Annenberg Institute
BROWN UNIVERSITY

EdWorkingPaper No. 24-1107

Effects of High-Impact Tutoring on Student Attendance: Evidence from the OSSE HIT Initiative in the District of Columbia

Monica G. Lee
Stanford University

Susanna Loeb
Stanford University

Carly D. Robinson
Stanford University

Student absenteeism, which skyrocketed during and after the COVID-19 pandemic, has negative consequences for student engagement and achievement. This study examines the impact of the High-Impact Tutoring (HIT) Initiative, implemented by the Office of the State Superintendent of Education in Washington DC, on reducing absenteeism. The HIT initiative was designed to mitigate learning loss by providing additional academic supports with a focus on students affected by the pandemic's disruptions. Leveraging detailed daily school attendance and tutoring session data, we employ a within-student approach with student and date fixed effects to isolate the causal effect of having a scheduled tutoring session on daily school attendance. We find that the likelihood of being absent decreases by 1.2 percentage points on days when students have a scheduled tutoring session; this translates to a 7.0% reduction in absenteeism. These effects are most pronounced among middle school students and those with extreme absenteeism in the prior year, with reductions of 13.7% and 7.0%, respectively. Furthermore, key features of high-impact tutoring, such as in-school delivery and smaller tutor-to-student ratios, amplify the effect. These findings underscore the dual benefits of high-impact tutoring for both academic and engagement outcomes, highlighting its potential as a scalable strategy to addressing chronic absenteeism and promoting equitable access to supportive educational environments.

VERSION: December 2024

Suggested citation: Lee, Monica G., Susanna Loeb, and Carly D. Robinson. (2024). Effects of High-Impact Tutoring on Student Attendance: Evidence from the OSSE HIT Initiative in the District of Columbia. (EdWorkingPaper: 24 -1107). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/wghb-4864

Effects of High-Impact Tutoring on Student Attendance: Evidence from the OSSE HIT Initiative in the District of Columbia

Monica G. Lee, Susanna Loeb, and Carly D. Robinson

Stanford University

Abstract

Student absenteeism, which skyrocketed during and after the COVID-19 pandemic, has negative consequences for student engagement and achievement. This study examines the impact of the High-Impact Tutoring (HIT) Initiative, implemented by the Office of the State Superintendent of Education in Washington DC, on reducing absenteeism. The HIT initiative was designed to mitigate learning loss by providing additional academic supports with a focus on students affected by the pandemic's disruptions. Leveraging detailed daily school attendance and tutoring session data, we employ a within-student approach with student and date fixed effects to isolate the causal effect of having a scheduled tutoring session on daily school attendance. We find that the likelihood of being absent decreases by 1.2 percentage points on days when students have a scheduled tutoring session; this translates to a 7.0% reduction in absenteeism. These effects are most pronounced among middle school students and those with extreme absenteeism in the prior year, with reductions of 13.7% and 7.0%, respectively. Furthermore, key features of high-impact tutoring, such as in-school delivery and smaller tutor-to-student ratios, amplify the effect. These findings underscore the dual benefits of high-impact tutoring for both academic and engagement outcomes, highlighting its potential as a scalable strategy to addressing chronic absenteeism and promoting equitable access to supportive educational environments.

Acknowledgements

We are grateful to our partners in this research, the DC Office of the State Superintendent of Education. We especially thank Sam Angileri, Alethia Hinds, Sarah Martin, and Jess Sobin for their invaluable contribution to project implementation. We received insightful feedback and support from the National Student Support Accelerator team, in particular Kristine Gaffaney, Demetra Kalogrides, Amanda Lu, and Nancy Waymack, as well as Cynthia Pollard, and Amirpasha Zandieh. For helpful comments, the authors thank participants of the Society for Research on Educational Effectiveness 2024 Conference and the Association for Public Policy Analysis & Management 2024 Annual Meeting. We thank the Smith Richardson Foundation (#2021-2497) as well as Arnold Ventures/Accelerate (#292303) for their support of our full research program. The findings, interpretations, and conclusions expressed in this paper are those of the authors and do not necessarily represent the views of the District of Columbia Public Schools, the DC Office of the State Superintendent of Education, funders, or Stanford University. This study was approved under Stanford University's IRB Protocol "National Student Support Accelerator: Effects of tutoring at school district test sites" (#68027). The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Introduction

Student absenteeism is a growing concern in schools nationwide. In the aftermath of the pandemic, chronic absenteeism (i.e., missing ten percent or more of the school year) doubled from 14.8 percent in 2018-19 to 28.3 percent during the 2021-22 school year (Dee, 2024). Post-pandemic, in the 2022-23 school year, the national chronic absenteeism rate remained persistently high at 26 percent. These rates have been highest in districts with larger shares of low-income and low-performing students, reflecting how the pandemic further exacerbated pre-existing inequalities (Malkus, 2024).

Districts leverage a range of strategies to reduce absenteeism in their schools. Some of these strategies are light-touch interventions – including mailers, phone calls, and text messages sent to parents of students who missed school – while others are more intensive, such as mentoring initiatives and home visits. While light touch interventions can have positive effects (e.g., Kalil et al., 2019; Lasky-Fink et al., 2021; Robinson et al., 2018), reaching less connected students with the highest absenteeism rates often requires more intensive approaches (Guryan et al., 2020).

Research provides evidence that school-based mentoring relationships can impact student attendance, even for the most disconnected students. As one example, the Check and Connect mentoring program decreased absenteeism rates by 22.9 percent for 5th through 7th grade students (Guryan et al., 2020). These results indicate that meaningful connections with a caring adult can increase student attendance. Yet, employing mentors is costly for schools and does not necessarily increase student achievement (Guryan et al., 2020). Schools may be put off by the high price tag to invest in initiatives that can only serve a select group of students and are not focused directly on learning. In theory, teachers and other school staff can fill these supportive roles, but these educators face competing demands for their time and schools are not set up to provide individualized instruction or intensive personalized outreach to encourage attendance (Kraft, Marinell, & Yee, 2016). The confluence of these factors often leaves students without opportunities to connect with a trusted adult who knows them and is invested in their success. This lack of connection is evident from student surveys across the country showing that many students, particularly in middle and high school, report feeling they do not have a close, caring adult in their school (Balfanz et al., 2024).

Schools do have options to increase the likelihood that high-need students have access to a caring adult. For instance, in response to the reduced learning and the increased achievement gaps across groups created by the pandemic, many schools sought to provide high-impact tutoring for struggling students. This intensive, relationship-based instruction has substantial evidence of effectiveness and has long been the choice of families who could afford to pay for tutoring outside of school (Kim et al., 2024). High-impact tutoring may not only improve learning. Like mentoring, it may improve student engagement in school and their attendance. In many ways, the relationship between students and their consistent tutor can mirror that of a mentoring relationship, and students may be more likely to attend school because they know they have a caring adult who expects to see them. Moreover, if tutoring improves academic learning, students may see themselves as being able to succeed in school, increasing their self-efficacy (Allensworth & Schwartz, 2020). When students feel that they belong and can succeed in school, they may be more likely to engage positively with school, translating into increased attendance.

Although scholars have hypothesized that tutoring may increase student engagement in school (Nickow et al., 2024; Robinson & Loeb, 2021), little research has rigorously assessed the effects of high-impact tutoring on students' school attendance. No studies have studied the impact of school-based tutoring on attendance during this post-pandemic wave of high chronic absenteeism. In a pre-pandemic randomized controlled trial testing the impact of a high school math tutoring program, researchers found no detectable effect on student attendance (Bhatt et al., 2024). However, a recent study by Carlana & Ferrara (2024) found that middle school students who received out-of-school virtual tutoring were more likely to attend school online during the pandemic, highlighting tutoring's potential to boost engagement and attendance.

In this paper, we provide insights into how high-impact tutoring affects students' school attendance. With leaders nationwide raising concerns about high student absenteeism (Dee, 2024) and ongoing academic struggles (Lewis & Kuhfeld, 2024), understanding how individualized, relationship-based instruction can enhance school engagement and achievement can help school leaders address these challenges. Beginning in 2021, the District of Columbia (DC) Office of the State Superintendent of Education (OSSE) launched a High-Impact Tutoring (HIT) initiative, providing access to math and English Language Arts (ELA) tutoring for K-12 students across DC schools with the greatest concentrations of students identified as at-risk. We study the effects of this tutoring on student attendance during the 2022-23 school year.

When tutoring is implemented at scale, and not as part of a randomized controlled trial, isolating the effect of tutoring on school attendance can be challenging. Students who receive tutoring differ from those who do not in both observable and unobservable ways. Students who are in school more consistently are generally more likely to attend tutoring sessions, while school staff who are selecting students for tutoring may opt not to include students who are frequently absent, in an effort to reach the least engaged students. So that these selection mechanisms do not bias our estimates of the effects of tutoring on attendance, we compare students to themselves. We combine students' daily school attendance records with fine-grained tutoring implementation data containing information on when each student's tutoring sessions were scheduled to occur. Using student and date fixed effects, we estimate the effects of having a tutoring session scheduled on whether the student misses school or not that day. This approach doesn't provide a summative estimate of the overall effect of tutoring on attendance, but it does provide clear evidence into whether having a scheduled tutoring session affects student attendance on that day, overcoming any potential biases due to unobservable factors that affect students' participation in tutoring.

