		0.029***
(Y = Peer % Abs)		.	(0.0008)	.	(0.0009)		(0.0008)
N		768,228	768,228	320,060	320,060	464,648	464,648

Note. TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect. The NIE is calculated by multiplying the impact of the pandemic on absences (eq. 2/3) by the post-pandemic impact of absences on test scores (eq. 1), while the PNIE is calculated by multiplying the impact of the pandemic on absences by the pre-pandemic impact of absences on test scores. "% NIE" ("% PNIE)" obtained by dividing the NIE (PNIE) by the TE. Covariates, not shown, include student demographics, educational classifications (e.g., disability status), school characteristics, and (in peer effects models) classroom averages of individual-level variables (see complete list in Appendix A). Potential sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was in the top 80 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. Models 1 and 2 include students in the bottom 20 percent of the baseline achievement distribution; Models 3 and 4 restrict to students in the 2018-19 and 2021-22 cohorts; and Models 5 and 6 restrict to students in the 2017-18, 2018-19, and 2021-22 cohorts. Standard errors, clustered by school-year, are shown in parentheses.

* $p < .05$, ** $p < .01$, *** $p < .001$

Our other alternative specification addresses the possibility that our mediators themselves may interact. For example, it may be that one's own absences are costly in a classroom where few peers are ever absent, but are less costly when many peers are frequently absent. Incorporating mediator-mediator interactions requires a different approach than that used in the rest of this study. We employ the counterfactual weighting approach of VanderWeele & Vansteelandt (2014). To do so, we run an outcome model that includes a triple interaction of both mediators and the treatment variable:

$$Y = \theta_1 a + \theta_2 m_1 + \theta_3 m_2 + \theta_4 a * m_1 + \theta_5 a * m_2 + \theta_6 m_1 m_2 + \theta_7 a * m_1 m_2 + \theta_8 c + \epsilon.$$

Using this model, we generate predictions of what pre-pandemic students' test scores would have been had they been affected by the pandemic (i.e., if treatment was equal to 1 instead of 0) but experienced no change in absences. That is, after running this model, we generate predicted outcome values for students in the pre-pandemic group using observed values of both mediators and all covariates but using a counterfactual value of "1" for treatment status. This provides an estimate of a counterfactual condition in which pre-pandemic students were affected by the pandemic but did not experience a change in absence rates. We subtract the mean of these predicted values for students in the pre-pandemic cohort from the observed mean in 2021-22 to estimate the NIE (i.e., the change in the outcome that is due to the change in absences).[1] We obtain the NDE, PNIE, and TNDE following a similar approach.

[1] Each mean is also weighted to account for differences in demographic composition over time. Specifically, the counterfactual mean is weighted by $\frac{\Pr(a=0)}{\Pr(a=0|c)}$ and the treatment group mean is weighted by $\frac{\Pr(a=1)}{\Pr(a=1|c)}$, where the numerators refer to the observed probability of being in the control (or treatment) group and the denominators refer to the probability of being in the control (or treatment) group conditional on covariates. We obtain this by running a logit model of control (or treatment) status on individual- and school-level covariates. We note that we exclude English Learner status from these logit models because the increase in English Learners from pre- to post-COVID results in a small number of extreme weights that create unstable estimates; however, we do control for English Learner status, as well as classroom-level covariates, in the outcome equation.

Results are shown in Appendix Table C2. Via this method, we find that absences account for 15 to 23 percent of the total effect of COVID on post-pandemic test scores (0.04 to 0.06 SDs), similar to the main specification. Results for racial/ethnic subgroups are also shown and are generally similar to the main results.

In addition, we note that this model shows that absences are less costly in environments where peers are more absent, as there is a positive interaction between own and peer absences. Further, in the full-sample model, there is no difference in the impact of own or peer absences between pre- and post-pandemic after adding the interaction between the mediators (though there is still a difference for Black and Hispanic students). For example, consider the impact of raising own and peer absences by 3 percentage points. This model suggests that this would decrease test scores by -0.075 SDs pre-pandemic and -0.074 SDs post-pandemic (note that the NIE and PNIE still differ in these models due to the weights described in footnote 1). This provides some evidence that the PNIE may be preferable in main full-sample estimates, as the impact of attendance may not have actually changed over time after accounting for this interaction, though we caution against overinterpreting this given that this does not hold within subgroups.

