

**Abstract Title Page**  
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**Title:** Differential impacts of intensive district-level technical assistance on student achievement: A study of California's District Assistance and Intervention Teams

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**Background / Context:**

The *No Child Left Behind* Act (NCLB) made sweeping changes to public education in the United States, mandating that all schools and districts in every state meet Adequate Yearly Progress (AYP) goals in English Language Arts (ELA) and math to avoid federal sanctions under Program Improvement (PI). Research has shown that NCLB and similar accountability policies appear to increase student achievement on both high- and low-stakes tests (Carnoy & Loeb, 2002; Dee & Jacob, 2011; Donovan, Figlio, & Rush, 2006; Figlio & Rouse, 2006; Hanushek & Raymond, 2005; Ladd & Lauen, 2010; Rockoff & Turner, 2010; Rouse, Hannaway, Goldhaber, & Figlio, 2007; Springer, 2008). However, little is known about how accountability policies achieve these positive achievement outcomes (Rouse, et al., 2007), and the evidence that the implementation of accountability policies not only raises average achievement, but also closes achievement gaps between the white/wealthy and minority/poor students is less clear (Figlio & Loeb, 2011). In addition, it is unclear whether such accountability policies, especially those based on proficiency counts, incent districts and schools to focus on students on the margin of scoring proficient (Krieg, 2008; Neal & Schanzenbach, 2010).

Although most of the research and policy discussions surrounding accountability policies and NCLB to date have focused on the existence and impact of sanctions on student outcomes, a little-discussed and often-overlooked aspect of NCLB mandates that, in addition to sanctions, states provide technical assistance (TA) to build the capacity of struggling schools and districts to help them improve student achievement. Under the current implementation of NCLB, each state is permitted to determine its own technical assistance program, and the content and focus of these programs vary widely across states. States' TA programs range from professional development to help teachers implement new curricula to targeted services to address specific troubles and to efforts to build schools administrators' capacities to implement reforms (Gottfried, Stecher, Hoover, & Cross, 2011; Weinstein, 2011). California, like 15 other states in the nation, fulfills their NCLB-mandated TA by requiring their lowest-performing districts to access assistance from state-recognized expert providers – called District Assistance and Intervention Teams (DAITs) in California. Although TA programs are provided in every state across the country, little is known about the actions of these capacity-building assistance programs and even less is understood about the efficacy of these interventions in building district capacity and improving student performance. The Obama Administration's plans for the re-authorization of NCLB make clear that technical assistance from states to low-performing schools and districts will remain a major policy mechanism in the immediate future (Dillon, 2011; United States Department of Education, 2011). As such, understanding the efficacy of such programs will be of particular importance as states strive to provide technical assistance to their struggling schools and districts.

In the first comprehensive empirical analysis of state-led technical assistance, Strunk, McEachin, and Westover (2011) found that California's implementation of DAITs led to small but significant gains in students' math (although not ELA) achievement.. However, it is important to not only understand how such technical assistance can raise average student achievement within a district, but also to explore whether the technical assistance interventions are similarly impacting different groups of students and schools within districts, and specifically the neediest students and schools. In this paper, we build on our previous analysis, exploring whether the average treatment effects of DAITs vary across school and student characteristics

**Setting & Population / Participants / Subjects:**

We use a five-year panel from California's student-level administrative dataset (from 2005-6 to 2009-10) that tracks approximately 4.9 million students, enrolled in 9,000 schools and

1,000 districts, across each of the five years. The 4.9 million students in the dataset represent the students we were able to match longitudinally over the 2005-6 to 2009-10 school years, constituting approximately 83% of the total population.

