White Paper: Estimating the Impact of Attendance Interventions on Student Attendance

Panorama Education

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Abstract

This study estimates the impact of completed attendance interventions on subsequent student attendance during the 2025–2026 school year using administrative data from Panorama's Success platform. To account for interventions beginning at different points during the school year, the analysis employs a staggered-adoption difference-in-differences event-study design. Results indicate that attendance interventions are associated with meaningful improvements in student attendance across all grade levels. Estimated impacts are largest for elementary and middle school students, increasing weekly attendance by approximately 5.9 percentage points—equivalent to roughly 5 additional days of attendance over 18 weeks (half a school year). High school students also experience statistically significant gains, though effects are smaller (approximately 2.5 percentage points, or 2 additional days over 18 weeks) and diminish over time. Analyses of individual intervention strategies suggest considerable heterogeneity in effectiveness across grade levels, with personalized outreach and attendance contracts demonstrating particularly strong associations with improved attendance in several contexts.

Introduction

Chronic absenteeism is one of the most persistent barriers to student success in U.S. schools. When students miss school, they miss important instruction, lose opportunities to practice new skills, and receive less feedback from teachers. Frequent absences can also be a sign that a student is experiencing broader challenges, such as transportation barriers, health concerns, family responsibilities, or feeling disconnected from school.

Attendance is also a leading indicator for school staff. Unlike many end-of-year outcomes, attendance patterns can be observed continuously throughout the school year, allowing schools to identify students in need of support and intervene before academic or behavioral consequences accumulate.

In response, many districts use structured attendance interventions as part of multi-tiered systems of support. These interventions may include problem-solving conversations with students and families, targeted outreach, attendance contracts or plans, mentoring, case management, referrals to school-based resources, or coordinated supports addressing student-specific barriers to attendance. Students do not receive these interventions at the same time. Some students begin attendance interventions early in the year and others much later. Other students, usually those with better attendance, never receive an intervention. This variation creates an opportunity to estimate the relationship between intervention participation and subsequent attendance using a quasi-experimental design.

Student Attendance and Educational Outcomes

Attendance is a foundational condition for learning. Students must be present to benefit from classroom instruction, academic feedback, peer interaction, and school-based supports. A large body of research links absenteeism to lower academic achievement, reduced course performance, weaker engagement, lower graduation rates, and poorer long-term outcomes, including employment and earnings (Liu & Lee, 2022). These associations are observed across grade levels, although the mechanisms differ. In the early grades, absenteeism can disrupt the development of foundational literacy and numeracy skills. In middle and high school, absenteeism often reflects disengagement, unmet social or behavioral needs, or accumulating academic difficulty, while simultaneously reducing opportunities to earn course credit and remain on track for graduation.

Since the COVID-19 pandemic, chronic absenteeism—typically defined as missing 10% or more of enrolled school days—has increased dramatically across the United States. Nationally, rates remain substantially higher than pre-pandemic levels and have become a major concern for educators, policymakers, and researchers. Using Panorama's national attendance database, which includes more than 11 million student-year records across over 7,000 schools, chronic absenteeism rates nearly doubled following the pandemic and remained elevated through the 2023–24 school year. Similar trends have been documented nationally, suggesting that chronic absenteeism has become one of the defining educational challenges of the post-pandemic period.

Attendance is an attractive outcome for educational intervention because it is observed continuously. Unlike annual standardized assessments, attendance data are collected daily and can be used to identify students experiencing emerging attendance problems. Schools routinely use attendance information within early warning systems to identify students for additional support (Stuit et al., 2016).

Although chronic absenteeism is strongly associated with poorer educational outcomes, identifying its underlying causes remains difficult. Schaper et al. (2025) found that chronic absenteeism is shaped by both student characteristics and school factors. Students' perceptions of school safety, climate, and teacher relationships are associated with absenteeism, although these patterns vary by grade level. Their findings suggest that improving school climate and strengthening student-teacher relationships may reduce absenteeism, while survey and attendance data can help guide targeted interventions. Kearney and Graczyk (2022) describe absenteeism as complex, heterogeneous, and opaque: it stems from interacting student, family, school, and community factors; includes both excused and unexcused absences with different underlying causes; and is difficult to address because schools often lack information about barriers outside school, such as physical and mental health challenges, housing instability, transportation, family responsibilities, and neighborhood safety (Hamlin, 2021).

Attendance Interventions in Schools

Schools employ a wide range of strategies to improve attendance. Universal approaches include schoolwide attendance campaigns, positive attendance messaging, monitoring systems, and recognition programs. More targeted interventions may involve family outreach, student conferences, mentoring, individualized attendance plans, home visits, referrals to community services, or coordination with behavioral health providers. Intensive supports often address barriers such as transportation, housing instability, health concerns, or legal requirements related to truancy.

Despite the wide use of these approaches, evidence regarding their effectiveness remains mixed. Early warning systems successfully identify students at risk for chronic absenteeism but, by themselves, appear to produce only small improvements in attendance (Canbolat, 2024). Incentive-based programs that reward attendance with symbolic recognition have generally produced null or even negative effects (Robinson et al., 2021). One-way communication strategies that inform families about student attendance have demonstrated modest improvements in attendance under specific conditions (Robinson et al., 2018; Rogers & Feller, 2018), although these effects tend to be small in schools with high baseline absenteeism and may negatively affect family-school relationships if perceived as punitive (Singer, 2024). More intensive case management approaches—including mentoring, home visits, and partnerships with community organizations—can improve attendance and strengthen relationships between families and schools (Jacob & Lovett, 2017), but these resource-intensive interventions become difficult to scale when large proportions of students are chronically absent.

Study Design

This study uses data from the Panorama Success platform, which schools can use to manage student interventions and track attendance. School staff record intervention strategies, start and end dates, and other implementation details. Together, these data provide the information needed to estimate the impact of interventions on attendance.

However, estimating the effectiveness of attendance interventions using administrative data is challenging because students who receive interventions are not randomly selected. They typically have more severe attendance problems and differ from other students in ways that also influence attendance outcomes, making simple comparisons between treated and untreated students prone to selection bias. For example, students often receive interventions after their attendance has already declined, so subsequent changes may reflect regression to the mean, seasonal patterns, or broader schoolwide trends rather than the intervention itself.