Appendix Table C2. *Mediator-Mediator Interaction Results*

	All (1)	Black (2)	Hispanic (3)	White (4)
TE	-0.272	-0.328	-0.336	-0.260
NIE	-0.040	-0.039	-0.060	-0.056
% NIE	15%	12%	18%	22%
PNIE	-0.061	-0.102	-0.130	-0.065
% PNIE	23%	31%	39%	25%
COVID	-0.229***	-0.372***	-0.344***	-0.187***
	(0.0276)	(0.0338)	(0.0342)	(0.0355)
% Abs	-1.788***	-1.942***	-1.967***	-1.707***
	(0.1173)	(0.1429)	(0.2175)	(0.1470)
Peer % Abs	-0.771*	-1.871***	-1.408**	-0.738
	(0.3034)	(0.3481)	(0.4325)	(0.3864)
COVID x % Abs	-0.047	0.514*	0.244	-0.315
	(0.1776)	(0.2204)	(0.2846)	(0.2719)

COVID x Peer % Abs	-0.022	1.553***	1.355**	-0.172
	(0.3707)	(0.4300)	(0.4936)	(0.5063)
% Abs x Peer % Abs	2.489	7.323***	2.881	1.785
	(1.9959)	(2.1208)	(3.6722)	(2.7303)
COVID x % Abs x Peer % Abs	3.404	-3.463	0.890	5.265
	(2.4323)	(2.6160)	(4.0609)	(3.8197)
N	611,644	103,434	85,926	251,401

Note. TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect. The NIE is calculated by subtracting predicted test scores for students in the pre-COVID group from observed test scores in the COVID group, with predicted test scores obtained from an outcome equation that includes a triple interaction of treatment and both mediators, where pre-COVID students' predicted values are generated for the counterfactual condition in which they were treated but experienced observed values of mediators and all covariates. Results are additionally weighted by the likelihood of being in the treatment/control group, obtained from a first-stage logit regression of treatment/control status on individual- and school-level covariates. The PNIE is obtained similarly under the counterfactual condition in which the treatment group was not treated but experienced observed values of mediators and all covariates. Covariates, not shown, include student demographics, educational classifications (e.g., disability status), school characteristics, and classroom averages of individual-level variables (see complete list in Appendix A). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was in the top 80 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. Standard errors, clustered by school-year, are shown in parentheses.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Online Appendix D. Detailed Subgroup Impacts

Appendix Table D1. *Mediation estimates, racial/ethnic subgroups*

		Black		Hispanic		White	
		(1)	(2)	(3)	(4)	(5)	(6)
TE		-0.313	-0.317	-0.301	-0.305	-0.229	-0.248
NIE		-0.039	-0.032	-0.048	-0.039	-0.038	-0.038
% NIE		12%	10%	16%	13%	17%	15%
PNIE		-0.062	-0.090	-0.069	-0.098	-0.043	-0.044
% PNIE		20%	28%	23%	32%	19%	18%
Eq. 1	COVID	-0.304***	-0.370***	-0.282***	-0.354***	-0.201***	-0.221***
(Y = test score)		(0.0139)	(0.0260)	(0.0146)	(0.0277)	(0.0131)	(0.0249)
	% Abs	-1.739***	-1.490***	-2.075***	-1.825***	-1.845***	-1.607***
		(0.0513)	(0.0433)	(0.0597)	(0.0516)	(0.0455)	(0.0328)
	Peer % Abs		-1.146***		-1.248***		-0.288
			(0.2525)		(0.3151)		(0.2920)
	COVID x % Abs	0.651***	0.485***	0.653***	0.522***	0.223**	0.200***
		(0.0760)	(0.0633)	(0.0835)	(0.0748)	(0.0717)	(0.0517)
	COVID x Peer % Abs		1.196***		1.309***		0.033
			(0.3105)		(0.3714)		(0.3381)
Eq. 2	COVID	0.035***	0.034***	0.033***	0.032***	0.023***	0.023***
(Y = % Abs)		(0.0012)	(0.0012)	(0.0010	(0.0010)	(0.0009)	(0.0009)
Eq. 3	COVID		0.035***		0.032***		0.026***
Y = Peer % Abs)			(0.0012)		(0.0009)		(0.0008)
N		126,247	126,247	107,185	107,185	322,424	322,424