Our dataset includes individual student math and ELA California Standards Test (CST) scores as well as important demographic characteristics (including student race, ethnicity, free- or reduced-price lunch eligibility, and parental income and education levels), linked to their schools and districts. Our data also include school- and district-level organizational information and average student and personnel characteristics. All California students in public schools take CSTs in the second through eleventh grades in both ELA and math. The CSTs are closely aligned with the California content standards for each grade; they are criterion-referenced tests, and are not vertically aligned from year to year. To compare student achievement on the CSTs over time we standardize these test score measures by year and grade and subject

### **Intervention / Program / Practice:**

Since the 2004-05 school year, when 142 California school districts first entered Program Improvement (PI), the California State Board of Education (SBE), State Department of Education and key interest groups have engaged in discussions about how the state might best assist districts as they struggle to make necessary changes that will improve student achievement, while still holding them accountable to meet federal law under NCLB. Based on the belief that districts play a pivotal role in the success of their schools, these key state-level stakeholders decided that a district capacity building policy would best help district administrators that are in the highest level of Program Improvement – PI3 (PI year 3 and beyond). In an effort to provide support alongside sanctions and to build district capacity to enact reforms, the California Legislature passed AB519 in 2008, which supplied \$100 million in funding for PI3 districts to access technical assistance based on the severity of the districts' achievement problems. The lowest performing PI3 districts were given substantial amounts of funding and were required to use it to contract with District Assistance and Intervention Teams, who work closely with district administrators to assess why the district is failing to increase student achievement and to develop reforms to help the district raise student performance. These districts are given a set amount of funding per PI3 school within the district, under the assumption that this will provide districts with more low-performing students with increased funding. These state-procured teams conduct comprehensive needs assessments of their districts, make recommendations for improvement which the districts are required to adopt, and provide two years of technical assistance to the districts as they work to implement the recommendations. The remaining PI3 districts receive a lesser amount of funding (again, allocated per PI3 school within the district) and are required to contract with non-DAIT technical assistance providers (non-DAIT TA). Districts in PI2 are not required to access any external technical assistance.

The lowest-performing PI3 districts were ranked by performance based on an algorithm generated by the CDE. The first cohort of “treated” districts was selected based on their 2007-8 performance ranking, and DAITs were first implemented in these districts in the summer before and early in the 2008-9 school year. As such, 2008-9 is considered “Year 1” of the intervention for the first cohort of selected districts (95 districts), and 2009-10 is considered “Year 2.”

The qualitative data from Strunk, McEachin, and Westover demonstrated that DAITs provided a highly localized, context-based service to districts. For the most part, DAITs and district personnel were able to begin working together quickly, and DAITs quickly moved to begin assessing district needs, making recommendations for reforms, and providing technical assistance themselves or helping districts to access technical assistance to enact these reforms. Initial surveys of both DAITs providers and district leaders suggest that the DAITs were

provided with access and information necessary for an appropriate understanding of the district and effectively engaged the leadership teams in nearly all treated districts, and that DAITs effectively diagnosed district needs and priorities and then provided support in the revision of the LEA plans.

**Purpose / Objective / Research Question / Focus of Study:**

Building on Strunk, McEachin, and Westover (2011), we examine whether or not DAITs have a differential impact on student performance across school and student characteristics. We use a quasi-experimental design to examine the impacts of DAITs on student achievement on math and English Language Arts (ELA) California Standards Tests (CSTs) based on preliminary evidence from the first two years of the DAIT intervention. We are specifically interested in how the treatment effect varies by grade-level, schools' Title 1 and NCLB accountability status, and students' prior achievement. Although increases in average achievement are important outcomes of technical assistance for low-performing districts, it is equally important to know who is actually benefitting from the assistance and whether the neediest students and schools within the lowest performing districts are also making significant achievement gains.

**Research Design/Data Collection/Analysis:**

The intent of this analysis is to isolate the impact of DAITs on student outcomes, specifically for different groups of students in different kinds of schools. First, to do this, we want to compare student outcomes in districts that received DAITs to some untreated set of students. A clear comparison group is the students in PI3 districts that received non-DAIT TA. This comparison solves the issue of bias stemming from the potential impacts of other reforms or trends that impact all PI3 students, but brings with it another set of potential biases: because the DAIT intervention was assigned to districts with the lowest performing students, there is reason to think that the inherent differences between students in DAIT districts and those without will impact eventual outcomes.

