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Using Data and the Human Touch: Evaluating the NYC Inter-Agency Campaign to Reduce Chronic Absenteeism

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ABSTRACT

Following a 2008 report that documented the extent of chronic absenteeism in New York City's schools, the city organized an interagency task force to develop and implement a citywide effort to reduce chronic absenteeism. Given the size of the city school system and the scope of chronic absenteeism, the effort became the nation's most comprehensive campaign against absenteeism. Analyses of the campaign's pilot in 100 schools, with over 80,000 students, found that its efforts, particularly the Success Mentors program, significantly improved students' attendance rates and reduced chronic absenteeism, particularly for students from a high-poverty background.

Chronic absence amongst students, typically defined as either missing 10 percent of the school year or 20 or more days, has been linked to key academic outcomes such as mathematics achievement and literacy, high school graduation, and post-secondary enrollment (Applied Survey Research, 2011; Balfanz & Byrnes, 2012; Barge, 2011; Chang & Romero, 2008; Connolly & Olson, 2012; ECONorthwest, 2011; Ginsburg, Jordan, & Chang, 2014; Gottfried, 2010; Musser, 2011; NYC Independent Budget Office, 2011; Ready, 2010). Chronic absence from schools is also tied to the intermediary outcomes of student discipline and course failure (Balfanz, & Byrnes, 2012), as students who are not attending school on a regular basis are likely to disengage, fall behind in course work, and struggle to earn credits. All three factors, attendance, behavior, and course passing, have been identified as key actionable levers for practitioners in trying to keep students on-track to high school graduation (Allensworth, & Easton, 2007; Balfanz, Herzog, & MacIver, 2007; Baltimore Education Research Consortium, 2011; Kieffer, Marinell, & Stephenson, 2011).

Despite its strong relationship to educational achievement and advancement, until very recently, chronic absenteeism was rarely tracked at the school, district, or state levels. Hence few schools were aware of their chronic absenteeism rates and as result, seldom took actions to address it (Bruner, Discher, & Chang, 2011). The U.S. Department of Education's Office of Civil Rights attempted to collect and release the first national school level data on chronic absenteeism with its' 2013–14 data collection (Office of Civil Rights [OCR], 2016). This data, however, is only available every two years. Further, the OCR's data on chronic absenteeism (defined as students missing 15 or more days of school), is self-reported through surveys, with data for some districts systematically underreported (NYC public schools) or even reported uniformly as zero (Prince George County, MD), while the data for some entire states have measurement error (Florida). Using the OCR data and other sources, recent studies have estimated levels of chronic absences to be quite prevalent at the national level, with rates of between 10–15%, or roughly 5 to 7.5 million students per year across the nation (Balfanz, & Byrnes, 2012;

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/hjsp.

meetings and the implementation of the Success Mentor model. In 2011–12, a second wave of 25 schools joined using the same criteria for selection. In the third and final year of the pilot program, 2012–13, another 50 schools joined for a total of 100 participating schools. However, this third and final wave of participating schools were selected through a different network based model, whereby some of the selected schools did not have above average chronic absence. Under the new selection model, some schools/networks were also not required to show the level of "buy-in" previously required, in terms of weekly principal-led meetings and implementing a Success Mentor model. For evaluation purposes, a group of 46 other NYC schools that had similar ranges of chronically absent, free/reduced lunch program eligible, and limited-English-proficiency students were identified to serve as comparison schools.

Design

To answer our primary research question and determine if the NYC Task Force's efforts were successful at reducing chronic absenteeism in pilot schools, we employed short interrupted time-series design that shows changes in each wave of schools' chronic absence rates from before implementation to after. The addition of a comparison group to the design adds another point of comparison. The design thus allows us to estimate the program's impacts by offering two counterfactuals of what chronic absence levels would have looked like at the pilot schools had they not participated. First, we can compare the pilot schools' post-implementation chronic absence levels to their levels before they started the programs. Second, we can compare their levels, as well as changes over time, to the trends at the comparison schools, which assures us that any changes seen in the pilot schools' chronic absence levels that aren't also seen in the control schools are in fact due to the program impact and not to historical events in a given year, or to improvements that were being made districtwide through other efforts or programs