We find that on average, the probability of being absent is 1.2 percentage points lower on days that a student has a tutoring session scheduled, a 7.0 percent decrease in students' overall likelihood of being absent. If tutoring were scheduled as a regular part of every school experience (i.e., 3 days per week), this would translate into participating students attending 1.3 more days of school over the course of the school year.[1] The effect of tutoring on improving attendance is particularly strong for middle school students and students with extreme absenteeism rates in the prior year (i.e., missed more than 30 percent of school days), who were 13.7 percent and 7.0 percent less likely to be absent when a tutoring session was scheduled, respectively. We estimate regular tutoring would result in middle school students attending an additional 2.1 days of school and highly absent students attending an additional 2.8 days of school. We also found comparatively larger decreases in absenteeism when tutoring was held during school hours or had smaller tutor-to-student ratios. Overall, this study provides some of the first causal estimates of the impact of high-impact tutoring on school attendance in the US across grade levels and subject areas.

---

[1] Assuming a 180 day school year, tutoring would occur on 108 days if tutoring was scheduled 3 days per week (180*0.6=108). If scheduled tutoring reduces tutoring by 1.2-percentage points, tutored students would attend an average of 1.3 days more over the course of the school year (108*.012=1.296).

Background

High-Impact Tutoring

Tutoring expanded significantly during and after the COVID-19 pandemic as a key strategy to accelerate student learning. During the pandemic, many students, particularly those from marginalized backgrounds, experienced setbacks in their academic progress. In response, districts across the U.S. implemented tutoring programs aimed at providing personalized, small-group instruction, at least in part due to the strong research base supporting the effectiveness of this approach (Nickow et al., 2024). These efforts often focused on math and literacy skills, providing regular tutoring sessions during the school day with a consistent tutor to ensure accessibility and consistency.

State and federal policies played a key role in the expansion of tutoring at scale. In the U.S., the Elementary and Secondary School Emergency Relief (ESSER) funds, provided as part of the federal COVID-19 relief packages, allowed states to allocate substantial resources for tutoring programs. States such as Tennessee and Texas leveraged these funds to develop robust tutoring initiatives. The Biden-Harris administration publicly highlighted high impact tutoring as a key strategy for educational recovery (The White House, 2024). States also enacted their own policies, with some mandating tutoring for students who are performing below grade level to ensure that tutoring is embedded as a key component in school intervention strategies (Hashim et al., 2024; National Student Support Accelerator, 2023).

Research shows that tutoring in reading and math can have strong benefits for students, although the effectiveness of individual programs varies (Heinrich et al., 2014; Nickow et al., 2024; Wanzek et al., 2016). These variations in tutoring-program effectiveness may be, in part, due to the wide range of interventions that people refer to as tutoring. While some tutoring takes the form of homework help and drop-in support which may not have strong effects on student learning (Robinson et al., 2022), tutoring interventions that provide students with extended one-on-one, personalized instruction embedded into the school day produce consistently strong effects (Cavanaugh et al., 2004; Gersten et al., 2020; Neitzel et al., 2022; Nickow et al., 2024; Slavin et al., 2011; Wanzek et al., 2018; Wanzek et al., 2016). The features that characterize effective high impact tutoring include small group size (i.e., no more than four students), regular and frequent sessions (occurring at least three times per week for at least 30 minutes per session), embeddedness during the school day, the provision of a well-trained consistent tutor, the use of data to identify students' assets and needs, and high-quality instructional materials (see Robinson & Loeb, 2021; Robinson et al., 2024). Ultimately, many hypothesize that the key to effective tutoring lies in regular, consistent interactions between students and tutors, which help build relationships that promote stronger self-beliefs and help students engage more deeply in academic settings (Kraft & Goldstein, 2021).

Absenteeism

Absenteeism is both a reflection of student engagement in school and the cause behind students' further disengagement and academic challenges. When students miss school, they miss out on in-class instructional time, as well as opportunities to learn from peer and teacher interactions. Chronic absenteeism is a leading indicator of school disengagement as measured by dropout rates or long-term academic difficulties (Balfanz & Byrnes, 2012). Student absenteeism is negatively associated with standardized test scores (Gottfried, 2014) as well as other long-run outcomes for success (Liu, Lee, & Gershenson, 2019). Absenteeism affects student learning opportunities and outcomes across all grade levels. In the younger grades, missing school can lead to learning gaps in foundational skills such as literacy and numeracy; gaps can compound over time, making it difficult to catch up (Gershenson, Jacknowitz, & Brannegan, 2017). In middle and high school, missing school can have long-term consequences like failure to graduate high school and lower college enrollment (Liu et al., 2019).

Multiple factors lead to students missing school. Some factors driving absenteeism are those that push students away from school, such as academic challenges (Romero & Lee, 2008) or poor academic performance (Gottfried, 2014), unsafe school climates (Balfanz & Byrnes, 2012; Gottfried & Hutt, 2019) or an excessively punitive school environment (Holt & Gershenson, 2017). Other external factors pull students away from school, such as economic or family obligations (Gershenson et al., 2017), transportation issues (Romero & Lee, 2008), chronic health issues (Kearney et al., 2023; Gottfried & Hutt, 2019), and neighborhood crime/violence (Gershenson et al., 2017). Often, multiple factors drive student absenteeism; for example, a student experiencing academic challenges in school might also be faced with family responsibilities in the home. Issues like poverty can affect students both within and outside of school walls.

The pandemic exacerbated factors contributing to student absenteeism. COVID-19 contributed to ongoing health concerns while school closures and isolation heightened stress and anxiety among students, making it challenging to engage in schools (Kuhfeld et al., 2020; Hough, 2021). Pre-existing economic pressures intensified, as students from low-income communities experienced unequal access to digital/remote learning resources (Lake & Pillow, 2022; Dorn et al., 2020). As a result, schools faced – and continue to experience – considerable challenges in meeting the mounting academic and relational needs of students.

Tutoring as a promising approach to reduce absenteeism

Returning to in-person instruction, schools struggled to effectively reengage students, particularly those who disengaged or fell off track during remote learning (Center on Reinventing Public Education, 2024). Improving student attendance rates can require a multifaceted approach that addresses the many factors contributing to students missing school. Beyond addressing external factors affecting attendance, schools can reduce absenteeism by creating supportive learning environments that effectively address ongoing academic challenges while fostering positive relationships and stronger connections to the school community (Osher et al., 2016).

The features of high-impact tutoring target many of the underlying factors that also drive absenteeism. When students meet with a consistent tutor frequently over the course of the school year, they can develop supportive relationships which can lead to a greater sense of belonging in the classroom (Allen et al., 2018; Goodenow, 1993). Similarly, small tutor-to-student ratios can help tutors cater to the individualized academic needs of struggling students, which can help them feel more connected to one another *and* to the academic content. When tutoring is integrated into the school day, fewer pull factors affect students' ability to participate (such as caring for siblings, transportation issues, or other extracurricular commitments that prevent students from getting to school), ensuring a structured and consistent time period for students to receive additional academic support. These features not only provide academic support but also have the potential to mitigate the overall feeling of disengagement from school.

Only a few studies have rigorously studied the impact of tutoring on students' school attendance, and the results are mixed. In one pre-pandemic study, Bhatt and colleagues (2024) found no statistically significant effects of Saga tutoring on high school student absenteeism in Chicago, even though the study found strong positive effects on student math learning. More recently, a study of middle school students found that Italian middle school students randomly assigned to out-of-school time virtual tutoring increased students' likelihood of attending online classes during the pandemic by 10 percentage points (Carlana & Ferrara, 2024). In addition, although not focused on school-based attendance, one study of virtual tutoring in the UK found that when students and tutors received feedback on what they had in common with one another student attendance in tutoring sessions increased by four percentage points, suggesting that improving tutor-student relationships may be one mechanism for increasing student engagement (Tagliaferri et al., 2022).

Despite the potential for high-impact tutoring to improve students' school attendance, isolating the effect of tutoring on attendance without conducting a randomized controlled trial is difficult. Students who attend tutoring sessions can differ from those who do not on unobserved characteristics. Students who attend tutoring may be those who would have attended school more consistently as well. School staff may opt to exclude students who they think are less likely to attend school in an effort to maximize the number of tutoring sessions provided. Alternatively, they may select students for tutoring who are least engaged in school to build those students' engagement with the motivating effects of tutoring. Given the range of factors affecting selection into tutoring, a simple comparison of attendance between students who receive tutoring and those who do not would be unlikely to measure the causal effects of tutoring.

To assess whether tutoring can increase attendance in the post-pandemic context, we study the District of Columbia Office of the State Superintendent of Education's (OSSE) High-Impact Tutoring Initiative ("the OSSE HIT Initiative" or "the Initiative"). This program has the benefit for understanding these effects of reaching many students in a district with high absenteeism rates. However, OSSE did not randomly assign students to tutoring, so the difference in school attendance between tutored and non-tutored students cannot be directly attributed to tutoring itself. Instead, we use detailed student-level data from the district and tutoring programs to conduct a within-student analysis, comparing school attendance on days when students had scheduled tutoring sessions to days when they did not. This approach provides a within-student causal estimate of the impact of having a scheduled tutoring session on the likelihood of attending school that day.

The OSSE High-Impact Tutoring Initiative

In 2021, OSSE launched the OSSE HIT Initiative, a three-year, $33 million investment focused on accelerating learning recovery from the disruptions students experienced during the COVID-19 pandemic. OSSE includes the 70 local education agencies (LEAs) located within the geographic bounds of Washington, DC; it provides support and oversight for all DC schools as the state education agency. District of Columbia Public Schools (DCPS) students make up approximately 52 percent of the total student population and 46 percent of these schools; public charter schools make up the remainder of OSSE students and schools.

