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Researchers, educators, and policymakers have long worried about the consequences of student absences for educational achievement and attainment—concerns that have grown with the significant rise in absenteeism during and following the Covid-19 pandemic. Using administrative data from Maryland, North Carolina, and a large urban school district, we find that the impact of absences on test scores was modestly (about 5 to 20%) smaller in 2022-23 than in 2018-19 but still practically and statistically significant. Consistent with prior research, these harmful effects of absences are approximately linear and exhibit little heterogeneity across race and gender pre-Covid. In Maryland, the impact of tenth-grade absences on high-school graduation and 2-year college enrollment was much (about 40%) smaller after the pandemic than before, but the impact of absences on any (2- or 4-year) college enrollment increased slightly. Post-Covid reductions in the harmful effects were larger for white students on test scores and larger for Black students on graduation.

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The Causal Effect of Student Absences Post Pandemic: Evidence from Three School Systems

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Abstract

Researchers, educators, and policymakers have long worried about the consequences of student absences for educational achievement and attainment—concerns that have grown with the significant rise in absenteeism during and following the Covid-19 pandemic. Using administrative data from Maryland, North Carolina, and a large urban school district, we find that the impact of absences on test scores was modestly (about 5 to 20%) smaller in 2022-23 than in 2018-19 but still practically and statistically significant. Consistent with prior research, these harmful effects of absences are approximately linear and exhibit little heterogeneity across race and gender pre-Covid. In Maryland, the impact of tenth-grade absences on high-school graduation and 2-year college enrollment was much (about 40%) smaller after the pandemic than before, but the impact of absences on any (2- or 4-year) college enrollment increased slightly. Post-Covid reductions in the harmful effects were larger for white students on test scores and larger for Black students on graduation. Exploratory analyses suggest that absenteeism accounts for a relatively small share of Covid-induced learning loss, though the harmful effects of absenteeism on immediate and longer-run outcomes indicates that it is and should remain a serious concern for policymakers, school leaders, and other stakeholders.

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1 Introduction

Average daily attendance rates were among the first education statistics used in the 19th century to measure school quality (Hutt, 2018). A century and a half later, most states have adopted chronic absenteeism (defined as missing more than 10 percent of school days) as a secondary accountability indicator under the Every Student Succeeds Act (2015). The interest in student attendance is intuitive: students must be present to learn and attendance will be greater, all else equal, when schools provide warm, inviting, safe environments that students (and their parents) want (them) to be in.

Numerous credible studies conducted in varied contexts document the causal effect of student absences on an array of educational outcomes including test scores, grades, and educational attainment (Aucejo and Romano, 2016; Cattan et al., 2023; Gershenson, Jacknowitz and Brannegan, 2017; Gottfried, 2009, 2011; Klein, Sosu and Dare, 2022; Liu, Lee and Gershenson, 2021). These studies find that absences consistently reduce standardized test scores and course grades, with even modest levels of absence producing measurable declines in academic performance. Additionally, higher absence rates lower the probability of high school graduation and college enrollment. However, with one exception (Swiderski, Fuller and Bastian, 2025*a*), these studies rely exclusively on pre-pandemic data.

Of course, the Covid-19 Pandemic changed a great many things in our society, including norms towards in-person gatherings, meetings, and attendance at work and school (Deshmukh, 2021; Tahlyan et al., 2024). Teachers, principals, and state officials observed these changing norms, first-hand when public schools reopened at varying points in 2021 and 2022. When schools resumed their usual operations, students had dramatically different attendance patterns. Districts around the country all reported a staggering rise in chronic absenteeism. For example, in North Carolina, one of our settings for this study, 17% of students were chronically absent at least once over the 3-year period before the pandemic, which increased to 38% in the three years following the pandemic (Swiderski, Fuller and Bastian, 2025*b*). Moreover, the percentage of students who were chronically absent in three consecutive years quadrupled from 2.4% before, to 9.6% after, the pandemic.

North Carolina is no outlier: nationally, in the years leading up to the pandemic, about 10 to 15% of American students were chronically absent. However, chronic absence rates doubled during the pandemic to about 30% in 2022. Since peaking in 2022, chronic absence rates have retreated but only slightly: in 2023 rates of chronic absenteeism fell 3 percentage points from their peak and another 2 percentage points in 2024. But the overall rate of chronic absenteeism at the end of 2024 (23.5%) remains well above pre-pandemic levels (15.1%) (Malkus, 2025). These increased rates of chronic absenteeism occurred in every state in the country, with states that had higher pre-pandemic rates of chronic absenteeism experiencing larger increases (Dee, 2024). For example, a similar analysis of Illinois data finds a stark increase in chronic absences rates in 2021 and 2022 in Chicago Public Schools, and a more muted jump elsewhere in the state, before modestly retreating in 2023 (Torres, 2025).

The rise in absenteeism during and after the pandemic should be interpreted alongside large amounts of learning loss experienced by students in the U.S. and throughout the world (Alasino et al., 2024) (Singh, Romero and Muralidharan, 2024). A meta analysis of dozens of studies found that about half of the immediate learning loss was recovered within a year or so of schools reopening (Cruz et al., 2025). In the U.S., somewhat representative data on nearly 5 million third through eighth graders suggests that as of spring 2021, they were about 0.2 SD behind pace in math and 0.1 SD behind in reading (Kuhfeld et al., 2022). Similarly, the "Nation's Report Card" National Assessment of Educational Progress (NAEP) tests administered by the U.S. Department of Education in 2022 documented 7 and 5 point declines in nine year olds' math and reading scores, respectively[1]—the first ever decline in math scores and the largest reading decline in more than 30 years. Moreover, these declines were largest among relatively low scoring students. Our analysis of North Carolina data shows that math test scores dropped by 0.5 standard deviations (SD) in the 2020-21 school year, relative to pre-pandemic scores from 2018-19, then recovered substantially to around 0.2 SD below pre-pandemic levels by 2021-22 (and increased again but to a much smaller degree the next year). This is all to say that the shock of an unprecedented pandemic that disrupted schools, households, and national economies caused, unsurprisingly, near immediate, sizable amounts of learning loss, as quantified by standardized testing, throughout the U.S. and, indeed, throughout much of the world.

[1] https://www.nationsreportcard.gov/highlights/ltt/2022/

In light of these dual trends, pundits, parents, educators, and school leaders began asking, and continue to ask, important questions about how changing attendance habits might influence student achievement and related educational outcomes. In real time during the pandemic, scholars referred to—and made inferences based on—the academic literature concerning the consequences of student absences that predated the pandemic (Kuhfeld et al., 2020). But there are legitimate questions regarding the external validity of those studies in the post-pandemic landscape. These questions run along several dimensions. First, the fact that learning recovery has occurred while absence rates have held steady indicates that absences are unlikely to be the sole source of achievement losses (and rebounds). Of course, learning loss is due to the pandemic generally, and not school closures or student absences specifically, as there is no disentangling the impacts of each of many shocks that the pandemic levied on students and their families. For example, household finances and the physical and mental health of students, parents, and teachers were all affected by the pandemic, which undoubtedly influenced student achievement independently of any effects of school closures and student absences.

Second, a potential explanation lies in the role of Covid-induced spending and new technologies. The pandemic resulted in districts spending billions of dollars on new technologies that provided students unprecedented virtual access to class content—lectures, notes, assignments, etc.—even when not physically present in school. The U.S. federal government alone provided nearly $190 billion to K-12 schools to fund and facilitate the recovery of those learning losses via the Elementary and Secondary School Emergency Relief (ESSER) fund, which rolled out in three installments between March 2020 and March 2021. While some of these funds were used to improve air quality and facilitate social distancing in schools, much was directly applied to evidence-based interventions for remediating learning loss that included tutoring, extended learning time, summer enrichment programs, and social-emotional learning initiatives (Dewey et al., 2024; Gershenson and Lomax, 2021; Lauen et al., 2025). Dewey et al. (2024) find that in a sample of districts throughout the U.S. in 2023, each $1,000 in ESSER spending per student was associated with a 0.009 SD improvement in math and a 0.005 SD improvement in reading.[2] In Union County, NC, for instance, a whole-grade, high-dosage tutoring program significantly

[2]Interestingly, these effects are quite similar to the estimates in a recent meta-analysis of the impacts of school spending (Jackson and Mackevicius, 2024).

improved average test scores of mainstream fourth and fifth graders by about 0.15 SD (Lauen et al., 2025). Given these considerable investments in technological infrastructure—as well as, possibly, teachers' greater experience during Covid-19 with creating lessons and materials that can accommodate students not physically present in the classroom—it is possible that absences are less harmful to student achievement than they were prior to the pandemic. Indeed, a recent study in North Carolina finds a small decline in the negative effects of each student absence in the post-pandemic period (Swiderski, Fuller and Bastian, 2025*a*). We build on this analysis to consider additional outcomes and additional contexts.

That said, it is possible that, as with many educational technologies, the effects are uneven such that the benefits accrue disproportionately to those who are already high achieving or who have access to more support at home (e.g., a home computer or dedicated workspace). In this case, even if the overall effect of absenteeism on achievement were reduced, the effect of absences on socio-demographic achievement gaps could increase. This could exacerbate the challenge facing teachers who must address the increased chronic absenteeism within their classrooms (as well as schools, districts, and states) seeking to close socio-demographic achievement gaps.

Altogether, these trends motivate the primary research questions of this paper: Have student absences become more or less harmful in the post-pandemic environment? And have they become more or less harmful for students of particular socio-demographic backgrounds? Answering these questions is necessary for assessing the costs of student absenteeism and for properly devising and targeting both proactive (absence reduction) and reactive (learning recovery) interventions.[3] It is also critical for understanding just how much of the remaining pandemic-induced learning loss is attributable to elevated absence rates, as opposed to the myriad other factors that interfered with student learning during and after the pandemic, including the shock of the pandemic itself.

To answer these questions regarding the relationship between absenteeism and student achievement, we use comparable pre- and post-pandemic statewide administrative data from Maryland and North Carolina, as well as from a large urban school district, to estimate the

[3]Our interest in these questions was prompted by a series of events organized by Nat Malkus of the American Enterprise Institute (AEI). The current manuscript formalizes and extends two short white papers published by AEI (Blazar, Gershenson and Hutt, 2025*a*,*b*). We thank Nat Malkus and Sam Hollon for providing constructive feedback on those projects and our research on student absenteeism generally.

effects of absences on student achievement in each time period and for students of different socio-demographic backgrounds. Following Gershenson, Jacknowitz and Brannegan (2017), we employ a lag-score classroom fixed effects strategy and find that the impact of absences on math test scores in both states and the urban school district was about 17% to 19% smaller in elementary school and 6% to 11% smaller in middle school post-Covid than pre-Covid, though it remained practically and statistically significant: ten absences reduce both elementary and middle school math scores by about 4 to 7 percentage points of a test-score standard deviation. These harmful effects of absences are approximately linear in days absent and showed little heterogeneity across race and gender pre-Covid. However, white students experienced a greater reduction in the harmful effects of absences compared to Black students post-Covid. Our estimates are similar to those produced by (Swiderski, Fuller and Bastian, 2025*a*), who also studied the differential effects of absenteeism on student achievement pre- versus post-pandemic in North Carolina. We extend that work showing that the effect is not unique to North Carolina, as we find remarkably consistent patterns in both Maryland and a large urban school district. Given the considerable variation across states and districts in remediation strategies (e.g., tutoring, technology adoption, and so on) this consistency suggests more structural reasons for the diminished effect.

Further extending (Swiderski, Fuller and Bastian, 2025*a*), we use our estimates of the impact of absenteeism on achievement to assess the potential for realistic improvements in student attendance rates to accelerate (or even complete) the learning recovery that is underway via a counterfactual exercise. Plausible reductions in the rate of chronic absenteeism could explain anywhere from 5 to 15% of remaining learning loss. Our best guess is that returning to 2019 rates of chronic absenteeism would reduce learning loss by about 8%. This a nontrivial reduction, but still leaves most (90%) of remaining learning loss unaccounted for. Part of the reason for this is that reducing chronic absence rates would change the attendance behavior of a subset of the student body, while the decline in average test scores is based on all students' scores. Changing our forecast model's assumptions about the impact of chronic absence or the size of the reduction in chronic absence rates does not change our finding that chronic absence plays only a modest role in learning loss and recovery.