We use a set of panel difference-in-difference regressions with controls for pertinent student, school, and district characteristics to isolate the differential effects that the DAITs had on students' ELA and math CST scores relative to students in districts with non-DAIT TA before and after the implementation of the DAIT intervention (Angrist & Krueger, 1999; Angrist & Pischke, 2009; Ashenfelter & Card, 1985; Imbens & Wooldridge, 2009; Reback, 2010). Essentially, we are comparing the ELA and math achievement of subsets of students in each group in the years previous to the intervention (2005-6 through 2007-8) with their achievement after the implementation of the DAIT and non-DAIT TA treatments (in the 2008-9 and 2009-10 school years).

Specifically, we take advantage of pre- and post-intervention student achievement, controlling for district fixed effects and year fixed effects to find the differences-in-differences estimates for a number of student and school subgroups:

$$Y_{ijdt} = \beta_1 DAIT_{dt} + X_{isdt}\beta_2 + S_{sdt}\beta_3 + Z_{dt}\beta_4 + \delta_d + \tau_t + \epsilon_{isdt} \quad (1)$$

where  $Y_{isdt}$  is the standardized ELA or Math CST test score for student  $i$  in school  $s$  in district  $d$  in year  $t$  and  $DAIT_{dt}$  is the district  $d$ 's assignment (treatment) status to DAIT or non-DAIT TA in year  $t$ .  $DAIT_{dt}$  takes a value of "0" between 2005-6 and 2007-8 for both DAIT and non-DAIT TA districts, and it only takes a "1" in 2008-9 and 2009-10 for DAIT districts. These difference-in-difference estimates should provide unbiased estimates of the average two-year effect of the DAIT intervention if omitted district-level variables are time invariant. In alternate specifications, we isolate the DAIT treatment effect in each of the first and second years of the

intervention by including separate treatment indicators for the first and second years of implementation

$X_{isd,t}$  is a vector of student control variables, including binary indicators for minority and special education students and for English language learners. Importantly,  $X_{isd,t}$  also includes a lagged student ELA or math test score,  $Y_{isd,t-1}$ . We include this measure because of potential biases that emerge from using the non-DAIT TA PI3 districts as a comparison set for DAIT districts. Specifically, because the CDE assigned the DAIT intervention to districts with the lowest aggregate student achievement, there is reason to think that the inherent differences between students in DAIT districts and those without will impact eventual outcomes.  $S_{sd,t}$  is a vector school controls, and  $Z_{dt}$  is a vector of district control variables. Other potentially important observable district-level variables are time invariant, and as such are accounted for by our district fixed effect.  $\epsilon_{isd,t}$  is an idiosyncratic error term. All errors are clustered to the district level.

In order to assess the variability in the impacts of DAITs on student achievement, we run equation (1) on the following subgroups of students and schools: 1) student demographic subgroups; 2) the students' proficiency levels (Far Below Basic, Below Basic, Basic, Proficient, and Advanced) from the 2007-8 school year (before treatment); 3) Title 1 versus non-Title 1 schools, and Title 1 schools that are not in PI status versus Title 1 schools that are in PI status; and 4) the students' grade-levels (3 to 5, 6 to 8, 9 to 11, and then by individual grade-levels).

### **Findings / Results:**

Impact of DAITs by Student Race/Ethnicity, Free- and Reduced-Price Lunch Status (Poverty), and ELL status: Tables 1 and 2 provide the results of equation (1) conditioned on important student subgroups. As seen from these tables most of the subgroups made significant gains in math achievement on the order of the overall ATE, with the exception of White students. Specifically, we see that ELL versus non-ELL students made significant gains in math achievement of the same magnitude in DAIT versus non-DAIT TA districts, and over both years. Students that qualified for Free and Reduced-Price Lunch (FRL) made significantly larger gains in math achievement compared to FRL students in non-DAIT TA districts, and these gains also continued in both treatment years. Interestingly, the FRL students made larger gains than the non-FRL students within the DAIT districts, indicating that the reform may be closing the achievement gap slightly between the poor and the non-poor. While we see that Hispanic, Black, and White students in DAIT districts appear to be making gains in math achievement versus such students in non-DAIT TA districts, Black and Hispanic students appear to make larger gains than White students. This is an important finding because it implies that the DAIT reform may be closing the achievement gap between White and Black/Hispanic students in DAIT districts. It also appears that ELL students are making more significant gains in ELA in DAIT versus non-DAIT TA districts than are non-ELL students, especially in the second year of the intervention. Similarly, the FRL students made more significant gains in ELA achievement in DAIT versus non-DAIT TA districts, and they also made larger gains than non-FRL students in DAIT districts. Lastly, Hispanic students appear to make significant gains in ELA achievement, especially in the second year of the intervention, while White and Black students' achievement does not appear impacted by the intervention.