On-the-ground implementation of the Initiative consisted of a multipronged approach that combined grant allocation to tutoring providers, community partnerships, an emphasis on at-risk students, and an extensive program evaluation. First, OSSE implemented a series of grant competitions awarded directly to tutoring services across the district. The first round of grants allocated $3.19 million to eight tutoring providers during the 2021–2022 school year, followed by an additional $19.56 million to eleven providers in spring 2022 and $7.19 million to nine providers in the winter of 2023 (OSSE, 2023). Schools were considered eligible for high impact tutoring from these providers if 40 percent or more of their students were categorized as at risk (OSSE, 2023).

The grant competition, aligned with partnerships with local and national organizations, led to quick scaling of high-impact tutoring for prioritized students. By the end of the 2022-23 school year, OSSE awarded grants directly to 14 organizations and 13 tutoring providers to support the incubation of HIT providers, community-based tutoring hubs in partnership with OSSE, tutoring design sprints, and the development of communities of practice (OSSE, 2023). The Initiative also funded 10 school-based HIT managers at DCPS middle and high schools to coordinate and support tutoring in their schools. Tutoring providers with grants partnered with eligible schools and at community-based locations (like public libraries) to conduct tutoring programs. By the end of the 2022-23 school year, OSSE was well underway to meet its original goal of serving 10,000 students across the three-year duration of the Initiative, in addition to fulfilling its yearly goal to provide expanded access to high-impact math and English Language Arts (ELA) tutoring for K-12 students across DC schools with the greatest concentrations of students identified as at-risk.

This investment was a core part of the city's strategy to address interrupted schooling as well as the persistent achievement gaps present before the pandemic. Students classified as at-risk accounted for 73% of those participating in OSSE-funded tutoring programs in fall 2022, a significantly higher percentage than the 51% observed across the general DCPS population (OSSE, 2023). Notably, students of color were overrepresented in tutoring programs; Black or African American students comprised 82% of tutored students while 16% were Hispanic. The program prioritized support for students with the greatest academic needs, with 81% of tutored scoring at the bottom two levels of their prior year standardized assessments in math and ELA. Students with disabilities and English Learners were represented in similar proportions relative to their representation in the overall student body.

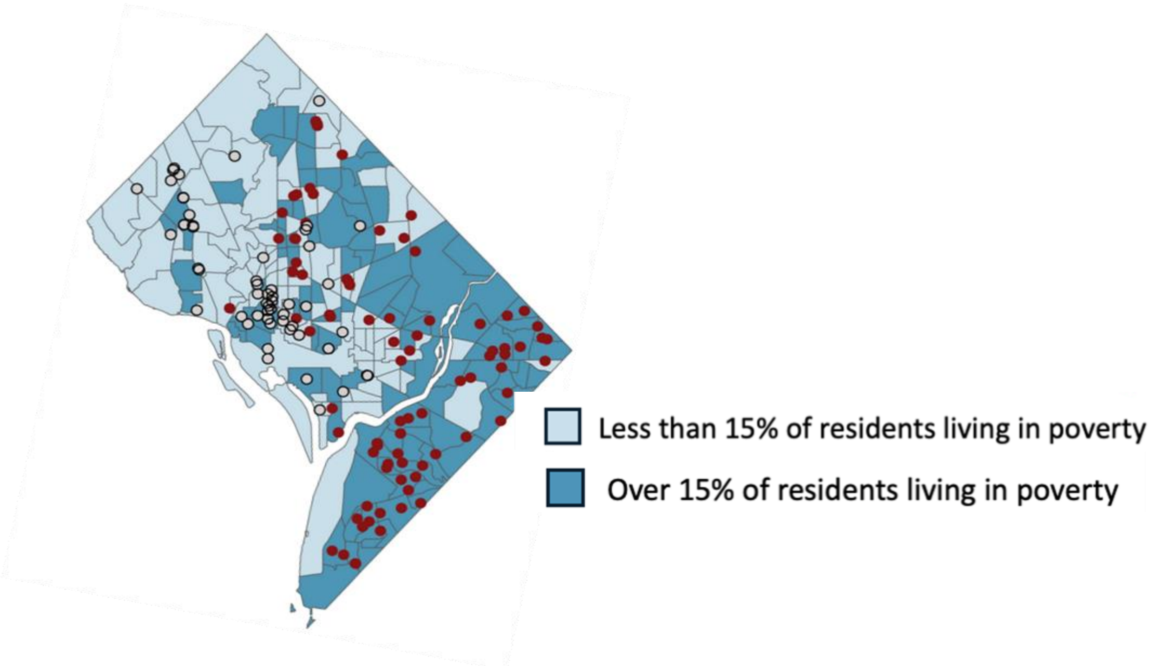
A program evaluation leveraging OSSE administrative data, tutoring session data, program documentation, and interviews and personal communication with program managers showed that the programs included many evidence-based features of effective tutoring. Across providers, OSSE students met in person with tutors one-on-one or in small groups and saw the same tutor multiple times per week. All tutoring had to occur in-person through the 2023-24 school year. Most organizations collaborated with school leaders to schedule at least some tutoring during the school day while eight providers offered out-of-school time tutoring at community-based sites such as community centers. The grant required tutoring programs to use high-quality instructional materials that were directly aligned to the classroom curriculum and/or were grounded in evidence (e.g., the science of reading). More information about the HIT Initiative in OSSE, detailed implementation characteristics, and exploration of effects on academic outcomes can be found in Pollard et al (2024).

Data and Methods

Sample

Students from 141 schools participated in OSSE-funded tutoring during the 2022-2023 school year at schools and community hubs; 71 schools provided tutoring during the school day for students. In total, the Initiative served 5,135 students in the 2022-2023 school year, 4,222 of whom are included in our analysis (data from four providers are excluded; see Data section for details). Of the students in our analysis, 2,694 received tutoring in ELA and 2,087 received tutoring in math. Figure 1 illustrates how existing private tutoring (indicated using gray dots) was concentrated in wealthier areas of the city while OSSE funded tutoring (red dots) were present largely on the east side of the city in wards 5, 7, and 8, areas of the city that tend to have fewer financial resources, effectively expanding the reach of tutoring in the District of Columbia.

Figure 1. Tutoring Participation by Ward



Note: Gray dots represent the coordinates indicating private tutoring facilities found through Google Maps searches for private tutoring establishments in Washington D.C. as of February 2024. Red dots signify the spatial distribution of 113 OSSE-funded HIT sites throughout the District of Columbia during the fiscal year 2024. Prior to the implementation of the OSSE HIT Initiative, most private tutoring was concentrated in wealthier areas of DC. The OSSE HIT Initiative increased access to tutoring in parts of DC with more residents living in poverty.

Methods

Our goal is to assess whether tutoring affects absenteeism. Depending on the approach, estimation of these effects could be subject to selection bias. One approach would be simply to compare the attendance of students who received tutoring to those who did not. These students, however, likely differ on their propensity to attend school regardless of whether they attended tutoring. To address those differences between students prior to starting tutoring, we could control for the prior year's attendance. However, students may be selected into tutoring not only on these measured attributes but on other factors observed by teachers or school leaders that lead their assignment to tutoring and affect attendance, again regardless of tutoring. As a result, we needed to find a way to accurately assess the effects of tutoring on attendance when we do not observe all the factors affecting attendance that could be correlated with tutoring.

For this estimation we leverage the rich data we have available on daily absenteeism and scheduling of tutoring sessions, taking a fixed-effects approach to compare student absences on the days when they have tutoring scheduled to the days when they do not. Equation 1 describes this linear probability model:

$$Absent_{it} = \beta_0 + \beta_1 TutoringScheduled_{it} + \alpha_i + \omega_{Date_t} + \epsilon_{it} \text{ (1)}$$

where $Absent_{it}$ is the outcome of interest for student *i* on day *t*, $TutoringScheduled_{it}$ is an indicator for whether student *i* had tutoring scheduled on day *t*, α_i is a student fixed effect, ω_{Date_t} is a fixed effect for the date, and ϵ_{it} is the residual. The coefficient β_1 estimates the probability of attending school on days when students have a tutoring session scheduled. Adding in student fixed effects accounts for students' average attendance rates, so that β_1 is the differential relative to that average when they do not have tutoring sessions scheduled. The date fixed effects, ω_{Date_t}, accounts for day-of-the-year specific variations. Schools often see higher absences on the day before Thanksgiving, for instance. This approach adjusts for those differences.

While equation 1 is our primary model, we also run a set of alternative models for comparison. We start with a model of scheduled tutoring on a given day predicting absenteeism (Model 1). We then introduce student demographics, as shown in Table 1, (Model 2); and then substitute those controls for student fixed effects (Model 3). We then add day-of-the-week fixed effects (Model 4) to account for variation attributable to the day of the week as students, for example, may be less likely to attend school on Fridays. Next, we include both day-of-the-week and month fixed effects (Model 5) to account for time of year specific variations, like how absences spike around the winter holidays. Model 6, which replaces day-of-the-week and month fixed effects with a date fixed effect, is our primary model and the most conservative model. We estimate this full set of models both for the full sample of students attending any public or charter school within OSSE, and for students who attend DCPS schools. We run the model on a more restricted sample (i.e., DCPS schools only) to consider what effects may look like for a conventional local educational agency as opposed to charter networks.

In addition to estimating the average effects of having tutoring scheduled on daily absenteeism, we also look at how the effects might differ by student characteristics and tutoring program characteristics. In particular, we assess effects separately based on key student characteristics that may be related to absenteeism such as prior year absences (10% or less, 10%-30%, and more than 30%), grade level (K-5, 6-8, and 9-12) and demographic characteristics for students. In addition, we examine the effects of tutoring on attendance by key program characteristics, including timing when tutoring was provided (during the school day or after school), tutor-student ratio (1:1 or 1:2 versus 1:3 or 1:4), and the subject area in which tutoring was provided (Math, English Language Arts, or both).