Finally, we investigate the effect of student absences on medium-term outcomes of educational attainment using state higher education administrative and National Student Clearinghouse data in Maryland. Specifically, we estimate the effect of tenth-grade absences on high-school graduation and college enrollment, following Liu, Lee and Gershenson (2021) whose analyses focus on pre-pandemic data only. The impact of absences in 10th grade on high school graduation was much smaller (by about 40%) post-Covid, though the effect remains practically and statistically significant: ten absences reduce high school graduation by 3 percentage points. Oster (2019) bounds suggest these estimates cannot be explained by selection into absences. We find similar patterns of reduction for the effect of absences on 2-year college enrollment. However, the negative effect of absences on enrollment in any college (including both 2- and 4-year institutions) actually worsens post-Covid, suggesting that the increase in the effect of absences on 4-year college enrollment exceeds the reduction in effect for 2-year college enrollment.

The rest of this paper is structured as follows. Section 2 describes the data we use. Section 3 discusses the methodology and Section 4 presents our main results. Section 5 presents the counterfactual analysis we conduct and Section 6 presents the additional medium-term results on educational attainment. Section 7 concludes.

2 Data

We use administrative data from three longitudinal data systems from the states of Maryland and North Carolina and from a large urban school district. The three datasets are broadly comparable in that they contain end-of-grade test scores in math and reading for grades 3 through 8 on the states' (district's) standardized tests, students' total annual absences, and rudimentary information about students' socio-demographic backgrounds.

The North Carolina data come from the North Carolina Education Research Data Center (NCERDC). In partnership with the North Carolina Department of Public Instruction, the NCERDC collects data on all public-school students in the state, including district-, school-, and teacher-level data. These data are made available to researchers who pay a usage fee and satisfy data security requirements (Gershenson and Langbein, 2015; Muschkin, Bonneau and Dodge, 2011). These are the same data used in previous analyses of student absenteeism in North Carolina (Aucejo and Romano, 2016; Gershenson, Jacknowitz and Brannegan, 2017).

The Maryland data come from the Maryland Longitudinal Data System Center (MLDSC), which collects and links person-level records from other state agencies including the Maryland State Department of Education (MSDE) and the Maryland Higher Education Commission (MHEC). Data coverage includes all students enrolled in K12 public schools in the state, accessible to researchers via application or becoming a staff member of the MLDSC. Maryland changed the high-stakes test administered from the Partnership for Assessment of Readiness for College and Careers (PARCC) to the Maryland Comprehensive Assessment Program (MCAP) right after the pandemic, meaning that we cannot directly compare learning rates pre- and post-pandemic. However, by standardizing the test scores within grade and year (and Maryland and the other two sites), we can still assess how absences in the current year affect achievement in that same year. Additionally, Maryland's data is unique from the other two locations we study in that it also includes state higher education administrative and National Student Clearinghouse data that allows us to examine medium-term outcomes of high school graduation and college enrollment. We focus these analyses on 10th grade absenteeism to compare to prior literature (Liu, Lee and Gershenson, 2021).

The urban school district data come from a research office as part of an ongoing partnership between the district and university-based researchers. These data include all students enrolled in traditional public schools and are made available to researchers for free following commitment from a staff member and research approval. The data covers all students in traditional public schools and includes the same demographic information as North Carolina and Maryland. Students are administered a common-core aligned assessment both pre- and post- pandemic, allowing for learning rate comparisons across the periods. Due to a test format change in the pre-Covid period, we do not have prior test scores for one pre-Covid cohort. Instead, we control for formative math and reading assessments that are common across all years and cohorts, with coverage rates that are the same as end-of-year, high-stakes tests.

In Maryland and the urban school district, tests were not administered in the spring of 2020 and testing data for spring 2021 is limited. Therefore, we exclude 2021 testing data from our analyses to ensure comparability across systems and to maximize the reliability of our data. Further, because our lag-score models require two years of testing data for estimation, we estimate models for 2018-19 (henceforth 2019) achievement as our pre-pandemic period and for 2022-23 (henceforth 2023) as our post-pandemic period.[4]

The educational attainment outcomes are not subject to the same data-availability limitations as the test scores. Moreover, by definition a few years must pass between tenth grade and high-school graduation and college enrollment, so in our analysis of the effect of absences on attainment in Maryland the pre- and post-pandemic windows are redefined as follows: pre-pandemic refers to 2016 and 2017 for high-school graduation and just 2016 for college enrollment. The post period includes 2021 and 2022 for college enrollment outcomes and just 2022 for high-school graduation.

?? Yu Hung take a shot at writing this attainment paragrpah. It is needlessly confusing talking bout the years of the absences – instead talk about years of the outcomes: pre-covid graduation is graduation in 19, post is in 23?

For high school graduation, the pre- period covers tenth graders in 2016 and 2017 (expected graduation 2018 and 2019) and the post- period covers tenth graders in 2021 and 2022 (expected graduation 2023 and 2024). For college enrollment, the pre period covers tenth graders in 2016 (expected enrollment 2019) and the post period covers tenth graders in 2021 (expected enrollment 2024).

2.1 Summary Statistics

Tables 1, 2, and 3 provide pre- and post-pandemic summary statistics for North Carolina, Maryland, and the large urban school district, respectively. We do so separately for elementary and middle schools, and for the pre- and post-Covid school years. For elementary and middle school, pre-Covid is 2019 and post-Covid is 2023 for consistent comparison across locations. Elementary grades are 4 and 5, where grade-3 scores are used as lags; middle grades are 7 and 8, where grade-6 scores are used as lags, and high-school grade is grade 10, with grade-8

[4] In Maryland we can actually use two years (2018 and 2019) in the pre period to increase power, though doing so does not appreciably change the point estimates.

scores used as lags. Students with more than 50 absences are dropped from the sample because some of these students may not be enrolled in the school; however, some of these might be accurate absence counts and therefore the numbers we report are conservative in that they likely undercount absences. The samples are further restricted to students for whom math scores and all socio-demographic data are observed, reflecting the samples used in the main empirical analyses.[5]

Across all three contexts, absences were generally higher in middle school than in elementary school, both before and after Covid. The only exception is Maryland, where elementary school absences (12.85) were slightly higher than middle school absences (12.74). Also, as discussed and documented elsewhere, absences sharply increased in both types of schools after the pandemic. In elementary school, the annual average count of absences jumped from about 9.6 in Maryland, 7.7 in North Carolina, and 8.2 in the urban school district in 2019 to more than 11 in all locations in 2023. In middle school, it jumped from about 10.1 in Maryland, 8.9 in North Carolina, and 11.8 in the urban school district, to more than 12 in all locations in 2023. In high school, it jumped from 11.0 pre-Covid to 11.4 post-Covid.

Chronic absenteeism rates similarly increased: in Maryland, pre-Covid rates of 14% in elementary schools and 16% in middle schools jumped to 25% by 2023, and pre-Covid rates of 20% in high school jumped to 24% post-Covid. In North Carolina, pre-Covid rates of 8% and 12% in elementary and middle schools, respectively, jumped to 18% and 24% by 2023. In the urban school district, pre-Covid rates of 10% in elementary schools and 22% in middle schools jumped to 24% and 28% by 2023. These increases are substantial in magnitude, representing 20% to 140% increases from pre-Covid levels. The standard deviation (SD) of annual absences also increased by about 1 to 2 absences after the pandemic, indicating that the distributions of absences widened. Because the count of absences is bounded from below at zero, this suggests that some, but not all, students experienced large increases in absences following the pandemic.

In all locations, the demographics of the samples changed in some notable ways between 2019 and 2023. The share of male, Asian, and Black students remained fairly constant (e.g.,

[5] The large drop in sample size post-Covid is driven by a few factors: in addition to a general decline in public school enrollments following Covid, the number of students missing complete background data and missing 50+ days of school also increased.

roughly one-third Black in Maryland, one-quarter Black in North Carolina, and roughly half Black in the urban school district). However, the Hispanic share increased a few percentage points, from roughly 18% to 22% in Maryland and roughly 20 to 23% in North Carolina and in the middle schools of the urban school district. There was also a 5 to 7 percentage point increase in the share of economically disadvantaged students across locations, representing a 12% to 17% increase relative to pre-Covid levels. This is likely due to some of the better-off students leaving the public school system during and immediately after the Covid pandemic. These changes highlight the importance of adjusting for student background in subsequent analyses and testing for heterogeneous effects across students of different backgrounds.

For Maryland, we also report summary statistics for high school students. Absences and chronic absences have increased for high school students by around 4% and 20% respectively. High school graduation rates and college attendance have all declined post-Covid. We analyze these medium-term attainment outcomes in more detail in Section 6.

3 Methodology

Identifying the causal effect of student absences on educational outcomes is challenging because of the myriad potential confounding factors that may influence both student absences and their educational outcomes (Liu, Lee and Gershenson, 2021). The most obvious potential confounders are the student's academic aptitude and attitude towards school. Engaged students are both more likely to attend school and to perform better on standardized tests. For example, students who have higher attendance rates may also spend more time studying outside of the traditional school day. Following Gershenson, Jacknowitz and Brannegan (2017), we adjust for these factors by controlling for students' prior performance on prior standardized test scores. Intuitively, these lag-score models use prior test scores to proxy for students' historical receipt of educational inputs and academic performance (Todd and Wolpin, 2003). We further adjust for students' sociodemographic characteristics such as race, gender, economic status, English Language Learner status, and special education status. These adjustments are sufficient for identifying the causal effect of school-provided inputs such as teachers (Chetty, Friedman and

Rockoff, 2014). Intuitively, we compare the outcomes of students who had different absence levels but similar prior achievement levels and shared socio-demographic backgrounds.

Classroom characteristics such as class size, class composition, and teacher quality comprise another class of potential confounders, as teachers, peers, and class size influence student attendance and achievement (Eren, 2017; Gershenson, 2016; Gottfried, 2013; Liu and Loeb, 2021; Tran and Gershenson, 2021). Accordingly, we exploit within-classroom comparisons by conditioning on classroom fixed effects (Gershenson, Jacknowitz and Brannegan, 2017).

The two-pronged strategy of adjusting for prior achievement while making within-classroom comparisons is discussed and validated in previous research (Gershenson, Jacknowitz and Brannegan, 2017). While this approach is the best we can do given the data limitations inherent in most state data systems, one additional type of possible confounder remains: time-varying unobserved shocks that affect a student or their household after the prior spring's test. Examples include an unexpected illness or job loss in the household that affects a child's school performance and school attendance. Our estimates may slightly overstate the impact of absences as a result, but not in a way that qualitatively changes the interpretation of our findings (Liu, Lee and Gershenson, 2021). Moreover, Gershenson, Jacknowitz and Brannegan (2017) show that in a nationally representative survey, adding more detailed, time-varying household-level controls to the model does not appreciably change the baseline estimates.

Formally, we estimate models akin to equation (1) in Gershenson, Jacknowitz and Brannegan (2017). Specifically, for each state, school type, and subject, we estimate models of the form

$$y_{ijt} = \alpha y_{i,t-1} + \beta X_{it} + \gamma f\left(absences_{it}\right) + \eta_j + \varepsilon_{ijt} \tag{1}$$

where i, j, and t index students, classrooms (or teachers), and years, respectively. The outcome y is the student's standardized (mean 0, SD 1) end-of-grade math or reading test score. The lag score term includes lagged scores in both math and reading. The vector X includes indicators of students' socio-demographic and academic backgrounds. Specifically, X includes binary indicators for race/ethnicity, gender, homelessness, being in the foster care system, economic disadvantage, current (and former) English Language Learner status, and having a current (and former) documented disability that requires special education services.

We test for heterogeneous effects by estimating equation (1) separately for different values of X. Similarly, we test whether effects changed post-Covid by estimating equation (1) separately in the pre and post datasets or by interacting absences with a *Post* dummy in the pooled dataset.

The treatment of interest, *absences*, is the annual count of student absences. It enters equation (1) via the general function f. The baseline model assumes absences enter the model linearly. Following Gershenson, Jacknowitz and Brannegan (2017) we also consider quadratic and nonparametric specifications of f that allow the marginal effect of an additional absence to vary with the number of cumulative absences. The nonparametric specification "dummies out" the absences variable: this specification includes an indicator for each exact absence count, leaving zero absences as the omitted category and top-coding 26 or more absences at 26. We also estimate models that replace $f(absences)$ with a binary indicator for chronic absenteeism (defined as 18 or more absences) (Wu, Weiland and Staines, 2026). Consistent with prior research, we find the effect of absences on test scores to be approximately linear both before and after Covid (Gershenson, Jacknowitz and Brannegan, 2017; Liu, Lee and Gershenson, 2021).