Data

All analyses make use of on school level covariates obtained from the Common Core of Data including, grade level (elementary, middle, high, transfer), school enrolment size, and the percent of minority students. Analyses that include individual student level data rely on administrative data sets obtained from the New York City Department of Education. These data sets provide individual-level information about students that were included in the models as covariates, such as their demographic backgrounds (gender, ethnicity, age) and their administrative statuses (special education, English Language Learner, economically disadvantaged, homeless). The NYC DOE data sets also provided an array of outcome measures for students, including course data (GPA and credit accumulation), attendance data, disciplinary incidents and suspensions, test scores, as well as program implementation information on whether a student received mentorship as part of the NYC Success Mentor Corps program. Table 1 displays the sample descriptive statistics, of both school and student level measures, for pilot and comparison schools taken from the baseline 2009–10 school year.

Our first set of analyses, using schools as the unit of analysis include 5,206 monthly observations for the 146 task-force and comparison schools, taken over time from 2009–10 to 2012–13, the three years of program implementation as well as one year prior as a baseline. Our second set of analyses, assessing student level outcomes, include 370,863 students from 579 cohorts observed at the 146 schools over the same four-year period. This includes all students that attended one of the 146 during 2009–10 to 2012–13 school years. While students may have moved between treatment and control schools between years, or left the district entirely, our analyses are based on an Intent-To-Treat model. Supplementary analyses addressing our secondary research question and focusing solely on the impact of the NYC Success Mentor Corps Program were conducted with a reduced sample that included only those 74,635 students who had been chronically absent in the prior school year, taken from 579 cohorts observed at the 146 schools over the four-year period.

Table 1. Sample descriptives.

		Wave 1	Wave 2	Wave 3	All Pilot Schools	Comparison Schools
School Level	N = (146)	25	25	50	100	46
	Elementary School	40%	32%	26%	31%	33%
	Middle School	32%	32%	26%	29%	35%
	High School	28%	28%	26%	27%	30%
	Transfer School	0%	8%	22%	13%	2%
	Enrollment Size	712 (598)	623 (831)	633 (660)	650 (686)	552 (348)
	Student/Teacher Ratio	14.0 (3.2)	13.9 (3.0)	15.8 (3.8)	14.9 (3.6)	14.7 (2.5)
Student Level	N = (95,895)	19,531	16,505	33,288	69,324	26,571
	Chronically Absent	46%	44%	43%	44%	43%
	Temporary Housing	5%	4%	3%	4%	5%
	LEP	14%	17%	9%	13%	14%
	Special Education	18%	19%	18%	18%	19%
	F/RL Eligible	78%	79%	65%	72%	79%
	Overage for grade	28%	27%	28%	28%	23%
	Female	50%	51%	46%	48%	50%
	White	3%	4%	13%	8%	3%
	Black	43%	39%	38%	40%	51%
	Asian	9%	4%	6%	6%	2%
	Hispanic	43%	52%	43%	45%	43%
	Other Ethnicity	1%	1%	1%	1%	1%

Analysis

As our method of statistical analysis, we use multi-level (hierarchical linear) regression models (Bryk, & Raudenbush, 2002; Snijders, & Bosker, 1999). Multi-level modeling is ideal for samples such as ours, as it explicitly accounts for the interdependence of observations taken over time from within the same schools. Such auto-correlation is common to time-series designs and violates the statistical assumptions of traditional regression modeling, and when unaccounted for can provide a threat to statistical conclusion validity.

A first set of analyses are focused on the school as the unit of analysis, where the outcome is school level rates of chronic absenteeism. The two-level models, with time points at Level-1 nested within schools at Level-2, estimate chronic absentee rates at the schools on a month by month basis over the course of four school years, from the start of the 2009–10 school year (the year before campaign kick-off) through to February of 2013. We thus create trend lines of the percent of students who were chronically absent at each of the three groups of implementing schools as well as for the comparison schools.

