High Dosage Tutoring for School Turnaround and Pandemic Learning Recovery in Union County, NC

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Introduction

To combat pandemic learning loss and promote academic acceleration, many researchers, advocates, and policymakers have promoted high dosage tutoring (HDT) as perhaps the field's best bet (Kraft & Falken, 2021; Learning Recovery Act, 2021; Dietrichson et al., 2017; Fryer, 2017; Nickow, Oreopoulos, & Quan, 2020). HDT is defined as frequent (three or more sessions per week), small group (three or four students per tutor) tutoring by an adult who has been trained to deliver instruction that helps students meet grade level standards (Robinson et al., 2021). While HDT has strong evidence of effectiveness, it is most often administered during the school day, which involves changing student schedules and juggling multiple pull-out programs, designing curriculum or purchasing it, and hiring tutors—all of which is costly and difficult to manage. Cost estimates for in-person tutoring range depending on locale, size of tutoring groups, and time spent tutoring, but a reasonable estimate of cost per tutored student is approximately $3,000–$4,000 per school year (Bonesrønning et al., 2022; Guryan et al., 2023).

In this study we examined the implementation, impacts, and cost of two versions of a HDT program for 4th grade mathematics embedded in a broader school turnaround effort in Union County Public Schools (UCPS), a district in the Charlotte metropolitan area of North Carolina. Our study reports implementation findings after two years of study including information gathered from site visits, staff interviews and focus groups, surveys, and document review; quantitative analyses aimed at disentangling the effects of tutoring from the broader school turn-around effort with a triple-difference design involving tutored grade levels compared with non-tutored grade levels; and a cost analysis of the two versions of the program, one targeted to lower achieving 4th grade students and one targeted to all 4th grade students.

We address the following research questions in this policy brief:

1. Did a high-dosage, in-school tutoring program for 4th graders in math raise student test scores?
2. Did the program work equally well in schools that assign tutoring to all students and schools that provide tutoring to the lowest performing students?
3. Were either or both versions of the program cost effective?

The HDT Program

The UCPS tutoring program has been in place since 2017–18 in four chronically underperforming schools. Schools assigned to the intervention by the district office are called "focus" schools because they have failed state "A–F" school grade accountability metrics based largely on test score proficiency levels. After the pandemic, five additional elementary schools received D/F grades on school report cards based on 2021–22 test scores. Compared to district and state averages, schools in the intervention have higher percentages of economically disadvantaged students, Black and Hispanic students, and English Language Learners. Poverty rates of the original focus schools are higher than for the newer focus schools.

A key difference between the older set of four schools and the newer set of five schools was the extent and targeting of the tutoring. Specifically, the older set assigned *all fourth graders* to tutoring; the newer set served only *lower performing 4th grade students* (those who received a level three or below on their 3rd grade EOG). The district moved towards a targeted model due to staff shortages faced in the early post-pandemic period. One purpose of the grant that funded this project is to allow local, state, and national practitioners and policymakers to weigh the costs and benefits of two different approaches to delivering tutoring: a whole grade (WG) model and a targeted tutoring (TT) model.

Intervention schools had tutors who delivered scripted daily tutoring sessions of 30 minutes in person to groups of three to four students. They worked with groups of students mostly through a pull-out model in a separate room, but in some cases a push-in model within the classroom throughout the day. Tutors worked with 9 to18 students total per day and were employed for up to 29.5 hours per week at a rate of $25 per hour. They were required to pass a math proficiency test (4th and 7th grade math standards) as an employment condition. They worked with 4th grade students in math for about half of their day, leaving about half of their day for tutoring and instructional assistance in other grade levels (e.g., 2nd grade math) or instructional support in 4th grade math classrooms. Most sites included some planning time for tutors, a lunch break, and PLC meetings to facilitate communication between tutors and teachers.