Baseline estimates of equation (1) treat η_j as a classroom fixed effect (FE). These subsume the school, teacher, and year FE that would typically be included in value-added models of the education production function, as there is only one teacher per classroom in self-contained elementary-school classrooms and classrooms are nested in schools and years. In middle school regressions we control for the student's math-class classroom FE. We verify that the results are robust to replacing classroom FE with a control for class size and separate teacher, year, and school FE. Doing so provides more identifying variation and perhaps increased efficiency of the estimates, at the cost of potentially introducing additional bias, if unobserved classroom-specific factors influence both student absences and test scores. Our baseline estimates are quite robust to this modeling decision, lending additional support to the validity of our findings. We estimate equation (1) and its variants using the Stata command reghdfe (Correia, 2023). Standard errors are clustered at the school level, and in sensitivity analyses we find that inference is quite robust to the level at which the standard errors are clustered.

4 Results

4.1 Absences harm achievement

Table 4 reports our main results for math scores, where $f(absences)$ is linear in absences and absences is scaled by 0.10, so coefficients reflect the marginal effect of ten additional absences. Panels A, B, and C do so separately for North Carolina, Maryland, and the urban school district, respectively. Columns (1) and (5) of Table 4 pool pre- and post-Covid data and restrict the effect of student absences to be constant over time, in elementary and middle schools, respectively. Estimates at all sites and in all grade levels are strongly statistically significant. Specifically, ten additional absences reduce math scores by about 5% to 7% of a test-score SD, consistent with extant research (Gershenson, Jacknowitz and Brannegan, 2017; Aucejo and Romano, 2016).

4.2 Absences became modestly less harmful post-Pandemic

We now turn to the question of whether, and to what extent, the effect of absences on achievement has changed in the post-pandemic environment. At all sites and in all grade levels absences are modestly less harmful post pandemic, though they remain economically and statistically significant. Columns (2) and (6) of Table 4 continue using the pooled pre- and post-pandemic data but augment equation (1) to include the interaction of absences with a "post" indicator that allows the effect of absences to vary over time. The coefficient on this interaction term captures the difference between the pre- and post-Covid effect of absences while maintaining that the effect of other inputs in the education production function remained constant.

These interaction terms are statistically significant in North Carolina and Maryland, but not in the urban school district; this is likely due to the significantly smaller sample size in the urban district, as the urban district's coefficients are of similar magnitudes but the standard errors are an order of magnitude larger. Specifically, at all three sites the effect of ten absences on math scores decreased by 1.0 to 1.4% of a test-score SD in elementary schools and by 0.3% to 0.7% of a test-score SD in middle schools. These changes reflect 5 to 20% reductions in the harmfulness of absences relative to pre-pandemic effects.

In columns 3 and 4, and in columns 7 and 8, of Table 4 we estimate the model separately by time period for elementary and middle schools, respectively. This allows the effect of all covariates to freely change over time. Changes in the coefficient on absences between columns 3 and 4, and between 7 and 8, are similar in magnitude to the corresponding changes identified by the interaction terms in columns 2 and 6. These differences are once again statistically significant in North Carolina and Maryland, indicating that the identified reduction in the harmfulness of absences is robust to allowing the effect of other inputs to change over time.

This represents a modest decline in the harmfulness of student absences, perhaps due to the advances in and experience with technology, virtual and distance learning, and home-school communication created and enhanced by pandemic-related school closures. However, whether one views this decline as large or small, absences remain a practically and statistically significant impediment to student learning in the post-pandemic landscape. Indeed, estimates from the post-period alone indicate that ten absences reduce math achievement by 4% to 7% of a test-score SD, which resemble estimates in the peer-reviewed, pre-Covid research literature; these extant findings have generated much concern and action amongst researchers, school leaders, and policymakers.

4.3 Impacts of Chronic Absenteeism

The public discourse on student absences frequently centers on chronic absenteeism, which is typically defined as 18 or more absences (about 10% of a 180-day school year). There is value in relying on this simple, familiar statistic. However, this definition is arbitrary (Wu, Weiland and Staines, 2026): it has been defined at this level for administrative purposes and not because the research suggests that there is anything unique about the effect on student achievement of crossing the threshold of 18 absences or 10% of school days. A student who misses "only" 15 or 16 days is not significantly better off than the classmate who misses 18 days, despite the fact that the student has not been labeled chronically absent. Indeed, prior research shows quite clearly that the harmful effects of student absences are approximately linear: that is, all absences are similarly harmful such that the individual impact of the 20$^{\text{th}}$ absence resembles that of the 2$^{\text{nd}}$, 10$^{\text{th}}$, 18$^{\text{th}}$, or any other absence (Gershenson, Jacknowitz and Brannegan, 2017; Liu, Lee and Gershenson, 2021).

That said, since our goal is to study how the harmful effects of student absences have changed in the post-pandemic educational environment, we must probe the degree to which these effects remain linear. We do so in two ways. First, we simply replace the count of absences in our models with a binary indicator for chronic absence. These estimates are shown in Table 5 for math achievement, pre- and post-pandemic, in all three settings and at both grade levels.

Analogous to Table 4, Table 5 shows that the effect of being chronically absent (relative to not) is large and strongly statistically significant in all three settings, in both types of schools, and in both time periods. Also consistent with our previous results, Table 5 shows that the effect of chronic absenteeism is modestly less harmful in the post- than in the pre-pandemic time period. For instance, the pooled estimates in columns 2 and 6 show that in elementary schools, the effect is about 2 percentage points smaller and this difference is statistically significant in both North Carolina and Maryland. The separate pre- and post-only estimates in columns 3 and 4 reaffirm this result.

Columns 4 and 8 of Table 5 show that post-pandemic, being chronically absent in elementary and middle schools reduced math achievement by about 10% of a test-score SD in North Carolina, 7% to 9% of a test-score SD in Maryland, and about 10% of a test-score SD in the urban school district. Comparing the post-pandemic elementary school estimates in column (4) to the pre-pandemic estimates presented in column 3 shows that the impact of chronic absenteeism decreased by about 2 to 3 percentage points (16 to 24%) in each site. Comparing estimates in columns 7 and 8, we see that the decline was much smaller in North Carolina, nonexistent in Maryland, and the urban school district estimate moved in the opposite direction, though it is imprecisely estimated.

Our results are consistent with the effect of absences being approximately linear, as scaling the estimates reported in Table 4 by 1.8 (18 versus 10 absences) yields similar numbers to those reported in Table 5. Thus, whether we study the impact of ten additional absences, or of being chronically absent versus not, we find similar results: absences are harmful to student achievement, the effects of absences are approximately linear, and this remains true in the post-pandemic educational environment.

Second, we trace out the regression-adjusted average math score for students at each level of absences to see exactly how linear (or not) the effect of absences is. Formally, this is done using a nonparametric step function specification of *f(absences)* in equation (1). The step function uses zero absences as the reference category, creates an indicator for each whole number of absences from 1 through 25, and consolidates all cases of 26 or more absences into a single top-coded category. Points along each of the plots can be interpreted as the achievement reduction attributable to "x" absences relative to having zero absences. This is more nuanced than simply comparing students above and below the 18-absence threshold of chronic absences and allows us to see whether any thresholds appear to be particularly important to student achievement. The approach relaxes the assumption that the effect of absences is constant and allows for any arbitrary type of nonlinearity. These results are depicted in Figure 1, for elementary school and middle school.

For all locations, time periods, and grade levels the lines are downward sloping, consistent with the parametric estimates discussed to this point. The jagged (nonparametric) solid lines are fairly straight and bounce around the dashed lines, which represent the baseline estimates reported in table 4, which assumed a constant (linear) marginal effect of absences. Particularly in the state datasets, which have more power to detect nonlinear effects, the data indicate that the marginal effect of absences is approximately constant. For this reason, we prefer the simple linear specification's estimates presented in Table 4, which are both more efficient and easier to interpret. For the urban school district, results are qualitatively similar though there is more variability in the nonparametric estimates, which is likely due to the substantially smaller sample size. Nevertheless, even in this setting, there is nothing that stands out about the 18-day definition of chronic absenteeism, consistent with prior research (Gershenson, Jacknowitz and Brannegan, 2017; Liu, Lee and Gershenson, 2021; Wu, Weiland and Staines, 2026).

4.4 Heterogeneous Effects

Next, we investigate whether the harmful effects of absences vary across student subgroups, such as gender, socioeconomic status, and race. The motivation is that students of different backgrounds may have different support structures at home that moderate their ability to catch-up following an absence. This is done by estimating equation (1) separately for different subgroups of students. These estimates are presented in Figure 2.

Regarding pre-Covid effects, our results for all three locations are fairly consistent with prior literature in that there is not much evidence of heterogeneity across student race and gender (Gershenson, Jacknowitz and Brannegan, 2017; Liu, Lee and Gershenson, 2021). We observe heterogeneity by economic disadvantage in select settings: in middle schools in North Carolina and Maryland the effect of absences is larger for non-economically disadvantaged students than economically disadvantaged students.

Post Covid, heterogeneity is most pronounced by student race, perhaps because Black households were more affected by the pandemic (Gaynor and Wilson, 2020). Specifically, post-Covid, white students experienced a greater reduction in the harmful effect of absences than did Black students. Interestingly, though, we find no evidence that heterogeneity by economic disadvantage changed in the post-pandemic period.

4.5 Effects of absences on ELA scores

Appendix Tables A.1 and A.2 report estimates of the baseline model for ELA scores instead of math scores; these tables are analogous to Tables 4 and 5, respectively. The corresponding effects on ELA scores are smaller, at about 1% to 6% of a test-score SD, but are nonetheless statistically significant. Importantly, these results mirror those documented elsewhere (Aucejo and Romano, 2016; Gershenson, Jacknowitz and Brannegan, 2017). Absences likely have larger impacts on math achievement because families have an easier time helping their children catch up on reading than math skills following an absence spell.

For the post- pandemic changes, the results for ELA are more mixed than for math. In North Carolina elementary schools, the reduction in the harmful effect of absences on reading was proportionally quite large, falling from 0.020 to 0.008 (about 60%), and the interaction term is statistically significant. This proportional decline exceeds the corresponding reduction observed for math in the same setting. However, in North Carolina middle schools the decline was more modest (from 0.023 to 0.018, roughly 22%), similar to the math results. In Maryland, the effect on ELA test scores diverge notably from math: neither the elementary nor middle school interaction terms are statistically significant, and the point estimates suggest little meaningful change in the harmfulness of absences for reading achievement post pandemic. In the urban school district, the ELA effects decline modestly post pandemic but the interaction terms are not statistically significant.

Taken together, these patterns suggest that the modest post-pandemic reductions in the marginal effect of absences observed for math do not uniformly extend to reading. Broadly, this comports with the well established finding that school inputs exert larger effects on math achievement than on ELA achievement.

4.6 Sensitivity Analysis

We compute cluster-robust standard errors (SE), which make our statistical inference robust to the presence of arbitrary forms of heteroskedasticity and serial correlation within groups (clusters) in the idiosyncratic error ε. The baseline estimates cluster at the school level, which is consistent with advice to cluster at the "highest level" (Angrist and Pischke, 2009) and acknowledges that absence-reporting norms may vary across schools. However, this approach is likely overly conservative, as the treatment of interest (student absences) varies at the student level (Abadie et al., 2023). Because the "correct" level at which to cluster is unclear, we compute SE clustered at five additional levels: student, teacher, teacher year, classroom, and school-year. We also compute five two-way clustered SE to allow for clustering along multiple dimensions (Cameron, Gelbach and Miller, 2011). One dimension here is always the student, and the second is either the classroom, teacher-year, teacher, school-year, or school. This discussion proves inconsequential, as the general findings are robust (and remain strongly statistically significant) to how and at what level(s) the SE are clustered. For example, in North Carolina, the baseline math estimates' estimated SE range from 0.001 to 0.002. Patterns are similar in the other sites.

We conduct a battery of additional sensitivity analyses. We show these estimates for North Carolina, Maryland the Urban School District in Appendix Tables A.3, A.4 and A.5, respectively. First, we estimate the baseline model without control variables. The idea here is to gauge the extent to which the fixed effects and lag scores control for selection into absences. In the spirit of Altonji, Elder and Taber (2005), if the estimates are not sensitive to omitting these controls, then it is unlikely that they are sensitive to additional omitted variables. Reassuringly, column

1 of Tables A.3 and A.4 shows that these results are quite similar to the baseline estimates reported in Table 4.

Second, we consider alternative FE structures. In column 2 of Tables A.3, A.4 and A.5, we replace classroom FE with teacher FE, which introduces more identifying variation and includes students whose exact math classroom could not be identified in the administrative data. These estimates are nearly identical to those from the baseline model, which is unsurprising given the overlap between teachers and classrooms. In column 3 of Tables A.3 and A.4 we replace the lag scores with student FE, as lag scores and student FE cannot be included in the same model (Nickell, 1981).[6] This sort of model is more appropriate if classroom sorting occurs along static (time invariant) rather than dynamic (time-varying) dimensions. These estimates are slightly smaller in magnitude than the baseline lag-score estimates and less precisely estimated, though they remain sizable and strongly statistically significant. Most importantly, the pattern of effect sizes declining post pandemic remains.