Data

The data for this study come from OSSE. OSSE grantees were required to submit student-level data on a quarterly basis to the agency with information on student enrollment, program features, session scheduling, and student attendance. These data are unusually rich in their detail of attendance - including daily attendance for each student - and in their detail on the scheduling and attendance of students for each tutoring session. While 26 providers were involved in the tutoring initiative, we exclude data from four providers. Two of these providers administered fewer than 15 sessions total during the entire school year. The other two excluded providers did not pre-schedule their sessions and, instead, chose students to receive tutoring if they were in attendance that day. As a result, they do not provide the variation needed for our empirical approach. We provide a specification check that examines this variation across all providers (see Appendix Table A1).

Table 1 describes the sample. The full dataset consists of all students who attended schools that participated in the OSSE HIT Initiative (Columns 1-2, Table 1). A select number of students from those schools received some type of tutoring. The sample of students we use in our main analyses are students who received any tutoring (Columns 3-4, Table 1). Table 1 also includes the demographic characteristics of students who did not receive any tutoring in the overall dataset for a full illustration of how the analytic sample compares to the rest of the student body (Columns 5-6).

Overall, we see that across the samples, approximately half of students are female, one-fifth are classified as a student with disabilities (SWD), and 13% are classified as an English learner. While the full sample is predominantly Black (71%) and economically disadvantaged (60%), the sample of students who received tutoring has an even higher proportion of Black (82%) and economically disadvantaged students (74%). Students who received tutoring were also more likely to have low scores in math (26% vs. 19%) and ELA (23% vs. 17%), and to be considered “At Risk” (77% vs. 63%).

Table 1. Student Demographic Breakdown by Sample

	All Students in Data		Received Any Tutoring		Did Not Receive Any Tutoring	
	Proportion	N	Proportion	N	Proportion	N
Female	0.49	24981	0.48	2019	0.49	22962
Male	0.51	26324	0.52	2203	0.51	24121
Asian	0.01	527	<0.10	18	0.01	509
Black	0.71	36435	0.82	3474	0.70	32961
Hispanic	0.19	9586	0.16	673	0.19	8913
Multi-Race	0.02	1053	<0.05	29	0.02	1024
White	0.07	3663	<0.05	25	0.08	3638
Students with Disabilities (SWD)	0.19	10005	0.19	790	0.20	9215
Non-SWD	0.81	41320	0.81	3432	0.80	37888
English Learner (EL)	0.13	6632	0.13	552	0.13	6080
Non-EL	0.87	44693	0.87	3670	0.87	41023
Economically Disadvantaged	0.60	30821	0.74	3113	0.59	27708
Not Economically Disadvantaged	0.40	20504	0.26	1109	0.41	19395
At Risk	0.63	32420	0.77	3270	0.62	29150
Not at Risk	0.37	18905	0.23	952	0.38	17953
Grades K-5	0.46	23701	0.48	2044	0.46	21657
Grades 6-8	0.27	13936	0.24	996	0.27	12940
Grades 9-12	0.27	13688	0.28	1182	0.27	12506
Prior Year Math Achievement						
Level 1 (Lowest)	0.19	9504	0.26	1081	0.18	8423
Level 2	0.17	8702	0.19	791	0.17	7911
Level 3	0.11	5403	0.08	317	0.11	5086
Level 4	0.06	3282	<0.05	DS	0.07	3209
Level 5 (Highest)	0.01	608	<0.10	DS	0.01	605
Prior Year ELA Achievement						
Level 1 (Lowest)	0.17	8478	0.23	976	0.16	7502
Level 2	0.12	6229	0.14	570	0.12	5659
Level 3	0.12	6107	0.10	420	0.12	5687
Level 4	0.11	5470	0.05	229	0.11	5241
Level 5 (Highest)	0.02	1248	<0.05	23	0.03	1225
Prior Year Absences						
Absent <10% of Days	0.47	22107	0.38	1477	0.48	20630
Absent 10-30% of Days	0.38	17778	0.45	1732	0.37	16046
Absent >30% of Days	0.16	7365	0.17	680	0.15	6685
Number of Observations		51325		4222		47103

Our initial dataset consists of students who attended schools that participated in the OSSE HIT Initiative excluding the four providers mentioned previously (Cols 1 and 2). A subset of students from those schools received some type of tutoring (Cols 3 and 4) and this is the sample we use to estimate our main model and effects by subgroups. We include a breakdown of demographic characteristics on students who did not receive any tutoring in the overall dataset (Cols 5 and 6) for a full illustration of how the sample compares to the rest of the student body. Total N across achievement category does not sum to the full analytic sample as test scores are only available for students enrolled grades 3-8 in prior year (roughly 54 percent of sample). DS: Dually Suppressed. Some values are left approximate per OSSE student privacy and data suppression policy.

The goal of this paper is to understand the effects of tutoring on student attendance. Table 2 describes the patterns of attendance in the sample in the year prior to the study. We see very high rates of absenteeism. Chronic absenteeism is usually defined as missing 10 percent or more of the school year. Sixty-two percent of the students in our sample were chronically absent in the prior year. Seventeen percent of students were absent more than 30% of the prior year, with rates higher for Black students (19%) and economically disadvantaged students (21%). In the DC schools in our sample, 34% of students were absent more than 30% of the prior year, with 36% of Black students and 35% of economically disadvantaged students absent at these alarmingly high rates (see Appendix Table A2).

Table 2. Prior Year Absences by Student Demographics

Group	Annual Absence Rate	Absent <10%	Absent 10%-30%	Absent >30%
All	0.18	0.38	0.45	0.17
Female	0.18	0.38	0.44	0.18
Male	0.18	0.38	0.45	0.17
Asian	0.13	0.77	0.08	0.15
Black	0.19	0.35	0.46	0.19
Hispanic	0.15	0.50	0.39	0.11
Multi-Race	0.17	0.35	0.50	0.15
White	0.08	0.83	0.17	<0.001
Students with Disabilities (SWD)	0.19	0.36	0.47	0.17
Non-SWD	0.18	0.39	0.44	0.18
English Learner (EL)	0.13	0.55	0.36	0.09
Non-EL	0.19	0.36	0.46	0.19
Economically Disadvantaged	0.20	0.32	0.48	0.20
Not Economically Disadvantaged	0.13	0.56	0.35	0.09
At Risk	0.20	0.32	0.47	0.21
Not at Risk	0.12	0.59	0.35	0.07
Grades K-5	0.16	0.40	0.47	0.13
Grades 6-8	0.16	0.43	0.43	0.14
Grades 9-12	0.24	0.30	0.41	0.29
Prior Year Math Achievement				
Level 1 (Lowest)	0.19	0.32	0.48	0.20
Level 2	0.15	0.42	0.45	0.12
Level 3	0.13	0.55	0.37	0.09
Level 4	0.08	0.74	0.25	0.01
Level 5 (Highest)	0.02	>0.999	<0.001	<0.001
Prior Year ELA Achievement				
Level 1 (Lowest)	0.19	0.33	0.48	0.19
Level 2	0.17	0.36	0.48	0.16
Level 3	0.15	0.49	0.40	0.11
Level 4	0.12	0.56	0.36	0.08
Level 5 (Highest)	0.08	0.78	0.17	0.04

Column 1 displays prior year absenteeism rates by student demographic / academic characteristics for all students in the analytic sample. Columns 2-4 displays the proportion of students with each demographic/academic characteristic who reported the following absenteeism levels: less than 10%, 10% to 30%, and over 30%. The number of students falling into each achievement category does not sum to the full analytic sample as test scores are only available for students who were enrolled in OSSE schools in the prior year in grades 3-8 or grade 11 (roughly 54 percent of sample). Some values are left approximate per OSSE student privacy and data suppression policy.

The data also provides insights into how much tutoring each group of students received. Appendix Table A3 describes these patterns. On average, those who received tutoring attended an average of 26.23 sessions for 29.73 of total hours spent tutoring. These numbers are substantially lower for students in the top two quintiles of math or ELA scores, who received less than 14 and 20 hours of tutoring the entire year, respectively.

Results

Table 3 displays our main results. Using Model 6, our most conservative approach accounting for student and date fixed effects, we observe that students are 1.2 percentage points less likely to be absent from school on a day when they have tutoring scheduled. Given the average absenteeism rate on a day with no scheduled tutoring session is 17.2 percent, this translates to a 7.0% decrease in the likelihood of being absent. This estimate is statistically different from zero (p<.001). Which model we use moderately affects the estimates. With no controls (Model 1), the effect is -0.014. Accounting for demographics, prior scores and attendance (Model 2) reduces the magnitude of the effect to -0.010. Swapping out student demographics with student fixed effects reverts the magnitude of the effect to what we observed in the null model. While it appears that accounting for month fixed effects increases the magnitude of the effect (B=-0.019; Model 5), this may be due to slight variation across months, though we estimated the effects separately by month (see Appendix Table A4) and found substantial consistency in estimates across months.

