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# THE IMPACT OF RELAY GRADUATE SCHOOL OF EDUCATION TEACHERS ON STUDENT ATTENDANCE

Evidence from New York City

# EXECUTIVE SUMMARY

This report examines the effects of educators who are prepared and developed by the Relay Graduate School of Education in New York City on students' attendance. Our analysis includes data from all students in New York City public schools in grades three to eight between 2014 and 2019. We provide descriptive statistics on the students in our sample, including those who took at least one course taught by Relay teachers and those who did not take any courses taught by Relay teachers. We then present results from our analysis of the impact of Relay teachers on students' attendance compared to non-Relay teachers, and examine how our results vary by students' gender, grade level, English language proficiency, eligibility for free and reduced-price lunch, special education status, and prior academic achievement. Our results show that Relay teachers were more likely to teach students of color (Black and Hispanic) and students with backgrounds that are associated, on average, with more absences, such as those eligible for free and reduced-price lunch (FRL), students receiving special education, or students who are English Language Learners (ELL). We also found that Relay-prepared teachers were more effective than non-Relay teachers in improving students' attendance. Finally, our analyses found that assignment to Relay-prepared teachers had positive impacts on attendance for students of color, students who always had FRL or ELL status, and students with low prior achievement in English Language Arts (ELA). We contextualize the results of the analysis, discuss considerations for interpreting the results, and outline possible future directions of this research.

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# INTRODUCTION

Existing empirical studies indicate a negative relationship between student absences and student achievement, in that students with higher rates of absence experience lower academic achievement (Aucejo & Romano, 2016; Gershenson, 2016; Gershenson, Jacknowitz, & Brannegan, 2017; Goodman, 2014; Gottfried, 2009, 2011). These studies used nationally representative datasets (e.g., Early Childhood Longitudinal Study-Kindergarten Cohort) or longitudinal datasets from districts or states and found negative effects of student absences on math and reading test scores. For example, Gershenson et al. (2017) found that a one standard deviation increase in absences is associated with decreases in reading and math achievement of 0.02 and 0.04 test-score standard deviations, respectively.

The Relay Graduate School of Education (Relay) is an accredited national non-profit institute of higher education focused on educator preparation and development. They have 19 campuses across the U.S. focused on training aspiring teachers via a two-year residency program, providing advanced certification and master's degree programs for current teachers, and developing school and systems leaders through leadership institutes and professional development programs.

In New York City, Relay has recruited and trained new teachers to prepare them to teach in high-needs schools within the New York City Department of Education (NYCDOE). Although Relay has experienced strong growth since its inception in 2012, its effects on student outcomes have not yet been well documented. In this report, we aim to estimate the Relay program's effect on student absences. Particularly, we use longitudinal student-level data linked to teacher data in New York City, and we estimate the effect of having a Relay teacher on student absences, compared to having a non-Relay teacher.

In this report, we focus on the following research questions:

- Does assignment to Relay-trained teachers reduce student absences?
- Do effects differ across student characteristics?

# DATA

To evaluate the impact of the Relay program on non-academic student outcomes, we used data received from the NYCDOE covering the 2014-15 through 2018-19 school years. First, we obtained a list of teachers who graduated from the Relay program from the Relay Graduate School of Education. Second, we received course-taking data from the NYCDOE, which included course ID, the number of credits attempted/earned, the course section, teacher ID, school ID, and course start and end dates. We used a data crosswalk available on the New

York State Department of Education (NYSED) website,[1] which lists all state course codes and their subjects, to identify the subject content area of each course in the NYCDOE data. The official state course ID variable was used to identify the courses that students were assigned to participate in each school year. We used these data to create course-level linkages, which match students to teachers in specific subject areas.

Lastly, we obtained student-level data from the NYCDOE on student demographics, yearly and total attendance, and state assessment scores. The demographic records contain information on student race/ethnicity, gender, English Language Learner (ELL) status, status for qualifying for free/reduced lunch (FRL), and receipt of an Individualized Education Plan (IEP).[2] The New York state assessments used in this analysis are state-mandated and grade-level specific, and they are taken in the spring of each school year.

## *Relay Measures*

For each course, the Relay indicator variable was assigned a "1" if a student received course instruction from a Relay teacher at a specified school during the school year. Although students in our sample took as many as 13 courses taught by Relay teachers, fewer than 4% of students across years took at least one course taught by Relay teachers in New York City.

Given that Relay's effects on outcomes could be larger among students with greater exposure to Relay teachers, we created a *Relay dosage variable* for each student in a given year, which was directly proportional to the number of courses in which a teacher instructed a student and inversely proportional to the number of teachers co-teaching a single course. If a student were to take a larger number of courses with one teacher, the teacher would be likely to spend more time with the student and exert more influence on the student's outcomes. For example, suppose that a student took four courses taught by two teachers, X and Y. Non-Relay Teacher X taught the student in three courses (identifiable by unique course IDs), and Relay Teacher Y taught the student in one course (distinct from Teacher X's courses). Non-Relay Teacher X would be assigned a weight of ¾ and Relay Teacher Y would be assigned a weight of ¼ for this specific student. As Relay Teacher Y taught the student 25% of the instructional time, the Relay dosage of Teacher Y would be 0.25. In cases where a course was co-taught, the Relay dosage variable was updated to reflect that instructional time was shared among multiple teachers. For example, if a course were co-taught by one Relay teacher and one Non-Relay teacher, then the instructional time for that course would be split and only half contributed to the Relay dosage. In the example above, if the course that Relay Teacher Y

[1] http://www.p12.nysed.gov/irs/courseCatalog/home.html

[2] The NYCDOE demographic data dictionary states that in order to comply with legal requirements, the DOE can no longer release the meal code for individual students. Instead, an indicator is provided that signifies if a student qualifies for a free lunch, a reduced lunch, or attends a universal feeding school.

taught was in fact co-taught with Non-Relay Teacher X, then the Relay dosage of teacher Y would become 0.125, because half of that instructional time was attributed to Non-Relay Teacher X.

## *Attendance Measures*

Because the average number of absences differs by grade and by year, we normalized the number of absences by grade and by year, meaning we transformed them to have a mean of zero and standard deviation equal to one.[3] This normalization allows for the estimated coefficient from our models to be interpreted as fractions of a standard deviation, which is a common metric for reporting effect sizes.

In order to explore whether the results were specific to certain ways of specifying attendance, we created alternative measures of attendance. Attendance rates for each student for a given school year were calculated by dividing the sum of the number of days the student was present in a particular school year by the total number of school days.[4] To reduce the skewness of the data, and to ease the interpretation of regression coefficients, we also used the log of the number of absences in each grade.[5] In this report, we only discuss results from the main attendance measure (i.e., average number of absences), as results did not differ significantly across these different attendance measures.

In addition to these alternative attendance measures, we calculated prior attendance measures, such as the number of prior absences and attendance rates. Each student received an attendance measure for each school that they attended in a given school year. To measure prior attendance, the number of days present and absent was added *across* each school that a student attended; these numbers were then used to calculate *overall prior attendance days* for each student, which were not linked to a particular school, and which we then normalized by grade and school year.

## *Test Scores*

We used standardized test scores in math and English language arts (ELA) for students in grades three through eight. The test scores were standardized by grade level, subject, and

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[3] We used student grade level as defined in the attendance dataset. As the attendance dataset is unique by school and year, it is only possible for a student to be enrolled in one grade level per year.

[4] Roughly 10% of students were designated as attending more than 180 total school days, which is likely due to the fact that students in different schools started at different times in the school year.

[5] By log-transforming the dependent variable, the estimated coefficient on the control variable indicates the percent change in the outcome associated with a one-unit increase in the control variable. For example, if the estimated coefficient on the Relay indicator were -0.2 when we use log-transformed absences, it means that Relay teachers would *decrease* the number of absences by 20% relative to non-Relay teachers.

school year. If a student had multiple test scores in a school year, we used the highest test score.