For North Carolina, we carry out two additional sensitivity checks that cannot be conducted in the other sites due to data limitations. First, in column 4 we implement the first-differenced instrumental variable (FD-IV) strategy proposed by (Anderson and Hsiao, 1982) that includes both student FE and lag scores, removes the FE by first differencing, and instruments for the endogenous differenced lag score using twice-lagged test scores. These estimates closely resemble those in column 3, suggesting that simultaneously accounting for student FE and lagged achievement is relatively unimportant, and again the pattern of absence effect sizes declining post pandemic remains. Finally, column 5 estimates the baseline model on the FD-IV sample, which is smaller due to the requirement of having two lagged scores per student, and yields estimates that closely resemble the baseline results. This suggests that the FD-IV sample does not change in ways that compromise the validity of those results.

5 Counterfactual Exercise

We use our estimates of absences' effects on achievement to conduct a simple counterfactual exercise to understand how much remaining learning loss can be attributed to elevated levels

[6] We are unable to carry out this check in the urban school district due to data limitations.

of absenteeism. Of paramount importance to this analysis is that in North Carolina and the urban school district, the same tests were administered regularly for several years spanning the pandemic. This continuity in test format and scale allows us to estimate equivalent models in both pre- and post-pandemic time periods. This is not possible in Maryland due to changes in the tests.

In North Carolina, our estimates indicate that the effect of being chronically absent post pandemic was about 10% of a test-score SD. Specifically, the estimates are 0.097 and 0.101 test-score SD in elementary and middle schools, respectively. In the urban school district, our estimates indicate that the effect of being chronically absent post pandemic was about 10% of a test-score SD. Specifically, the estimates are 0.105 and 0.101 test-score SD in elementary and middle schools, respectively. To acknowledge uncertainty in these estimates, we also conduct this exercise using effect sizes of 0.08 and 0.12 to provide reasonable bounds for our results.[7]

We must also assume reasonable counterfactual levels of absenteeism for this analysis, as our goal is to determine what achievement levels would look like today had student absenteeism not increased so markedly during and after the pandemic. Specifically, we show the learning loss that would be recovered for all possible levels of absence reduction (i.e., from none, or leaving rates unchanged, to complete, or cutting rates to zero). Within that range we will highlight some realistic goals, such as reducing chronic absence rates to 2019 levels.

Formally, our counterfactual exercise is described by the following equation:

$$Explained\ Learning\ Loss_{23} = (\tau \times Reduction)/Loss_{23}, \tag{2}$$

where τ is the impact of chronic absence and $Loss_{23}$ is the learning loss still present in 2023, relative to 2019. We plot equation (2) as a function of possible (counterfactual) values of the 2023 chronic absence rate, *Reduction*, using each of the three plausible values of τ described above: 0.08, 0.10, and 0.12. We do so for both 5th and 8th grade, whose adjusted values of $Loss_{23}$ were 0.115 and 0.205, respectively, in NC. In the urban school district they were 0.255 for 5th grade and 0.197 for 8th grade.

[7]These bounds are slightly larger than the 95% confidence intervals for the North Carolina estimates, which are based on standard errors clustered by school, of (0.088, 0.105) for elementary schools and (0.094, 0.108) for middle schools.

The results of our simulation are presented in Figure 3. Three vertical reference lines show, in ascending order, the reductions necessary to reach 2019 levels of chronic absence, 5% chronically absent, and eliminating chronic absence completely. Assuming that being chronically absent reduces test scores by 0.1 test-score SDs, the baseline estimate in our main analysis, returning chronic absence rates to 2019 levels would reduce the learning loss still present in 2023 by roughly 8% and 6%, for 5th and 8th grade, respectively, in North Carolina. In the urban school district, the corresponding estimates are roughly 7% in grade 5 and 3% in grade 8. More extreme reductions to 5% or 0% chronic absence rates would reduce learning loss by no more than 20% in either site or grade. These are laudable and important reductions to be sure, though clearly there is more to the learning loss story than just higher rates of absenteeism. Even assuming a larger (0.12 SD) effect of chronic absence, completely eliminating chronic absence would only reduce learning loss by roughly 18% (grade 5) and 14% (grade 8) in North Carolina, and by 15% (grade 5) and 21% (grade 8) in the urban school district.

In the urban school district, where baseline chronic absenteeism rates were higher than in North Carolina, eliminating chronic absenteeism or reducing it to 5% is a much greater feat. Even making the unrealistic assumptions that we underestimated the harmful effect of chronic absence and that chronic absence can be eliminated, more than 80% of remaining learning loss is still unexplained. Intuitively, the reason for the modest contribution of chronic absence to learning loss despite the impact of chronic absence being similar in size to the remaining learning loss in 2023 is that the average test-score drop applies to all students, but all students did not become chronically absent.

In North Carolina, the absolute level of learning loss still present in 2023 in grade 8 is almost twice as large as that in grade 5. But, because the impact of chronic absence is the same and chronic absence rates were not twice as large, even less learning loss can be explained by reducing chronic absence rates in middle school. Patterns are slightly different in the urban school district, where continued learning loss was slightly smaller in grade 8 in 2023 compared to grade 5.

Given that the post-pandemic slide in achievement and increase in absenteeism was greater among more economically disadvantaged students, it is also worth conducting our thought experiment separately for low- versus higher-income students. The results of this exercise are displayed in Figure 4, which as in Figure 3, plots the share of "recoverable" learning loss as a function of reductions in the chronic absence rate. However, in Figure 4 we do so separately for students who were and were not identified as economically disadvantaged. To simplify the graph we only show results for the baseline of $\tau = 0.10$. Given the large disparities by economic disadvantage status in the effect of chronic absenteeism before and after the pandemic depicted in Figure A.1, we provide two sets of vertical reference lines in Figure 4, as the hypothetical reductions to consider are nearly twice as large for the disadvantaged students.

Here, patterns between sites diverge to a larger degree. In North Carolina, the slope for the non-disadvantaged students is actually steeper than for disadvantaged students in grade 5, indicating greater potential for reductions in chronic absence to reduce learning loss for less as opposed to more disadvantaged students. However, this is somewhat misleading because the two lines really begin to separate for reductions greater than 15 percentage points or so. This is an "out of sample" change for non-disadvantaged students, whose baseline chronic absence rate was only 10.3% in 2023. Focusing on the three dashed vertical reference lines, which indicate plausible reductions, we see that for non-disadvantaged students, returning to the 2019 chronic absence rate would reduce learning loss by about 4% and eliminating chronic absence entirely would reduce learning loss by about 8%. Again, these small shares are largely due to the fact that chronic absence rates for this group are fairly small to begin with, so there is limited room for improvement. Grade-5 economically disadvantaged students, however, would see an 8% reduction in learning loss from a return to 2019 chronic absence levels and cutting their chronic absence rate to 5% would recover 15% of the remaining learning loss. This highlights the scale of the chronic absenteeism crisis and the large learning gains that could be made, particularly among disadvantaged students, by substantially reducing the prevalence of chronic absenteeism.

For 8th graders in North Carolina, it is disadvantaged students who stand to benefit more (recoup more of their learning loss) from reducing chronic absenteeism, though again the comparison only makes sense for reductions smaller than 13 or 14 percentage points. The recovery associated with returning to 2019 rates of chronic absence are similar to what was observed for fifth graders: about 5% of losses for non-disadvantaged students and about 8%

of losses for disadvantaged students. Fully 15% of losses could be eliminated by cutting disadvantaged students' chronic absence rates to 5%.

In the urban school district, the slopes of the lines for economically disadvantaged students are flatter than for advantaged students in both grades. However, the vertical lines differ substantially (just as in North Carolina) such that returning to 2019 levels would recover roughly 10% of learning loss for both economically disadvantaged and non-disadvantaged students in grade 5, and even less than that in grade 8. The most extreme reductions in chronic absenteeism explain roughly 20% of learning loss across groups and grades.

6 Effects on Educational Attainment

6.1 Identification Strategy

While the math and reading test scores in our main analysis are useful proxies for the long-run outcomes we ultimately care about, short-run effects of schooling inputs on test scores do not always perfectly predict corresponding effects on medium- or long-run outcomes. Accordingly, we adapt the methodology used in our main analysis to investigate the impacts of absences and chronic absenteeism in 10th grade on various downstream outcomes, namely high-school graduation and college enrollment. We only perform this analysis using the data from Maryland high schools as we do not have post-secondary data in North Carolina or the urban school district. We track these 10th grade students longitudinally to measure high school graduation (observed two years later upon completion of grade 12) and immediate college enrollment (observed three years later, or one year after an on-time high-school graduation).

The identification strategy employed here resembles that in section 3, with two changes. First, instead of controlling for once-lagged end-of-grade math and reading test scores, we use twice-lagged 8th-grade test scores, as that is the most recent grade where standardized testing occurs; we also control for lagged cumulative grade point average (GPA) in 9th grade. Second, due to the lack of a unique subject-specific classroom for attainment outcomes, we instead control for course-set fixed effects that identify students who took the same math and reading classes (Delhommer, 2022; Ran and Xu, 2019).

A potential concern with our estimates of the effect of tenth grade absences on educational attainment is that, despite the rich set of controls in our model, students who are absent more often may differ from their peers along dimensions we do not observe. This concern is more pronounced for the attainment outcomes than for the test score outcomes analyzed in Section 4. Our test score models rely on a lag-score classroom fixed effects design where the classroom fixed effects absorb teacher, peer, and school inputs and the lagged scores absorb time-invariant student ability and historical educational inputs. The attainment models, by contrast, cannot draw on the same identifying variation since there is no within-student variation in graduation or college enrollment.

Accordingly, we follow Liu, Lee and Gershenson (2021) and compute bounds following Altonji, Elder and Taber (2005) and Oster (2019). This procedure compares an "uncontrolled" specification that omits our covariates to the "controlled" specification reported in Table 6, and uses the movement in both the coefficient and the R^2 between these two regressions to bound the bias-adjusted treatment effect under the assumption that selection on unobservables is proportional to selection on observables. Following the recommended convention in Oster (2019), and consistent with Liu, Lee and Gershenson (2021), we set the maximum attainable R^2 to 1.3 times that of the controlled regression. We report two quantities alongside our main estimates: an Oster bound that assumes an equal degree of selection on observed and unobserved characteristics ($\delta = 1$), and the value of δ that would be required to fully attribute our estimated effect to selection bias (i.e., to drive the coefficient to zero).

6.2 Results

The results in Table 6 reflect a negative effect of absences on both high school graduation and college enrollment. Ten additional absences result in a 1% to 6% decline in these outcomes.[8] College enrollment (any) refers to enrolling in either a 2- or 4-year post-secondary institution. Similar to our main results for student achievement, the positive and significant coefficients on the post-absences interaction term in columns 1 and 4 imply that the negative impact of

[8]These estimates are generally larger than those estimated in a similar analysis conducted in Liu, Lee and Gershenson (2021), who find that ten absences in tenth grade reduce attainment outcomes by 0.8% to 1.3% in a (different) large and diverse urban school district.

absences on high-school graduation and college enrollment (2-year) shrank in the post-Covid period. In column 7, this interaction term is not significant, highlighting that the mitigated effects we observe for 2-year college enrollment are offset by worsening effects for 4-year college enrollment. This is also why the post-Covid effects of absences in column 9 are more negative than the pre-Covid effects of absences in column 8. Regardless, these negative coefficients provide evidence of the harmful effects of absences beyond just student achievement. Actual educational attainment has been adversely affected as well, and just like for student achievement, the small improvements observed in the post-Covid era fall far short of fully eliminating these harmful effects.

The Oster bounds and δ values reported in Table 6 support a causal interpretation of our attainment estimates. For high-school graduation and any college enrollment, the Oster bounds remain negative and economically meaningful in both the pre- and post-Covid periods, and the corresponding values of δ are substantially greater than one, ranging from 2.2 to 13.6 across outcomes, periods, and specifications. This indicates that selection on unobservables would need to be at least twice, and in some cases more than ten times, as strong as selection on the rich set of observables we include to fully attribute the estimated effects to selection bias; this is implausible. Furthermore, the post-Covid δ values for high school graduation and any college enrollment are generally larger than their pre-Covid counterparts, with the exception of the chronic absenteeism specification for high school graduation, where δ falls modestly from 6.2 to 5.1 but remains well above one. This pattern suggests that the attainment effects are, if anything, more robust to unobserved selection in the post-pandemic period than they were before. For two-year college enrollment, the inclusion of controls in some specifications moves the coefficient slightly away from zero rather than toward it, which makes the standard δ-to-zero calculation uninformative (Oster, 2019). We therefore do not report δ for this outcome, though the Oster bounds under $\delta = 1$ are almost identical in magnitude to the original estimates, consistent with a causal interpretation. Taken together, these bounds indicate that unobservables would need to be more important than the set of observables we include to overturn our findings.