Table 3. Average Effect of Tutoring Session Scheduled on Absence

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Session Scheduled	-0.014	***	-0.010	***	-0.014	***	-0.010	***	-0.019	***	-0.012	***
	(0.003)		(0.003)		(0.002)		(0.002)		(0.002)		(0.002)	
N	803719		749973		803719		803719		803719		803719	
Student Demographics	-		X		-		-		-		-	
Student FE	-		-		X		X		X		X	
Day of week FE	-		-		-		X		X		-	
Month FE	-		-		-		-		X		-	
Date FE	-		-		-		-		-		X	

Each column shows a separate regression model incorporating the indicated control variables and/or fixed effects. Student demographics as control variables include indicators for race/ethnicity, indicator for whether OSSE has flagged the student as at-risk, indicator for economic disadvantage, indicator for student with disabilities, indicator for gender, grade level, and prior year absence rate (linear and quadratic). The control means (average absence rate for students in the sample on a day when tutoring was not scheduled) for all models is 0.172. Constant omitted from display. Standard errors in parentheses and clustered at the student level. + $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

These results have the benefit of adjusting for unobserved characteristics of both students and days of the year. For comparison, if we had just estimated the absentee rate as a function of receiving tutoring, controlling for prior absenteeism, prior scores and demographics, our estimate would have been -0.018 (see Appendix Table A5). That is, students who received tutoring had yearly absence rates that were 1.8 percentage points lower than their peers who did not receive tutoring. This naive analysis in Table A4, like Models 1 and 2, is likely subject to omitted variable bias; however, we see that this association between receiving tutoring and overall school year absence rate is surprisingly similar in magnitude to the effect of having tutoring scheduled on daily attendance.

By Student Characteristics

Table 4 provides the results separately by prior year absences and by grade level. The effects of a scheduled session are substantially greater for students with higher prior year absences. While the estimates are statistically significant regardless of prior year absences, for those with a prior absenteeism rate greater than 30%, the estimate more than doubles to -0.026.

The estimates are also higher for middle school students (-0.019), than they are for elementary (-0.012) or high school students (-0.002). Estimates are significant at the *p*<.001 level for all groups except high school students.

Table 4. Heterogeneity Analysis by Student Characteristics (Prior Year Absence, Grade Level)

A. Prior Year Absence	<10%		10%-30%		30%+	
Session Scheduled	-0.010	***	-0.012	***	-0.026	***
	(0.002)		(0.002)		(0.006)	
Control Mean	0.083		0.166		0.373	
N	277389		336845		135739	
B. Grade Level	K-5		6-8		9-12	
Session Scheduled	-0.012	***	-0.019	***	-0.002	
	(0.002)		(0.004)		(0.004)	
Control Mean	0.138		0.139		0.246	
N	371966		185749		245636	

Each column displays estimates from regression models restricted to the indicated subsample. All models include student and date fixed effects. Panel A shows estimates using subsamples based on prior year absence rates, while Panel B shows estimates using subsamples based on student grade levels. Standard errors in parentheses and clustered at the student level. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

Table 5 shows the difference by prior absence rates for each grade level. Focusing on middle school students, who experience the greatest attendance effect from tutoring, we see that students with high prior absences reduce their probability of being absent on a given day by 3.1 percentage points when they had a scheduled tutoring session, a 10.4 percent decrease in absence rates compared to days they had no tutoring scheduled. For extremely absent elementary students, the effect of scheduled tutoring is a 2.5 percentage point reduction from an average of 29.3 percent absenteeism rate on days without scheduled tutoring. We do not see an effect for high school students at any level of prior absenteeism.

Table 5. Effects by Prior Absence and by Grade Level

	<10%		10%-30%		>30%	
A. Grades K to 5						
Session Scheduled	-0.007	**	-0.011	***	-0.025	***
	(0.002)		(0.003)		(0.007)	
Control Mean	0.072		0.149		0.293	
N	138776		166220		45108	
B. Grades 6 to 8						
	<10%		10%-30%		>30%	
Session Scheduled	-0.019	***	-0.014	*	-0.031	*
	(0.004)		(0.006)		(0.014)	
Control Mean	0.078		0.150		0.297	
N	74922		76440		24390	
C. Grades 9 to 12						
	<10%		10%-30%		>30%	
Session Scheduled	0.001		0.001		-0.010	
	(0.005)		(0.006)		(0.010)	
Control Mean	0.109		0.205		0.452	
N	63691		94185		66241	

Each column displays estimates from regression models restricted to the indicated subsample. Panels restrict to separate grade levels. All models include student and date fixed effects. Standard errors in parentheses and clustered at the student level. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

We also assessed the effects of having tutoring scheduled on student absenteeism separately for demographic groups of particular interest to OSSE when developing the tutoring policy: Black students, Hispanic students, economically disadvantaged students, English learners, students with disabilities, and low-performing students. Table 6 provides the results for these groups (see Appendix Table A6 for these results separately by demographics and prior absences). We see a consistent negative effect of scheduled tutoring on the likelihood of being absent across student subgroups, and particularly strong results for Black students (-0.012), economically disadvantaged students (-0.015), students with disabilities (-0.015).

Table 6: Effects by Student Demographic Subgroups

A. Race/Ethnicity Subgroups						
	Black		Hispanic			
Session Scheduled	-0.013	***	-0.009	*		
	(0.002)		(0.005)			
Control Mean	662953		125885			
N	0.173		0.172			
B. EL, Socioeconomic Disadvantage, and Disability Status						
	English Learners		Economically Disadvantaged		Students with Disabilities (SWD)	
Session Scheduled	-0.004		-0.015	***	-0.015	***
	(0.005)		(0.002)		(0.004)	
Control Mean	101316		590995		154964	
N	0.154		0.184		0.172	
C. Prior Year Achievement						
	Students Not Proficient, Prior Year Math		Students Not Proficient, Prior Year ELA			
Session Scheduled	-0.009	***	-0.009	***		
	(0.002)		(0.003)			
Control Mean	431462		387821			
N	0.168		0.171			

Each column within panels displays estimates from regression models restricted to the indicated subsample. All models include student and date fixed effects. Standard errors in parentheses and clustered at the student level. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

By Tutoring Program Characteristics

The effects of tutoring on absenteeism could also differ based on the characteristics of the tutoring program. Table 7 explores this variation based on two key elements of tutoring - when the tutoring occurs, and the number of students per tutor in the sessions. The results are, in some ways, predictable. The effects are substantially larger for programs operating during the school day (-0.019) than after school (-0.007), and they are substantially larger for smaller tutor-student ratios (1:1 or 1:2; -0.038) than for bigger ones (1:3 or larger; -0.007). The differences by group size are particularly evident at each grade level, with tutoring with smaller ratios predicting greater reductions in absenteeism even for high school students (see Appendix Table A7).

Table 7. Effects by Tutoring Characteristics (Tutoring Time of Day and Group Size)

	Tutoring Time of Day						Group Size			
	During School		After School		Both During and After School		1:1 or 1:2		1:3 or 1:4	
Session Scheduled	-0.019	***	-0.007	**	-0.001		-0.038	***	-0.007	***
	(0.002)		(0.002)		(0.011)		(0.003)		(0.002)	
Control Mean	0.173		0.130		0.119		0.152		0.162	
N	454023		187303		10557		173102		532809	

Each column displays estimates from regression models restricted to the indicated subsample. Subsamples for time of day and group size were derived based on information from tutoring providers on their tutoring models. All models include student and date fixed effects. Standard errors in parentheses and clustered at the student level. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

In addition to assessing the effects by tutoring program structure, we also examine effects by subject tutored – Math, ELA, or both. Overall, 50% of students (N=2,108) received only ELA tutoring, 35% (N=1,484) received only math tutoring and 14% (N=604) received both math and ELA tutoring.[2] Table 8 shows that the estimated effects of scheduling tutoring are greater for students receiving both ELA and math focused tutoring (-0.028) and ELA tutoring alone (-0.016) than for math tutoring alone (0.001), the latter of which is indistinguishable from zero. While the estimates for high school students were not statistically different from zero overall (Table 4, Panel B), they are statistically significant for high school students who received ELA (-0.028) and those who received the combined ELA and math tutoring (-0.022), but not for those who received math tutoring alone. Middle school students also experience greatest benefits from tutoring when administered in ELA (-0.017) or in ELA and math jointly (-0.044), although effects across all three types of tutoring are statistically significant. On the other hand, elementary school students experience similar effects from tutoring on their absences, regardless of subject. A similar pattern is evident across prior attendance levels, with effects larger for ELA

[2] Percentages do not sum to 100 as some providers did not offer this information.

and the ELA-math combination than for math alone, regardless of prior attendance (see Appendix Table A8).

Table 8. Effects by Subject and Grade Level

	All Students	K-5	6-8	9-12
A. Math Only				
Session Scheduled	0.001	-0.013 +	-0.011*	0.005
	(0.003)	(0.007)	(0.005)	(0.004)
Control Mean	0.179	0.120	0.126	0.230
N	288382	42170	96707	149505
B. ELA Only				
Session Scheduled	-0.016 ***	-0.012 ***	-0.017*	-0.028 *
	(0.002)	(0.002)	(0.008)	(0.013)
Control Mean	0.159	0.142	0.152	0.267
N	376416	294538	35309	46569
C. Math and ELA				
Session Scheduled	-0.028 ***	-0.012 +	-0.044***	-0.022 *
	(0.005)	(0.007)	(0.009)	(0.009)
Control Mean	0.171	0.109	0.162	0.222
N	107806	27154	40087	40565

Within a panel, each column displays estimates from regression models restricted to the indicated subsample. Panel A and Panel B estimate effects for various samples of students whose tutoring provider(s) administered tutoring sessions in either Math only or ELA only, respectively. Panel C estimates effects for students who received tutoring sessions in both subjects, which is a mutually exclusive group of students separate from those included in Panels A or B. Columns indicate subsamples by grade levels. All models include student and date fixed effects. Standard errors in parentheses and clustered at the student level. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

Restricting to DCPS

We replicate the analyses using only data on DCPS to understand how tutoring at scale may affect absenteeism in traditional local educational agencies. Table 9 provides these results. The estimates are larger in DCPS, with scheduled tutoring predicting a 1.9 percentage point decrease in absenteeism. The estimated effects for DCPS students are particularly strong for those with high prior absenteeism. For students who had prior year absence rates greater than 30%, being scheduled for tutoring on a given day reduced their probability of being absent that day by 5.7 percentage points.