A second set of analyses are based on end-of-year student level data, measuring student level outcomes such as individual students' average daily attendance and categorical/dummy variables capturing whether students were chronically absent or not. These analyses, in which students are the unit of analysis, employ three-level models with students nested within years/cohorts, nested within schools. Schools remain the unit of assignment (treatment) with comparisons of outcomes being made both within waves of treatment schools (from before implementation to after) and from treatments schools to comparison school trends, in keeping with our interrupted time-series design.

A supplemental set of analyses are then used to address our secondary research question focusing solely on the impact of the NYC Success Mentor Corps Program as a key component of the campaign's efforts. For these analyses, the sample is reduced only to those students who were chronically absent in the prior school year, as this was the primary criterion for determining which students would receive mentoring. Therefore, for these supplementary analyses, the evaluation design is a much simpler one of pre-post with a comparison group. Students who were chronically absent in the prior school year are measured the following year to see if they were still chronically absent, with comparisons made between those students who received mentors and those who did not. For these analyses, students are the unit of assignment as well as the unit of analysis, and statistical analyses are again based on three-level models with students nested within years/cohorts, nested within schools.

Results

From the results of our first set of analyses, using school level outcomes, several basic points emerge. Figure 1 shows the trends in schools' chronic absence rates as derived from our two-level model estimates and the interrupted time series design. The trend lines are not raw numbers, as the statistical models control for several factors including cyclical/monthly differences in chronic absence rates, school size, and the percent of minority students. The trend lines presented are also centered for a high school with an average enrolment size for the total sample of 146 schools and average proportions of minority students (619 students and 96% minority), but the trends and impacts hold for schools of all levels, sizes, and student populations. Looking across the four years of data presented in the figure, we see a seasonal cycle where chronic absence rates are lowest in September and increase slightly throughout the year by up to 4% from January through May and reaching a high point in June, 7–8% higher than the start of the school year. While chronic absenteeism rates across the sample of schools were higher in the 2010–11 school year, there were no overall trends upwards or downwards from 2009–10 to 2012–13. Between the various school levels, Elementary schools had the lowest rates of Chronically Absent students, with rates roughly 4% higher in Middle schools and 14% higher in High schools (controlling for school size and student background). Controlling for background, chronic absence rates were an exceptional 46% higher in transfer schools than in elementary schools, though as transfer schools made up only 14 out of the 146 schools in our sample (10%), the sample is too small for this result to be considered anything more than speculative. The rates of chronic absenteeism amongst schools' student populations were significantly higher for schools with larger proportions of minority students. Within each different school level, total enrollment was also significantly related to chronic absentee rates, with larger school sizes being associated with higher rates of chronic absenteeism.

Turning to the evaluation of the NYC Campaign against Chronic Absenteeism, chronic absentee rates were 1.5% lower in pilot schools during the years that they participated in the Truancy Prevention Programs (Table 2). This impact is pooled across all years and for all three waves of participating schools and is statistically significant ($p < .004$; ES $= 0.14$). As illustrated in Figure 1, each separate wave of schools that participated in the truancy prevention programs experienced a positive change in their rates of chronic absenteeism after having implemented the programs, in comparison to non-participating schools. That is to say, initial differences in chronic absence rates between the participant schools and comparison schools, were more favorable in years after program implementation. For the first wave of participating schools, they began with significantly higher chronic absence rates than comparison schools in 2009–10, but had reduced gaps in post implementation years (equal in 2011–12).