### *Student Demographics*

We used the following demographic variables in our analysis: student race/ethnicity, gender, English Language Learner (ELL) status, status for qualifying for free/reduced lunch (FRL), and receipt of an Individualized Education Plan (IEP). Note that the labels and categories (e.g., the categories for student race/ethnicity) that we used in the analysis and that we reference in this report are the variables that were included in the dataset.

Some of these student program variables are *time variant*, meaning that students can be identified as ELL, receiving FRL, or receiving an IEP in some years and not in other years. For example, a student may be identified as ELL when they are in elementary school, but by the time they enter middle school, they may no longer be identified as ELL. In addition to these program variables, we calculated *time invariant* program variables to reflect if students were (i) ever, (ii) always, or (iii) never identified as ELL, qualifying for an IEP, or receiving FRL across years.

We also saw cases in which a student's gender or race/ethnicity changed across school years (for example, from White to Hispanic). In these cases, the student's race/ethnicity and gender variables were updated to be time invariant; specifically, the student's race/ethnicity or gender variable was set to the value that appeared most frequently across years. If a student had multiple values for the same number of years, then the most recent value was prioritized and set as the student's race/ethnicity or gender (because it is closest in time to when they last had an opportunity to express their racial/ethnic or gender identity). Although we recognize this may ignore the potential effect of evolving student identities over time, the number of students where this was the case was relatively small. In our sample, 0.36% of students were assigned multiple gender categories across years, and 2.53% of students were assigned multiple racial identifications across years.

## SAMPLE

This report estimates the effect of Relay teachers on student absences using longitudinal administrative data from the population of third through eighth graders who attended New York City's public schools between the 2013-14 and 2018-19 school years.

We used data on all third- to eighth-grade students attending public schools in New York City between 2014 and 2019, and we made a series of sample restrictions. First, we focused on four academic subjects: math, ELA, social studies, and science.[6] This restriction excluded 51,470 courses, leaving 59,801 courses for inclusion. Second, for students who repeated a grade, we used the last observation available. Third, we excluded students who were reported to exhibit extreme attendance behaviors; in particular, we dropped observations when a student was reported to be absent for more than 50 of the 180 days for the current or the prior school year (2.16% of the sample). We also dropped students whose total number of school days (sum of the number of days absent and number of days present) was below 175 days for a school year or the prior school year. We further dropped students whose teacher-student linkage or demographic information was not available (1.96% of the sample).

Summary statistics are presented in Table 1. The analysis sample contains 2.2 million student-year observations and 803,851 unique students attending 1,239 schools from 33 NYC geographic districts. The course data cover 786,058 unique classrooms taught by 52,215 unique teachers. All test scores and numbers of absences were normalized by grade and year to have means equal to zero and standard deviations equal to one.[7] On average, students were absent about 9 times per year, and the standard deviation of about 9 indicates that there is substantial variation across student-years in the sample.

[6] By restricting to four key academic courses, we implicitly assumed that each teacher in these key subjects, including co-teaching teachers, contributed equally to changes in students' attendance outcomes.

[7] Note that the means and standard deviations of these standardized measures are not precisely zero and one in the analysis sample, because they were standardized using all available test scores and absences prior to the sample restrictions.

Table 1. Descriptive Statistics of Analysis Sample

| | All students **(N= 2,218,414)** | | Students who took at least one course by Relay teachers **(N= 84,056)** | | Students who did not take any courses by Relay teachers **(N= 2,134,358)** | | Mean Diff-erence **(3-5)** |
|---|---|---|---|---|---|---|---|
| | Mean **(1)** | SD **(2)** | Mean **(3)** | SD **(4)** | Mean **(5)** | SD **(6)** | **(7)** |
| **Absences (Days)** | 9.365 | 9.040 | 10.639 | 9.759 | 9.314 | 9.007 | 1.325* |
| **Absences (Normalized)** | -0.077 | 0.773 | -0.007 | 0.739 | -0.080 | 0.774 | 0.073* |
| **Chronically Absent** | 0.158 | 0.365 | 0.198 | 0.398 | 0.157 | 0.363 | 0.041* |
| **Prior Year Outcomes** | | | | | | | |
| Math (Normalized) | 0.041 | 0.986 | -0.241 | 0.903 | 0.054 | 0.988 | **-0.296*** |
| Reading (Normalized) | 0.036 | 0.996 | -0.222 | 0.916 | 0.049 | 0.998 | **-0.270*** |
| Absences (Days) | 9.190 | 8.868 | 10.187 | 9.389 | 9.15 | 8.845 | 1.037* |
| Absences (Normalized) | -0.125 | 0.741 | -0.033 | 0.736 | -0.129 | 0.741 | 0.096* |
| **Gender** | | | | | | | |
| Female | 0.486 | 0.500 | 0.486 | 0.500 | 0.486 | 0.500 | -0.001 |
| Male | 0.514 | 0.500 | 0.514 | 0.500 | 0.514 | 0.500 | 0.001 |
| **Race/Ethnicity** | | | | | | | |
| Non-Hispanic White | 0.17 | 0.375 | 0.074 | 0.262 | 0.174 | 0.379 | -0.100* |
| Non-Hispanic Black | 0.225 | 0.417 | 0.284 | 0.451 | 0.222 | 0.416 | 0.061* |
| Hispanic | 0.412 | 0.492 | 0.534 | 0.499 | 0.407 | 0.491 | 0.127* |
| Asian | 0.178 | 0.383 | 0.096 | 0.294 | 0.181 | 0.385 | -0.086* |
| Other | 0.008 | 0.088 | 0.007 | 0.083 | 0.008 | 0.088 | -0.001* |
| **FRL** | | | | | | | |
| FRL | 0.723 | 0.447 | 0.834 | 0.372 | 0.719 | 0.45 | 0.115* |
| Non-FRL | 0.277 | 0.447 | 0.166 | 0.372 | 0.281 | 0.45 | -0.115* |
| Always-FRL | 0.510 | 0.500 | 0.634 | 0.482 | 0.505 | 0.500 | 0.129* |
| Ever-FRL | 0.348 | 0.476 | 0.300 | 0.458 | 0.350 | 0.477 | -0.050* |
| Never-FRL | 0.142 | 0.349 | 0.066 | 0.248 | 0.145 | 0.352 | -0.079* |
| **IEP** | | | | | | | |
| IEP | 0.219 | 0.413 | 0.241 | 0.428 | 0.218 | 0.413 | 0.023* |
| Non-IEP | 0.781 | 0.413 | 0.759 | 0.428 | 0.782 | 0.413 | -0.232* |
| Always-IEP | 0.134 | 0.340 | 0.140 | 0.347 | 0.134 | 0.340 | 0.007* |
| Ever-IEP | 0.119 | 0.324 | 0.133 | 0.339 | 0.119 | 0.324 | 0.014* |
| Never-IEP | 0.747 | 0.435 | 0.727 | 0.445 | 0.748 | 0.434 | -0.020* |

| | All students (N= 2,218,414) | | Students who took at least one course by Relay teachers (N= 84,056) | | Students who did not take any courses by Relay teachers (N= 2,134,358) | | Mean Diff-erence (3-5) |
|---|---|---|---|---|---|---|---|
| | Mean (1) | SD (2) | Mean (3) | SD (4) | Mean (5) | SD (6) | (7) |
| **ELL** | | | | | | | |
| ELL | 0.120 | 0.325 | 0.128 | 0.335 | 0.120 | 0.324 | 0.009* |
| Non-ELL | 0.880 | 0.325 | 0.872 | 0.335 | 0.880 | 0.324 | -0.009* |
| Always-ELL | 0.072 | 0.259 | 0.096 | 0.294 | 0.072 | 0.258 | 0.024* |
| Ever-ELL | 0.137 | 0.344 | 0.154 | 0.361 | 0.136 | 0.343 | 0.018* |
| Never-ELL | 0.791 | 0.407 | 0.750 | 0.433 | 0.792 | 0.406 | -0.042* |
| **Grade** | | | | | | | |
| Grade 3 | 0.173 | 0.379 | 0.013 | 0.111 | 0.180 | 0.384 | -0.167* |
| Grade 4 | 0.174 | 0.379 | 0.011 | 0.105 | 0.180 | 0.384 | -0.169* |
| Grade 5 | 0.171 | 0.377 | 0.027 | 0.162 | 0.177 | 0.382 | -0.150* |
| Grade 6 | 0.161 | 0.368 | 0.31 | 0.463 | 0.155 | 0.362 | 0.155* |
| Grade 7 | 0.160 | 0.367 | 0.351 | 0.477 | 0.153 | 0.360 | 0.198* |
| Grade 8 | 0.160 | 0.366 | 0.289 | 0.453 | 0.155 | 0.362 | 0.134* |
| **No. of Unique Students** | 803,851 | | 68,250 | | 796,670 | | |

*Note: The analysis sample consists of third- to eighth-grade students between 2014 and 2019. SD indicates standard deviation.*
**Difference in means between students who took at least one course by Relay teachers and students who have never taken any courses by Relay teachers is statistically significant at* $p < 0.05$.