Through two years of collaboration and qualitative analysis including site visits, interviews, focus groups, and surveys, we have learned that the Union County version of high dosage tutoring conformed with nationwide standards for this intervention in its tutoring group sizes and intensity. Fidelity to the intervention was monitored by district staff and was aided by the fact that it was embedded in a broader school turnaround program with many "non-negotiables." Another key factor aiding fidelity was a scripted tutoring curriculum with day-by-day lesson plans. Both varieties of the program (WG and TT) used the same binder of lessons created by district instructional specialists and teachers in the first year of the WG intervention (2017). The binder contained a set of highly detailed lessons aligned with North Carolina state academic standards and the scope and sequence of 4th grade math lessons in UCPS. Lessons were intended to be delivered about one week after the topic had been introduced by the classroom teacher. In discussion with our district partners, they felt that a binder of scripted lesson plans was critical to ensure alignment with classroom instruction and necessary because tutors were not certified teachers.

The tutoring program was described by district leadership as the most important pillar in a school turnaround program for focus schools that began in the fall of 2017 for the four original focus schools and in the fall of 2022 for the five newer focus schools. In addition to daily intensive tutoring, other interventions implemented in these focus schools included programs aimed at promoting:

- Effective leadership (principal supervision and coaching, principal PLCs, incentive pay)
- Effective teachers (flexible staffing, professional development, instructional coaching, dual language program, doubled local salary supplement, incentive pay for teachers)
- More time for instruction (summer bridge programming to get students in schools earlier, ended year-round schooling in three elementary schools)
- Wraparound services (flexible staffing for mental health, behavior therapist, social workers, EL support, nurses)

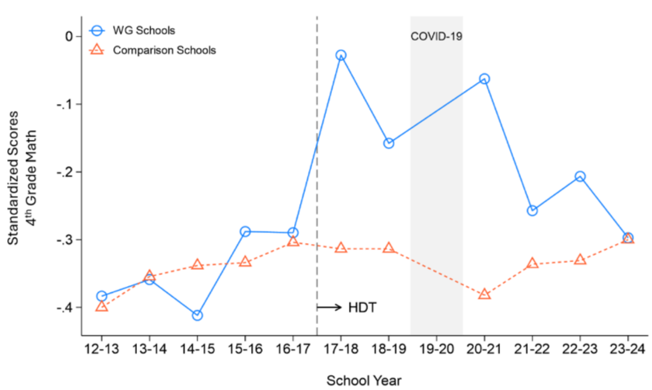
Findings

1. *The impact of the* ***whole grade tutoring model*** *was positive and robust.*

We found that students in WG schools outgained their peers in comparable schools by .18 standard deviations (SD) in 4th grade math during the intervention period, an effect that was about as large as the effect on 5th grade students one year later (.15 SD). The validity of this inference hinges on what is called the parallel trends assumption. As shown in the figures in the appendix, we found parallel trends between the WG and comparison school averages before the intervention started. To be more certain about this, we conducted two additional tests.

First, we subtract the 4th grade difference from the 3rd grade difference (4th graders got tutoring while 3rd graders did not). Drilling down to this comparison purges any confounding effect of concurrent interventions that effects students in all grade levels. This triple-difference estimate is even larger, at .31 SD. Second, we examined reading scores, which should *not* have been affected by math tutoring. As expected, we did not find a boost in 4th grade reading scores. Together, these two additional checks strongly suggest that intensive math tutoring raised math test scores and were not due to other concurrent interventions in the school turnaround program. Additionally, we find that tutoring raised 5th grade science test scores by .21 SD a year after students received 4th grade math tutoring, a result that may be due to increased quantitative literacy on sections of the science test such as interpreting graphs.[1]

Figure 1. Simple Trends of WG Model



*2. The impact of the **targeted tutoring model** on 4th grade math EOG scores was weaker than the whole grade model and less robust.*

Students in TT schools did not have large and reliable gains from tutoring. Students in TT schools outgained their peers in comparable schools by only .08 standard deviations in 4th grade math during the intervention period, a result that is not statistically significant at the 95% confidence level. The effect on 5th grade math scores one year later for the same students was −.09 (also not statistically significant). Our triple difference comparison of 3rd and 4th grade gains indicates a small but statistically insignificant effect. Unlike students in the WG schools, students in TT schools did not enjoy boosts in 5th grade science scores.

3. The effects of WG program on 4th grade math scores are somewhat uniform across students of prior achievement levels. The effects of TT program are concentrated in students at and below grade level.