Impact of DAITs by Prior Proficiency Level: Table 3 shows our results from the specification of equations (1) for students who are labeled Far Below Basic, Below Basic, Basic, Proficient, and Advanced in ELA or math in the year previous to the implementation of the DAIT intervention (2007-8). We see that, similar to research that shows a focus on students at

the basic/proficient cut point or on the lowest-achieving students, the DAIT impacts found in earlier work appear driven by gains in the achievement of students around the proficiency cut score. In addition, earlier ELA results that show a small increase in student achievement in the second year of the DAIT intervention appear to be driven by students scoring below basic and basic in 2007-8.

Impact of DAITs by School Achievement Level: Tables 4 and 5 show the results of equation (1) conditioned on the schools' Title 1 and PI statuses from the 2007-8 school year, the year before the implementation of the DAITs. Notably, the first column in Tables 4 and 5 replicate the ATE from Strunk, McEachin, and Westover (2011). Although the technical assistance as implemented in California was supposed to raise student achievement in the lowest performing districts, the legislation lacked specific provisions on how the student achievement gains should be allocated throughout the districts (e.g., the districts should focus on the schools in higher levels of PI status). Table 4 shows that non-Title 1 schools in DAIT districts did better than non-Title 1 schools in non-DAIT TA districts, and the magnitude of the treatment effect is larger for non-Title 1 schools than for Title 1 schools. Within Title 1 schools, which represent the higher poverty schools in California, the non-PI schools do better than the PI schools within the DAIT districts. The surprising result is that the PI3+ schools within the DAIT districts do no better than their PI3+ counterparts in the non-DAIT TA districts. This is problematic because the funding structure of the DAIT reform was based on the number of failing schools, or schools in PI status, within the districts. Table 5 also shows us that PI3+ schools are not making larger gains in ELA than their PI3+ counterparts in the non-DAIT TA districts. However, it does appear that the PI1 and PI2 schools in DAIT districts are making significant improvements in ELA achievement compared to their counterparts in the non-DAIT TA districts, and this is true across both years of the intervention.

Impact of DAITs by school grade levels: Table 6 shows that the two-year average math results discussed above are largely driven by 3-5th graders and to some extent by 9-11th graders. It does not appear that 6-8th grade students enrolled in districts with DAITs perform any better than 6-8th grade students in districts with non-DAIT TA. In addition, we see that the disaggregated year-by-year results show a consistent impact of DAITs on student achievement in 3-5th grades in both years of the intervention, but only in the first year for 9-11th graders. There are no evident DAIT impacts in any grade for ELA. Table 7 shows that the average two-year effect of DAITs on student math achievement is driven by students in 3rd, 4th and 5th grades, with the largest impacts on 5th grade students. We find some evidence that students in the 9th and 10th grades in districts with DAITs also see improvements in their math CST scores.

### **Conclusions:**

With the current administration's focus on building system capacity in the suggested NCLB reauthorization and waiver plans (United States Department of Education, 2011), it is becoming even more important to understand how such technical assistance programs already in existence impact student outcomes, and specifically how they may differentially impact achievement for students in various important subgroups. As our results indicate, the significant increases in math achievement found in Strunk, McEachin, and Westover (2011) are not necessarily consistent across students and schools, and they intervention does not always appear to affect the neediest students and schools within the lowest performing districts. Our results also indicate that while average treatment effects often provide useful and tangible answers to policy questions, they often mask important variation among populations of interest.