We also investigate whether the harmful effects of absences vary by the same student subgroups considered in our test-score analysis. This is once again accomplished by estimating our baseline model on different subsamples; the results are presented in Figure 5. In terms of pre-Covid heterogeneity, we observe heterogeneity in gender and economic disadvantage: the effect of absences on college (2-year) enrollment and high school graduation is smaller for non-economically disadvantaged students than for economically disadvantaged students, and the effect of absences on high school graduation is smaller for female than male students. In terms of changes post-Covid, heterogeneity is prevalent for race for college (2-year) enrollment and high school graduation. Black students experienced a greater decrease in the adverse effects of absences following Covid compared to White students. This is the opposite of what we found for math achievement. Furthermore, we also find substantial evidence that the harmful effects of absences vary by students' gender and socioeconomic background. Male students experienced a greater decline in the negative impact of absences on graduation rates post-Covid than female students did. Economically disadvantaged students also experienced a larger reduction in the negative effect of absences post-Covid relative to economically advantaged students.

7 Discussion and Conclusion

There has been a great deal of concern both before and after the pandemic about students' rates of school attendance. Given the disruptions caused by the pandemic and the massive investments and changes made in schools in the wake of the pandemic—specifically regarding educational technologies that facilitate asynchronous schooling—it was important to determine whether absences remain as harmful as they were before the pandemic.

Our findings demonstrate that what has been true for decades remains true in the current post-pandemic environment: student absences harm both achievement and attainment. Even though the marginal effect of absences on test scores decreased slightly after the pandemic, the number of days students are absent from school has increased substantially. Since the negative marginal impact of absences is approximately linear, this large rise in absenteeism following the pandemic means that, for the average student, the aggregate harm caused by missing school has risen. These findings extend to high school completion and college enrollment as well, with the negative effects of absences on these outcomes persisting after the pandemic and even worsening in the case of college enrollment. Policymakers, school leaders, and parents should remain concerned about student absences and their consequences for school systems, classrooms, and students' future academic success and career readiness.

Unsurprisingly in light of the large increases in absenteeism rates throughout the country, absence reduction is fast becoming a priority in state and local education policy. In North Carolina, districts are experimenting with a number of interventions ranging from the way that schools notify parents about absences to providing principals with the discretion to penalize excessive absenteeism by revoking student privileges (e.g., participation in extracurricular activities) or lowering student grades. In Maryland, a state policy initiative is to reduce current rates of chronic absenteeism by 50%, which would return rates roughly back to pre-pandemic levels. Initiatives that improve attendance would, necessarily, benefit students and schools. That said, we must recognize that new technologies likely contribute to the modest declines in the consequences of absences. Formally evaluating the role of those technologies in mitigating the determinants and consequences of absenteeism and absenteeism-induced learning loss is an important next step.

States also need to be realistic in their expectations about what will be gained when it comes to absenteeism reduction. Returning to pre-pandemic rates of absenteeism may be a difficult and long road given how broadly absence rates and attitudes towards physically attending school have changed post pandemic—across the country and across grade levels. The pandemic fundamentally changed many elements of schooling, including how both families and schools view absenteeism amidst health concerns, the widespread embrace of technologies that facilitate virtual and distance learning, etc. School and district leaders, along with state education officials, must be mindful of this new and continually evolving landscape.

Still, just because it will be difficult does not mean we should give up. Reducing absenteeism is a fight worth fighting. To do so, state and local education agencies must be familiar with the tools at their disposal. A recent meta-analysis describes four types of policy interventions: behavioral (e.g., developing students' socio-emotional skills to increase school engagement), academic (e.g., focusing on academic skills with presumed spillover effects on attendance), family-school partnerships (e.g., directly involving parents and families in efforts to increase student attendance), and policy interventions (e.g., new attendance policies or mandates) (Eklund et al., 2022). While some programs, particularly those targeting behavior, have led to meaningful increases in student attendance, the authors conclude that too few intervention studies exist and those that do often return modest effects. Teachers, class size, and classroom environments remain important drivers of student attendance (Gershenson, 2016; Liu and Loeb, 2021; Tran and Gershenson, 2021), though we should not place the full burden of alleviating the absenteeism crisis on teachers. Nor do we yet know how teachers' impacts on student absences may have changed post pandemic; this is an area for continued exploration.

Importantly, absenteeism reduction alone is not a silver bullet for the problems that students face. Our findings indicate that the reasonable goal of returning to 2019 levels of chronic absence would eliminate only 6 to 8% of remaining learning loss in both North Carolina and the urban school district. Even reducing chronic absenteeism to 5%, well below 2019 levels, would only eliminate about 10% of the remaining learning loss. This highlights the fact that the pandemic and associated school closures affected schools, students, and their families in many ways; the rise in chronic absenteeism is but one symptom of the disruption wrought by the pandemic.

Regardless, the fact that halving chronic absence rates would not complete the learning recovery is no reason to lessen efforts to reduce chronic absenteeism for several reasons. First, even a 5 or 10% reduction in learning loss is a nontrivial and worthwhile accomplishment. Second, halving the rate of chronic absenteeism would create spillover effects not captured by the reduction in learning loss. For example, this would lessen teachers' workloads by reducing the time they spend helping absent students to catch up following an absence spell, allowing them more time to lesson plan for—and connect with—the present students, thereby benefitting all students in the classroom. Third, as emphasized above, good attendance begets good attendance by forming regular attendance habits and building confidence. Sustained attendance, and the skills and attitudes that undergird regular attendance, will allow students to reach their full potential in later grades, in higher education, and ultimately in the workforce.

Before schools go about reducing absences, they should remember that:

1. Because the effects of absences are linear and cumulative, any reduction in

absenteeism is meaningful and worthwhile – even modest reductions that do not reclassify individual students as non-chronically absent or return schools to their pre-pandemic absence rates.

2. Despite the modest decline in harm associated with a single absence observed post pandemic, the increased number of absences means that addressing absenteeism—both in terms of reducing absences and reducing the harm caused by absences—is as pressing a goal as ever.

3. Despite the fairly similar consequences of absenteeism for students of different sociodemographic backgrounds, schools may still want to target interventions or resources to particular student subgroups, as absence rates do vary by student background. This is particularly true when doing so may increase attendance in ways that help students hit important learning thresholds (e.g., avoid failing a class or repeating a grade) or reduce socio-demographic disparities in achievement.

The upswing in absenteeism is a crisis and should be treated as such. The consequences of chronic absenteeism are well documented, and that is just for the measurable outcomes like test scores, high school completion, and so on. But absences are more than just an input in the educational process or determinant of test scores: regular attendance is a skill valued in labor markets and a proxy for determination, persistence, and reliability. Both healthy and unhealthy habits form young, and we risk sending a generation of young people into higher education and the workforce with poor attendance habits, to the detriment of much more than just test scores. Thus, when we see effects of absenteeism on test scores and grade progression, remember that this is the tip of the iceberg.

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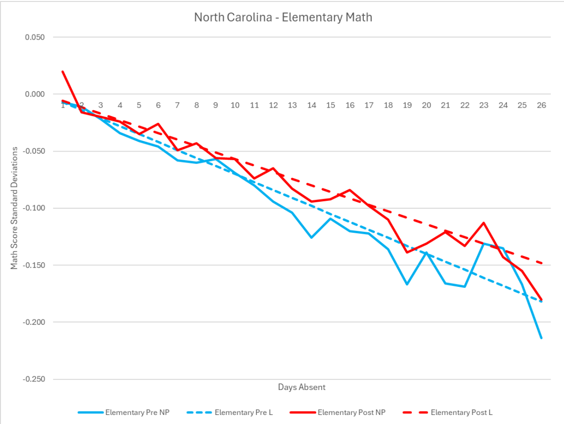
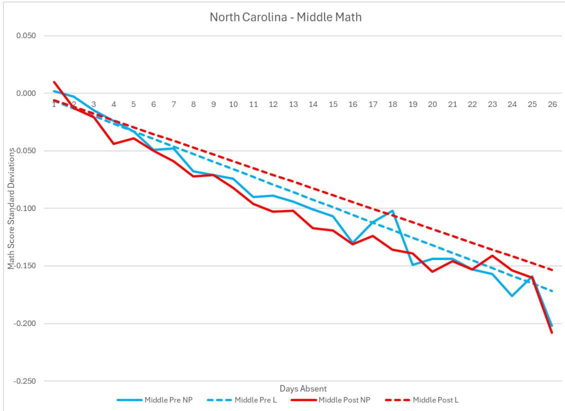
Figures and Tables