Note. TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect. The NIE is calculated by multiplying the impact of the pandemic on absences (eq. 2/3) by the post-pandemic impact of absences on test scores (eq. 1), while the PNIE is calculated by multiplying the impact of the pandemic on absences by the pre-pandemic impact of absences on test scores. "% NIE" ("% PNIE)" obtained by dividing the NIE (PNIE) by the TE. Covariates, not shown, include student demographics, educational classifications (e.g., disability status), school characteristics, and (in peer effects models) classroom averages of individual-level variables (see complete list in Appendix A). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was in the top 80 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. Standard errors, clustered by school-year, are shown in parentheses.
* p < .05, ** p < .01, *** p < .001

Table D2. *Mediation estimates, ED subgroups*

		ED		Not ED	
		(1)	(2)	(3)	(4)
TE		-0.289	-0.301	-0.247	-0.257
NIE		-0.047	-0.035	-0.037	-0.042
% NIE		16%	12%	15%	16%
PNIE		-0.071	-0.091	-0.043	-0.047
% PNIE		25%	30%	17%	18%
Eq. 1	COVID	-0.276***	-0.350***	-0.221***	-0.226***
(Y = test score)		(0.0114)	(0.0220)	(0.0126)	(0.0245)
	% Abs	-1.788***	-1.584***	-2.034***	-1.755***
		(0.0364)	(0.0290)	(0.0523)	(0.0382)
	Peer % Abs		-0.904***		-0.440
			(0.2197)		(0.3020)
	COVID x % Abs	0.612***	0.507***	0.280***	0.282***
		(0.0543)	(0.0448)	(0.0773)	(0.0567)
	COVID x Peer % Abs		1.095***		-0.003
			(0.2655)		(0.3354)
Eq. 2	COVID	0.040***	0.038***	0.021***	0.021***
(Y = % Abs)		(0.0010)	(0.0010)	(0.0007)	(0.0007)
Eq. 3	COVID		0.034***		0.026***
Y = Peer % Abs)			(0.0009)		(0.0008)
N		250,303	250,303	361,341	361,341

Note. ED = economically disadvantaged, TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect. The NIE is calculated by multiplying the impact of the pandemic on absences (eq. 2/3) by the post-pandemic impact of absences on test scores (eq. 1), while the PNIE is calculated by multiplying the impact of the pandemic on absences by the pre-pandemic impact of absences on test scores. "% NIE" ("% PNIE)" obtained by dividing the NIE (PNIE) by the TE. Covariates, not shown, include student demographics, educational classifications (e.g., disability status), school characteristics, and (in peer effects models) classroom averages of individual-level variables (see complete list in Appendix A). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was in the top 80 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. Standard errors, clustered by school-year, are shown in parentheses.