Difference-in-differences designs help address this challenge by comparing changes in attendance over time rather than attendance levels. Traditional two-way fixed-effects difference-in-differences models are widely used, but they can be problematic when treatment begins at different times and effects vary by cohort or over time since treatment. In staggered settings, already-treated students may inadvertently serve as comparisons for later-treated units, and coefficient weights can be difficult to interpret (de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021). Recent methodological work recommends estimators that explicitly define treatment cohorts and estimate group-time average treatment effects (Callaway & Sant'Anna, 2021).

This study uses a staggered-adoption differences-in-differences framework in which each treated student belongs to a cohort defined by the week of first completed attendance intervention. The estimator compares each cohort's change in weekly attendance from a pre-treatment reference period to outcome weeks against the corresponding change among never-treated comparison students observed in the same calendar weeks (Callaway & Sant'Anna, 2021). These group-time effects are then aggregated into event-study estimates (Callaway & Sant'Anna, 2021). The event-study structure provides evidence on pre-treatment trends, which is central for assessing the plausibility of the parallel trends assumption (Marcus & Sant'Anna, 2021; Sun & Abraham, 2021).

Data Sources

The study combines three primary administrative data sources for the 2025–2026 school year.

1. Attendance records

The attendance file provides daily student attendance records. The binary absence variable equals one when the cleaned absence value equals 1.0 and zero otherwise. Daily attendance records are then aggregated to the weekly level by averaging the absence values in each week. Weekly attendance rate is defined as one minus this weekly mean absence rate. Attendance records from around the holidays are excluded since more students are likely to miss around those days due to factors not related to regular attendance.

2. Intervention records

The intervention file includes student-level intervention records. Intervention records include dates such as start date, created date, and completed date. The treatment date is based on the earliest usable intervention date, defined as start date when available and created date otherwise. The data also include intervention names and strategy names where available. A single intervention can include multiple strategies. These data are transformed into a weekly file by indicating whether or not the student received an intervention in that week.

3. Student demographic records

Demographic data include gender, race/ethnicity, free or reduced price lunch status, english language learner status and grade level.

Study Sample

The study focuses on students enrolled in schools using Panorama's Success Platform during the 2025–2026 school year. Separate analysis files are prepared for elementary, middle, and high school grade bands.

To be included in the analysis students must have at least 60 observed attendance days. Students observed in more than one school during the school year are excluded to avoid confounding intervention exposure and attendance patterns with within-year school mobility.

The final sample is further restricted to students in schools with both treated and comparison students, at least 100 total students, and more than 20 treated students. These restrictions are intended to ensure that the analysis is conducted in schools where both intervention and comparison conditions are represented and where there is sufficient treated-student sample size for estimation.

Intervention Group

The intervention group consists of students who completed at least one attendance intervention. If a student has multiple completed attendance interventions, the first eligible intervention date defines the treatment start date. Students that started but did not finish an attendance intervention were excluded from both the intervention and comparison groups. Students whose treatment week equals the first week are excluded because they do not have a baseline pre-treatment week available for difference-in-differences estimation.

The primary intervention group includes all attendance interventions logged in Panorama. Depending on local implementation, attendance interventions may involve different strategies, intervention names, or school-level practices. The primary estimand should therefore be understood as the average effect of completing an attendance intervention as implemented across participating schools, not the effect of a single standardized intervention model.

Strategy specific estimates are based on sub-samples limiting the intervention group to just students that received an intervention tagged with that strategy and only that strategy. Students that received interventions tagged with multiple strategies were removed since the effect would not be able to be attributed to a single strategy.

Comparison Group

The comparison group consists of students attending the same eligible schools as treated students who did not start an attendance intervention during the school year. The comparison group is designed to represent the attendance trajectories that treated students might have followed absent intervention. Because the comparison students come from the same schools and school year, they are exposed to many of the same calendar-time shocks, school schedules, district policies, and broad attendance conditions. The key assumption is that, in the absence of treatment, treated students would have experienced attendance changes parallel to those of the comparison students.

Estimator

The analysis uses the Callaway-Sant'Anna staggered difference-in-differences framework implemented through an aggregated ATT estimator using the student-week data. We used the authors' recommended doubly robust estimation approach and clustered the standard errors at the school level. The estimator calculates effects on each weekly cohort of intervention students. We tested three ways of aggregating this data: 1) event-study estimates by week relative to treatment start (our preferred method), 2) event-study estimates like #1, but with a narrower pre and post intervention time period, 3) average effects by intervention cohort. The week the intervention started in part of the post-intervention time period.

The primary unadjusted model uses no covariates. We also tested models with covariates (gender and race) as a sensitivity check. The covariate-adjusted model uses inverse probability weighting instead of the doubly robust estimator. Generally results were similar with and without covariates. A limitation of this approach is that we do not control for time-invariant unobserved school or district level factors which may bias our estimates.

The analysis is conducted separately for elementary, middle, and high school samples. This is appropriate because attendance patterns, intervention practices, developmental needs, and school contexts may differ substantially across grade levels. Separate grade-band estimates also avoid imposing a single average effect across potentially heterogeneous populations.

Sample Descriptives

The sample is large and covers multiple schools and districts. Table 1 includes the details.