Table 9: Replication of Main Analysis for Subsample of DCPS Students

		By Prior Year Absence		
	All Students	<10%	10%-30%	>30%
Session Scheduled	-0.019 ***	0.002	-0.018 **	-0.057 ***
	(0.005)	(0.008)	(0.007)	(0.012)
Control Mean	0.261	0.110	0.204	0.500
N	118587	27828	41427	32171

Each column displays estimates from regression models restricted to the indicated subsample of DCPS students. All models include student and date fixed effects. Standard errors in parentheses and clustered at the student level. + $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Discussion

This study shows that having a scheduled tutoring session reduces the likelihood of student absenteeism for that day by 1.2 percentage points, translating to a 7.0 percent overall reduction in absenteeism. Students were more likely to attend school on days when tutoring sessions were scheduled, suggesting that they are motivated to participate in tutoring.

We found differences in the size of this effect across student groups which provide information on how to best direct tutoring to increase student engagement in school. First, students who were absent more often during the previous year benefited the most from having tutoring scheduled, with scheduled tutoring reducing their likelihood of being absent on a given day by 2.6 percentage points – more than double the average effect, a 7.0 percent decrease. Second, middle school students experienced the largest reductions in absenteeism compared to elementary and high school students, with a 13.7 percent reduction on a day with tutoring scheduled. These findings suggest that tutoring can be a valuable tool for reducing absenteeism, particularly among middle school students in urban school settings who can be particularly vulnerable to disengagement.

We also observe meaningful variation in the impact of tutoring across program characteristics. These findings provide insights into the mechanisms by which tutoring might contribute to improving student attendance. A larger effect for scheduled in-school tutoring compared to after school tutoring suggests that it is not simply receiving tutoring that increases engagement in school – having tutoring embedded into the school day likely positively changes students' school experience leading to decreased absenteeism. Additionally, the largest effects were observed among students who received tutoring in 1:1 or 1:2 tutor-student ratios, indicating that the opportunity to receive individualized attention and build relationships with their tutors may be particularly motivating for students. Our findings suggest that tailoring tutoring programs to the needs of specific student groups and contexts can maximize their effectiveness.

Our findings hold several implications for education policy and practice. First, a critical element highlighted by this study is the importance of relationships in promoting student engagement, learning, and attendance. The consistent presence of a caring adult, such as a tutor, can significantly enhance students' sense of belonging and connection to school. Second, our findings indicate that high-impact tutoring most positively influenced middle school students' engagement. This differential effect is especially important given that student engagement commonly starts to decline in middle school (Eccles and Roeser, 2011), so expanding tutoring offerings for this age group may be a key priority for future interventions that seek to reduce absenteeism. Moreover, the large effects on attendance for this age level mirror those found in middle school with the Check and Connect program (Guryan et al., 2020), suggesting that built-in individualized attention from a caring adult in students' early adolescence may be particularly important. Finally, the results point to the importance of embedding tutoring within the school day and maintaining small tutor-to-student ratios as critical components for success. Policies prioritizing funding for tutoring programs that integrate these features, particularly in schools serving high-risk students, could lend to meaningful reductions in absenteeism.

Ultimately, these results indicate that a relationship-based, individualized approach to learning may be especially crucial for students who often miss school. The bond that students form with their tutors may be motivating them to attend school more regularly, because they feel seen, supported, and understood. Expanding the focus of high-impact tutoring beyond academic support to include relationship-building can foster greater student engagement, ultimately reducing absenteeism and supporting student success overall.

References

Allen, K., Kern, M.L., Vella-Brodrick, D. *et al.* (2018). What Schools Need to Know About Fostering School Belonging: A Meta-analysis. *Educ Psychol Rev* 30, 1–34. https://doi-org.stanford.idm.oclc.org/10.1007/s10648-016-9389-8

Allensworth, E., & Schwartz, N. (2020). The importance of relationships for supporting engagement and achievement among students. *Educational Leadership, 77*(8), 14-20.

Balfanz, R., Jerabek, A., Payne, K., & Scala, J. (2024). Strengthening school connectedness to increase student success. EdResearch for Action Brief. Retrieved from https://edresearchforaction.org/wp-content/uploads/55011-EdResearch-School-Connectedness-Brief-29-REV.pdf

Balfanz, R., & Byrnes, V. (2012). *The importance of being in school: A report on absenteeism in the nation's public schools*. Education Digest: Essential Readings Condensed for Quick Review, 78(2), 4–9. https://eric.ed.gov/?id=EJ1002822

Bhatt, M. P., Guryan, J., Khan, S. A., LaForest-Tucker, M., & Mishra, B. (2024). Can Technology Facilitate Scale? Evidence from a Randomized Evaluation of High Dosage Tutoring (NBER Working Paper No. w32510). National Bureau of Economic Research.

Carlana, Michela, and Eliana La Ferrara. (March 2024). Apart but Connected: Online Tutoring and Student Outcomes during the COVID-19 Pandemic. Retrieved from https://michelacarlana.com/wp-content/uploads/2024/03/TOP_CarlanaLaFerrara.pdf

Cavanaugh, C. L., Gillan, K. J., Kromrey, J., Hess, M., & Blomeyer, R. (2004). *The effects of distance education on K–12 student outcomes: A meta-analysis*. Learning Point Associates/North Central Regional Educational Laboratory. https://files.eric.ed.gov/fulltext/ED489533.pdf

Center on Reinventing Public Education. (2024). *Solve for the Most Complex Needs: A Path Forward as Pandemic Effects Reverberate.* The State of the American Student: Fall 2024. Center on Reinventing Public Education. Retrieved from https://crpe.org/wp-content/uploads/CRPE_SOS2024_FINAL.pdf

Dee, T. S. (2024). Higher chronic absenteeism threatens academic recovery from the COVID-19 pandemic. *Proceedings of the National Academy of Sciences of the United States of America*, *121*(3), e2312249121.

Dorn, E., Hancock, B., Sarakatsannis, J., & Viruleg, E. (2020). COVID-19 and student learning in the United States: The hurt could last a lifetime. *McKinsey & Company*, *1*, 1-9.

Eccles, J.S. and Roeser, R.W. (2011), Schools as Developmental Contexts During Adolescence. Journal of Research on Adolescence, 21: 225-241. https://doi-org.stanford.idm.oclc.org/10.1111/j.1532-7795.2010.00725.x

Gersten, R., Newman-Gonchar, R., Haymond, K., & Dimino, J. (2020). *Evidence-based practices for comprehensive literacy instruction: A review of the research*. Exceptional Children, 86(3), 328–347. https://doi.org/10.1177/0014402920909596

Gershenson, S., Jacknowitz, A., & Brannegan, A. (2017). *Are student absences worth the worry in U.S. primary schools?*. Education Finance and Policy, 12(2), 137-165. https://doi.org/10.1162/EDFP_a_00200

Gottfried, M. A. (2014). *Chronic absenteeism and its effects on students' academic and socioemotional outcomes*. Teachers College Record, 116(9), 1-30.

Gottfried, M. A., & Hutt, E. L. (2019). *Absent from school: Understanding and addressing student absenteeism*. Harvard Education Press.

Goodenow, C. (1993). Classroom Belonging among Early Adolescent Students: Relationships to Motivation and Achievement. The Journal of Early Adolescence, 13(1), 21-43. https://doi-org.stanford.idm.oclc.org/10.1177/0272431693013001002

Guryan, J., Christenson, S., Cureton, A., Lai, I., Ludwig, J., Schwarz, C., Shirey, E. and Turner, M.C. (2021), The Effect of Mentoring on School Attendance and Academic Outcomes: A Randomized Evaluation of the Check & Connect Program. *Journal of Policy Analysis and Management*, 40: 841-882. https://doi.org/10.1002/pam.22264

Hashim, A., Davison, M., Postell, S., & Isaacs, J. (2024, January 30). *High dosage tutoring for academically at-risk students*. NWEA. https://www.nwea.org/research/publication/high-dosage-tutoring

Heinrich, C. J., Meyer, R. H., & Whitten, G. (2014). *Supplemental education services under No Child Left Behind: Who signs up, and what do they gain?* Educational Evaluation and Policy Analysis, 32(2), 273-298. https://doi.org/10.3102/0162373711405012

Holt, Stephen B., and Seth Gershenson. "The impact of demographic representation on absences and suspensions." *Policy Studies Journal* 47.4 (2019): 1069-1099.

Hough, H. J. (2021). COVID-19, the educational equity crisis, and the opportunity ahead. Brookings Institution Commentary. Retrieved from https://www.brookings.edu/articles/covid-19-the-educational-equity-crisis-and-the-opportunity-ahead/

Kalil, A., Mayer S. E., Gallegos S. (2019). Using behavioral insights to increase attendance at subsidized preschool programs: The Show Up to Grow Up intervention. *Organizational Behavior and Human Decision Processes*. Advance online publication. https://doi.org/10.1016/j.obhdp.2019.11.002

Kearney, C. A., Childs, J., & Burke, S. (2023). Social forces, social justice, and school attendance problems in youth. *Contemporary School Psychology*, *27*(1), 136-151.