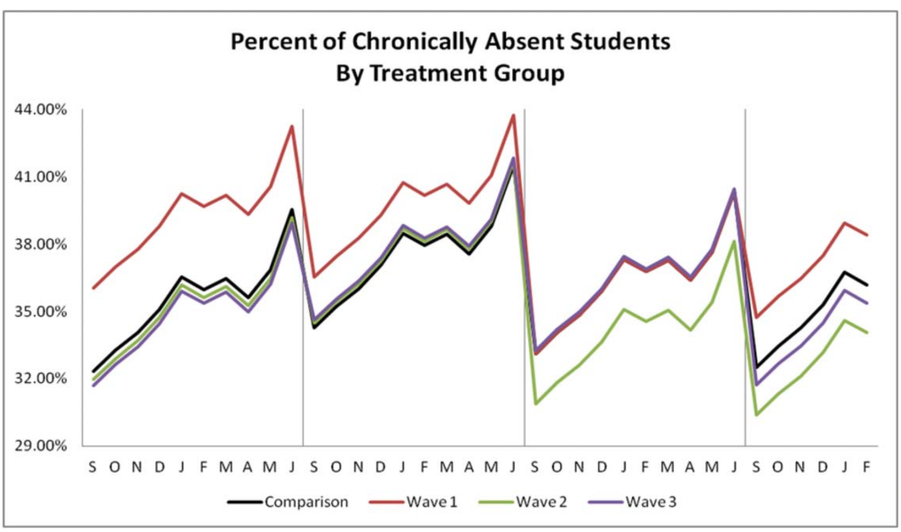

Figure 1. Percent of chronically absent students, by month and year.

Table 2. Model results – school level chronic absence rates.

Fixed Effect	Coefficient	Std. Error	P-Value
Intercept, P0			
Intercept, B00	33.16616	1.148624	0.000
Elementary School, B01	−14.9436	1.216496	0.000
Middle School, B02	−11.0805	1.317078	0.000
Transfer School, B03	29.63703	2.412233	0.000
Total Student Enrollment, B04	0.002337	0.00065	0.001
Percent Minority, B05	0.38023	0.040945	0.000
Slope for October, P1			
Intercept, B10	0.954976	0.290266	0.002
Slope for November, P2			
Intercept, B20	1.743036	0.45267	0.000
Slope for December, P3			
Intercept, B30	2.775166	0.531363	0.000
Slope for January, P4			
Intercept, B40	4.207314	0.535864	0.000
Slope for February, P5			
Intercept, B50	3.656783	0.49609	0.000
Slope for March, P6			
Intercept, B60	4.15541	0.512514	0.000
Slope for April, P7			
Intercept, B70	3.291713	0.555028	0.000
Slope for May, P8			
Intercept, B80	4.521836	0.615429	0.000
Slope for June, P9			
Intercept, B90	7.225765	0.572713	0.000
Slope for 2010–11 School Year, P10			
Intercept, B100	2.382423	0.419361	0.000
Slope for 2011–12 School Year, P11			
Intercept, B110	0.607632	0.53153	0.255
Slope for 2012–13 School Year, P12			
Intercept, B120	0.619661	0.705634	0.382
Slope for Treatment, P13			
Intercept, B130	−1.52785	0.526086	0.004

For the second and third waves of participating schools, both began with chronic absence rates equivalent to those of comparison schools, but had lower rates than comparison schools after initiating program participation.

However, while the overall program impact was to reduce chronic absence rates at participating schools by 1.5%, there were substantial differences between the groups of schools, and across the years of participation. For the first wave of schools, the program impact was 1.5% in year 2010–11, 3.7% in 2011–12, and 1.5% in 2012–13 (statistically significant difference in 2011–12). For the second wave of schools the impact was 2.4% in 2011–12 and 2.3% in 2012–13 (statistically significant in both years). For the third group of schools, impact was 0.9% in 2012–13, their only year of implementation. To contextualize the size of the changes, the improvements in chronic absentee rates for the participating school groups range from .06 to .26 in terms of effect sizes, depending on group and year. The overall estimate of program impact (1.5%) is equivalent to an effect size of 0.14, considered educationally meaningful when applied to a population as large as this.