Table 1: Sample Sizes

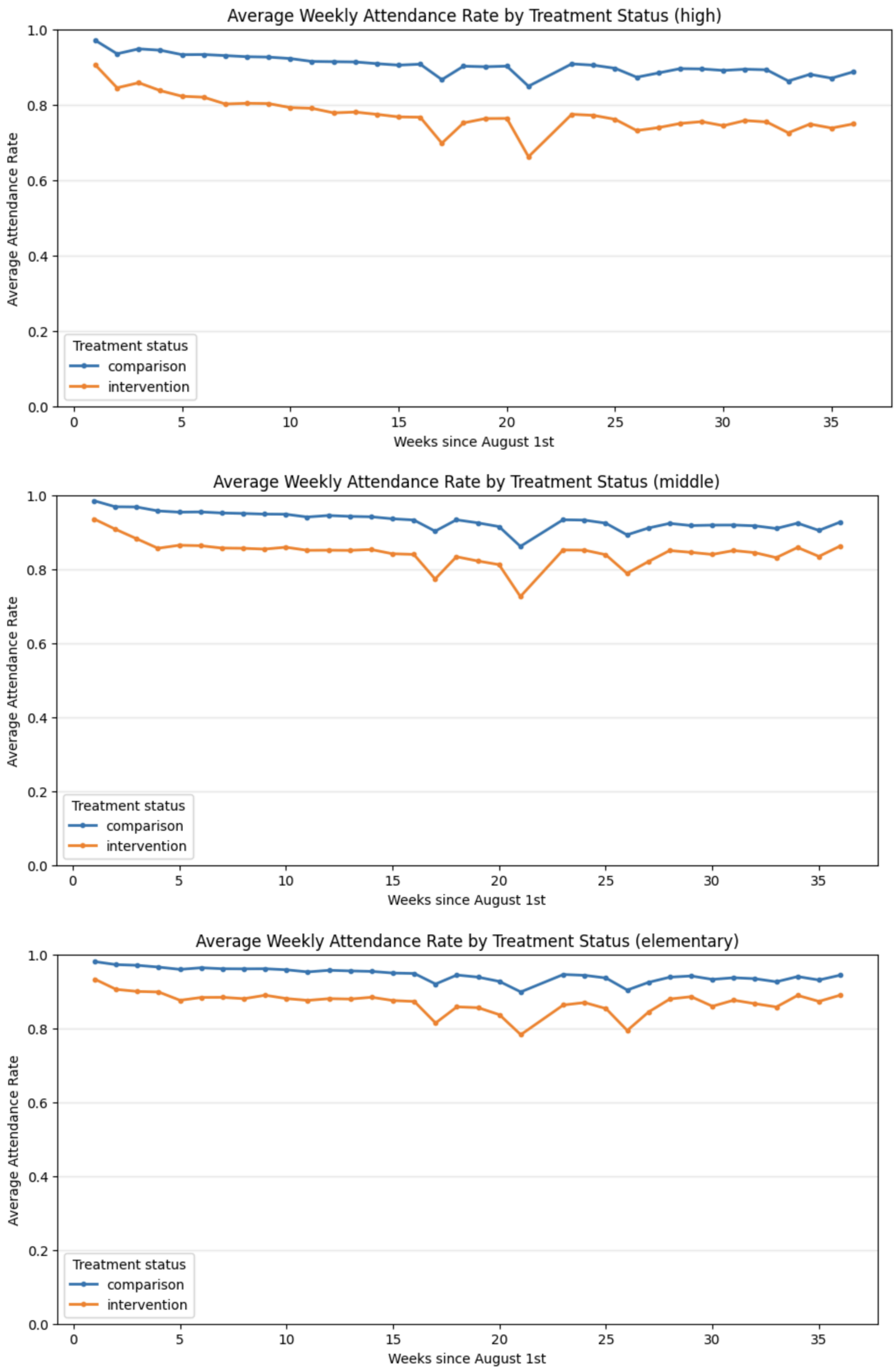
Sample	Student-week rows	Total students	Intervention Students	Comparison Students	Total schools*	Total districts*
High	3,797,336	104,409	9,563	94,846	102	50
Middle	1,986,940	54,029	7,992	46,037	107	59
Elementary	2,664,002	73,321	11,584	61,737	205	73

Notes: * all schools and districts include both intervention and comparison students

The appendix includes a descriptive table with the demographics of each group. As expected there are differences between the intervention and comparison students. Black and Latinx students are over-represented in the intervention group as are students that are eligible for free and reduced priced lunches and students that are English language learners.

The graphs below shows attendance rates by week of the school year (starting August 1, 2025). As expected, students in the intervention group had notably lower attendance rates than students in the comparison groups. The key assumption is that the trends in attendance over time are the same among the two groups and demonstrate similar trends between the two groups in each grade level.

Figure 1: Average Weekly Attendance Rates by Grade Level and Treatment Status



Treatment start dates ranged from the 2nd week of school till very late in the school year with the average start week around 20 weeks for all three grade levels.

Table 2: Treatment Start Date Distribution

Sample	Average	Minimum	25th percentile	Median	75th percentile	Maximum
High	20.43	2	13	20	29	44
Middle	19.22	3	11	23	25	42
Elementary	20.14	2	11	23	28	45

The specifics of interventions varied throughout the intervention sample. Each intervention is tagged with one or more strategies. The table below shows the number and most common strategies for each grade level (only shown in table if 10% or more of the students got that strategy). There is definitely variation in the strategies used to improve attendance at the different grade levels.

Table 3: Number and types of strategies by grade level

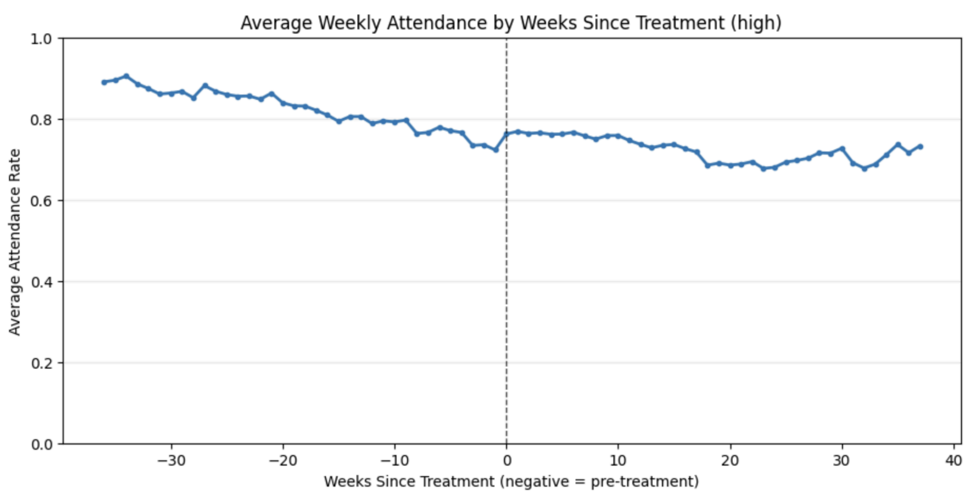
Number of strategies	High	Middle	Elementary
Intervention tagged with 1 strategy	60%	44%	53%
Intervention tagged with 2+ strategies	40%	56%	47%
Most Common Strategies			
Attendance Contract	15%	20%	10%
Attendance Group	11%	19%	10%
Attendance Incentive Plan	13%	16%	16%
Attendance Motivational Interviewing	—	12%	—
Check and Connect	26%	30%	16%