Students of all levels of prior achievement benefit from the WG tutoring model. While the TT model has weaker and less robust effects on math test scores overall, the effects for students at or below grade level in third grade math achievement are significant. Compared to their peers in similar schools across the state, students *below* grade level in TT schools increased scores by more than .20 SD and students *at* grade level increased scores by more than .30 SD. Students above grade level had increases that were comparable to increases in comparison schools. This means that higher achieving students were not harmed by the tutoring program, but did not benefit as much as their peers with lower achievement levels in the same schools.

4. Students with exceptionalities did not benefit from tutoring.

We tested the effect of 4th grade tutoring on the following subgroups, comparing the focal group to their counterparts: female, non-white, students with disabilities, and multi-language learners. With one important exception, effects did not differ between these student subgroups and their counterparts. Students with exceptionalities benefited much less from tutoring; in fact, our findings suggest that the

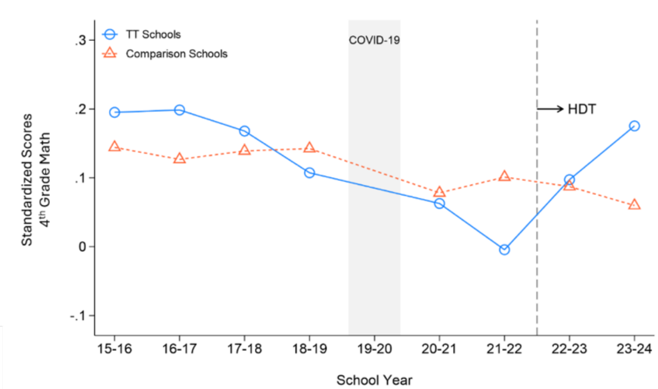
[1] Unless stated otherwise, all results discussed in text are statistically significant at the 95% confidence level.

effect of tutoring for students with exceptionalities is close to zero.

5. *The tutoring program was cost effective relative to other tutoring programs and educational interventions.*

Start-up costs of the program totaled about $233,409 and consisted of designing the program and creating a book of day-by-day lessons for the tutors to use. Annual costs to hire, evaluate, and pay the tutors ranged from $750 to $2,500 per pupil depending on the assumptions in the analysis and whether start-up cost was amortized into the annual cost. At the low end, we counted only the time tutors spent tutoring 4th grade students in math. We learned, however, that this 4th grade tutoring time was not sufficient to fill out tutor schedules to the target of 29.5 hours per week (we estimated it to be about 15 hours a week in most schools). At the higher end, we counted all the time tutors spent at the school fulfilling all assigned duties. In short, the higher end estimate is the amount the district spent to hire a tutor; the lower end estimate is specific to the outcome we measured in our study: 4th grade math. Cost effectiveness ratios are in line with or superior to many highly regarded educational interventions, including lengthening the school day, increasing teacher salaries, and class size reduction.

Figure 2. Simple Trends of TT Model



Per-pupil costs of the whole grade and targeted programs differed (about $2500 for WG and $1800 for TT, including amortized start-up costs). Our analysis found that WG schools reported a higher number of hours per student than TT schools (97 versus 81 per year, on average), which suggests that WG schools spent more money utilizing tutors in other roles since the number of tutoring hours was fixed by district policy. Secondly the variation across schools in the number of tutored hours per pupil was higher for TT schools than WG schools. This indicates that TT schools reported a wider spread of hours than WG schools.

Conclusion

UCPS's whole-grade HDT program succeeded in raising math test scores in 4th grade and had lasting effects into 5th grade in both math and science. The district's targeted program raised the 4th grade math test scores for students with initial achievement at grade level and below. Students with exceptional needs, however, did not benefit from tutoring, an issue that could have been due to less time for pull out programs targeted to individual student's needs. The cost of the program was comparable to or less than most published figures reported in the literature, which reports costs ranging from $900–$10,000 per student from a wide variety of tutoring programs across different grade levels and subjects.

As shown in the figures in the appendix, the size of the test score boosts experienced by students in WG schools was not consistent across time; it was quite strong in the first three years of the intervention and has weakened over time during the post pandemic period. The targeted tutoring program, which was implemented after the pandemic, however, had positive impacts on the students who got tutoring.