## Appendices

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### Appendix A. References

- Angrist, J. D., & Krueger, A. (1999). Empirical strategies in labor economics. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics*. New York, NY: New Holland.
- Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton, NJ: Princeton University Press.
- Ashenfelter, O., & Card, D. (1985). Using the longitudinal structure of earnings to estimate the effect of training programs. *The Review of Economics and Statistics*, 67(4), 648-660.
- Carnoy, M., & Loeb, S. (2002). Does external accountability affect student outcomes ? A cross-state analysis. *Educational Evaluation and Policy Analysis*, 24(4), 305-331.
- Dee, T. S., & Jacob, B. A. (2011). The impact of no Child Left Behind on student achievement. *Journal of Policy Analysis and Management*, n/a-n/a.
- Dillon, S. (2011, September, 23, 2011). Obama turns some powers of education back to states. *New York Times*.
- Donovan, C., Figlio, D. N., & Rush, M. (2006). *Cramming: The effects of school accountability on college-bound students*. Unpublished manuscript.
- Figlio, D. N., & Rouse, C. E. (2006). Do accountability and voucher threats improve low-performing schools? *Journal of Public Economics*, 90(1-2), 239-255.
- Gottfried, M. A., Stecher, B. M., Hoover, M., & Cross, A. B. (2011). *Federal and state roles and capacity for improving schools*. Santa Monica, CA: the Rand Corporation.
- Hanushek, E. A., & Raymond, M. E. (2005). Does school accountability lead to improved student performance? *Journal of Policy Analysis and Management*, 24(2), 297-327.
- Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1), 5-86.
- Krieg, J. M. (2008). Are students left behind? The distributional effects of the No Child Left Behind Act. *Education Finance and Policy*, 3(2), 250-281.
- Ladd, H. F., & Lauen, D. L. (2010). Status versus growth: The distributional effects of school accountability policies. *Journal of Policy Analysis and Management*, 29(3), 426-450.
- Neal, D., & Schanzenbach, D. W. (2010). Left behind by design: Proficiency counts and test-based accountability. *Review of Economics and Statistics*, 92(2), 263-283.
- Reback, R. (2010). Schools' mental health services and young children's emotions, behavior, and learning. *Journal of Policy Analysis and Management*, 29(4), 698-725.
- Rockoff, J. E., & Turner, L. (2010). Short run impacts of accountability on school quality. *American Economic Journal: Economic Policy*, 2, 119-147.
- Rouse, C. E., Hannaway, J., Goldhaber, D., & Figlio, D. N. (2007). Feeling the Florida heat? How low-performing schools respond to voucher and accountability pressure. *NBER Working Paper, Working Pa.*
- Springer, M. (2008). The influence of an NCLB accountability plan on the distribution of student test score gains. *Economics of Education Review*, 27(5), 556-563.
- United States Department of Education. (2011). *ESEA Flexibility*.
- Weinstein, T. (2011). *Interpreting No Child Left Behind corrective action and technical assistance programs: A review of state policy*. Paper presented at the American Educational Research Association.





## Appendix B. Tables and Figures

**Table 1: DID Estimates of the Impact of DAITs Math Achievement Gains by Student Subgroups**

	ELL	Non-ELL	FRPL	Non-FRPL	White	Black	Hispanic
<b>DAIT 2-Year ATE</b>	0.035** (0.010)	0.032** (0.011)	0.034*** (0.009)	0.029* (0.011)	0.026+ (0.013)	0.034** (0.013)	0.035*** (0.009)
<b>Adj. R-squared</b>	0.536	0.562	0.521	0.563	0.532	0.511	0.506
<b>N(Student)</b>	2092889	1360645	2698527	1034838	531845	323834	2558926
<b>N(Districts)</b>	95	95	95	93	95	93	95
<b>DAIT Year 1 Effect</b>	0.036** (0.013)	0.032* (0.015)	0.037** (0.013)	0.029+ (0.016)	0.026 (0.017)	0.043* (0.017)	0.035** (0.013)
<b>DAIT Year 2 Effect</b>	0.035** (0.011)	0.031** (0.012)	0.032** (0.010)	0.029* (0.011)	0.026* (0.013)	0.026 (0.016)	0.034*** (0.009)
<b>Adj. R-squared</b>	0.536	0.562	0.521	0.563	0.532	0.511	0.506
<b>N(Student)</b>	2092889	1360645	2698527	1034838	531845	323834	2558926
<b>N(Districts)</b>	95	95	95	93	95	93	95