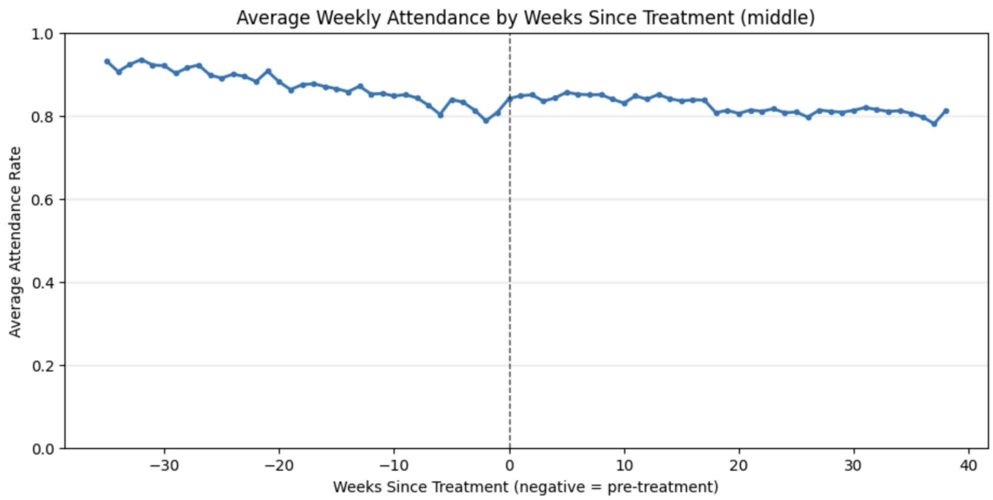
Chronic Absence Letter	7%	7%	23%
Nudge Letters	7%	13%	19%
Phone Call Home	11%	22%	13%

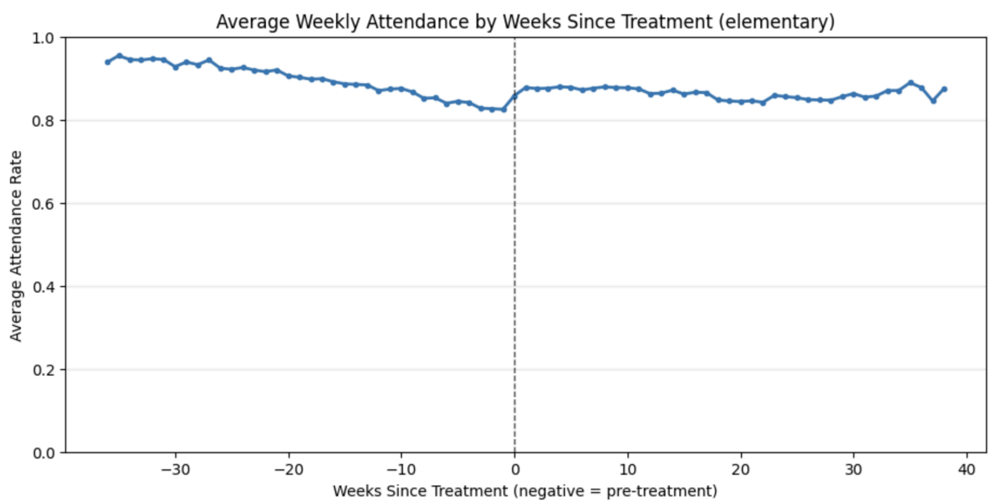
Note: Table only shows strategies where 10% or more of students completed that strategy.

Looking at the raw event-study aligned attendance patterns for intervention students (see graphs below) we can see a notable improvement in attendance in elementary school, with a smaller effect in middle school and possibly a very small or no effect in high school. The effects are concentrated in the first few weeks after intervention and fade over time. Lacking a comparison group this chart is not causal, merely descriptive. Still these charts are promising evidence that attendance improves post-intervention, especially in elementary school.

Figure 2: Average Weekly Attendance for Intervention Group Aligned by Intervention Start Week







Findings

This section presents the full findings for each grade level. For each, there are six estimates testing two aggregation methods (group and event study) and one narrower timeframe on the event study. Each of those three is run without and then with covariates. Our preferred estimate uses event study aggregation and does not include the covariates. Each section includes a table with the estimated coefficients, and then translates these coefficients into the number of days per week and total days over 18 weeks (half of a standard 36-week school year).

Elementary school sample

The magnitude of the event study model covering all time frames is 0.059 without covariates. This means that each week students that received the intervention are attending 5.9 percentage points more of the week, which can be translated to 0.3 more days per week and 5.3 days over 18 weeks. Based on the graphs you can see that the effect seems relatively sustained through the end of the school year. The event study analysis that only considers the four weeks prior to intervention and the 15 weeks after intervention shows a smaller overall effect, again suggesting sustained effects.

Table 4: Elementary School Overall Effects

Aggregation Method	Time frame	Without covariates			With covariates		
		Effect	Days per Week	Total Days Over 18 Weeks	Effect	Days per Week	Total Days Over 18 Weeks
Group	All	0.0459 (0.0035)*	0.23	4.1	0.047 (0.0035)*	0.24	4.2
Event study	All	0.059 (0.0044)*	0.30	5.3	0.0613 (0.0046)*	0.31	5.5
Event study	Limited to 4 weeks pre-intervention to 15 week post-intervention	0.0464 (0.0027)*	0.23	4.2	0.0469 (0.0027)*	0.23	4.2

Notes: * statistically significant at the 5% level.