Our second set of analyses then repeated the interrupted time-series design using individual student level outcomes and three-level models for students nested within years/cohorts, nested within schools. Similar to the above school level analyses, the models controlled for school characteristics such as school size and % minority students, as well as individual students' characteristics, such as: gender, race, grade level, special education and LEP statuses, Free/Reduced Lunch eligibility, temporary housing status, and overage for grade status. The specific outcome modeled was whether an individual student would be chronically absent or not, with the results being in terms of a student's probability of being chronically absent. Estimated program impact was statistically significant ($p < .001$), and students who attended one of the participating schools during an implementation year were on average nine percent less likely to be chronically absent than either students who attended one of the comparison schools or students who attended a pilot school in a year prior to implementation (Table 3). Students at participating schools were also significantly less likely (7%) to be severely chronically absent (attendance under 80%) and, conversely, significantly more likely (8%) to be "good attenders" with attendance rates at or above 95%. Overall, results followed the same pattern as those for school level outcomes, with results being strongest for students at the first two waves of schools (statistically significant in 2010–11 & 2011–12), and negligible for students at the third group of schools.

One reason why impacts may have been weaker in year three of implementation, 2012–13, may be the historical events that occurred during the school year, including Hurricane Sandy as well as a brief bus strike, both of which disrupted school attendance for students across New York City (albeit for both task force and comparison schools alike). The rapid expansion and doubling of pilot schools from 50 to 100 in one year also contributed to further spread intervention resources and water down implementation levels across schools in 2012–13, by reducing the amount of technical assistance visits and resources that could be offered to each pilot school throughout the year. Thus, the smaller impacts in 2012–13 must be viewed in context of the unique historical events that disrupted attendance patterns, and doubling of participating schools that occurred.

Where the program impact was much lower for the third wave of schools, several aspects of pilot school selection and implementation differentiate this group of schools from the first two. As noted earlier, the third wave of pilot schools were selected through a different mechanism without the same selection criteria as the first two waves of pilot schools. In some cases, they lacked above average rates of chronic absenteeism and they were additionally not required to make a commitment to implementing some aspects of the model, such as principal-led meetings and the success mentor program. Thus, initial selection bias and lower levels of fidelity coincide with the smaller impacts experienced by the third group of pilot schools.

Repeated statistical models were also run for different student level outcomes, such as daily attendance rate, suspension rate, and achievement outcomes (GPA, credit accumulation, and test scores). While students at participating schools consistently had more positive outcomes than students attending comparison schools, the differences were only statistically significant for the odds of being chronically absent, and not for other measured outcomes. Interactions between treatment effect and all student and school level characteristics were tested. There were statistically significant interactions between pilot treatment impact and students who were either in temporary housing or Free/Reduced Lunch eligible. Free/Reduced Lunch eligible students were 15% less likely to be chronically absent if attending a participating school than were students attending comparison schools or students attending pilot schools in years prior to implementation. Similarly, students in temporary housing who attended a pilot school during an implementation year were 31% less likely to be chronically absent. This result is of particular relevance given that those two sub-groups of students who have among the highest rates of chronic absenteeism and were specifically targeted by the campaign efforts. One of the campaign's key programmatic efforts was a partnership with the city's homeless shelters geared towards addressing the chronic absence of students placed in temporary housing situations.

Turning to our supplementary analyses that focus specifically on the impact of the NYC Success Mentor Corps Program and students who were chronically absent the year before, we did not find that mentored students were any more likely to exit chronic absenteeism. However, this is not a surprise given the challenges facing those students targeted for mentoring. The initial attendance rates of mentored students, in the year prior to mentoring, were on average 75.6%, with an average of 42 days missed. Thus the typically mentored student was very far away from the threshold of not being chronically absent (attendance at 90% or higher). Mentored students did, however, see a statistically significant increase in their overall attendance rates as well as several other key academic outcomes. Results found that students who received individualized mentoring had average daily attendance rates five percent higher than previously chronically absent students who did not receive mentoring ($p < .000$; ES = 0.19), representing an increase in attendance of roughly two weeks of school per year (Table 4). Mentored students also earned significantly more credits (0.9 more on average, $p < .010$; ES = 0.05) and were 27% more likely to still be enrolled in the NYC school system the following year ($p < .000$).

Table 3. Model results – student level probability of being chronically absent.