The sample was 17% White, 23% African American, 41% Hispanic, and 18% Asian. Students were 49% female. 12% of students were designated as English language learners, 22% of students had an IEP, and 72% of students qualified for FRL. The analysis sample is roughly evenly split across grades.

In addition to the overall sample statistics (Columns 1 and 2), we present statistics among students who took at least one course taught by Relay teachers (Columns 3 and 4), and among students who never took any courses by Relay teachers (Columns 5 and 6) in a given year. In Column 7, we also present the difference in means between students taught by Relay teachers (Column 3) and those never taught by Relay teachers (Column 5), along with the *p*-value of this difference in Column 8.

Approximately 4% of students were taught by a Relay teacher in a given year.[8] In our sample, 68,250 students took at least one course instructed by a Relay teacher, and they took on

[8] Appendix Table 1 shows that the number of first-year Relay teachers increased from 118 in 2014 to 342 in 2018. Relay teachers made up roughly 4% of all first-year teachers and 1% of all New York City public school teachers

average the equivalent of 1.6 courses instructed by Relay teachers. The 90th percentile of the distribution is the equivalent of 3 courses (meaning 90% of students in our sample took between 0 and 3 courses instructed by a Relay teacher), and there is a long right-hand tail extending to the equivalent of 13 courses (meaning there is a small number of students who took a large number of courses instructed by Relay teachers).

Comparing Columns 3 and 5 shows there are statistically significant differences between students taught by Relay teachers and those not taking courses by Relay teachers, both in terms of their outcomes and student characteristics. For example, students of Relay teachers missed school for 1.3 additional days, compared to students of non-Relay teachers. If we compare their prior year outcomes, students taught by Relay teachers had lower test scores and more absences in the prior year than students never taught by Relay teachers. Thus, Relay teachers appear to be assigned, on average, to lower-achieving students.

In terms of students' demographic characteristics, Relay teachers instruct more students of color (i.e., higher percentages of Black and Hispanic students), more ELL students, more students qualifying for FRL, more students receiving an IEP, and more students in upper grades (i.e., higher percentages in grades six to eight). Thus, if there are differential rates of student absences across these characteristics—for example, more absences for students of color—then a direct comparisons of students' absences between those two groups is likely to underestimate Relay program effects.[9]

Next, we explore the differences in student absence by grade level, gender, race/ethnicity, ELL status, FRL status, and IEP status. We are particularly interested in whether there are differences in absences across student demographic groups and program participation status, and how these differences relate to estimating Relay program effectiveness. Table 2 shows a small but statistically significant difference of less than a full day of absence across grades and between boys and girls.[10] We found a larger difference in the number of absences between racial/ethnic student groups; for example, Black and Hispanic students experienced roughly two more absences than White students, whereas Asian students experienced fewer absences than White students. We found a significant but small difference between ELL and non-ELL

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since 2014. In 2018 and 2019, Relay teachers consisted of 6% of all first-year teachers. The share of Relay teachers was similar when we restricted the sample to key academic subjects, including math, ELA, social studies, and science (Appendix Table 2).

[9] Additional descriptive analyses comparing first-year Relay teachers with non-Relay teachers showed that a larger proportion of Relay teachers were from racial/ethnic minority backgrounds, such as Black and Hispanic (Appendix Table 3). About 56% of Relay teachers were non-White, compared to 42% among non-Relay teachers. In addition, Relay teachers had a larger proportion of male teachers (30%) compared to non-Relay teachers (21%). We found similar patterns if we included all teachers (Appendix Table 4) or only first-year teachers in grades six to eight (Appendix Table 5).

[10] We also found that the number of absences as well as the standard deviation of absences increased over grades, indicating that the meaning of one day of absence differs by grade. Thus, we use the *standardized absence by grade and by year* as our main outcome.

students. Students eligible for FRL experienced nearly three more absences than their non-eligible peers. When we compared students who were *always* eligible for FRL with those *never* eligible for FRL, the difference increased to four days of absences, corresponding to half the sample standard deviation reported in Table 1. Note that students who took courses with Relay teachers are more likely to be Always-FRL than those who did not. Finally, we found large differences in the number of absences by IEP status: about four additional absences for students who have an IEP.

**We found that the following student groups experienced significantly more absences: Black and Hispanic students, students qualifying for FRL, and students receiving an IEP.**

In sum, the differences in the number of absences are both large and statistically significant across race/ethnicity, FRL, and IEP status (in addition to a small but statistically significant difference for ELL students). As Relay teachers are more likely to teach students of color and students from historically marginalized backgrounds (Table 1), not accounting for these differences is likely to underestimate the Relay program’s effects on absences. We describe the empirical strategy in the next section.

Table 2. Differences in Student Absences

| | Mean | SD | N | Mean Difference |
|---|---|---|---|---|
| **Female** | 9.135 | 8.897 | 1,078,691 | |
| **Male** | 9.582 | 9.168 | 1,139,723 | 0.448* |
| **Race/Ethnicity** | | | | |
| Non-Hispanic White | 8.431 | 7.528 | 376,732 | |
| Non-Hispanic Black | 11.102 | 9.852 | 498,376 | 2.671* |
| Hispanic | 10.762 | 9.398 | 913,394 | 2.331* |
| Asian | 4.898 | 6.543 | 394,853 | -3.534* |
| Other | 9.513 | 8.862 | 17,318 | 1.082* |
| **FRL** | | | | |
| FRL | 10.093 | 9.552 | 1,604,379 | 2.631* |
| Non FRL | 7.462 | 7.199 | 614,035 | |
| Always-FRL | 10.623 | 9.878 | 1,131,664 | 4.168* |
| Ever-FRL | 8.705 | 8.401 | 772,668 | 2.251 |
| Never-FRL | 6.454 | 6.064 | 314,082 | |
| **IEP** | | | | |
| IEP | 12.460 | 10.337 | 485,244 | 3.962* |
| Non-IEP | 8.498 | 8.441 | 1,733,170 | |
| Always-IEP | 12.739 | 10.438 | 296,773 | 4.277* |
| Ever-IEP | 11.229 | 9.886 | 264,927 | 2.767* |
| Never-IEP | 8.462 | 8.419 | 1,656,714 | |
| **ELL** | | | | |
| ELL | 9.402 | 8.983 | 265,982 | 0.043* |
| Non-ELL | 9.360 | 9.048 | 1,952,432 | |
| Always-ELL | 10.397 | 9.451 | 160,730 | 0.762* |
| Ever-ELL | 7.256 | 7.846 | 303,683 | -2.379* |
| Never-ELL | 9.635 | 9.142 | 1,754,001 | |
| **Grade** | | | | |
| Grade 3 | 9.562 | 8.871 | 384,473 | |
| Grade 4 | 9.139 | 8.860 | 385,870 | -0.423* |
| Grade 5 | 9.126 | 8.775 | 380,236 | -0.436* |
| Grade 6 | 8.904 | 8.907 | 357,870 | -0.658* |
| Grade 7 | 9.068 | 9.246 | 355,751 | -0.493* |
| Grade 8 | 10.417 | 9.521 | 354,214 | 0.855* |