Figure 3: Average Effect by Length of Exposure for All Time Frames, Elementary

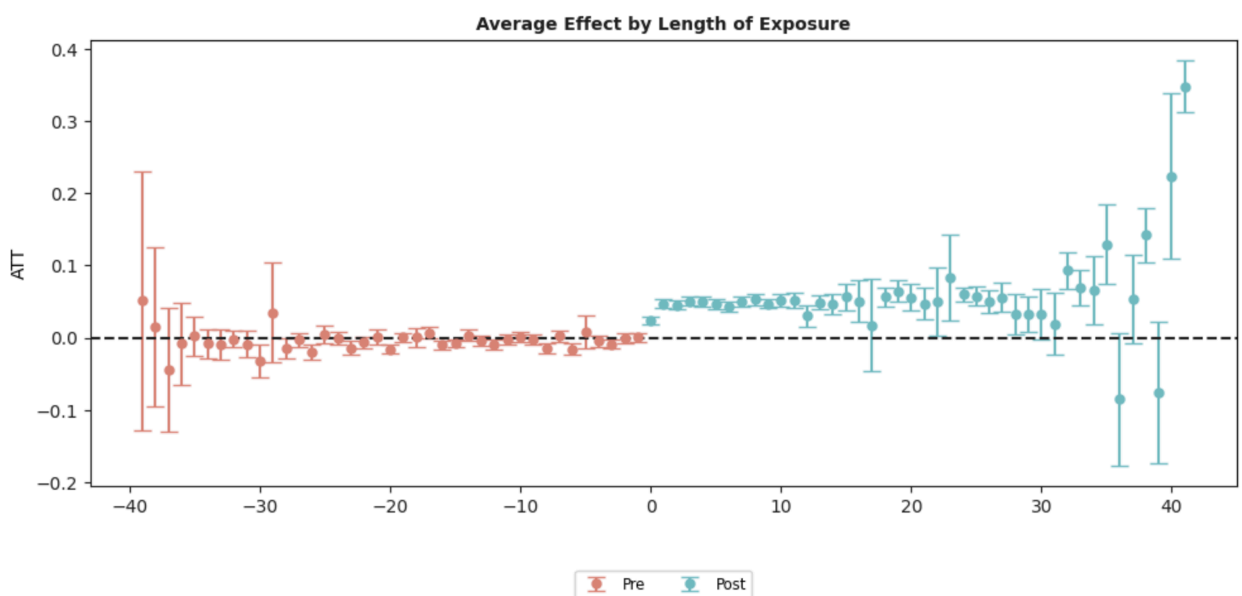
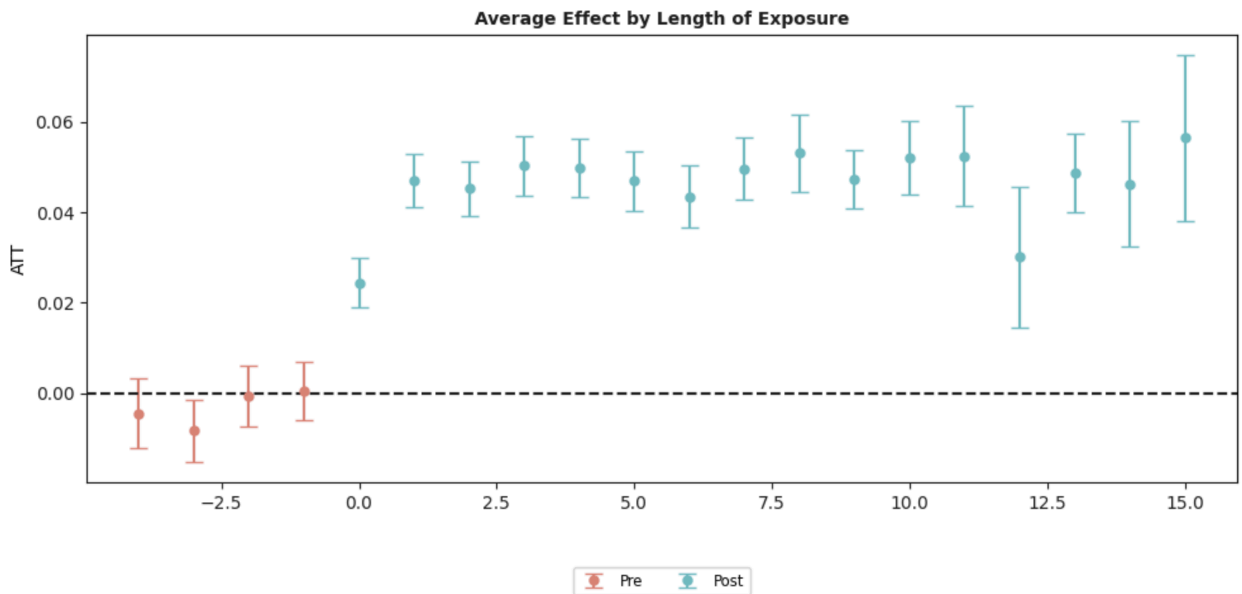


Figure 4: Average Effect by Length of Exposure for Limited Time Frame, Elementary



When the results are broken down by specific common strategies we can see the impact of specific strategies.[1] It's important to note that different strategies were used with different groups of students, and school staff likely provided more intensive interventions to students with poorer attendance. As a result, differences in effectiveness across strategies may reflect differences in the students who received them, rather than the strategies themselves. This is an important limitation of the analysis, but we believe the findings are still valuable to examine.

For elementary school, there are many effective strategies that yield large effects. A chronic absence letter to parents is the most effective with data suggesting it helps increase attendance by 13 days per student over 18 weeks. There are many other effective strategies including attendance contracts, nudge letters, arrival check-in, attendance lunch bunch, attendance activities planning tool and personalized attendance plan.

Table 5: Elementary School Effects by Strategy

Strategy	Effect	Days Per Week	Days Per 18 Week School Year
Check and Connect	0.013 (0.010)	-	-
Attendance Incentive Plan	0.072 (0.019)*	0.36	6.5
Attendance Group	0.063 (0.015)*	0.32	5.7

[1] For the break out analysis for all grade levels, we removed all students that received an intervention tagged with multiple strategies (those students were included in the overall analysis above). We did this to isolate the impact of specific strategies.