Based on these findings, we recommend broader adoption of HDT in low performing schools. We urge state policymakers to create a pilot program to give districts enough funding to implement high dosage tutoring at a scale and for a length of time sufficient for adequate evaluation of program impacts. Critical to increase the chance of positive impacts and wise use of public funding will be to ensure that funding is allocated with key design principles and non-negotiables in place. These include adhering to the research-based recommendations about group size and intensity (3–4 students per tutor, at least three times per week, every week during the school year, and during the school day). Another key is scripted lesson plans to guide tutors work and simplify the teaching task for non-certified teachers.

Strategies for supporting implementation of HDT should accompany this roll out. As noted, tutoring PLCs, planning time, and professional development comprised integral aspects of UCPS's tutoring program. As these are additional components to schedule, school leaders must receive adequate guidance to balance inclusion of HDT with the other demands of serving their students. Further, as HDT was ineffective for students with exceptionalities, we advise that HDT rollout include some flexibility for professional discretion regarding student receipt of services.

The state could consider matching local funding with the state share being inversely proportional to district wealth and including sufficient funding to evaluate implementation, cost, and impact on student outcomes for each program. This could potentially fund research to explore variation of implementation, cost, and impact across sites to permit learning what works, where, and why. These evaluation results could inform continued funding commitments and adapt design principles and non-negotiables as needed.

As the state moves forward with learning more about HDT, we would like to learn more about whether it is more cost effective for districts to develop their own curriculum or contract out for a book of daily lesson plans and whether HDT can be implemented with fidelity to nationwide standards when it is not mandated on the principals of low performing schools.

References

Bonesrønning, H., Finseraas, H., Hardoy, I., Iversen, J. M. V., Nyhus, O. H., Opheim, V., Salvanes, K. V., Sandsør, A. M. J., & Schøne, P. (2022). Small-group instruction to improve student performance in mathematics in early grades: Results from a randomized field experiment. *Journal of Public Economics, 216*, 104765. https://doi.org/10.1016/j.jpubeco.2022.104765

Dietrichson, J., Bøg, M., Filges, T., & Jørgensen, A.-M. K. (2017). Academic interventions for elementary and middle school students with low socioeconomic status: A systematic review and meta-analysis. *Review of Educational Research, 87*(2), 243–282. https://doi.org/10.3102/0034654316687036

Fryer, R. G., Jr. (2017). The production of human capital in developed countries: Evidence from 196 randomized field experiments. In E. Duflo & A. Banerjee (Eds.), *Handbook of economic field experiments* (Vol. 2, pp. 95–322). North Holland. https://doi.org/10.1016/bs.hefe.2016.08.006

Guryan, J., Ludwig, J., Bhatt, M. P., Cook, P. J., Davis, J. M. V., Dodge, K., Farkas, G., Fryer, R. G., Mayer, S., Pollack, H., Steinberg, L., & Stoddard, G. (2023). Not too late: Improving academic outcomes among adolescents. *American Economic Review, 113*(3), 738–765. https://doi.org/10.1257/aer.20210434

Kraft, M. A., & Falken, G. T. (2021). A blueprint for scaling tutoring and mentoring across public schools. *AERA Open, 7*(1), 1–21. https://doi.org/10.1177/23328584211042858

Learning Recovery Act, H.R. 676, 117th Cong. (2021). https://www.congress.gov/bill/117th-congress/house-bill/676

Nickow, A., Oreopoulos, P., & Quan, V. (2020). *The impressive effects of tutoring on PreK–12 learning: A systematic review and meta-analysis of the experimental evidence* (Working Paper No. 27476). National Bureau of Economic Research. https://doi.org/10.3386/w27476

Robinson, C. D., Kraft, M. A., Loeb, S., & Schueler, B. (2021). *Accelerating student learning with high-dosage tutoring*. EdResearch for Recovery Project.

Appendix

Data

Data Source—This study uses student-level administrative data housed at the Education Policy Initiative at Carolina (EPIC) and shared by North Carolina Department of Public Instruction (NCDPI) through a data use agreement. This paper uses the data on all elementary school students in the state from 2012–13 through 2023–24 school years. The WG analysis uses data from 2012–13 onward, and the TT analysis from 2015–16. In both analyses, the 2019–20 school year is excluded due to disruptions caused by the COVID-19 pandemic. Data from other districts are used to build matched comparison groups. The structure of the data is repeated cross sections of 4th graders, with variables on enrollment, demographics, and test scores.