* $p < .05$, ** $p < .01$, *** $p < .001$

Table D3. *Mediation estimates, baseline achievement subgroups*

		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TE		-0.254	-0.265	-0.299	-0.308	-0.277	-0.294	-0.222	-0.228
NIE		-0.036	-0.026	-0.044	-0.045	-0.047	-0.041	-0.042	-0.051
% NIE		14%	10%	15%	15%	17%	14%	19%	22%
PNIE		-0.064	-0.087	-0.059	-0.078	-0.051	-0.057	-0.041	-0.037
% PNIE		25%	33%	20%	25%	18%	20%	19%	16%
Eq. 1	COVID	-0.259***	-0.332***	-0.277***	-0.317***	-0.237***	-0.281***	-0.178***	-0.150***
(Y = test score)		(0.0116)	(0.0230)	(0.0128)	(0.0265)	(0.0137)	(0.0277)	(0.0132)	(0.0252)
	% Abs	-1.729***	-1.569***	-1.930***	-1.652***	-2.022***	-1.708***	-2.031***	-1.836***
		(0.0422)	(0.0364)	(0.0516)	(0.0430)	(0.0573)	(0.0475)	(0.0649)	(0.0543)
	Peer % Abs		-0.880***		-0.944***		-0.626*		-0.061
			(0.2232)		(0.2709)		(0.2989)		(0.3431)
	COVID x	0.759***	0.650***	0.475***	0.409***	0.151	0.131	-0.049	0.018
	% Abs	(0.0600)	(0.0527)	(0.0752)	(0.0621)	(0.0869)	(0.0721)	(0.1003)	(0.0843)
	COVID x		1.071***		0.671*		0.492		-0.687
	Peer % Abs		(0.2682)		(0.3314)		(0.3746)		(0.4008)
Eq. 2	COVID	0.037***	0.036***	0.031***	0.029***	0.025***	0.024***	0.020***	0.019***
(Y = % Abs)		(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Eq. 3	COVID		0.036***		0.032***		0.027***		0.021***
Y = Peer % Abs)			(0.0009)		(0.0008)		(0.0008)		(0.0008)
N		159,802	159,802	158,211	158,211	143,908	143,908	149,723	149,723

Note. Quintile = position in baseline achievement distribution from three years' prior, where 1 is the lowest quintile and 5 is the highest; TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect. The NIE is calculated by multiplying the impact of the pandemic on absences (eq. 2/3) by the post-pandemic impact of absences on test scores (eq. 1), while the PNIE is calculated by multiplying the impact of the pandemic on absences by the pre-pandemic impact of absences on test scores. "% NIE" ("% PNIE") obtained by dividing the NIE (PNIE) by the TE. Covariates, not shown, include student demographics, educational classifications (e.g., disability status), school characteristics, and (in peer effects models) classroom averages of individual-level variables (see complete list in Appendix A). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior who had at least 90 days in attendance and less than 50 percent days absent. Standard errors, clustered by school-year, are shown in parentheses.

* p < .05, ** p < .01, *** p < .001.

Appendix Table D4. *Mediation estimates, racial/ethnic subgroups in baseline achievement quintiles 4/5*

		Black		Hispanic		White	
		(1)	(2)	(3)	(4)	(5)	(6)
TE		-0.337	-0.335	-0.320	-0.324	-0.218	-0.234
NIE		-0.050	-0.057	-0.055	-0.052	-0.039	-0.040
% NIE		15%	17%	17%	16%	18%	17%
PNIE		-0.061	-0.078	-0.063	-0.077	-0.037	-0.033
% PNIE		18%	23%	20%	24%	17%	14%
Eq. 1	COVID	-0.300***	-0.311***	-0.276***	-0.312***	-0.175***	-0.182***
(Y = test score)		(0.0178)	(0.0344)	(0.0175)	(0.0337)	(0.0138)	(0.0267)
	% Abs	-2.096***	-1.759***	-2.149***	-1.874***	-1.894***	-1.641***
		(0.0980)	(0.0863)	(0.0948)	(0.0866)	(0.0580)	(0.0459)
	Peer % Abs		-1.065**		-0.923*		-0.081
			(0.3599)		(0.4111)		(0.3418)
	COVID x % Abs	0.362*	0.276*	0.260	0.225	-0.088	-0.073
		(0.1496)	(0.1354)	(0.1342)	(0.1274)	(0.0917)	(0.0744)
	COVID x Peer % Abs		0.484		0.682		-0.233
			(0.4686)		(0.4960)		(0.4064)
Eq. 2	COVID	0.029***	0.027***	0.029***	0.027***	0.020***	0.019***
(Y = % Abs)		(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0008)	(0.0008)
Eq. 3	COVID		0.029***		0.028***		0.022***
Y = Peer % Abs)			(0.0011)		(0.0009)		(0.0008)
N		37,607	37,607	40,469	40,469	185,384	185,384