*Note: The analysis sample consists of third- to eighth-grade students between 2014 and 2019. SD indicates standard deviation. Mean difference t-tests were performed to compare third to upper grades, males and females, students who are and are not ELL, students who are and are not eligible for FRL, and students receiving and not receiving an IEP. For longitudinal program participation status, we use the never-participated students (i.e., Never-FRL, Never-IEP, and Never-ELL) as the reference group.*
** Difference in means statistically significant at $p < 0.05$.*

# METHODS

We used longitudinal student-level data linked to teachers to estimate the effectiveness of Relay program teachers in improving student attendance. As previously described, Relay teachers are different from non-Relay teachers with respect to the students they teach. Relay teachers are more likely to teach students of color and those with historically marginalized backgrounds, who are more likely to be absent (see Table 2), indicating that teacher assignment is not random. Because we see that prior student performance, as measured by previous test scores and number of absences, is related to teacher assignment, the non-random matching of teachers to students is likely to bias the estimates from our models. For example, if Relay teachers are systematically assigned to students with a greater tendency to be absent, then the estimated effects of Relay teachers on students' attendance are likely to be biased downward (i.e., underestimated). In addition, if Relay teachers are assigned to courses with students who have differences in unobservable factors (e.g., student motivation or academic ability), then cross-sectional approaches that do not account for the non-random matching of teachers and students are likely to produce biased estimates of the Relay program effects on absences.

To address the non-random sorting of teachers and students, both across and within schools, we are using plausibly random variation in assignment to Relay teachers within students and within schools over time. Specifically, we use student fixed effects models that take advantage of the longitudinal data where we can observe both changes in student absences and exposure to Relay teachers over time. We additionally control for school fixed effects, grade-by-year fixed effects, and any time-varying student characteristics, including ELL, FRL, and IEP status. Relay teacher effects on student absences are identified by estimating the following model:

$$A_{ist} = \alpha Relay_{it} + \gamma X_{it} + \mu_i + \omega_s + \pi_{gt} + \epsilon_{it} \qquad (1)$$

where:

- $A_{ist}$ is the attendance outcome for student *i* attending school *s* in year *t,* normalized by grade and by year, and with mean of zero and standard deviation equal to one;
- $Relay_{it}$ is the fraction of courses that student *i* was taught by Relay teachers in year *t;*
- $X_{it}$ is a vector of time-varying student characteristics (including ELL, FRL, and IEP status);
- $\mu_i$ are student fixed effects;
- $\omega_s$ are school fixed effects;
- $\pi_{gt}$ are grade-by-year fixed effects; and
- $\epsilon_{it}$ is the random error term.

The parameter of interest is $\alpha$, which provides an estimate of the effect of being taught by Relay-trained teachers on student attendance.[11] The identification of Relay effects in this model comes from students whose exposure to Relay teachers varies across years. School fixed effects control for non-random sorting of teachers across schools, and grade-by-year fixed effects account for time-varying differences in absences across grade and year. The student fixed effect examines the relationship between (i) within-student variation in exposure to Relay teachers and (ii) student absences, among students who are in the same school, year, and grade.[12]

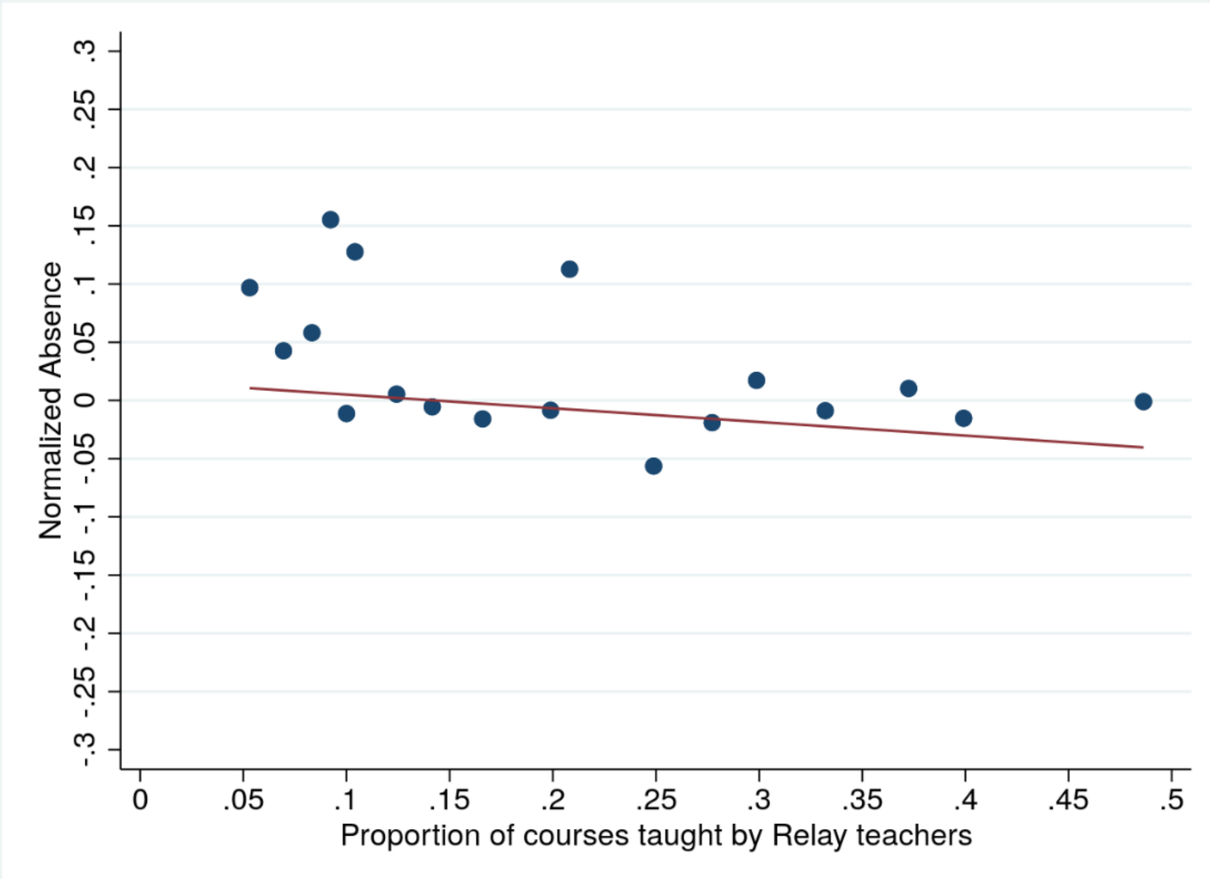
Figure 1 depicts the relationship between the number of student absences and exposure to Relay teachers using all students (grades 3-12) from 2014 to 2019.[13] As Figure 1 shows, the fraction of courses taught by Relay teachers for each student-year is concentrated between 0.05 and 0.15, and there are some students who took more than 25% of their courses by Relay teachers. The negative slope of the fitted line indicates that students who took more courses by Relay teachers have a smaller number of absences. As the exposure to Relay teacher also varies for each student, we used the within-student variation to estimate the effect of Relay teachers on student absences.

[11] Note that we are not estimating individual teacher's contribution to student absences but, rather, the effectiveness of Relay program on the student absences.

[12] As Rothstein (2010) noted, this approach does not fully address the bias if course assignments are associated with time-varying unobserved determinants of student absences.

[13] We grouped the x-axis into 50 equal-sized bins, computed the mean of the x-axis (proportion of courses taught by Relay teachers) and y-axis (number of absences) variables within each bin, and created the scatterplot of these data points.

Figure 1. Number of Absences and Exposure to Relay Teachers




*Note: Observations are counts of student absences from 2014-2019 for students from grades 3-12.*

# RESULTS

As mentioned above, we used student fixed-effects models to estimate the effect of Relay teachers on student absences, accounting for the non-random sorting of teachers to students both across and within schools. To understand the extent to which student fixed effects models help us identify Relay effects on absences, we add lagged standardized outcomes (i.e., prior-year outcomes) to Equation (1) and estimate the following model,

$$A_{it} = \alpha Relay_{it} + \beta y_{i,t-1} + \gamma X_{it} + \mu_i + \omega_s + \pi_{gt} + \epsilon_{it} \qquad (2)$$

where:

- $y_{i,t-1}$ is a vector of standardized math test scores, ELA test scores, and number of absences from the previous year.