Sample Construction—The WG analysis includes four high-poverty, underperforming schools that implemented HDT since 2017–18 school year. The TT analysis includes five additional schools identified due to post-COVID academic declines and began HDT in 2022–23 school year. To estimate causal effects, 100 comparison schools were selected from across the state based on similar average pre-intervention test scores. All scores were standardized by grade and year to enable comparisons.

Dataset Construction

Variable Construction—The main outcome is the fourth grade EOG math scores standardized at the state level within the school year. Additional outcomes include 4th grade reading and 5th grade science scores. Covariates include race/ethnicity, female, academically or intellectually gifted (AIG) status, students with disabilities (SWD), and English language learners (ELL), the schoolwide share of teachers with 3 years or less experience, and the school proportion of minority students. Due to inconsistencies in measurement caused by the roll out of the Community Eligibility Provision (CEP) during the period of our study we did not use economically disadvantaged students (EDS) as a control variable. The analysis sample was restricted to students who remained enrolled from the first 20 days of the school year through April and had test scores. There are no missing values in control variables. However, students missing prior test scores were excluded from subgroup analyses by prior achievement level, affecting 13–14% of students each year.

Descriptive Statistics—For both the WG and TT models, standardized math scores are nearly identical between the treatment and comparison groups during the pre-treatment period (difference=0.001 SD in both cases). However, these differences widen significantly in the post-treatment period, increasing to 0.168 SD for WG and 0.064 SD for TT. This pattern reflects the sample construction approach, where comparison schools were selected based on the smallest distance in average pre-treatment outcome compared to the treatment group. It also reflects that test scores appear to have increased for the treatment group during the post-treatment period.

Other variables exhibit notable differences during the pre-treatment period. In the WG model, the share of White students is much lower in the treatment group, than in the comparison group. In contrast, the treatment group includes a substantially higher proportion of Hispanic students, accounting for 48.8 percent compared to 23.4 percent in the comparison group. Similarly, the proportion of ELL is nearly double in the treatment group relative to the comparison group. These differences simply reflect the socio-demographics of the student population in UCPS compared to other districts. To adjust for the potential for differences in trends, we control these variables in our analytic models. Contrary to the WG sample, the treatment and comparison groups in the TT sample are quite similar in terms of student race/ethnicity. Note, however, that the share of the AIG students in the comparison group is twice the treatment group. Furthermore, the share of teachers with 3 years or less experience is significantly lower in the comparison group.

For the WG analysis, four treatment schools and 100 comparison schools are included. The pre-treatment period spans the 2012–13 to 2016–17 school years, while the post-treatment period covers the 2017–18 to 2023–24 school years. The treatment group consists of 3,264 observations (1,546 in the pre-treatment period; 1,718 in the post-treatment period). The comparison group includes 77,747 observations (36,452 in the pre-treatment period; 41,295 in the post-treatment period). For the TT analysis, five treatment schools and 100 comparison schools are included. The pre-treatment period spans the 2015–16 to 2021–22 school years, while the post-treatment period covers the 2022–23 and 2023–24 school years. The treatment group has 3,976 observations (2,986 in the pre-treatment period; 990 in the post-treatment period). The comparison group includes 57,176 observations (43,671 in the pre-treatment period; 13,505 in the post-treatment period).

Methods

Difference-in-Differences (DD)—To analyze whether the WG and TT models improve student achievement, merely comparing post-treatment test scores between groups is insufficient to identify causal effects. Confounding bias is a key threat to the internal validity of a trend analysis in a non-equivalent comparison group design such as this one. Since tutoring was targeted to lower-performing schools, such comparisons are likely to yield downwardly biased estimates. To reduce such bias and improve internal validity, we use two empirical models. The first model is the difference-in-differences (DD) model, which reduces confounding by comparing changes over time between treatment and comparison schools. Our preferred specification compares the intervention group (WG or TT) to 100 comparison schools statewide with the most similar pre-treatment average test scores. We estimate the following DD model:

$$Y_{ist} = \beta_0 + \beta_1 T_{ist} + \beta_2 P_{ist} + \beta_3 T_{ist} P_{ist} + \boldsymbol{X}\gamma + \varepsilon_{ist}. \quad (1)$$

In equation (1), Y_{ist} denotes the standardized 4th grade EOG test scores for student i in school s in school year t. T_{ist} is an indicator for whether student i is enrolled in a treated school in school year t (1=treated, 0=otherwise). $P_i st$ indicates the post-treatment periods (1=post, 0=pre). $T_{ist}P_{ist}$ is an interaction term between T_{ist} and P_{ist}. $\boldsymbol{X}$ is a vector of covariates and ε_{ist} is an idiosyncratic error term. The main coefficient of interest, β_3, represents the difference in the test score trends among 4th graders pre and post implementation among schools that did and did not implement a tutoring program.