Kim, E., Goodman, J., & West, M. R. (2024). Kumon In: The Recent, Rapid Rise of Private Tutoring Centers. *Education Finance and Policy*, 1–41. https://doi.org/10.1162/edfp_a_00438

Kraft, M. A., Bolves, A. J., & Hurd, N. M. (2023). How informal mentoring by teachers, counselors, and coaches supports students' long-run academic success. *Economics of Education Review*, *95*, 102411. https://doi.org/10.1016/j.econedurev.2023.102411

Kraft, M. A., & Goldstein, M. (2021). *Getting tutoring right to reduce COVID-19 learning loss*. Brookings Institution. Retrieved from https://www.brookings.edu/articles/getting-tutoring-right-to-reduce-covid-19-learning-loss/

Kraft, M. A., Marinell, W. H., & Yee, D. S. (2016). *School organizational contexts, teacher turnover, and student achievement: Evidence from panel data. American Educational Research Journal*, *53*(5), 1411-1449. https://doi.org/10.3102/0002831216667478

Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E., & Liu, J. (2020). Projecting the potential impact of COVID-19 school closures on academic achievement. *Educational Researcher*, *49*(8), 549-565.

Lake, R., & Pillow, T. (2022). The State of the American Student: Fall 2022. A Guide to Pandemic Recovery and Reinvention. *Center on Reinventing Public Education*.

Lasky-Fink, J., Robinson, C. D., Chang, H. N.-L., & Rogers, T. (2021). Using Behavioral Insights to Improve School Administrative Communications: The Case of Truancy Notifications. Educational Researcher, 50(7), 442-450. https://doi.org/10.3102/0013189X211000749

Lewis, K., & Kuhfeld, M. (2024). Recovery still elusive: 2023-24 student achievement highlights persistent achievement gaps and a long road ahead [Research brief]. NWEA. Retrieved from https://files.eric.ed.gov/fulltext/ED657294.pdf

Liu, J., Lee, M., & Gershenson, S. (2021). The short-and long-run impacts of secondary school absences. *Journal of Public Economics*, *199*, 104441. https://doi.org/10.1016/j.jpubeco.2021.104441

Malkus, N. (2024). Long COVID for Public Schools: Chronic Absenteeism Before and After the Pandemic. American Enterprise Institute. Retrieved from https://www.aei.org/research-products/report/long-covid-for-public-schools-chronic-absenteeism-before-and-after-the-pandemic/

National Student Support Accelerator. (November 2023). *Snapshot of state tutoring policies*. https://studentsupportaccelerator.org/sites/default/files/Snapshot%20of%20State%20Tutoring%20Policies.pdf

Neitzel, A. J., Springer, M. G., Loeb, S., & Kraft, M. A. (2022). *Understanding the effects of different tutoring models on student learning outcomes*. National Student Support Accelerator. https://studentsupportaccelerator.org/sites/default/files/ai22-756.pdf

Nickow, A., Oreopoulos, P., & Quan, V. (2024). The Promise of Tutoring for PreK–12 Learning: A Systematic Review and Meta-Analysis of the Experimental Evidence. American Educational Research Journal, 61(1), 74-107. https://doi.org/10.3102/00028312231208687

Office of the State Superintendent of Education. (July 2023). *High-impact Tutoring Report: Fiscal Year 2023.* Retrieved from https://osse.dc.gov/sites/default/files/dc/sites/osse/page_content/attachments/FY23%20HIT%20Report.pdf

Osher, D., Kidron, Y., Brackett, M., Dymnicki, A., Jones, S., & Weissberg, R. P. (2016). Advancing the science and practice of social and emotional learning: Looking back and moving forward. *Review of Research in Education, 40*(1), 644-681. https://doi.org/10.3102/0091732X16673595

Pollard, C., Lu, A., Zandieh, A., Robinson, C. D., Loeb, S., & Waymack, N (2024). Implementation of the OSSE High Impact Tutoring Initiative: First Year Report School Year 2022 – 2023. National Student Support Accelerator Report. https://studentsupportaccelerator.org/briefs/implementation-osse-high-impact-tutoring-initiative

Robinson, C. D., Kraft, M. A., Loeb, S., & Schueler, B. (n.d.). *Design Principles for Accelerating Student Learning With High-Impact Tutoring*. EdResearch for Action, 30. Retrieved August 30, 2024, from https://edresearchforaction.org/research-briefs/design-principles-for-accelerating-student-learning-with-high-impact-tutoring/

Robinson, C., Lee, M., Dearing, E., & Rogers, T. (2018). Reducing student absenteeism in the early grades by targeting parental beliefs. *American Educational Research Journal*, 26(3), 353–383. https://doi.org/10.3102/0002831218772274

Robinson, C. D., & Loeb, S. (2021). *High-impact tutoring: State of the research and priorities for future learning*. EdWorkingPaper 21-384. Annenberg Institute at Brown University. https://doi.org/10.26300/qf76-rj21

Romero, M., & Lee, Y. S. (2008). *A national portrait of chronic absenteeism in the early grades*. National Center for Children in Poverty. Retrieved from https://academiccommons.columbia.edu/doi/10.7916/D8708956/download

Slavin, R. E., Lake, C., Davis, S., & Madden, N. A. (2011). *Effective programs for struggling readers: A best-evidence synthesis*. Educational Research Review, 6(1), 1–26. https://doi.org/10.1016/j.edurev.2010.07.002

Tagliaferri, G., Chadeesingh, L., Xu, Y., Malik, R., Holt, M., Bohling, K., Sreshta, P., & Kelly, S. (2022). *Leveraging Pupil-Tutor Similarity to Improve Pupil Attendance*. The Behavioural Insights Team. https://educationendowmentfoundation.org.uk/projects-and-evaluation/projects/national-tutoring-programme-nimble-rcts

The White House. (2024, January 17). *Fact sheet: Biden-Harris administration announces improving student achievement agenda in 2024*. https://www.whitehouse.gov/briefing-room/statements-releases/2024/01/17/fact-sheet-biden-harris-administration-announces-improving-student-achievement-agenda-in-2024/

Wanzek, J., Vaughn, S., Scammacca, N., Gatlin, B., Walker, M. A., & Capin, P. (2016). *Meta-analyses of the effects of tier 2 type reading interventions in grades K-3*. Educational Psychology Review, 28(3), 551-576. https://doi.org/10.1007/s10648-015-9321-7

Wanzek, J., Roberts, G., & Al Otaiba, S. (2018). *Supporting students with reading difficulties through tiered interventions*. Journal of Learning Disabilities, 51(2), 144–158. https://doi.org/10.1177/0022219417719787

Appendix

Appendix Table A1: Scheduled vs Attended Sessions and Effect of Scheduled Sessions on Absence, by Provider

		Scheduled vs Attended Sessions			Effects of Scheduled Tutoring Sessions on Daily Absences				
Tutoring Provider	Tutoring Session Timing	N, Sessions Scheduled	N, Sessions Attended	Proportion of Scheduled Sessions Attended	B	SE	N	t	*p*<0.05
A	After School	38137	27073	0.71	0.00	0.00	106066	0.49	No
B	After School	7419	2862	0.39	0.00	0.01	31986	0.27	No
C	After School	2186	1365	0.62	-0.03	0.01	14935	2.54	Yes
D	After School	1969	1774	0.90	-0.03	0.01	10571	3.09	Yes
E*	After School	1719	1719	1.00	0.00	0.01	24517	0.33	No
F	After School	1406	1045	0.74	-0.02	0.01	12002	3.20	Yes
G	After School	1231	850	0.69	-0.02	0.01	9709	1.96	Yes
H	After School	1059	981	0.93	-0.04	0.02	9385	2.17	Yes
I	After School	325	294	0.90	0.00	0.02	7464	0.05	No
J	After School	249	181	0.73	-0.05	0.02	3472	3.05	Yes
K	During School	26214	15550	0.59	0.01	0.01	52176	1.20	No
L*	During School	24872	24370	0.98	-0.08	0.00	111886	16.29	Yes
M	During School	14200	9255	0.65	-0.01	0.01	30291	0.80	No
N	During School	9947	6797	0.68	-0.03	0.00	55264	5.64	Yes
O	During School	7858	5886	0.75	-0.02	0.01	70540	1.88	No
P	During School	6259	5265	0.84	-0.02	0.01	66727	4.12	Yes
Q	During School	5154	2831	0.55	-0.02	0.01	19348	1.68	No
R	During School	4737	3574	0.75	-0.04	0.01	29454	5.53	Yes
S	During School	3920	3613	0.92	-0.08	0.01	30372	8.16	Yes
T	During School	3700	1900	0.51	-0.02	0.01	37274	2.51	Yes
U	During School	2207	1833	0.83	0.00	0.01	18993	0.28	No
V	During School	1870	1721	0.92	-0.06	0.01	25581	5.85	Yes
W	During School	801	606	0.76	0.02	0.01	14574	1.67	No
X	During School	295	243	0.82	0.01	0.02	3473	0.63	No
Y	Timing Unknown	27314	19926	0.73	-0.02	0.00	118468	4.61	Yes
Z*	Timing Unknown	14	11	0.79	-0.17	0.08	16336	2.22	Yes
AA*	Timing Unknown	12	11	0.92	0.11	0.08	5575	1.38	No

All providers are anonymized. Asterisk (*) denotes providers whose data are excluded from subsequent analysis.