Because we used prior-year outcomes, we included fourth- to eighth-grade students between 2015 and 2019.

Table 3 summarizes the coefficients estimated in Equation (2), where the outcome (displayed in the first row) is the standardized number of absences. Each column reports the results from a variation of the basic model, all of which include controls for student demographic characteristics, lagged outcomes, grade-by-year fixed effects, and corresponding fixed effects. Column 1 indicates that students who took all of their courses taught by Relay teachers had a 0.017 standard deviation reduction in absences, compared to those who took no courses by Relay teachers. Column 2 shows results from a model that controls for school-level differences in attendance and teacher assignment; here, the estimated coefficient on the Relay indicator is closer to zero and not statistically significant. However, when we additionally control for student fixed effects, as shown in Column 3, the estimated coefficient increases to 0.026, which is significant at the $p$ = .01 significance level. These results suggest that students who took more courses by Relay teachers are less likely to be absent and the magnitude is not negligible.

Table 3. Estimated Relay Program Effects on Standardized Absences

| | (1) | (2) | (3) |
|---|---|---|---|
| Relay | -0.017* | -0.006 | -0.026** |
| | (0.008) | (0.009) | (0.009) |
| | | | |
| Grade-by-Year FE | O | O | O |
| School FE | | O | O |
| Student FE | | | O |
| $R^2$ | 0.556 | 0.562 | 0.801 |
| Observations | 1,215,725 | 1,215,725 | 1,215,725 |

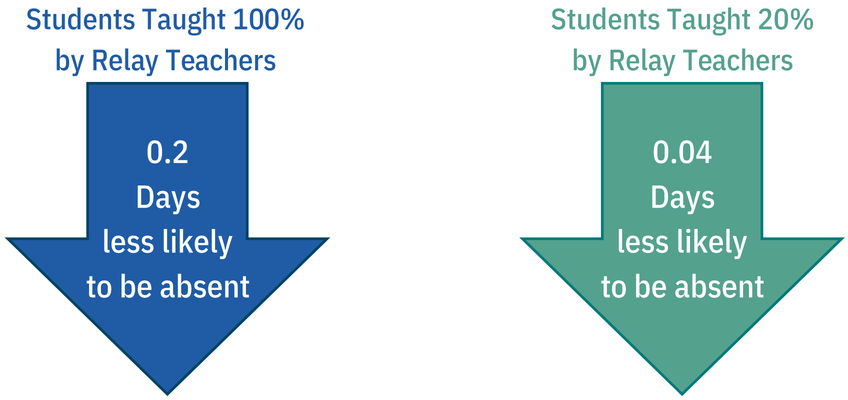
*Note: The outcome is the number of absences standardized by grade and by year. Each column includes controls for student demographics (gender, race/ethnicity, ELL, IEP, and FRL), lagged outcomes (math test scores, ELA test scores, and number of absences, all of them standardized by grade and by year), and grade-by-year fixed effects. Robust standard errors are in the parentheses.*

* $p < 0.05$, ** $p < 0.01$

For example, the estimated coefficient of -0.026 indicates that students who were *taught entirely by Relay teachers* (i.e., for 100% of their courses) are 0.026 standard deviations, or 0.2 days, less likely to be absent compared to students who took no courses by Relay teachers (i.e., 0% of their courses). In our sample, for those students who took at least one course from a Relay teacher, they were exposed to Relay teachers, on average, in 20% of their courses; therefore, we can translate the -0.026 coefficient into the effect for students who were *taught by Relay teachers 20% of the time*: for those students, they are expected to experience 0.04 days fewer absences.

**Students taught by Relay teachers were significantly less likely to be absent than students taught by non-Relay teachers.**

Figure 2. Estimated Relay Program Effects on Standardized Attendance




Given that the current number of absences and lagged academic and absence measures are highly correlated, the addition of lagged outcomes in Equation (2) might not add much exploratory power to the model. If this is the case, then we can drop the lagged outcomes and add an additional grade and year of data (i.e., grade 3, since we would no longer require data from the prior year), which is expected to improve the precision of our estimates. Table 4 presents the estimates when we include one additional year of data (Column 2), drop lagged outcomes (Column 3), and include an additional grade in the model (Column 4). The estimates in Column 1 (which are identical to Column 3 in Table 3) are qualitatively similar to each of the estimates in Columns 2, 3, and 4, which range from -0.026 to -.023. As the estimates are similar to each other in their magnitudes and statistical powers, we use the sample and specification in Column 4 as the main model, which adds roughly 800,000 observations to the model enabling us to more precisely estimate the Relay effects not only in full sample but also in subgroup analyses.[14]

[14] We also estimate a model where the dependent variable is the log of the number of absences plus 1. The estimated coefficient is -0.016, significant at the $p < .10$ level, suggesting that students who were entirely taught by Relay teachers are 1.6 percentage points, or 16%, less likely to be absent compared to students of non-Relay teachers.

Table 4. Relay Effects on Standardized Absences, by Grade and Year Span

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Relay | -0.026** | -0.026** | -0.023** | -0.025*** |
| | (0.009) | (0.008) | (0.008) | (0.008) |
| | | | | |
| Grades Included | 4-8 | 4-8 | 4-8 | 3-8 |
| Years Included | 2015-2019 | 2014-2019 | 2014-2019 | 2014-2019 |
| Lagged Outcomes | O | O | X | X |
| $R^2$ | 0.801 | 0.793 | 0.793 | 0.786 |
| Observations | 1,215,725 | 1,504,323 | 1,624,015 | 2,002,970 |

*Note: The outcome is the number of absences standardized by grade and by year. Each column includes controls for student demographics (ELL, FRL, and IEP), student fixed effects, school fixed effects, and grade-by-year fixed effects. Lagged outcomes include math test scores, ELA test scores, and number of absences, all standardized by grade and by year. Standard errors in parentheses.*

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## *Relay Program Effects by Grade Level*

Next, we estimated the effect of Relay teachers on student absences separately by grade band, with grades 3-5 defined as elementary school and grades 6-8 as middle school. Table 5 summarizes the relationship between exposure to Relay teachers and student absences for these grade bands. Column 1 includes all grades (and is thus identical to Column 4 in Table 4). Column 2 presents the results for elementary grades, and Column 3 for middle school grades. Results are similar across elementary school grades (-0.017, in Column 2) and middle school grades (-0.019, in Column 3). Note that Columns 2 and 3 use a shorter span of data (at most three years for each student) compared to the full dataset, where we can observe a student's outcome for up to 6 years, which means the estimated coefficients in those columns may be less precise.

To test whether the Relay effects are different between elementary and middle schools, we re-estimated Equation (1) in the full sample by including an interaction term for Relay teachers and an elementary school indicator. The elementary school indicator equaled one if a student's grade was between third and fifth. Because the fixed effects approach benefits from a longer span of data, including more years of data allows us to more reliably estimate within-student variation (i.e., the effect of Relay teachers on absences), rather than estimating the effects separately in Columns 2 and 3. The results in Column 4 show that the estimated coefficient on the interaction term, 0.031, is not statistically significant, confirming our earlier finding that Relay program effects in middle school grades are not different from those in elementary school grades.[15]

[15] Note that the estimated coefficients on the Relay term are no longer comparable to each other, because we included the interaction term in Column 4.