The coefficient β_3 captures the causal impact of the two programs under two key assumptions. The first is the *parallel trends assumption*, which requires that test score trends for treatment and comparison groups would have evolved similarly in the absence of the intervention. If this condition holds, deviations in the treatment groups' trend after the intervention can be attributed to the programs. Our analysis finds evidence of parallel trends in both the WG and TT analysis. The second key assumption is the absence of other concurrent interventions that could confound interpretation of the tutoring effect. If treated schools implemented additional interventions along with tutoring, then the effect might reflect either the broader package or the interaction between tutoring and other components. This concern is relevant in our context, as both tutoring programs were implemented at the same time as other school turnaround reforms.

Difference-in-Difference-in-Differences (DDD)—To address the concern about the confounding effect of concurrent interventions, we conducted a difference-in-difference-in-differences (DDD) analysis by comparing the DD estimates for 4th graders (the target of tutoring) and 3rd graders (who did not receive tutoring). Including 3rd graders helps account for the influence of school-wide turnaround efforts that may have affected all students regardless of grade. The DDD estimates can be interpreted as the impact of the tutoring programs on 4th graders, after accounting for school-wide improvements that may have also affected 3rd graders. The DDD estimate is derived using the following regression specification:

$$\begin{aligned} Y_{ist} = {} & \beta_0 + \beta_1 T_{ist} + \beta_2 G_{ist} + \beta_3 P_{ist} \\ & + \beta_4 T_{ist} G_{ist} + \beta_5 T_{ist} P_{ist} + \beta_6 G_{ist} P_{ist} \\ & + \beta_7 T_{ist} G_{ist} P_{ist} + \boldsymbol{X}\gamma + \varepsilon_{ist}. \quad (2) \end{aligned}$$

In equation (2), Y_{ist}, T_{ist} and, P_{ist} are defined as in equation (1). The main difference is the addition of G_{ist}, an indicator for whether a student is a 4th grader. The model also includes interactions between G_{ist} and other variables. The main coefficient of interest, β_7, represents the DDD effect. Specifically, β_7 indicates the difference in the DD estimate between the fourth and third graders. Using the 3rd graders as another comparison group, the DDD strategy helps address concerns about the existence of concurrent interventions.

Event-Study Analysis—The internal validity of our estimates relies on the parallel trend assumption. In Figures 3 and 4, we present visual evidence supporting this assumption; each dot indicates the difference in the average standardized test scores between the treated and comparison groups, relative to the baseline difference (i.e., 2016–17) between the two groups. The lines associated with each dot are the 95% confidence intervals.

For example, in Figure 3 (WG model), the first dot in the 2012–13 school year is located close to zero, suggesting that the difference in the test scores between the two groups is very similar to the baseline difference in the 2016–17 school year. The 95% confidence interval crosses the zero line, indicating that the estimate is statistically insignificant and that the difference in 2012–13 is not statistically different from the baseline. When pre-treatment estimates are located close to zero and their confidence intervals include zero, this supports the plausibility of the parallel trend assumption.

Overall, Figure 3 shows that all pre-treatment estimates in the WG model are close to zero and statistically insignificant, supporting the parallel trend assumption. In Figure 4 (TT model), while the pre-treatment estimates are not located near the horizontal line, they are statistically insignificant, again suggesting that the parallel trend assumption holds in the TT analysis. Post-treatment estimates, however, diverge upward, and their confidence interval no longer includes zero, indicating a positive impact of the HDT programs.