+ p<0.10, \* p<0.05, \*\* p<0.01, \*\*\* p<0.001

*District-clustered standard errors in parentheses. All models include district and year fixed effects.*

**Table 2: DID Estimates of the Impact of DAITs ELA Achievement Gains by Student Subgroups**

	ELL	Non-ELL	FRPL	Non-FRPL	White	Black	Hispanic
<b>DAIT 2-Year ATE</b>	0.012+ (0.006)	0.003 (0.005)	0.010+ (0.006)	0.004 (0.007)	-0.003 (0.007)	0.005 (0.005)	0.011+ (0.006)
<b>Adj. R-squared</b>	0.655	0.671	0.634	0.683	0.649	0.622	0.634
<b>N(Student)</b>	2150135	1409622	2778881	1085506	555806	339285	2641912
<b>N(Districts)</b>	95	95	95	93	95	94	95
<b>DAIT Year 1 Effect</b>	0.01 (0.009)	-0.001 (0.008)	0.008 (0.009)	-0.001 (0.010)	-0.007 (0.009)	0 (0.009)	0.009 (0.009)
<b>DAIT Year 2 Effect</b>	0.014* (0.005)	0.008 (0.007)	0.011* (0.005)	0.009 (0.007)	0.001 (0.008)	0.009 (0.008)	0.012* (0.005)
<b>Adj. R-squared</b>	0.655	0.671	0.634	0.683	0.649	0.622	0.634
<b>N(Student)</b>	2150135	1409622	2778881	1085506	555806	339285	2641912
<b>N(Districts)</b>	95	95	95	93	95	94	95

+ p<0.10, \* p<0.05, \*\* p<0.01, \*\*\* p<0.001

*District-clustered standard errors in parentheses. All models include district and year fixed effects.*

**Table 3: Treatment Coefficient from Difference-in Difference Estimates of the 2-year ATE of DAITs on Math and ELA Achievement Gains for Students Across the CST Proficiency Distribution**

		<b>Far Below Basic</b>	<b>Below Basic</b>	<b>Basic</b>	<b>Proficient</b>	<b>Advanced</b>
<b>Math</b>	<b>DAIT 2-Year ATE</b>	0.007	0.027	0.036*	0.036*	0.019
		(0.017)	(0.019)	(0.017)	(0.017)	(0.016)
		<b>R-squared</b>	0.212	0.216	0.257	0.321
		<b>N (students)</b>	335191	899154	915788	792187
	<b>DAIT Year 1 Effect</b>	0.005	0.018	0.028+	0.031+	0.012
		(0.022)	(0.021)	(0.016)	(0.017)	(0.019)
		0.011	0.037*	0.045*	0.042*	0.025
		(0.013)	(0.019)	(0.020)	(0.019)	(0.018)
<b>ELA</b>	<b>DAIT 2-Year ATE</b>	0.008	0.015	0.009	0.008	0.000
		(0.012)	(0.009)	(0.007)	(0.006)	(0.009)
		<b>R-squared</b>	0.45	0.528	0.543	0.489
		<b>N (students)</b>	352124	923421	927088	798163
	<b>DAIT Year 1 Effect</b>	0.003	0.011	0.005	0.005	-0.007
		(0.013)	(0.012)	(0.009)	(0.009)	(0.012)
		0.014	0.019*	0.013+	0.011	0.007
		(0.015)	(0.009)	(0.008)	(0.007)	(0.008)
<b>ELA</b>	<b>DAIT Year 2 Effect</b>	0.450	0.528	0.549	0.543	0.489
		<b>R-squared</b>	0.450	0.528	0.549	0.543
		<b>N (students)</b>	352124	923421	927088	798163

+  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

*District-clustered standard errors in parentheses. All models include district and year fixed effects, and samples selected based on a student's 2007-8 (pre-intervention) proficiency level.*