**Relay teachers had a similar impact on student attendance in both elementary and middle school grades.**

Table 5. Relay Effects on Standardized Absences, by Grade Bands

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | All Grades (3-8) | Elementary Grades (3-5) | Middle Grades (6-8) | All Grades (3-8) |
| Relay | -0.025*** | -0.017 | -0.019* | -0.031*** |
| | (0.008) | (0.019) | (0.008) | (0.008) |
| Relay x ES | | | | 0.031 |
| | | | | (0.020) |
| $R^2$ | 0.786 | 0.841 | 0.829 | 0.786 |
| Observations | 2,002,970 | 958,876 | 882,072 | 2,002,970 |

*Note: The sample is restricted to students in grades 3 to 8 between 2014 and 2019. The outcome is the number of absences standardized by grade and by year. Each column includes controls for student demographics (gender, race/ethnicity, ELL, IEP, and FRL), student fixed effects, school fixed effects, and grade-by-year fixed effects. Standard errors in parentheses*

** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

## *Effects by Race/Ethnicity and Gender*

The results presented in earlier sections (see Tables 3, 4, and 5) were based on the full sample. However, because Relay teachers are more likely to teach students of color and students from historically marginalized backgrounds (see Table 1), the effects of Relay teachers on attendance could be larger among students who are more exposed to Relay teachers. Given that prior research indicates that the negative effect of absences on test scores is stronger among students from disadvantaged backgrounds (e.g., Gershenson et al., 2017), we examined whether the effect of Relay teachers on absences differ by student demographic characteristics. If the effect is larger among students from historically marginalized backgrounds, then we might expect that having a Relay teacher could contribute to closing achievement gaps.

Table 6 shows the estimated effects of Relay teachers on student absences by race/ethnicity (Columns 1 – 5) and gender (Columns 6 and 7). We also present the average standardized number of absences by demographic subgroup, so that we can compare the effect of Relay teachers across subgroups. For example, the mean standardized number of absences is the largest among Black students, indicating that Black students have the highest number of absences (as reported in Table 2).

The estimated coefficients shown in Columns 1-5 indicate a positive, statistically significant of Relay teachers on students of color, especially Hispanic students. We did not find any Relay effects among White or Asian students, who had a relatively smaller number of absences compared to Black and Hispanic students; this could mean that there was less of an opportunity for improvement to those students' attendance.[16] When we examined Relay effects by gender, results showed that the Relay effects on absences are stronger among male students (Column 6) compared to female students (Column 7).

**Relay teachers had a significantly greater impact on attendance for students of color, especially Hispanic students, and for male students.**

Table 6. Relay Effects on Standardized Absences, by Race/Ethnicity and Gender

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | **Black** | **Hispanic** | **Asian** | **White** | **Non-White** | **Male** | **Female** |
| Relay | -0.025 | -0.026$^{*}$ | -0.033 | 0.009 | -0.029$^{***}$ | -0.032$^{**}$ | -0.017 |
| | (0.016) | (0.011) | (0.021) | (0.025) | (0.008) | (0.011) | (0.011) |
| $R^2$ | 0.773 | 0.781 | 0.743 | 0.761 | 0.789 | 0.789 | 0.783 |
| Mean | 0.070 | 0.043 | -0.458 | -0.158 | -0.061 | -0.059 | -0.097 |
| Observations | 443,103 | 826,265 | 359,404 | 343,232 | 1,659,719 | 1,027,637 | 975,331 |

*Note: The sample is restricted to students in grades 3 to 8 between 2014 and 2019. The outcome is the number of absences standardized by grade and by year. Each column includes controls for student demographics (ELL, IEP, and FRL), student fixed effects, school fixed effects, and grade-by-year fixed effects. Standard errors in parentheses.*

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

## *Effects by Program Participation Status*

Next, we examined whether Relay effects on attendance differ by program participation status, specifically FRL eligibility and ELL status.[17] Because students who have been always eligible for FRL are different from students who were eligible for only one or two years (Michelmore & Dynarski, 2017), we constructed longitudinal measures for FRL eligibility and ELL status, and we estimated effects separately for each group. For example, if a student was eligible for FRL during all observed years, then the student was designated as "Always FRL."

[16] It could also be the case that Relay teachers are less likely to teach White students, and we do not observe significant Relay effects among them. More work on teacher assignment to students is required to fully answer this question.

[17] We also examined Relay effects among IEP recipients. Unlike FRL and ELL status, existing studies show that IEP eligibility and participation differ across schools and/or within school (e.g., Elder, Figlio, Imberman, & Persico, 2021). In NYC, there are 13 disability classifications (https://www.schools.nyc.gov/learning/special-education/the-iep-process/the-iep), but we do not have detailed classification information available in the dataset. Thus, we do not present estimated Relay effects by IEP status here.

Table 7 shows that the effects of Relay teachers are larger among students who were always eligible for FRL (Column 2) and among those who were ever eligible for FRL (Column 3), compared to students who were never eligible for FRL (Column 1). When we estimated Relay effects by ELL status, the effects were largest among students who were always ELL (Column 5). The estimated coefficient is -0.116, which is about four times larger than the overall effects of Relay teachers on students' absences.

**Relay teachers had the largest impact on attendance for students who were ever eligible for FRL, students who were always eligible for FRL in our data, and students who were always designated as ELL in our data.**

Table 7. Relay Effects on Standardized Absences, by Longitudinal Program Status

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Never FRL | Always FRL | Ever FRL | Never ELL | Always ELL | Ever ELL |
| Relay | -0.010 | -0.018$^{+}$ | -0.041$^{**}$ | -0.017$^{*}$ | -0.116$^{***}$ | -0.022 |
| | (0.019) | (0.011) | (0.013 | (0.009) | (0.032) | (0.019 |
| $R^2$ | 0.745 | 0.787 | 0.776 | 0.789 | 0.767 | 0.764 |
| Mean | -0.324 | 0.032 | -0.136 | -0.054 | 0.010 | -0.258 |
| Observations | 281,374 | 1,011,635 | 709,932 | 1,588,973 | 134,683 | 279,282 |

*Note: The sample is restricted to students in grades 3 to 8 between 2014 and 2019. The outcome is the number of absences standardized by grade and by year. Each column includes controls for student demographics (ELL, IEP, and FRL), student fixed effects, school fixed effects, and grade-by-year fixed effects. Standard errors in parentheses.*

*$^{+}$ $p < 0.1$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$*

## *Effects by Prior Performance*

Finally, we studied whether Relay effects differ by students' prior academic performance. We used standardized test scores from the previous year to assign students to a *high-performing* group if their standardized test scores were greater than 1, and to a *low-performing* group if the standardized value was less than -1. Table 8 shows no effects of Relay teachers on student absences among high- and low-math performing students; the estimated effects are not statistically significant. Conversely, we find statically significant Relay effects among low-ELA students (Column 4). The magnitude of the effect is about two times larger than the overall Relay effect, but only about two-thirds of the magnitude among Always-ELL students (Column 5 in Table 7).[18]

[18] Data indicate that one third of Always-ELL students are ELA low-achieving (and vice versa). When we restricted the sample to those who were both Always-ELL and ELA low-achieving, the estimated coefficient was -0.160,

**Relay teachers had a significant impact on attendance for students who had low prior achievement in English language arts.**

Table 8. Relay Effects on Standardized Absence, by Performance Levels

| | (1) Math High | (2) Math Low | (3) ELA High | (4) ELA Low |
|---|---|---|---|---|
| Relay | -0.012 | -0.030 | 0.010 | -0.070* |
| | (0.024) | (0.042) | (0.029) | (0.035) |
| $R^2$ | 0.736 | 0.786 | 0.769 | 0.788 |
| Mean | -0.499 | 0.409 | -0.416 | 0.257 |
| Observations | 177,128 | 112,742 | 139,158 | 143,118 |

*Note: The sample is restricted to students in grades 3 to 8 between 2014 and 2019. The outcome is the number of absences standardized by grade and by year. Each column includes controls for student demographics (ELL, IEP, and FRL), student fixed effects, school fixed effects, and grade-by-year fixed effects. Standard errors in parentheses.*
** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

## *Sensitivity Analyses*

We examined how sensitive our estimates are based on the number of years that students were observed in our data. If a student is present in the data only for a couple of years, within-student variation in absences (across years) are likely to be less reliable than for those students whose data are available for more years. To explore this sensitivity, we estimated effects separately by the number of available years for each student. Results in Appendix Table 6 show that the estimates were robust to the number of observed years.