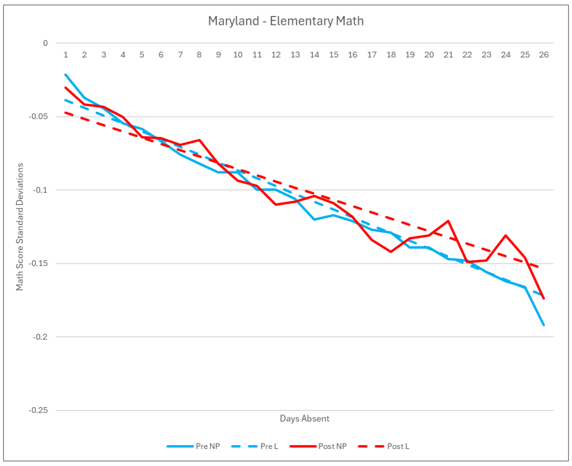
Figure 1: Linearity in Effect

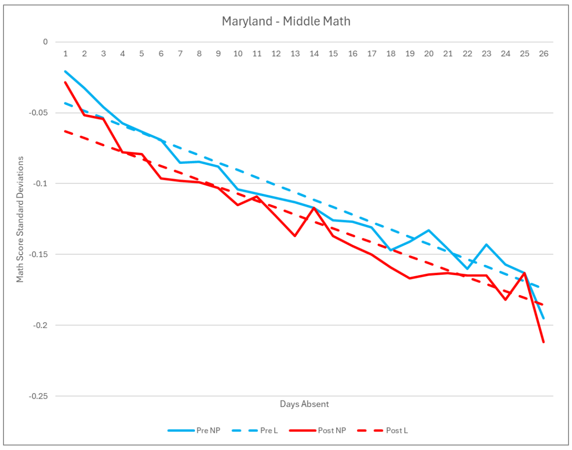
North Carolina



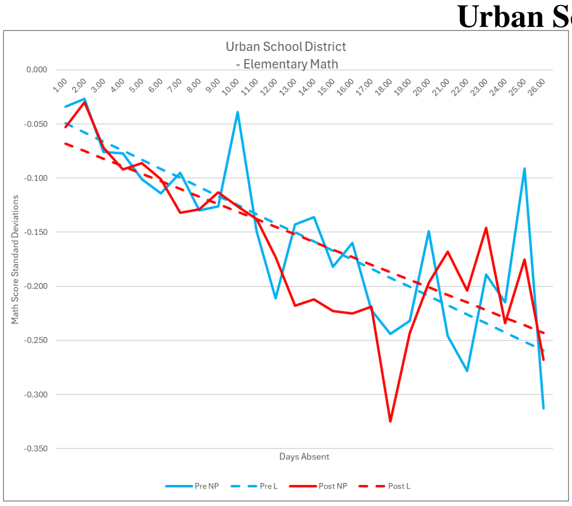


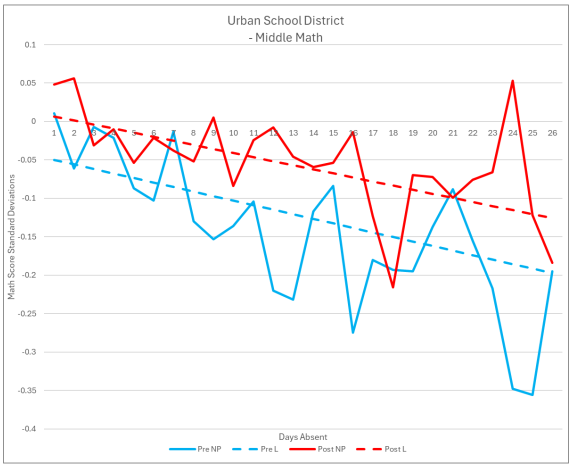
Maryland





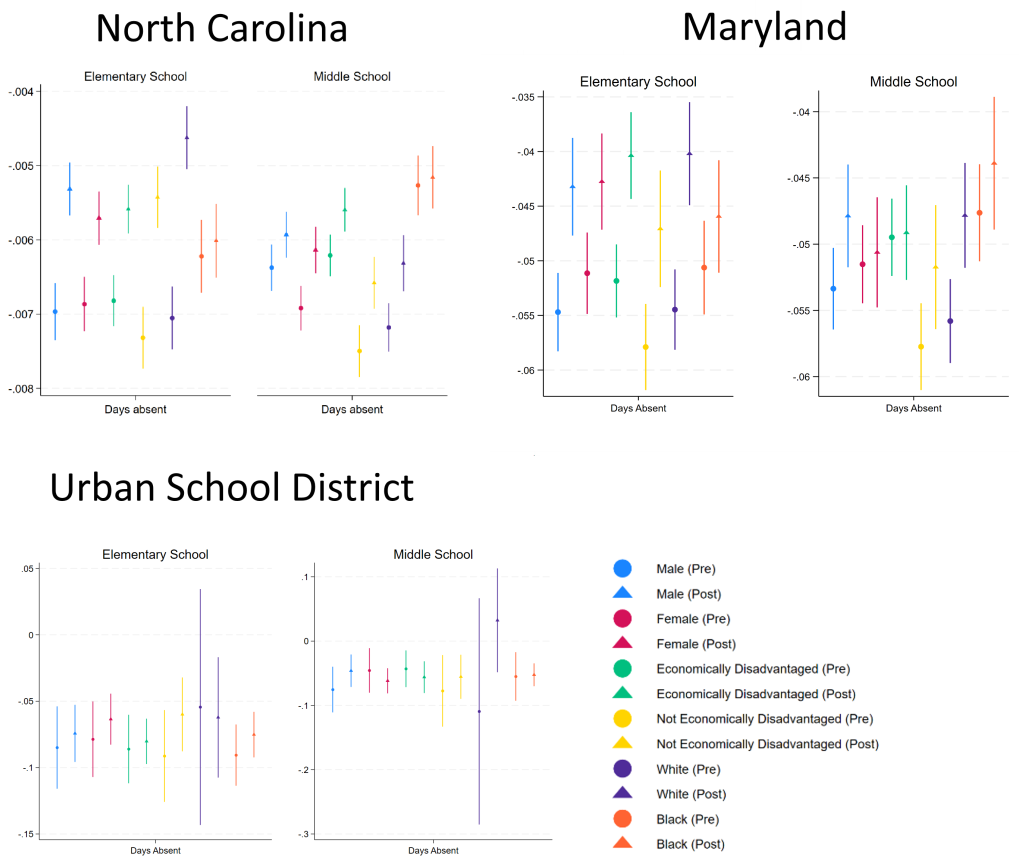
Urban School District





Notes. Effects of Absences on Math Achievement in North Carolina, Maryland and the Urban School District. The solid lines reflect coefficients of Equation 1, where $f(absences)$ is an indicator for each exact absence count, leaving zero absences as the omitted category and top-coding 26 or more absences at 26. The dotted lines reflect coefficients of equation 1, where $f(absences)$ is the number of absences. Pre refers to the 2019 school year for North Carolina and Urban School District, and to 2018 and 2019 for Maryland. Post refers to the 2023 school year for all three sites.

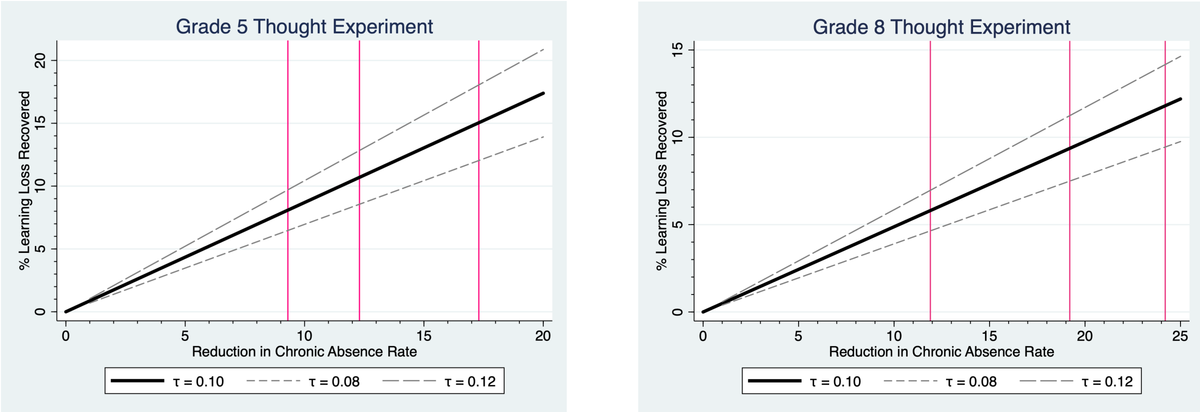
Figure 2: Heterogeneity for Elementary and Middle School



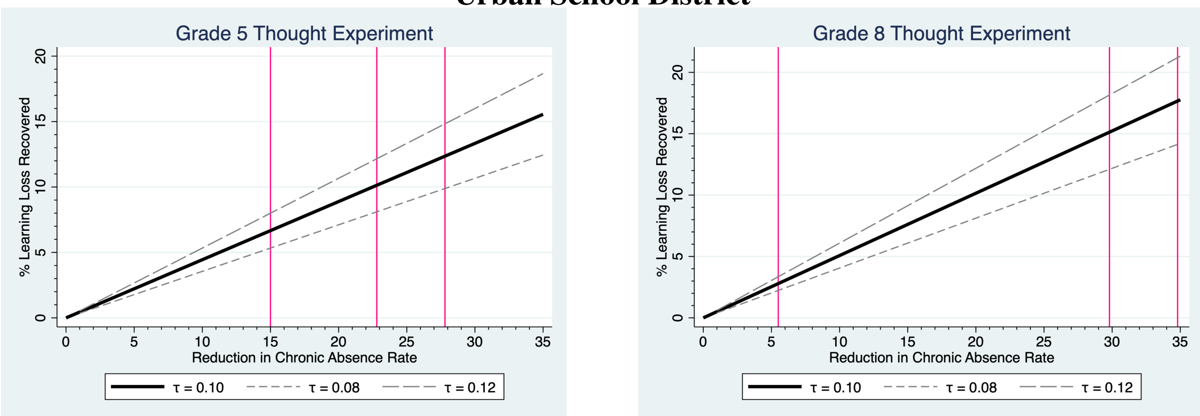
Notes. Each point estimate represents the effect of one additional absence on standardized math test scores for the indicated subgroup, scaled by 0.10 to reflect the effect of ten absences. Circles denote pre-Covid estimates (2019) and triangles denote post-Covid estimates (2023). Vertical lines represent 95% confidence intervals. Standard errors are clustered at the school level. All regressions condition on lagged math and reading scores, student sociodemographic controls, and classroom fixed effects.

Figure 3: Counterfactual Analysis

North Carolina



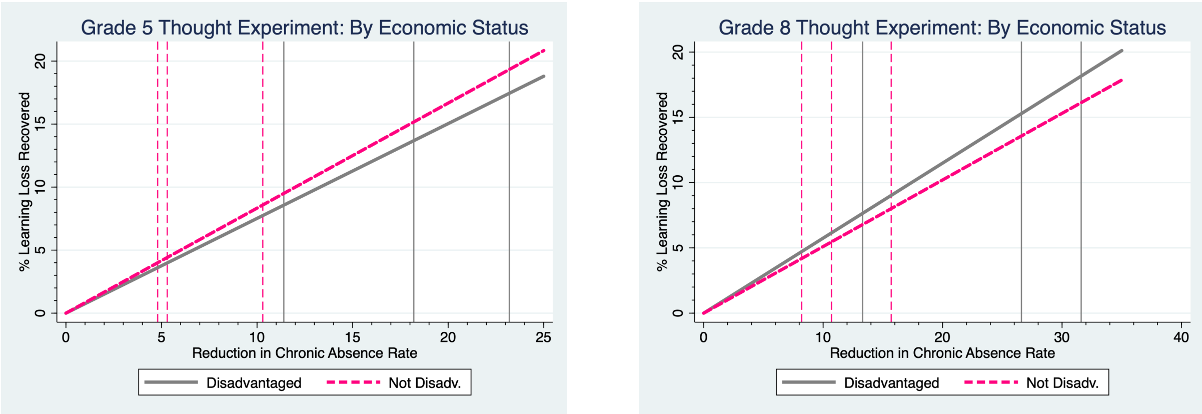
Urban School District



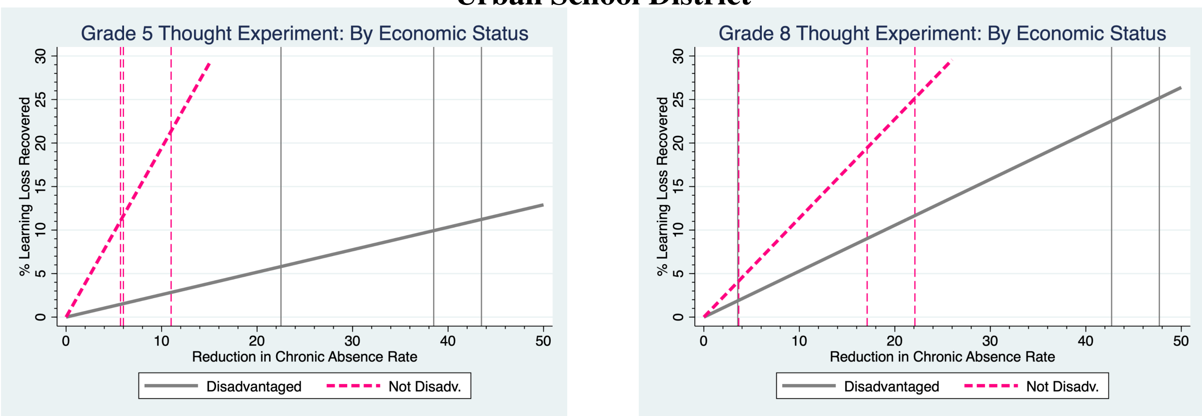
Notes. Each panel plots the share of remaining 2023 learning loss that would be recovered as a function of reductions in the chronic absence rate, for grades 5 and 8 separately. The three vertical reference lines indicate, from left to right, the reduction necessary to return to 2019 chronic absence levels, a reduction to 5% chronic absence, and full elimination of chronic absence. The three lines within each panel correspond to assumed effect sizes of chronic absence on test scores of 0.08, 0.10, and 0.12 test-score standard deviations, where 0.10 is the baseline estimate from the main analysis. Learning loss is measured relative to 2019 test score levels. Top panels show results for North Carolina and bottom panels show results for the Urban School District.

Figure 4: Counterfactual Analysis by Socioeconomic Status

North Carolina

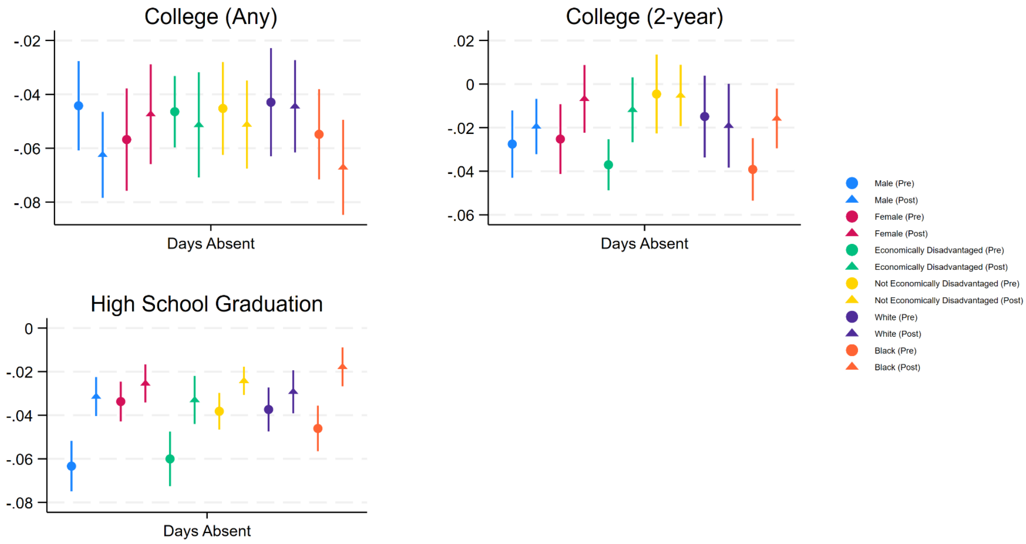


Urban School District



Notes. Each panel plots the share of remaining 2023 learning loss that would be recovered as a function of reductions in the chronic absence rate, for grades 5 and 8 separately. The three vertical reference lines indicate, from left to right, the reduction necessary to return to 2019 chronic absence levels, a reduction to 5% chronic absence, and full elimination of chronic absence. The solid and dashed lines within each panel corresponds to assumed effect sizes of chronic absence on test scores of 0.10 test-score standard deviations, for economically disadvantaged and not economically disadvantaged groups respectively. Learning loss is measured relative to 2019 test score levels. Top panels show results for North Carolina and bottom panels show results for the Urban School District.