**Table 4: DID Estimates of the Impact of DAITs Math Achievement Gains by School Title 1 and PI status**

	All Schools	non-Title 1 Schools	All Title 1 Schools	non-PI Title 1 Schools	PI Title 1 Schools	PI1 & PI2 Schools	PI3+ Schools
<b>DAIT 2-year ATE</b>	0.032*** (0.009)	0.062* (0.026)	0.028* (0.011)	0.040* (0.018)	0.019+ (0.011)	0.037+ (0.020)	0.006 (0.012)
<b>Adj. R-squared</b>	0.548	0.535	0.546	0.551	0.526	0.53	0.523
<b>N(Students/year Obs)</b>	3734900	577018	2876516	979728	1896788	503984	1392804
<b>N(Districts)</b>	95	95	95	95	95	95	95
<b>DAIT Year 1 ATE</b>	0.033* (0.013)	0.065* (0.032)	0.028* (0.013)	0.034+ (0.020)	0.02 (0.013)	0.037 (0.023)	0.008 (0.013)
<b>DAIT Year 2 ATE</b>	0.031** (0.010)	0.059* (0.023)	0.028* (0.012)	0.047* (0.019)	0.017 (0.012)	0.038+ (0.021)	0.004 (0.014)
<b>Adj. R-squared</b>	0.548	0.535	0.546	0.551	0.526	0.53	0.523
<b>N(Students/year Obs)</b>	3734900	577018	2876516	979728	1896788	503984	1392804
<b>N(Districts)</b>	95	95	95	95	95	91	92

+ p<0.10, \* p<0.05, \*\* p<0.01, \*\*\* p<0.001

*Note: District-clustered standard errors in parentheses. All models include district and year fixed effects. The All Title 1 schools includes the four columns to the right. It is also important to note that these models only include schools in DAIT and non-DAIT TA districts and not all schools throughout the state.*

**Table 5: DID Estimates of the Impact of DAITs ELA Achievement Gains by School Title 1 and PI status**

	All Schools	non-Title 1 Schools	Title 1 Schools	non-PI Title 1 Schools	PI Title 1 Schools	PI1 & PI2 Schools	PI3+ Schools
<b>DAIT 2-year ATE</b>	0.007 (0.006)	0.011 (0.007)	0.009 (0.005)	0.008 (0.009)	0.012+ (0.007)	0.030* (0.013)	0.004 (0.007)
<b>Adj. R-squared</b>	0.668	0.678	0.66	0.655	0.649	0.65	0.647
<b>N(Students/year Obs)</b>	3866090	609394	2950363	1008693	1941670	518144	1423526
<b>N(Districts)</b>	95	95	95	95	95	95	95
<b>DAIT Year 1 ATE</b>	0.004 (0.010)	0.013 (0.011)	0.006 (0.008)	0.001 (0.012)	0.012 (0.010)	0.035* (0.015)	0.002 (0.010)
<b>DAIT Year 2 ATE</b>	0.010* (0.005)	0.008 (0.012)	0.012* (0.005)	0.016+ (0.009)	0.013* (0.006)	0.024+ (0.013)	0.007 (0.007)
<b>Adj. R-squared</b>	0.668	0.678	0.66	0.655	0.649	0.65	0.647
<b>N(Students/year Obs)</b>	3866090	609394	2950363	1008693	1941670	518144	1423526
<b>N(Districts)</b>	95	95	95	95	95	95	95

+ p<0.10, \* p<0.05, \*\* p<0.01, \*\*\* p<0.001

*Note: District-clustered standard errors in parentheses. All models include district and year fixed effects. The All Title 1 schools includes the four columns to the right. It is also important to note that these models only include schools in DAIT and non-DAIT TA districts and not all schools throughout the state.*

**Table 6: Treatment Coefficient from Difference-in Difference Estimates of the Impact of DAITs on ELA and Math Achievement Gains for Students Across Grade Spans**