Figure 3. Event Study Analysis of WG Model

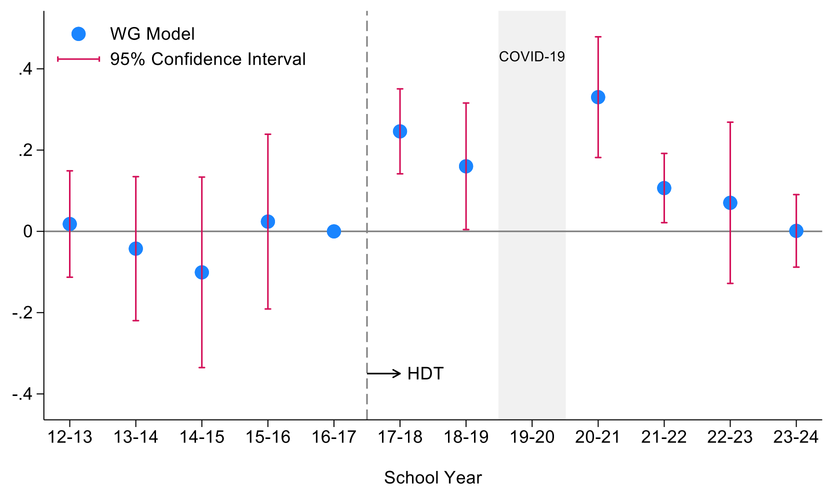


Figure 4. Event Study Analysis of TT Model

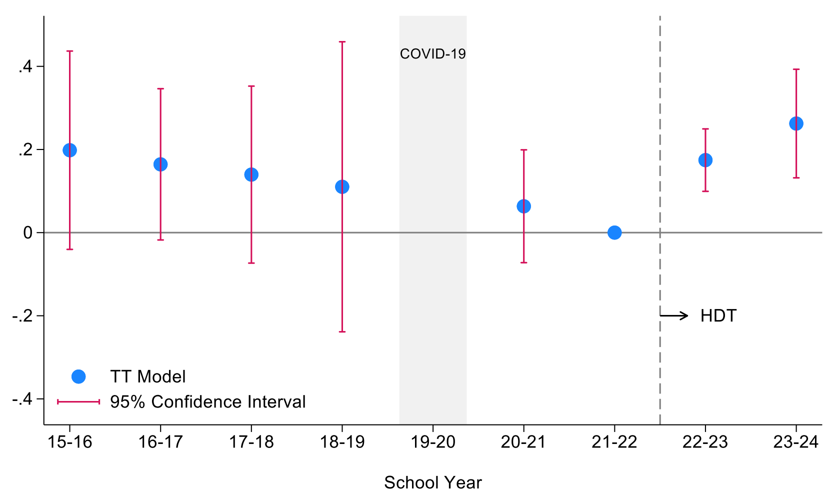


Table 1. Analysis Results

	WG				TT			
	DD Math	DDD Math	DD Reading	DD Science	DD Math	DDD Math	DD Reading	DD Science
				Panel A: Main Analysis				
4th Grade	0.179**	0.310**	−0.031		0.103	0.084	−0.045	
	(0.058)	(0.097)	(0.052)		(0.094)	(0.053)	(0.059)	
5th Grade	0.146***			0.219***	−0.089			−0.166
	(0.022)			(0.064)	(0.070)			(0.106)
				Panel B: Effects by Post Treatment Year				
Year 1	0.264***				0.058			
	(0.048)				(0.090)			
Year 2	0.178*				0.146			
	(0.072)				(0.105)			
Year 3	0.349***							
	(0.073)							
Year 4	0.126*							
	(0.060)							
Year 5	0.089							
	(0.108)							
Year 6	0.020							
	(0.078)							
				Panel C: Effects by Prior Achievement Level				
Below Grade Level	0.137†				0.226***			
	(0.076)				(0.031)			
At Grade Level	0.132				0.333***			
	(0.126)				(0.063)			
Above Grade Level	0.195†				0.076			
	(0.104)				(0.072)			

Note: † *p*<.1, * *p*<.05, ** *p*<.01, *** *p*<.001. Standard errors clustered at the school level are in parentheses. For the 5th grade analysis, the post-treatment period was defined as starting one year after the implementation of the 4th grade high dosage math tutoring. In the DD analysis, the parallel trend assumption holds for all cases except for the reading and 5th grade analyses in the TT model at the 5 percent level. All regression estimates are conditional on baseline covariates.

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