Figure 5: Heterogeneity for High School Outcomes (Maryland)



Notes. Each point estimate represents the effect of one additional absence on standardized math test scores for the indicated subgroup, scaled by 0.10 to reflect the effect of ten absences. Circles denote pre-Covid estimates (2019) and triangles denote post-Covid estimates (2023). Vertical lines represent 95% confidence intervals. Standard errors are clustered at the school level. All regressions condition on lagged math and reading scores, student sociodemographic controls, and classroom fixed effects.

Table 1: Summary Statistics: North Carolina

	Elementary School		Middle School	
	2019	2023	2019	2023
	(1)	(2)	(3)	(4)
Absences	7.67	11.05	8.88	12.65
	(6.64)	(8.42)	(7.80)	(9.74)
Chronic	0.08	0.18	0.12	0.24
Math	0.02	-0.02	0.01	-0.01
	(0.99)	(0.99)	(1.00)	(0.98)
ELA	0.01	-0.04	-0.08	-0.12
	(0.99)	(0.99)	(0.98)	(0.96)
Lag Math	0.01	-0.03	-0.11	-0.13
	(0.99)	(0.99)	(0.96)	(0.94)
Lag ELA	-0.00	-0.05	-0.09	-0.12
	(0.99)	(0.99)	(0.98)	(0.97)
Male	0.51	0.51	0.51	0.51
Asian	0.03	0.04	0.03	0.03
Black	0.25	0.26	0.26	0.28
Hispanic	0.20	0.22	0.20	0.23
Native	0.01	0.00	0.01	0.00
Multiple Races	0.05	0.06	0.04	0.05
Pacific Islander	0.00	0.00	0.00	0.00
White	0.46	0.42	0.46	0.40
Econ. Disadvantage	0.51	0.57	0.52	0.59
N	198,616	110,229	259,021	149,375

Notes. Each column reports means for the indicated school level and year. Standard deviations in parentheses for continuous variables. Absences is the annual count of days absent. Chronic is a binary indicator equal to 1 if the student missed 18 or more days. Math, ELA, Lag Math, and Lag ELA are standardized test scores with mean 0 and standard deviation 1 within grade, year, and subject. Male, Asian, Black, Hispanic, Native, Multiple Races, Pacific Islander, White, and Econ. Disadvantage are binary indicators. The sample is restricted to students with non-missing math scores and complete sociodemographic data, and excludes students with more than 50 absences.

Table 2: Summary Statistics: Maryland

	Elementary School		Middle School		High School	
	2019	2023	2019	2023	2016 to 2017	2021 to 2022
	(1)	(2)	(3)	(4)	(5)	(6)
Absences	9.63	12.85	10.11	12.74	10.98	11.42
	(8.28)	(9.74)	(8.94)	(10.17)	(10.41)	(12.00)
Chronic	0.14	0.25	0.16	0.25	0.20	0.24
Math	0.03	0.05	0.05	0.08	—	—
	(0.99)	(0.99)	(0.99)	(0.98)		
ELA	0.02	0.05	0.05	0.08	—	—
	(0.99)	(0.99)	(0.99)	(0.98)		
Lag Math	0.02	0.04	0.05	0.07	0.09	0.02
	(0.99)	(0.99)	(0.99)	(0.98)	(0.98)	(0.99)
Lag ELA	0.01	0.03	0.04	0.06	0.09	0.02
	(1.00)	(1.00)	(0.99)	(0.98)	(0.96)	(0.99)
Male	0.51	0.51	0.51	0.51	0.51	0.51
Asian	0.07	0.07	0.07	0.07	0.07	0.08
Black	0.33	0.31	0.33	0.32	0.34	0.32
Hispanic	0.19	0.22	0.18	0.22	0.16	0.19
Native	0.00	0.00	0.00	0.00	0.00	0.00
Multiple Races	0.05	0.05	0.04	0.05	0.04	0.04
Pacific Islander	0.00	0.00	0.00	0.00	0.00	0.00
White	0.36	0.34	0.38	0.34	0.40	0.37
Econ. Disadvantage	0.45	0.51	0.41	0.48	0.37	0.36
N	126,371	112,223	179,561	164,076	126,236	122,452

Notes. Each column reports means for the indicated school level and year. Standard deviations in parentheses for continuous variables. Absences is the annual count of days absent. Chronic is a binary indicator equal to 1 if the student missed 18 or more days. Math, ELA, Lag Math, and Lag ELA are standardized test scores with mean 0 and standard deviation 1 within grade, year, and subject. Male, Asian, Black, Hispanic, Native, Multiple Races, Pacific Islander, White, and Econ. Disadvantage are binary indicators. The sample is restricted to students with non-missing math scores and complete sociodemographic data, and excludes students with more than 50 absences.

Table 3: Summary Statistics: Urban School District

	Elementary School		Middle School	
	2019	2023	2019	2023
	(1)	(2)	(3)	(4)
Absences	8.24	12.53	11.82	13.78
	(7.56)	(10.14)	(10.06)	(10.47)
Chronic	0.10	0.24	0.22	0.28
	(0.30)	(0.43)	(0.42)	(0.45)
Math	0.11	0.11	0.13	0.09
	(0.99)	(0.98)	(1.01)	(1.00)
ELA	0.09	0.08	0.07	0.04
	(1.00)	(1.00)	(0.95)	(0.95)
Lag Math	0.09	0.10	0.16	0.13
	(0.96)	(0.94)	(0.94)	(0.92)
Lag ELA	0.07	0.03	0.07	0.00
	(1.00)	(0.99)	(0.91)	(0.96)
Male	0.51	0.51	0.51	0.51
Asian	0.02	0.02	0.02	0.02
Black	0.56	0.52	0.62	0.59
Hispanic	0.23	0.24	0.20	0.23
Other Race	0.02	0.04	0.02	0.03
White	0.16	0.19	0.14	0.14
Econ. Disadvantage	0.41	0.46	0.41	0.48
N	5,747	6,108	4,615	5,769

Notes. Each column reports means for the indicated school level and year. Standard deviations in parentheses for continuous variables. Absences is the annual count of days absent. Chronic is a binary indicator equal to 1 if the student missed 18 or more days. Math, ELA, Lag Math, and Lag ELA are standardized test scores with mean 0 and standard deviation 1 within grade, year, and subject. Male, Asian, Black, Hispanic, Native, Multiple Races, Pacific Islander, White, and Econ. Disadvantage are binary indicators. The sample is restricted to students with non-missing math scores and complete sociodemographic data, and excludes students with more than 50 absences.

Table 4: Days Absent Effect on Math Test Scores

	Elementary School				Middle School			
Sample:	Pooled (1)	Pooled (2)	Pre (3)	Post (4)	Pooled (5)	Pooled (6)	Pre (7)	Post (8)
Panel A: North Carolina								
Absences	-0.064^{***}	-0.071^{***}	-0.070^{***}	-0.057^{***}	-0.063^{***}	-0.067^{***}	-0.066^{***}	-0.059^{***}
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Post*Abs		0.016^{***}				0.009^{***}		
		(0.003)				(0.003)		
N	308,845	308,845	198,616	110,229	408,396	408,396	259,021	149,375
Panel B: Maryland								
Absences	-0.049^{***}	-0.055^{***}	-0.053^{***}	-0.043^{***}	-0.051^{***}	-0.054^{***}	-0.052^{***}	-0.049^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post*Abs		0.016^{***}				0.007^{***}		
		(0.002)				(0.002)		
N	359,413	359,413	247,190	112,223	513,887	513,887	349,811	164,076
Panel C: Urban School District								
Absences	-0.074^{***}	-0.085^{***}	-0.084^{***}	-0.070^{***}	-0.056^{***}	-0.064^{***}	-0.059^{***}	-0.053^{***}
	(0.006)	(0.010)	(0.011)	(0.007)	(0.007)	(0.016)	(0.015)	(0.007)
Post*Abs		0.016				0.012		
		(0.011)				(0.017)		
N	11,855	11,855	5,747	6,108	10,384	10,384	4,615	5,769

Notes. The outcome variable is the standardized (mean 0, SD 1) end-of-grade math test score. Pre refers to the 2019 school year for North Carolina and Urban School District, and to 2018 and 2019 for Maryland. Post refers to the 2023 school year for all three sites. Absences is scaled by 0.10, so coefficients reflect the effect of ten absences. Parentheses contain standard errors clustered by school. All regressions condition on lagged math and reading scores, student sociodemographic controls, and classroom fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Chronic Absenteeism Effect on Math Test Scores

	Elementary School				Middle School			
Sample:	Pooled (1)	Pooled (2)	Pre (3)	Post (4)	Pooled (5)	Pooled (6)	Pre (7)	Post (8)
Panel A: North Carolina								
Chronic	-0.105^{***}	-0.117^{***}	-0.115^{***}	-0.097^{***}	-0.104^{***}	-0.110^{***}	-0.109^{***}	-0.101^{***}
	(0.003)	(0.005)	(0.005)	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)
Post*Chronic		0.023^{***}				0.012^{**}		
		(0.006)				(0.005)		
N	308,845	308,845	198,616	110,229	408,396	408,396	259,021	149,375
Panel B: Maryland								
Chronic	-0.080^{***}	-0.091^{***}	-0.088^{***}	-0.071^{***}	-0.087^{***}	-0.090^{***}	-0.087^{***}	-0.087^{***}
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Post*Chronic		0.022^{***}				0.005		
		(0.004)				(0.004)		
N	359,413	359,413	247,190	112,223	513,887	513,887	349,811	164,076
Panel C: Urban School District								
Chronic	-0.115^{***}	-0.139^{***}	-0.138^{***}	-0.105^{***}	-0.092^{***}	-0.089^{***}	-0.082^{**}	-0.101^{***}
	(0.013)	(0.023)	(0.024)	(0.016)	(0.016)	(0.032)	(0.031)	(0.020)
Post*Chronic		0.036				−0.005		
		(0.027)				(0.038)		
N	11,855	11,855	5,747	6,108	10,384	10,384	4,615	5,769

Notes. The outcome variable is the standardized (mean 0, SD 1) end-of-grade math test score. Chronic is a binary indicator equal to 1 if the student was chronically absent (18 or more absences), and 0 otherwise. Pre refers to the 2019 school year for North Carolina and Urban School District, and to 2018 and 2019 for Maryland. Post refers to the 2023 school year for all three sites. Parentheses contain standard errors clustered by school. All regressions condition on lagged math and reading scores, student sociodemographic controls, and classroom fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: College-Going Outcomes (Maryland, 10th Grade)

	HS Graduation			College Enrollment (2-year)			College Enrollment (Any)		
	Pooled (1)	Pre (2)	Post (3)	Pooled (4)	Pre (5)	Post (6)	Pooled (7)	Pre (8)	Post (9)
Panel A: Days Absent									
Absences	−0.050***	−0.048***	−0.028***	−0.028***	−0.026***	−0.014***	−0.053***	−0.049***	−0.054***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Post*Abs	0.023***			0.016***			0.003		
	(0.004)			(0.005)			(0.006)		
Oster Bound		−0.042	−0.026		−0.028	−0.015		−0.030	−0.049
Delta		7.684	13.570		n/a	n/a		2.572	11.584
N	93,017	49,060	43,957	47,531	24,831	22,700	47,531	24,831	22,700
Panel B: Chronic Absences									
Chronic	−0.102***	−0.098***	−0.046***	−0.058***	−0.054***	−0.021*	−0.098***	−0.090***	−0.115***
	(0.008)	(0.008)	(0.006)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.015)
Post*Chronic	0.058***			0.041***			−0.008		
	(0.009)			(0.015)			(0.017)		
Oster Bound		−0.082	−0.037		−0.054	−0.020		−0.050	−0.097
Delta		6.234	5.144		n/a	1073.641		2.248	6.258
N	93,017	49,060	43,957	47,531	24,831	22,700	47,531	24,831	22,700