Appendix Table A2: Prior Year Absences by Student Demographics, DCPS Only

	Annual Absence Rate	Absent <10%	Absent 10%-30%	Absent >30%	N
All	0.28	0.27	0.39	0.34	760
Female	0.26	0.31	0.36	0.32	326
Male	0.29	0.24	0.40	0.36	434
Asian	0.06	1.00	<0.001	<0.001	DS
Black	0.28	0.26	0.38	0.36	604
Hispanic	0.27	0.29	0.43	0.29	145
Multi-Race	0.11	0.67	0.33	<0.001	DS
White	0.04	1.00	0.00	<0.001	DS
Students with Disabilities (SWD)	0.28	0.30	0.39	0.31	139
Non-SWD	0.28	0.26	0.39	0.35	621
English Learner (EL)	0.21	0.35	0.46	0.19	115
Non-EL	0.29	0.26	0.38	0.36	645
Economically Disadvantaged	0.28	0.26	0.39	0.35	575
Not Economically Disadvantaged	0.27	0.32	0.36	0.32	185
At Risk	0.29	0.25	0.39	0.36	653
Not at Risk	0.20	0.39	0.38	0.22	107
Grades K-5	0.18	0.37	0.46	0.16	218
Grades 6-8	0.20	0.35	0.42	0.23	143
Grades 9-12	0.37	0.17	0.32	0.50	399
Prior Year Math Achievement					
Level 1 (Lowest)	0.26	0.27	0.39	0.34	225
Level 2	0.20	0.32	0.48	0.20	144
Level 3	0.20	0.40	0.40	0.20	30
Level 4	0.13	0.50	0.50	<0.001	DS
Level 5 (Highest)	<0.001	<0.001	<0.001	<0.001	DS
Prior Year ELA Achievement					
Level 1 (Lowest)	0.27	0.25	0.39	0.36	197
Level 2	0.22	0.34	0.40	0.25	119
Level 3	0.20	0.25	0.57	0.18	56
Level 4	0.22	0.40	0.30	0.30	20
Level 5 (Highest)	0.18	0.50	0.50	<0.001	DS

This table shows prior year absence statistics for all students and for subgroups of students by demographic / academic characteristics for a subsample of students (n=760) who were enrolled in DCPS. DS: Dually Suppressed. Some values shown as approximate per OSSE student privacy and data suppression policy.

Appendix Table A3. Tutoring Rates and Dosage by Student Demographics

Group	Total Number of Sessions Received	Total Number of Hours Tutored
All	26.24	29.73
Female	26.08	29.55
Male	26.38	29.90
Asian	32.33	40.23
Black	26.48	30.59
Hispanic	24.82	24.62
Multi-Race	27.14	29.13
White	21.24	28.53
Students with Disabilities (SWD)	24.13	28.91
Non-SWD	26.72	29.92
English Learner (EL)	24.63	24.88
Non-EL	26.48	30.45
Economically Disadvantaged	26.52	30.07
Not Economically Disadvantaged	25.46	28.82
At Risk	26.34	29.78
Not at Risk	25.88	29.58
Grades K-5	32.77	41.68
Grades 6-8	19.58	14.22
Grades 9-12	20.56	21.52
Prior Year Math Achievement		
Level 1 (Lowest)	22.16	20.82
Level 2	21.92	21.27
Level 3	19.29	19.08
Level 4	18.42	13.78
Level 5 (Highest)	14.67	11.00
Prior Year ELA Achievement		
Level 1 (Lowest)	21.33	20.19
Level 2	21.88	20.77
Level 3	21.05	19.24
Level 4	20.14	19.30
Level 5 (Highest)	16.17	13.15

Each cell represents tutoring statistics by student demographic / academic characteristics for all students in the analytic sample. The number of students falling into each achievement category does not sum to the full analytic sample as test scores are only available for students who were enrolled in OSSE schools in the prior year in grades 3-8 (roughly 54 percent of sample).

Appendix Table A4: Average Effects by Month of the Year

	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Session Scheduled	-0.001	-0.019 *	0.002	-0.018 ***	-0.009 +	-0.01 **	-0.012 **	-0.008 **	-0.015 ***	-0.014 ***	-0.009
	(0.059)	(0.008)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.007)
N	19196	88429	80428	72078	68695	85647	68004	96697	64410	98594	61459

Each column displays estimates from regression models restricted to the indicated subsample. All models include student and date fixed effects. Standard errors in parentheses and clustered at the student level. + $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Appendix Table A5: Naive Model Estimation of Effects of Tutoring on Yearly Absence Rate

	(1)	
Received Tutoring	-0.018	***
	(0.002)	
Asian	-0.005	
	(0.007)	
Black	-0.010	**
	(0.003)	
Hispanic	-0.005	
	(0.004)	
Multi-Race	0.001	
	(0.005)	
At Risk	0.033	***
	(0.005)	
Economically Disadvantaged	-0.020	***
	(0.005)	
Student with Disabilities	-0.002	
	(0.002)	
English Learner	-0.009	**
	(0.003)	
Female	0.001	
	(0.001)	
Prior Year Math Score	-0.006	***
	(0.001)	
Prior Year Math Score^2	0.001	
	(0.001)	
Prior Year ELA Score	-0.005	***
	(0.001)	
Prior Year ELA Score^2	0.001	
	(0.001)	
Prior Year Days Absent	0.631	***
	(0.014)	
Prior Year Days Absent^2	-0.004	
	(0.023)	
Constant	0.054	+
	(0.029)	
N	27209	

Model shown includes fixed effects for student grade level. Reference group is students that did not receive any tutoring. Standard errors in parentheses and clustered at school level. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

Appendix Table A6: Effects by Student Demographic Subgroups and by Prior Absences

A. Race/Ethnicity Subgroups

	Black			Hispanic		
	<10%	10%-30%	>30%	<10%	10%-30%	>30%
Session Scheduled	-0.008 ***	-0.011 ***	-0.027 ***	-0.013 **	-0.015 +	-0.017
	(0.002)	(0.003)	(0.006)	(0.005)	(0.008)	(0.023)
Control Mean	0.082	0.163	0.359	0.087	0.180	0.503
N	217458	289753	121219	52419	43021	13436

B. English Learner, Economic Disadvantage, and Disability Status

	English Learner			Economically Disadvantaged			Students with Disabilities		
	<10%	10%-30%	>30%	<10%	10%-30%	>30%	<10%	10%-30%	>30%
Session Scheduled	-0.006	-0.012	-0.020	-0.010 ***	-0.015 ***	-0.026 ***	-0.010 *	-0.012 *	-0.026 *
	(0.005)	(0.009)	(0.026)	(0.003)	(0.003)	(0.006)	(0.005)	(0.006)	(0.012)
Control Mean	0.082	0.183	0.500	0.089	0.169	0.364	0.088	0.160	0.362
N	44790	30677	8055	174461	266701	117535	51832	71041	27537

C. Prior Year Achievement

	Prior Year Math, Not Proficient			Prior Year ELA, Not Proficient		
	<10%	10%-30%	>30%	<10%	10%-30%	>30%
Session Scheduled	-0.009 **	-0.009 *	-0.020 *	-0.007 *	-0.008 *	-0.023 **
	(0.003)	(0.004)	(0.008)	(0.003)	(0.004)	(0.008)
Control Mean	0.086	0.169	0.357	0.083	0.169	0.363
N	163113	197392	70190	139666	180310	67078

Each column displays estimates from regression models restricted to the indicated subsample. All models include student and date fixed effects. Panel A shows estimates using subsamples based on student race/ethnicity and prior year absence subgroups. Panel B does the same for English Learners, Economically Disadvantaged students, and Students with Disabilities, and Panel C shows estimates for subsamples based on prior year achievement. Standard errors in parentheses and clustered at the student level. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

Appendix Table A7: Effects by Grade Level and Tutoring Ratio

	Grades K-5		Grades 6-8		Grades 9-12	
A. Tutoring During School						
Session Scheduled	-0.019	***	-0.030	***	-0.004	
	(0.003)		(0.005)		(0.004)	
Control Mean	0.142		0.138		0.220	
N	148300		122953		182770	
B. Tutoring After School						
Session Scheduled	-0.007	*	-0.010		.	
	(0.003)		(0.007)		.	
Control Mean	0.131		0.122		.	
N	161633		25670		.	
C. Any Sessions with 1:1 or 1:2 Tutor: Student Ratio						
Session Scheduled	-0.020	***	-0.051	***	-0.110	***
	(0.003)		(0.010)		(0.013)	
Control Mean	0.126		0.143		0.227	
N	117330		16998		38774	
D. Any Sessions with 1:3+ Tutor: Student Ratio						
Session Scheduled	-0.006	*	-0.020	***	0.007	
	(0.002)		(0.004)		(0.004)	
Control Mean	0.138		0.133		0.218	
N	220672		146079		166058	

Each column within panel displays estimates from regression models restricted to the indicated subsample. All models include student and date fixed effects. Panels A and B show estimates when restricted to a subsample of tutoring sessions offered during or after school, respectively. Estimates for after school tutoring among high school students are not shown due to insufficient sample size Panels C and D show estimates when restricted to a subsample of sessions with a 1:1 or 1:2 tutor-student ratio and 1:3 tutor-student ratio or greater, respectively, separately by grade level. Standard errors in parentheses and clustered at the student level. + $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Appendix Table A8: Effects by Subject Area Tutored and Prior Year Absence Rate

	Tutoring in Math Only			Tutoring in ELA Only			Tutoring in both Math and ELA		
	<10%	10%-30%	>30%	<10%	10%-30%	>30%	<10%	10%-30%	>30%
Session Scheduled	-0.002	0.002	-0.005	-0.009 ***	-0.016 ***	-0.034 ***	-0.027 ***	-0.012	-0.048 ***
	(0.003)	(0.005)	(0.011)	(0.002)	(0.003)	(0.007)	(0.007)	(0.007)	(0.014)
Control Mean	0.084	0.173	0.428	0.080	0.160	0.329	0.085	0.168	0.319
N	107563	113911	44912	127666	165717	58843	36731	42814	22952

Each column displays estimates from regression models restricted to the indicated subsample. For instance, Column 1 shows estimates for a subsample of students who had a prior year absence rate of less than ten percent and received tutoring in Math only. All models include student and date fixed effects. Standard errors in parentheses and clustered at the student level. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.