We also included classroom characteristics (e.g., the average proportion of White students, students with FRL eligibility, average prior test scores) to improve the precision of the estimated program effects, and we found that our estimates were not statistically different from the main estimates reported here. Results were also robust when including school average measures and school-grade average measures.

Because Relay teachers are relatively less experienced compared to the full set of non-Relay teachers in NYC, we risk underestimating the effects of Relay teachers on student absences when using the full sample (i.e., the sample including both experienced and novice teachers), if we suppose that students' attendance behaviors may be related to teachers' experience. As an exploratory exercise, we calculated the average years of experience among teachers who taught the student in a given year, and we added it to Equation (1). The estimated coefficient on the Relay variable was –0.026 (with a standard error of 0.008), which is statistically very

statistically significant at the $p < .001$ level, which is about seven times larger than the estimated overall Relay effects.

similar to our main estimate of –0.025. The estimated coefficient on teachers' years of experience is -0.0002, statistically significant at the $p < .001$ level, indicating that 10 additional years of teacher experience is associated with a reduction in absences of 0.002 standard deviations. From this, we concluded that teacher experience is in fact related to students' absences, but the magnitude is not big enough to invalidate our inference.[19]

# CONCLUSION

In this report, we estimated the effect of being assigned to a Relay-trained teacher on student attendance. Overall results indicated that assignment to a Relay teacher reduced student absences, with larger impacts on students of color, male students, students who are Engilsh language learners and who are eligible for free and reduced price lunch, and students with low prior achievement in English language arts (ELA). Compared to students who were entirely taught by non-Relay teachers, students who took 100% of their courses with Relay teachers experienced:

- About 1/4 of a day (0.025 standard deviations) fewer absences
- About 1 day (0.116 standard deviations) fewer absences for students who were always designated as an ELL
- About 3/5 of a day (0.07 standard deviations) fewer absences for students who had low prior achievement in ELA[20]

In other words, Relay program teachers are more likely to teach groups of students who already tend to experience more absences, and therefore need the most support for improving their attendance—and those are the students for whom Relay teachers have larger effects. Below we include a few considerations for interpreting these results, and possible future directions of this research.

First, Relay teachers are different from non-Relay teachers—not only in terms of the students they are teaching but also with respect to their demographics. Relay teachers are more diverse (i.e., there are more non-White teachers) than non-Relay teachers, and they teach subjects that are often hard to recruit for, such as math and science. The extent to which the Relay program has improved the diversity of the teacher workforce, and how this has affected students' outcomes, is important to study.

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[19] If we wanted to estimate the relationship between teacher experience and student absences more accurately, we would need class-by-class attendance information.

[20] There are fewer than 500 students who were *entirely* taught by Relay teachers in a given year, comprising 0.6% of students who took at least one course by Relay teachers in a given year. As the average Relay dose is around 20%, the expected realized benefits of the Relay program are about one-fifth the size of the full effects based on 100% dosage.

Second, as there are multiple pathways that teachers in New York City can enter teaching (such as traditional university-based programs and other teaching fellow programs), it is important to consider how the impacts that Relay teachers have may compare to the impacts of other kinds of teachers, based on factors like their educational background or training. In this report, we grouped all pathways together as non-Relay pathways. But there may be important differences in how Relay teachers' effects compare to those of teachers from other backgrounds. Access to other teachers' pathway information would help us more precisely estimate the effectiveness of the Relay program.

Finally, this report does not include high school student absences as an outcome, because these students may choose to skip specific courses or periods, rather than skipping full-day classes—but our attendance data is only available at the daily level, rather than at the course level. At the same time, high school students may have more unexcused absences than elementary and middle school students. As unexcused absences are shown to have more harmful effects on student achievement compared to excused absences, more detailed information on the absences (such as distinguishing between excused and unexcused absences and/or classroom-level absences) would be needed to help us better understand the mechanism through which the Relay program is affecting high school students' absence behaviors.

# REFERENCES


Aucejo, Esteban M., and Teresa Foy Romano. 2016. Assessing the effect of school days and absences on test score performance. *Economics of Education Review* 55:70–87. doi:10.1016/j.econedurev.2016.08.007.

Elder, T. E., Figlio, D. N., Imberman, S. A., & Persico, C. L. (2021). School Segregation and Racial Gaps in Special Education Identification. *Journal of Labor Economics*, *39*(S1), S151-S197.

Gershenson, S. (2016). Linking teacher quality, student attendance, and student achievement. *Education Finance and Policy*, *11*(2), 125-149.

Gershenson, S., Jacknowitz, A., & Brannegan, A. (2017). Are student absences worth the worry in US primary schools?. *Education Finance and Policy*, *12*(2), 137-165.

Goodman, Joshua. 2014. Flaking out: Student absences and snow days as disruptions of instructional time. NBER Working Paper No. w20221.

Gottfried, Michael A. 2009. Excused versus unexcused: How student absences in elementary school affect academic achievement. *Educational Evaluation and Policy Analysis* 31(4):392–419.

Gottfried, Michael A. 2011. The detrimental effects of missing school: Evidence from urban siblings. *American Journal of Education* 117(2):147–182. doi:10.1086/657886.

Michelmore, K., & Dynarski, S. (2017). The gap within the gap: Using longitudinal data to understand income differences in educational outcomes. *AERA Open*, *3*(1), 2332858417692958.

Rothstein, J. (2010). Teacher quality in educational production: Tracking, decay, and student achievement. *Quarterly Journal of Economics*, *125*(1), 175-214.

# APPENDIX

TABLE A1. Total Number of Relay and Non-Relay First Teachers in New York City Public Schools by Year, Overall and Among First-Year Teachers

| | First-Year Teachers | | Overall | |
|---|---|---|---|---|
| **Year** | **Relay** | **Non-Relay** | **Relay** | **Non-Relay** |
| 2014 | 67 | 2,415 | 117 | 4,549 |
| 2015 | 69 | 2,959 | 129 | 5,245 |
| 2016 | 63 | 2,923 | 121 | 5,657 |
| 2017 | 104 | 3,063 | 165 | 5,751 |
| 2018 | 174 | 2,836 | 268 | 5,535 |
| 2019 | 153 | 2,463 | 312 | 4,994 |
| ***Total*** | ***616*** | ***16,480*** | ***684*** | ***20,347*** |

*Note: Sample is restricted to teachers who taught any courses in grades 3 to 8 in NYC between 2014-2019.*

TABLE A2. Total Number of Relay and Non-Relay Teachers in New York City Public Schools in Key Academic Courses by Year, Overall and Among First-Year Teachers

| | First-Year Teachers | | Overall | |
|---|---|---|---|---|
| **Year** | **Relay** | **Non-Relay** | **Relay** | **Non-Relay** |
| 2014 | 65 | 2,144 | 114 | 3,998 |
| 2015 | 67 | 2,507 | 126 | 4,548 |
| 2016 | 61 | 2,483 | 119 | 4,809 |
| 2017 | 102 | 2,594 | 161 | 4,889 |
| 2018 | 163 | 2,315 | 256 | 4,613 |
| 2019 | 149 | 2,007 | 302 | 4,061 |
| ***Total*** | ***593*** | ***13,901*** | ***663*** | ***17,387*** |

*Note: Sample is restricted to teachers who taught four key academic courses (math, ELA, social studies, and science) in grades 3 to 8 in NYC between 2014-2019.*