Notes. Each column shows estimates from a separate regression for 10th grade students in Maryland. Absences are scaled by 0.10, so coefficients reflect the effect of ten absences. Pre refers to school years 2016 and 2017 for high school graduation and 2016 for college enrollment. Post refers to 2021 and 2022 for high school graduation and 2021 for college enrollment. Chronic is a binary indicator equal to 1 if the student was chronically absent (18 or more absen ces). All models control for student-level covariates, lagged GPA, lagged 8th grade test scores, and a course-taking fixed effect. Oster bounds and Delta values follow are computed under the convention that the maximum attainable R^2 is 1.3 times that of the controlled regression. The Oster bound is the bias-adjusted treatment effect under the assumption of equal selection on observed and unobserved characteristics ($\delta = 1$), and Delta is the value of the proportional selection parameter that would be required to drive the estimated effect to zero. Delta is not reported for models where the inclusion of controls moves the coefficient away from zero, which makes the standard calculation uninformative. The bias-adjusted Oster bound under $\delta = 1$ remains well-defined and is reported. Standard errors clustered at the course level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A Additional Tables and Figures

Appendix Table A.1: Days Absent Effect on Reading Test Scores

	Elementary School				Middle School			
Sample:	Pooled (1)	Pooled (2)	Pre (3)	Post (4)	Pooled (5)	Pooled (6)	Pre (7)	Post (8)
Panel A: North Carolina								
Absences	−0.014***	−0.020***	−0.020***	−0.008***	−0.020***	−0.023***	−0.023***	−0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Post*Abs		0.013***				0.005**		
		(0.003)				(0.002)		
N	284,793	284,793	184,150	100,643	451,532	451,532	286,331	165,201
Panel B: Maryland								
Absences	−0.018***	−0.018***	−0.018***	−0.018***	−0.039***	−0.040***	−0.037***	−0.041***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Post*Abs		0.001				0.004		
		(0.002)				(0.004)		
N	307,272	307,272	209,412	97,860	432,211	432,211	292,114	140,097
Panel C: Urban School District								
Absences	−0.038***	−0.046***	−0.046***	−0.033***	−0.056***	−0.063***	−0.060***	−0.054***
	(0.006)	(0.010)	(0.010)	(0.007)	(0.008)	(0.010)	(0.011)	(0.009)
Post*Abs		0.012				0.012		
		(0.012)				(0.009)		
N	11,841	11,841	5,748	6,093	10,588	10,588	4,793	5,795

Notes. The outcome variable is the standardized (mean 0, SD 1) end-of-grade reading test score. Pre refers to the 2019 school year for North Carolina and Urban School District, and to 2018 and 2019 for Maryland. Post refers to the 2023 school year for all three sites. Absences is scaled by 0.10, so coefficients reflect the effect of ten absences. Parentheses contain standard errors clustered by school. All regressions condition on lagged math and reading scores, student sociodemographic controls, and classroom fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A.2: Chronic Absenteeism Effect on Reading Test Scores

	Elementary School				Middle School			
Sample:	Pooled (1)	Pooled (2)	Pre (3)	Post (4)	Pooled (5)	Pooled (6)	Pre (7)	Post (8)
Panel A: North Carolina								
Chronic	−0.024***	−0.040***	−0.039***	−0.011**	−0.037***	−0.041***	−0.040***	−0.034***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Post*Chronic		0.030***				0.009*		
		(0.007)				(0.005)		
N	284,793	284,793	184,150	100,643	451,532	451,532	286,331	165,201
Panel B: Maryland								
Chronic	−0.031***	−0.032***	−0.032***	−0.030***	−0.065***	−0.067***	−0.062***	−0.072***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)
Post*Chronic		0.00394				0.00344		
		(0.005)				(0.005)		
N	307,272	307,272	209,412	97,860	432,211	432,211	292,114	140,097
Panel C: Urban School District								
Chronic	−0.063***	−0.065***	−0.066***	−0.060***	−0.094***	−0.113***	−0.107***	−0.087***
	(0.012)	(0.024)	(0.025)	(0.016)	(0.017)	(0.024)	(0.024)	(0.023)
Post*Chronic		0.003				0.031		
		(0.031)				(0.032)		
N	11,841	11,841	5,748	6,093	10,588	10,588	4,793	5,795

Notes. The outcome variable is the standardized (mean 0, SD 1) end-of-grade reading test score. Chronic is a binary indicator equal to 1 if the student was chronically absent (18 or more absences). Pre refers to the 2019 school year for North Carolina and Urban School District, and to 2018 and 2019 for Maryland. Post refers to the 2023 school year for all three sites. Parentheses contain standard errors clustered by school. All regressions condition on lagged math and reading scores, student sociodemographic controls, and classroom fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A.3: Sensitivity Analysis - North Carolina Math

	Base Model No Controls (1)	Lag Score Teacher FE (2)	Student FE & Classroom FE (3)	First Difference IV (4)	Base Model FD IV Sample (5)
Panel A: Elementary School, Pre-Covid					
Absences	-0.074^{***}	-0.070^{***}	-0.042^{***}	-0.046^{***}	-0.075^{***}
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
N	198,616	199,857	364,368	96,024	96,024
Panel B: Elementary School, Post-Covid					
Absences	-0.059^{***}	-0.057^{***}	-0.036^{***}	-0.032^{***}	-0.062^{***}
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
N	110,229	110,760	196,922	50,435	50,435
Panel C: Middle School, Pre-Covid					
Absences	-0.069^{***}	-0.065^{***}	-0.049^{***}	-0.045^{***}	-0.065^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
N	259,021	259,935	300,124	246,473	246,473
Panel D: Middle School, Post-Covid					
Absences	-0.061^{***}	-0.060^{***}	-0.033^{***}	-0.027^{***}	-0.060^{***}
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
N	149,375	150,296	171,606	134,621	134,621

Notes. The outcome variable is the standardized (mean 0, SD 1) end-of-grade math score. Pre and Post refer to the 2019 and 2023 school years, respectively. Column 3 uses two years of data to implement student fixed effect estimators and omits lag scores. Absences is scaled by 0.10, so coefficients reflect the effect of ten absences. Parentheses contain standard errors clustered by school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A.4: Sensitivity Analysis - Maryland Math

	Base Model, No Controls (1)	Lag Score, Teacher FE (2)	Student FE & Classroom FE (3)
Panel A: Elementary School, Pre-Covid			
Absences	-0.055^{***}	-0.056^{***}	-0.029^{***}
	(0.001)	(0.001)	(0.005)
N	247,190	247,407	116,456
Panel B: Elementary School, Post-Covid			
Absences	-0.042^{***}	-0.042^{***}	-0.026^{***}
	(0.002)	(0.002)	(0.004)
N	112,223	112,516	107,142
Panel C: Middle School, Pre-Covid			
Absences	-0.054^{***}	-0.055^{***}	-0.038^{***}
	(0.001)	(0.001)	(0.003)
N	349,811	350,546	222,046
Panel D: Middle School, Post-Covid			
Absences	-0.052^{***}	-0.052^{***}	-0.032^{***}
	(0.002)	(0.002)	(0.004)
N	164,077	164,482	208,164

Notes. The outcome variable is the standardized (mean 0, SD 1) end-of-grade math score. Pre refers to the 2018 and 2019 school years and Post refers to 2023. Column 3 uses two years of data to implement student fixed effect estimators and omits lag scores. Absences is scaled by 0.10, so coefficients reflect the effect of ten absences. Parentheses contain standard errors clustered by school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

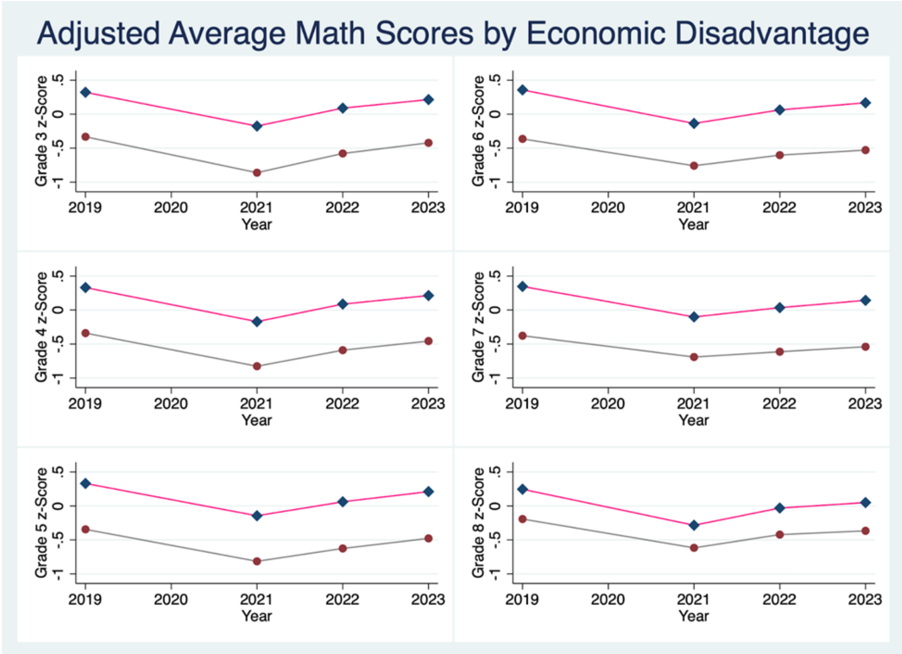
Appendix Table A.5: Sensitivity Analysis - Urban School District Math

	Base Model, No Controls (1)	Lag Score, Teacher FE (2)
Panel A: Elementary School, Pre-Covid		
Absences	-0.091^{***}	-0.087^{***}
	(0.010)	(0.010)
N	5,747	5,998
Panel B: Elementary School, Post-Covid		
Absences	-0.079^{***}	-0.079^{***}
	(0.007)	(0.008)
N	6,108	6,148
Panel C: Middle School, Pre-Covid		
Absences	-0.064^{***}	-0.067^{***}
	(0.016)	(0.014)
N	4,615	5,108
Panel D: Middle School, Post-Covid		
Absences	-0.069^{***}	-0.068^{***}
	(0.008)	(0.009)
N	5,769	5,867

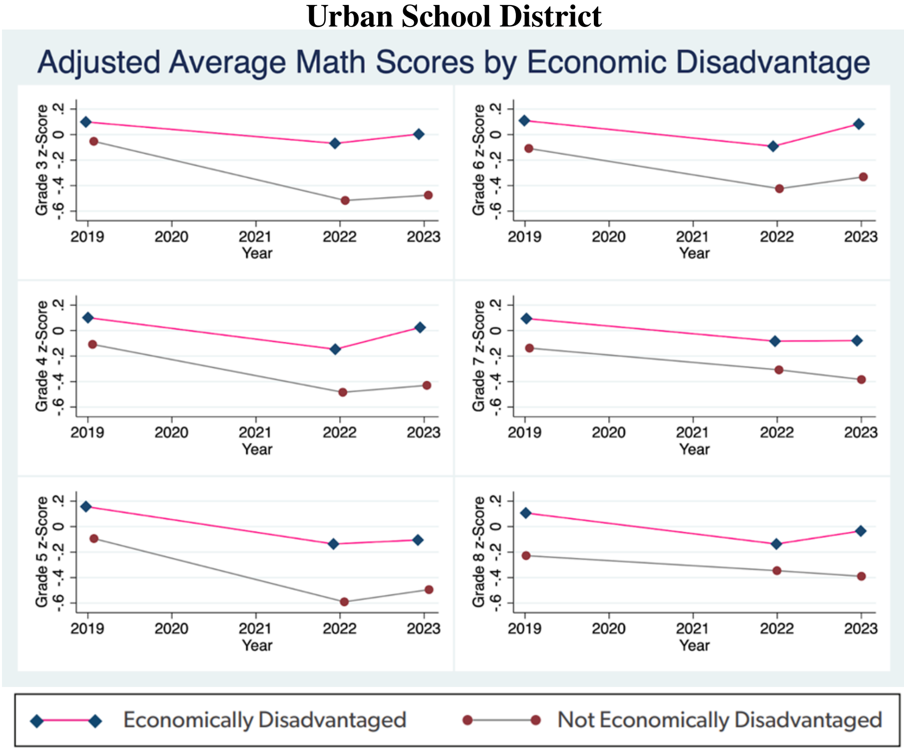
Notes. The outcome variable is the standardized (mean 0, SD 1) end-of-grade math score. Pre and Post refer to the 2019 and 2023 school years, respectively. Absences is scaled by 0.10, so coefficients reflect the effect of ten absences. Parentheses contain standard errors clustered by school. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Figure A.1: Differences in Learning Loss in Math, by Economic Disadvantage

North Carolina



Urban School District



Notes. Each figure presents adjusted average math scores from 2019 to 2023 separately for grades 3 through 8 in North Carolina and the Urban School District. Each figure tracks the economically disadvantaged students (blue/diamond) and not economically disadvantaged students (red/circle) separately.