	Math			English		
	3 to 5	6 to 8	9 to 11	3 to 5	6 to 8	9 to 11
<b>DAIT 2-year ATE</b>	0.056** (0.017)	0.016 (0.015)	0.024* (0.011)	0.008 (0.007)	0.010 (0.009)	0.004 (0.010)
<b>R-squared</b>	0.572	0.589	0.428	0.642	0.687	0.677
<b>N(Student/year Obs)</b>	1354566	1318035	1062299	1355421	1325697	1184972
<b>N(Districts)</b>	87	89	52	87	89	52
<b>DAIT Year 1 ATE</b>	0.058* (0.023)	0.026 (0.016)	0.022+ (0.011)	0.006 (0.011)	0.013 (0.011)	-0.009 (0.015)
<b>DAIT Year 2 ATE</b>	0.055*** (0.015)	0.007 (0.019)	0.026 (0.015)	0.010 (0.007)	0.007 (0.008)	0.015 (0.010)
<b>Adj. R-squared</b>	0.572	0.589	0.428	0.642	0.687	0.677
<b>N(Student/year Obs)</b>	1354566	1318035	1062299	1355421	1325697	1184972
<b>N(Districts)</b>	87	89	52	87	89	52

+  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

*District-clustered standard errors in parentheses. All models include district and year fixed effects.*

**Table 7: Treatment Coefficient from Difference-in Difference Estimates of the Impact of DAITs on ELA and Math Achievement Gains for Students Across Individual Grades**

		<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>	<b>11</b>
<b>Math</b>	<b>DAIT 2-year ATE</b>	0.036+ (0.021)	0.036* (0.016)	0.098*** (0.025)	0.009 (0.013)	0.03 (0.022)	0.027 (0.029)	0.031+ (0.016)	0.028* (0.011)	0.023 (0.015)
	<b>Adj. R-squared</b>	0.544	0.574	0.605	0.638	0.66	0.521	0.437	0.444	0.366
	<b>N(Student/year Obs)</b>	459074	447832	447660	450221	433038	434776	337056	391502	333741
	<b>N(Districts)</b>	85	86	87	86	85	84	52	52	52
	<b>DAIT Year 1 ATE</b>	0.039 (0.027)	0.045+ (0.026)	0.093*** (0.027)	0.030+ (0.016)	0.034 (0.023)	0.022 (0.031)	0.027 (0.019)	0.036* (0.014)	0.015 (0.016)
	<b>DAIT Year 2 ATE</b>	0.033+ (0.018)	0.029+ (0.017)	0.103*** (0.026)	-0.011 (0.017)	0.026 (0.024)	0.031 (0.035)	0.035 (0.028)	0.021 (0.013)	0.031 (0.020)
	<b>Adj. R-squared</b>	0.544	0.574	0.605	0.638	0.66	0.521	0.437	0.444	0.366
	<b>N(Student/year Obs)</b>	459074	447832	447660	450221	433038	434776	337056	391502	333741
	<b>N(Districts)</b>	85	86	87	86	85	84	52	52	52
	<b>DAIT 2-year ATE</b>	-0.008 (0.014)	0.008 (0.010)	0.027* (0.011)	0.01 (0.011)	0.017 (0.014)	0.004 (0.014)	0.025+ (0.013)	0.002 (0.014)	-0.015 (0.012)
<b>ELA</b>	<b>Adj. R-squared</b>	0.603	0.649	0.684	0.671	0.701	0.697	0.667	0.685	0.679
	<b>N(Student/year Obs)</b>	459919	448032	447470	450440	435052	440205	344431	428513	412028
	<b>N(Districts)</b>	85	86	87	86	85	84	52	52	52
	<b>DAIT Year 1 ATE</b>	-0.008 (0.019)	0.000 (0.010)	0.025+ (0.013)	0.024* (0.012)	0.012 (0.015)	0.002 (0.015)	0.012 (0.016)	0.002 (0.018)	-0.038* (0.018)
	<b>DAIT Year 2 ATE</b>	-0.008 (0.013)	0.014 (0.013)	0.029** (0.011)	-0.003 (0.012)	0.021 (0.014)	0.005 (0.014)	0.038* (0.015)	0.003 (0.014)	0.008 (0.012)
	<b>Adj. R-squared</b>	0.603	0.649	0.684	0.671	0.701	0.697	0.667	0.685	0.679
	<b>N(Student/year Obs)</b>	459919	448032	447470	450440	435052	440205	344431	428513	412028
	<b>N(Districts)</b>	85	86	87	86	85	84	52	52	52

+  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

District-clustered standard errors in parentheses. All models include district and year fixed effects.