Note. TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect. The NIE is calculated by multiplying the impact of the pandemic on absences (eq. 2/3) by the post-pandemic impact of absences on test scores (eq. 1), while the PNIE is calculated by multiplying the impact of the pandemic on absences by the pre-pandemic impact of absences on test scores. "% NIE" ("% PNIE)" obtained by dividing the NIE (PNIE) by the TE. Covariates, not shown, include student demographics, educational classifications (e.g., disability status), school characteristics, and (in peer effects models) classroom averages of individual-level variables (see complete list in Appendix A). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was in the top 40 percent of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. Standard errors, clustered by school-year, are shown in parentheses.
* p < .05, ** p < .01, *** p < .001

Appendix Table D5. *Mediation estimates, racial/ethnic subgroups in baseline achievement quintiles 2/3*

		Black		Hispanic		White	
		(1)	(2)	(3)	(4)	(5)	(6)
TE		-0.303	-0.308	-0.289	-0.293	-0.245	-0.268
NIE		-0.036	-0.024	-0.044	-0.034	-0.036	-0.030
% NIE		12%	8%	15%	11%	15%	11%
PNIE		-0.063	-0.096	-0.074	-0.109	-0.051	-0.062
% PNIE		21%	31%	26%	37%	21%	23%
Eq. 1	COVID	-0.303***	-0.387***	-0.283***	-0.368***	-0.236***	-0.294***
(Y = test score)		(0.0140)	(0.0269)	(0.0156)	(0.0299)	(0.0142)	(0.0291)
	% Abs	-1.641***	-1.426***	-2.029***	-1.806***	-1.801***	-1.587***
		(0.0538)	(0.0478)	(0.0690)	(0.0624)	(0.0529)	(0.0433)
	Peer % Abs		-1.163***		-1.306***		-0.592*
			(0.2550)		(0.3263)		(0.3012)
	COVID x % Abs	0.707***	0.545***	0.824***	0.674***	0.524***	0.456***
		(0.0769)	(0.0683)	(0.0943)	(0.0876)	(0.0812)	(0.0671)
	COVID x Peer % Abs		1.385***		1.462***		0.642
			(0.3122)		(0.3860)		(0.3647)
Eq. 2	COVID	0.038***	0.037***	0.036***	0.035***	0.028***	0.028***
(Y = % Abs)		(0.0013)	(0.0013)	(0.0011)	(0.0011)	(0.0010)	(0.0010)
Eq. 3	COVID		0.037***		0.035***		0.031***
Y = Peer % Abs)			(0.0012)		(0.0010)		(0.0009)
N		88,640	88,640	66,716	66,716	137,040	137,040

Note. TE = total effect, NIE = natural indirect effect, PNIE = pure natural indirect effect. The NIE is calculated by multiplying the impact of the pandemic on absences (eq. 2/3) by the post-pandemic impact of absences on test scores (eq. 1), while the PNIE is calculated by multiplying the impact of the pandemic on absences by the pre-pandemic impact of absences on test scores. "% NIE" ("% PNIE)" obtained by dividing the NIE (PNIE) by the TE. Covariates, not shown, include student demographics, educational classifications (e.g., disability status), school characteristics, and (in peer effects models) classroom averages of individual-level variables (see complete list in Appendix A). Sample includes students enrolled in grade 6 or 7 in a traditional public school in North Carolina between 2016-17 and 2018-19 or 2021-22, whose baseline achievement from three years' prior was between the 20th and 60th percentile of the achievement distribution and who had at least 90 days in attendance and less than 50 percent days absent. Standard errors, clustered by school-year, are shown in parentheses.
* p < .05, ** p < .01, *** p < .001