Fixed Effect	Coefficient	Std. Error	P-Value	Odds Ratio
Intercept, P0				
Intercept, G000	−0.28323	0.077142	0.001	0.75
Elementary School, G001	0.0193	0.154631	0.901	1.02
Middle School, G002	0.06907	0.105695	0.514	1.07
Transfer School, G003	1.930259	0.111156	0.000	6.89
Total Student Enrollment, G004	0.000119	0.000076	0.117	1.00
Percent Minority, G005	0.01953	0.003376	0.000	1.02
Slope for Treatment, B01				
Intercept, G010	−0.09189	0.027489	0.001	0.91
Slope for School Year 2010-11, B02				
Intercept, G020	0.055678	0.020806	0.009	1.06
Slope for School Year 2011-12, B03				
Intercept, G030	−0.24495	0.028816	0.000	.078
Slope for School Year 2012-13, B04				
Intercept, G040	0.028457	0.035786	0.428	1.03
Slope for Student in Shelter or Temporary Housing, P1				
Intercept, G100	0.539576	0.029344	0.000	1.72
Slope for Limited English Proficiency, P2				
Intercept, G200	−0.3889	0.038067	0.000	0.68
Slope for Special Education, P3				
Intercept, G300	0.338695	0.01946	0.000	1.40
Slope for Free/Reduced Lunch Eligible, P4				
Intercept, G400	0.109844	0.053733	0.041	1.12
Slope for Overage for Grade, P5				
Intercept, G500	1.082219	0.058245	0.000	2.95
Slope for Female, P6				
Intercept, G600	0.084052	0.014538	0.000	1.09
Slope for White, P7				
Intercept, G700	−0.17594	0.045886	0.000	0.84
Slope for Black, P8				
Intercept, G800	−0.26622	0.029849	0.000	0.77
Slope for Asian, P9				
Intercept, G900	−0.75107	0.100135	0.000	0.47
Slope for Other Ethnicity, P10				
Intercept, G1000	−0.15796	0.072165	0.028	0.85
Slope for Pre-K, P11				
Intercept, G1100	0.232933	0.145981	0.110	1.26
Slope for Kindergarten, P12				
Intercept, G1200	0.000153	0.142677	0.999	1.00
Slope for Grade 1, P13				
Intercept, G1300	−0.27536	0.144038	0.055	0.76
Slope for Grade 2, P14				
Intercept, G1400	−0.58283	0.143966	0.000	0.56
Slope for Grade 3, P15				
Intercept, G1500	−0.78289	0.142781	0.000	0.46
Slope for Grade 4, P16				
Intercept, G1600	−0.9013	0.141887	0.000	0.41
Slope for Grade 5, P17				
Intercept, G1700	−0.97485	0.140243	0.000	0.38
Slope for Grade 6, P18				
Intercept, G1800	−0.78227	0.087747	0.000	0.46
Slope for Grade 7, P19				
Intercept, G1900	−0.73342	0.090749	0.000	0.48
Slope for Grade 8, P20				
Intercept, G2000	−0.50069	0.08962	0.000	0.61
Slope for Grade 10, P21				
Intercept, G2100	−0.13428	0.048633	0.006	0.87
Slope for Grade 11, P22				
Intercept, G2200	−0.28334	0.082546	0.001	0.75
Slope for Grade 12, P23				
Intercept, G2300	0.082895	0.106624	0.437	1.09

Table 4. Model results – student level impact of mentoring on attendance rates.