Nudge Letters	0.075 (0.016)*	0.37	6.8
Phone Call Home	0.075 (0.015)*	0.38	6.8
Chronic Absence Letter	0.145 (0.021)*	0.72	13.0
Success Mentor	0.091 (0.018)*	0.45	8.1
Monitoring	0.106 (0.020)*	0.53	9.5
Attendance Contract	0.138 (0.022)*	0.69	12.4
Attendance Lunch Bunch	0.119 (0.026)*	0.59	10.7
Arrival Check-In	0.123 (0.028)*	0.62	11.1
Attendance Postcard	0.114 (0.025)*	0.57	10.3
Attendance Activities Planning Tool	0.120 (0.025)*	0.60	10.8
Nudge Letter	0.128 (0.023)*	0.64	11.6
School-to-Home Attendance Updates	0.106 (0.032)*	0.53	9.6
Personalized Attendance Plan	0.126 (0.027)*	0.63	11.3
Check In/Check Out	0.097 (0.023)*	0.48	8.7

Notes: * statistically significant at the 5% level.

Middle school sample

Overall results for middle school students are similar to elementary students: 5.85% more days attended per week, which translates to 0.29 more days per week and 5.3 more days over the half of the school year. The covariate adjusted results are very similar. Like the elementary sample, effects seem sustained for several weeks post intervention and limiting the study sample window produces a smaller effect.

Table 6: Middle School Overall Effects

Aggregation Method	Time frame	Without covariates			With covariates		
		Effect	Days per Week	Total Days Over 18 Weeks	Effect	Days per Week	Total Days Over 18 Weeks
Group	All	0.052 (0.0038)*	0.26	4.7	0.0526 (0.0042)*	0.26	4.7
Event study	All	0.0585 (0.0087)*	0.29	5.3	0.0593 (0.009)*	0.30	5.3
Event study	Limited to 4 weeks pre-intervention to 15 week post-intervention	0.048 (0.0036)*	0.24	4.3	0.0486 (0.0035)*	0.24	4.4

Notes: * statistically significant at the 5% level.

Figure 5: Average Effect by Length of Exposure for All Time Frames, Middle

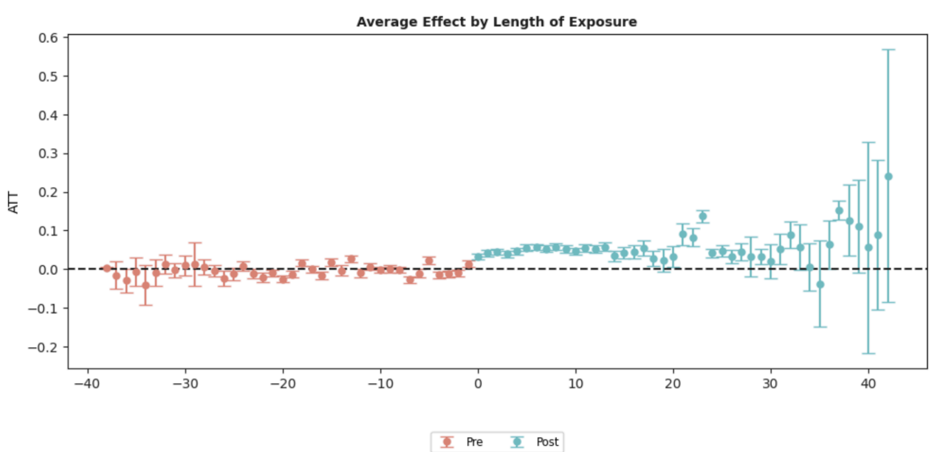
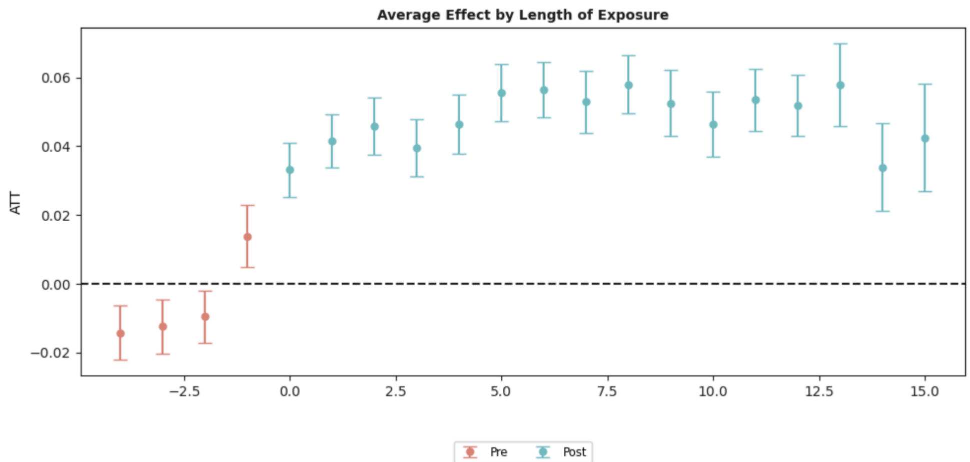


Figure 6: Average Effect by Length of Exposure for Limited Time Frame, Middle



Breaking out the results by strategy shows only two strategies with statistically significant effects: attendance incentive plan and attendance postcard. The postcard has a similarly sized effect to the overall effect (5.5 days over the course of half of the school year) and the attendance incentive plan has about half that effect (2.4 days over the course of half of the school year). Like the elementary sample these effects are only among students that received an intervention tagged with a single strategy. Given such positive results among all students, the lack of effect of individual strategies may suggest that multiple strategy interventions are more effective for middle school students.

Table 7: Middle School Effects by Strategy

Strategy	Effect	Days Per Week	Days Per 18 Weeks
Attendance Group	0.004 (0.013)	-	-
Attendance Contract	0.011 (0.016)	-	-
Attendance Incentive Plan	0.027 (0.013)*	0.13	2.4
Check and Connect	0.030 (0.018)	-	-
Attendance Motivational Interviewing	0.086 (0.045)	-	-
Check in/Check out	0.032 (0.034)	-	-
Attendance Postcard	0.060 (0.026)*	0.30	5.5

2x10 Relationship Building	0.023 (0.029)	-	-

Notes: * statistically significant at the 5% level.

High school sample

In high school we see a different pattern, but still see a small effect of attendance interventions. Students that received an attendance intervention attended an estimated 2.48 percentage points more of days, which is 0.12 days per week and 2.2 days over half of the school year. Covariate adjusted results are very similar. When the time frame is limited to the 4 weeks prior to intervention and the 15 weeks after the intervention, the effect increases to 0.18 days per week or 3.3 days over half of the school year. This suggests interventions for high school students are more effective than our primary estimate suggests, but that the effects fade over time. We can see this in the charts below that suggest a drop off of effect right at the 15 weeks post-intervention.