TABLE A3. Descriptive Statistics of Relay and Non-Relay Teachers in New York City Public Schools, Among First-Year Teachers in Grades 3 to 8

| | All Teachers | | Relay | | Non-Relay | | Mean Difference (3-5) |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Male** | 0.211 | 0.408 | 0.294 | 0.456 | 0.208 | 0.406 | 0.086* |
| **Race** | | | | | | | |
| White | 0.576 | 0.494 | 0.438 | 0.497 | 0.582 | 0.493 | -0.144* |
| Non-White | 0.424 | 0.494 | 0.562 | 0.497 | 0.418 | 0.493 | 0.144* |
| Black | 0.152 | 0.359 | 0.258 | 0.438 | 0.147 | 0.354 | 0.111* |
| Hispanic | 0.158 | 0.365 | 0.164 | 0.371 | 0.158 | 0.365 | 0.006* |
| Asian | 0.08 | 0.271 | 0.103 | 0.305 | 0.079 | 0.27 | 0.025* |
| **Years of Experience** | 0.228 | 0.211 | 0.183 | 0.138 | 0.23 | 0.214 | -0.047* |
| **Subject** | 0.645 | 0.479 | 0.533 | 0.499 | 0.65 | 0.477 | -0.116* |
| Math | | | | | | | |
| ELA | 0.721 | 0.448 | 0.396 | 0.49 | 0.736 | 0.441 | -0.340* |
| Social Studies | 0.597 | 0.49 | 0.261 | 0.439 | 0.613 | 0.487 | -0.352* |
| Science | 0.515 | 0.5 | 0.482 | 0.5 | 0.517 | 0.5 | -0.035* |
| **Grade** | | | | | | | |
| Grade 3 | 0.16 | 0.367 | 0.027 | 0.164 | 0.166 | 0.372 | -0.139* |
| Grade 4 | 0.158 | 0.365 | 0.01 | 0.101 | 0.165 | 0.371 | -0.155* |
| Grade 5 | 0.142 | 0.349 | 0.043 | 0.203 | 0.146 | 0.354 | -0.104* |
| Grade 6 | 0.197 | 0.397 | 0.28 | 0.449 | 0.193 | 0.395 | 0.087* |
| Grade 7 | 0.185 | 0.389 | 0.338 | 0.473 | 0.179 | 0.383 | 0.159* |
| Grade 8 | 0.157 | 0.364 | 0.302 | 0.459 | 0.151 | 0.358 | 0.151* |

*Note: Sample is restricted to first-year teachers who taught any of the four key academic courses (math, ELA, social studies, and science) in grades 3 to 8 between 2014-2019. It is possible for a teacher to instruct multiple courses across grades within a year. To simplify the analysis, we constructed a variable which indicates the grade in which a teacher instructed the highest proportion of their students during a school year. We used that variable to determine which grade the teacher was teaching in the analyses.*
**Difference in means between Relay and non-Relay teachers is statistically significant at $p < 0.05$.*

TABLE A4. Descriptive Statistics of Relay and Non-Relay Teachers in New York City Public Schools, Among All Teachers in Grades 3 to 8

| | All Teachers | | Relay | | Non-Relay | | Mean Difference (3-5) |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Male** | 0.184 | 0.388 | 0.273 | 0.446 | 0.183 | 0.387 | 0.090* |
| **Race** | | | | | | | |
| White | 0.575 | 0.494 | 0.463 | 0.499 | 0.576 | 0.494 | -0.113* |
| Non-White | 0.425 | 0.494 | 0.537 | 0.499 | 0.424 | 0.494 | 0.113* |
| Black | 0.195 | 0.396 | 0.241 | 0.428 | 0.195 | 0.396 | 0.047* |
| Hispanic | 0.146 | 0.353 | 0.16 | 0.367 | 0.146 | 0.353 | 0.014 |
| Asian | 0.058 | 0.233 | 0.106 | 0.308 | 0.057 | 0.232 | 0.049* |
| **Years of Experience** | 9.572 | 7.372 | 1.405 | 1.375 | 9.651 | 7.363 | -8.246* |
| **Subject** | | | | | | | |
| Math | 0.631 | 0.482 | 0.488 | 0.5 | 0.633 | 0.482 | -0.144* |
| ELA | 0.697 | 0.459 | 0.364 | 0.481 | 0.7 | 0.458 | -0.337* |
| Social Studies | 0.556 | 0.497 | 0.232 | 0.422 | 0.559 | 0.496 | -0.327* |
| Science | 0.492 | 0.5 | 0.454 | 0.498 | 0.492 | 0.5 | -0.038* |
| **Grade** | | | | | | | |
| Grade 3 | 0.175 | 0.38 | 0.022 | 0.148 | 0.177 | 0.382 | -0.155* |
| Grade 4 | 0.175 | 0.38 | 0.01 | 0.102 | 0.177 | 0.381 | -0.166* |
| Grade 5 | 0.17 | 0.375 | 0.042 | 0.2 | 0.171 | 0.376 | -0.129* |
| Grade 6 | 0.169 | 0.374 | 0.297 | 0.457 | 0.167 | 0.373 | 0.130* |
| Grade 7 | 0.152 | 0.359 | 0.339 | 0.474 | 0.151 | 0.358 | 0.188* |
| Grade 8 | 0.159 | 0.366 | 0.289 | 0.454 | 0.158 | 0.365 | 0.131* |

*Note: Sample is restricted to first-year teachers who taught any of the four key academic courses (math, ELA, social studies, and science) in grades 3 to 8 between 2014-2019. The same approach for determining the grade a teacher instructed described in Table A3 was used here.*

TABLE A5. Descriptive Statistics of Relay and Non-Relay Teachers in New York City Public Schools, Among First-Year Teachers in Grades 6 to 8

| | All Teachers | | Relay | | Non-Relay | | Mean Difference (3-5) |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Male** | 0.291 | 0.454 | 0.304 | 0.46 | 0.29 | 0.454 | 0.013 |
| **Race** | | | | | | | |
| White | 0.537 | 0.499 | 0.435 | 0.496 | 0.544 | 0.498 | -0.110* |
| Non-White | 0.463 | 0.499 | 0.565 | 0.496 | 0.456 | 0.498 | 0.110* |
| Black | 0.179 | 0.384 | 0.264 | 0.441 | 0.173 | 0.379 | 0.091* |
| Hispanic | 0.164 | 0.37 | 0.158 | 0.365 | 0.164 | 0.371 | -0.006 |
| Asian | 0.082 | 0.274 | 0.106 | 0.308 | 0.08 | 0.271 | 0.026 |
| **Years of Experience** | 0.221 | 0.203 | 0.182 | 0.136 | 0.224 | 0.207 | -0.042* |
| **Subject** | | | | | | | |
| Math | 0.433 | 0.496 | 0.506 | 0.5 | 0.428 | 0.495 | 0.078* |
| ELA | 0.53 | 0.499 | 0.354 | 0.479 | 0.543 | 0.498 | -0.189* |
| Social Studies | 0.365 | 0.482 | 0.209 | 0.407 | 0.378 | 0.485 | -0.169* |
| Science | 0.357 | 0.479 | 0.459 | 0.499 | 0.349 | 0.477 | 0.11* |
| **Grade** | | | | | | | |
| Grade 6 | 0.364 | 0.481 | 0.304 | 0.46 | 0.369 | 0.483 | -0.065* |
| Grade 7 | 0.344 | 0.475 | 0.368 | 0.483 | 0.342 | 0.474 | 0.026 |
| Grade 8 | 0.292 | 0.455 | 0.328 | 0.47 | 0.289 | 0.453 | 0.039 |

*Note: Sample is restricted to first-year teachers who taught any of the four key academic courses (math, ELA, social studies, and science) in grades 6 and 8 between 2014-2019. The same approach for determining the grade a teacher instructed described in Table A3 was used here.*
**Difference in means between Relay and non-Relay teachers is statistically significant at $p < 0.05$.*

TABLE A6. Relay Effects on Standardized Absence, by the Number of Available Years

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **Any** | **At Least 3 Years** | **Exactly 4 Years** | **Exactly 5 Years** | **Exactly 6 Years** |
| Relay | -0.025*** | -0.025** | -0.028*** | -0.020* | -0.019+ |
| | (0.008) | (0.008) | (0.008) | (0.009) | (0.011) |
| $R^2$ | 0.786 | 0.769 | 0.75302 | 0.742 | 0.737 |
| Observations | 2,002,970 | 1,773,908 | 1,449,905 | 1,091,832 | 662,671 |

*Note: The sample is restricted to students in grades 3 to 8 between 2014 and 2019. The outcome is the number of absences standardized by grade and by year. Each column includes controls for student demographics (ELL, FRL, and IEP), student fixed effects, school fixed effects, and grade-by-year fixed effects. Standard errors in parentheses*

*$^{+}$ $p < 0.1$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$*