Table 8: High School Overall Effects

Aggregation Method	Time frame	Without covariates			With covariates		
		Effect	Days per Week	Total Days Over 18 Weeks	Effect	Days per Week	Total Days Over 18 Weeks
Group	All	0.0332 (0.0047)*	0.17	3.0	0.0355 (0.0044)*	0.18	3.2
Event study	All	0.0248 (0.0112)*	0.12	2.2	0.0285 (0.0106)*	0.14	2.6
Event study	Limited to 4 weeks pre-intervention to 15 week post-intervention	0.0364 (0.0035)*	0.18	3.3	0.0375 (0.0033)*	0.19	3.4

Notes: * statistically significant at the 5% level.

Figure 7: Average Effect by Length of Exposure for All Time Frames, High

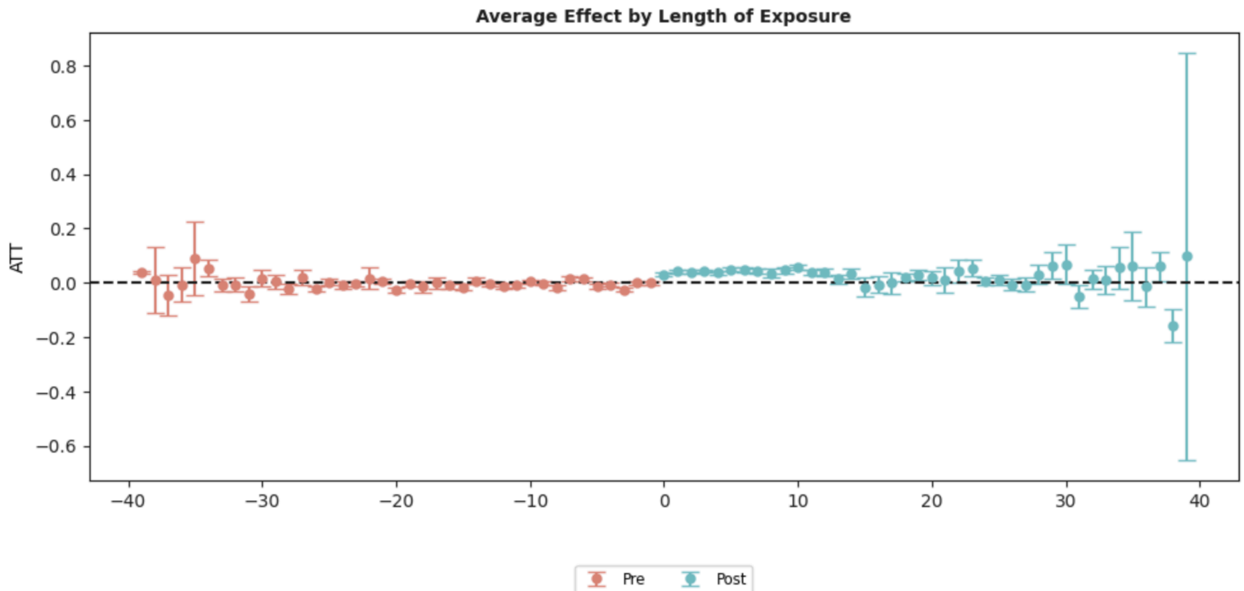
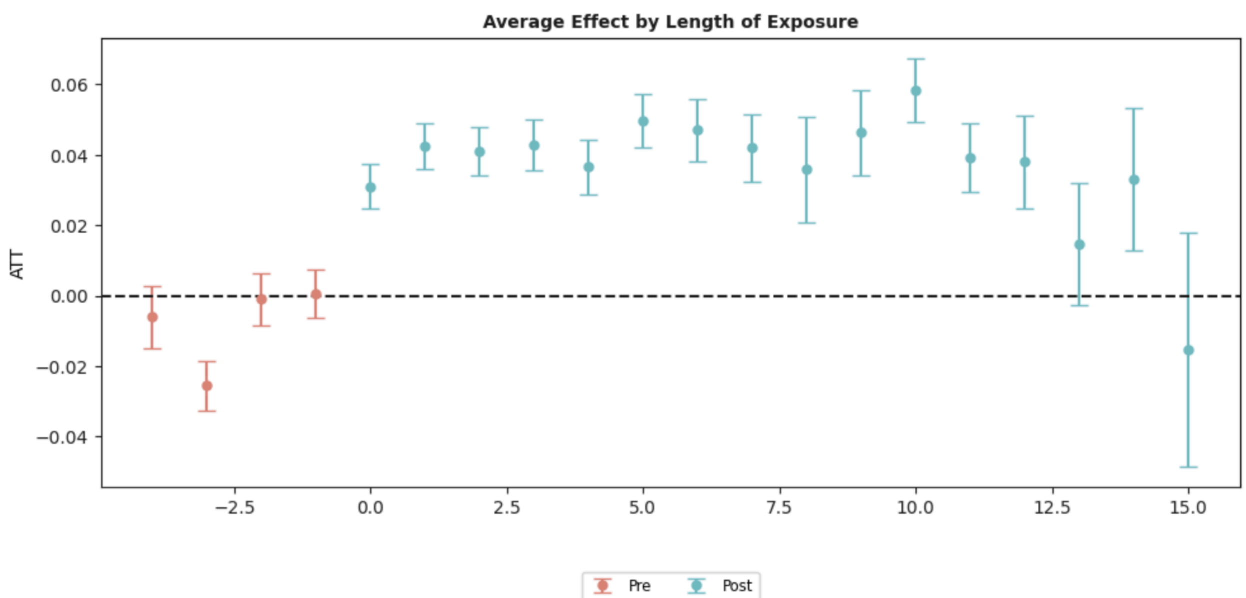


Figure 8: Average Effect by Length of Exposure for Limited Time Frame, High



Looking at the strategy breakouts for high school, we can see some pretty effective strategies with larger effects than our overall effect. Attendance contracts seem to be the most effective followed by nudge letters, phone calls home and finally attendance incentive plans. These effects are notably larger than our overall high school effect suggesting very heterogeneous effects for this grade level.

Table 9: High School Effects by Strategy

Strategy	Effect	Days Per Week	Days Per 18 Weeks
Check and Connect	-0.009 (0.012)	-	-
Attendance Incentive Plan	0.048 (0.012)*	0.24	4.4
Attendance Contract	0.084 (0.018)*	0.42	7.5
Attendance Group	-0.019 (0.013)	-	-
Success Mentor	-0.023 (0.015)	-	-
Check and Connect Goal Setting	-0.001 (0.021)	-	-
Phone Call Home	0.057 (0.020)*	0.29	5.2
Nudge Letters	0.061 (0.022)*	0.30	5.5

Notes: * statistically significant at the 5% level.

Discussion

This study provides evidence that structured attendance interventions, as implemented across schools using Panorama's Success platform, are associated with meaningful improvements in student attendance. Using a staggered-adoption difference-in-differences design that accounts for variation in intervention timing, we find consistent positive effects across elementary, middle, and high schools, with the largest and most sustained improvements occurring in elementary and middle grades. Although intervention effects are smaller for high school students, they remain statistically significant, suggesting that attendance interventions can improve attendance throughout the K–12 continuum.

Beyond estimating overall impacts, the results highlight substantial heterogeneity across intervention strategies. Several strategies—including attendance contracts, personalized outreach, attendance postcards, and family communication approaches—were associated with particularly large improvements in attendance, although the most effective strategies differed across grade levels.

Several limitations warrant consideration. Because interventions were not randomly assigned, the estimates rely on the assumption that treated and comparison students would have followed parallel attendance trends in the absence of intervention. In addition, attendance interventions varied considerably in their content, duration, intensity, and implementation across schools, meaning the estimated effects represent the average impact of real-world implementation rather than a standardized intervention model. Finally, the study excludes students with incomplete attendance interventions, students observed in multiple schools, students with fewer than 60 observed attendance days, and schools with small treated samples or no comparison group. These restrictions improve internal validity and estimation feasibility but may reduce generalizability to other contexts.

Future work should examine which students benefit most from attendance interventions, whether intervention timing influences effectiveness, and how combinations of intervention strategies compare with single-strategy approaches. Additional analyses incorporating implementation fidelity, intervention dosage, and longer-term student outcomes would further strengthen the evidence base. Together, these findings suggest that structured attendance interventions can be an important component of school attendance improvement efforts and demonstrate how routinely collected administrative data can be leveraged to evaluate and refine educational practice at scale.

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Appendix Table A: Demographic Characteristics of Intervention and Comparison Students

Variable	Category	Comparison	Intervention	Comparison	Intervention	Comparison	Intervention
		High School		Middle School		Elementary School	
ELL	English language learner	12,580 (13.2%)	1,815 (18.9%)	7,964 (17.1%)	1,766 (22.0%)	14,349 (23.1%)	2,652 (22.8%)
	English proficient	60,831 (63.9%)	5,688 (59.3%)	29,331 (63.1%)	5,073 (63.3%)	33,381 (53.7%)	6,800 (58.5%)
	Missing	16,812 (17.7%)	1,773 (18.5%)	7,578 (16.3%)	993 (12.4%)	11,147 (17.9%)	1,649 (14.2%)
	Unknown	4,906 (5.2%)	316 (3.3%)	1,614 (3.5%)	184 (2.3%)	3,322 (5.3%)	529 (4.5%)
FRPL	FRPL	22,867 (24.0%)	3,053 (31.8%)	12,592 (27.1%)	3,449 (43.0%)	20,929 (33.6%)	5,586 (48.0%)
	FRPL ineligible	16,638 (17.5%)	1,457 (15.2%)	8,341 (17.9%)	707 (8.8%)	8,330 (13.4%)	1,046 (9.0%)
	Missing	53,811 (56.6%)	4,871 (50.8%)	24,219 (52.1%)	3,657 (45.6%)	30,857 (49.6%)	4,812 (41.4%)
	Unknown	1,813 (1.9%)	211 (2.2%)	1,335 (2.9%)	203 (2.5%)	2,083 (3.3%)	186 (1.6%)
Gender	Female	45,660 (48.0%)	4,748 (49.5%)	21,835 (47.0%)	3,906 (48.7%)	30,029 (48.3%)	5,617 (48.3%)
	Male	48,107 (50.6%)	4,808 (50.1%)	23,618 (50.8%)	4,068 (50.7%)	31,801 (51.1%)	5,964 (51.3%)
	Missing	1,279 (1.3%)	34 (0.4%)	1,018 (2.2%)	38 (0.5%)	363 (0.6%)	47 (0.4%)
	Non-binary	81 (0.1%)	2 (0.0%)	16 (0.0%)	4 (0.0%)	6 (0.0%)	2 (0.0%)
	Unknown	2 (0.0%)	—	—	—		

Variable	Category	Comparison	Intervention	Comparison	Intervention	Comparison	Intervention
		High School		Middle School		Elementary School	
Race/Ethnicity	Asian	6,077 (6.4%)	396 (4.1%)	1,612 (3.5%)	106 (1.3%)	1,448 (2.3%)	120 (1.0%)
	Black	19,198 (20.2%)	2,512 (26.2%)	10,637 (22.9%)	2,105 (26.3%)	12,921 (20.8%)	3,229 (27.8%)
	Latinx	22,503 (23.7%)	2,647 (27.6%)	12,678 (27.3%)	2,526 (31.5%)	16,764 (27.0%)	3,342 (28.7%)
	Missing	8,611 (9.1%)	1,082 (11.3%)	1,495 (3.2%)	416 (5.2%)	9,206 (14.8%)	1,561 (13.4%)
	Multiracial	2,600 (2.7%)	211 (2.2%)	1,561 (3.4%)	237 (3.0%)	2,063 (3.3%)	364 (3.1%)
	Native American	1,581 (1.7%)	287 (3.0%)	723 (1.6%)	171 (2.1%)	839 (1.3%)	151 (1.3%)
	Pacific Islander	523 (0.5%)	34 (0.4%)	336 (0.7%)	30 (0.4%)	412 (0.7%)	70 (0.6%)
	White	34,036 (35.8%)	2,423 (25.3%)	17,445 (37.5%)	2,425 (30.3%)	18,546 (29.8%)	2,793 (24.0%)