Fixed Effect	Coefficient	Std. Error	P-Value
Intercept, P0			
Intercept, G000	55.36932	1.485013	0.000
Elementary School, G001	9.389013	2.379201	0.000
Middle School, G002	7.258144	2.06169	0.001
Transfer School, G003	−5.26713	1.632555	0.002
Total Student Enrollment, G004	−0.00101	0.000673	0.134
Percent Minority, G005	−0.08903	0.028188	0.002
Slope for School Year 2011–12, B01			
Intercept, G010	4.178634	0.39576	0.000
Slope for School Year 2012–13, B02			
Intercept, G020	−3.93457	0.490687	0.000
Slope for Student in Shelter or Temporary Housing, P1			
Intercept, G100	−1.7368	0.4331	0.000
Slope for Limited English Proficiency, P2			
Intercept, G200	0.514979	0.422509	0.223
Slope for Special Education, P3			
Intercept, G300	−0.26639	0.34549	0.441
Slope for Free/Reduced Lunch Eligible, P4			
Intercept, G400	7.038828	0.663343	0.000
Slope for Mentoring, P5			
Intercept, G500	4.744859	0.737878	0.000
Slope for Overage for Grade, P6			
Intercept, G600	−13.011	0.763504	0.000
Slope for Female, P7			
Intercept, G700	−1.10772	0.228432	0.000
Slope for White, P8			
Intercept, G800	0.424714	1.068963	0.691
Slope for Black, P9			
Intercept, G900	0.974243	0.317776	0.003
Slope for Asian, P10			
Intercept, G1000	2.22293	0.968308	0.022
Slope for Other Ethnicity, P11			
Intercept, G1100	0.24945	1.543262	0.872
Slope for Pre-K, P12			
Intercept, G1200	8.956661	3.890781	0.021
Slope for Kindergarten, P13			
Intercept, G1300	13.18588	2.523085	0.000
Slope for Grade 1, P14			
Intercept, G1400	12.58326	2.384104	0.000
Slope for Grade 2, P15			
Intercept, G1500	13.43677	2.402684	0.000
Slope for Grade 3, P16			
Intercept, G1600	14.68085	2.35274	0.000
Slope for Grade 4, P17			
Intercept, G1700	15.23722	2.385879	0.000
Slope for Grade 5, P18			
Intercept, G1800	15.74253	2.348187	0.000
Slope for Grade 6, P19			
Intercept, G1900	14.38373	2.081247	0.000
Slope for Grade 7, P20			
Intercept, G2000	14.36186	1.988569	0.000
Slope for Grade 8, P21			
Intercept, G2100	12.05563	1.906038	0.000
Slope for Grade 10, P22			
Intercept, G2200	12.22372	0.998762	0.000
Slope for Grade 11, P23			
Intercept, G2300	15.39689	1.457552	0.000
Slope for Grade 12, P24			
Intercept, G2400	14.28101	1.573761	0.000

Conversely, mentored students were 22% more likely to be suspended during the respective school year ($p < .010$).

That students' attendance rates increased is a primary impact of mentoring, while increased credit accrual is a logical secondary outcome and indirect result of having been in class more. That mentored students were also more likely to receive a suspension may also have be an indirect result of increased attendance rates, as by having the most at-risk students remain in school more frequently may lead to the unintended consequence of school staff having to deal with more frequent disciplinary incidents. This is nominally supported by the pattern of suspension rates for mentored students which were 11% in 2010–11, 13% in 2011–12, and 9% in 2012–13, and which follow the same pattern of the overall program impacts as found in the above analyses of school and student level outcomes conducted as part of the interrupted time-series design. Further, while mentored students were more likely to be suspended, the actual numbers of students being suspended are quite low. Suspension rates for mentored students were 10% as compared to 9% for students who were chronically absent the year before but did not receive a mentor. Thus while mentored students were more likely to be suspended, it is relative to a very small percentage of students from both groups who were actually suspended over the three years.

The impact of mentoring was particularly strong for students who were overage for their grade level. Overage students who were chronically absent in the prior year and received mentoring, improved their attendance rates by 6.5% on average, earned 1.3 more credits, increased their cumulative GPA by 0.8 points, were 17% less likely to be severely chronically absent, and 34% more likely to still be enrolled in the NYC school system the following year. Also, in terms of the specific types of mentor programs used as part of the NYC Success Mentor program, the primary impacts on attendance were equivalent when comparing the internal and external models. (Too few schools made use of the peer-based model to produce reliable comparisons).

In 2012–13, across the participating schools, 6,037 students who had been chronically absent the year before had Success Mentors. Given that the task force directed its efforts to the schools with above average rates of chronic absenteeism and, as noted at the outset of the report, that chronic absenteeism in the task force schools was in many grades the norm, it is not surprising that not all students who were eligible for a Success Mentor received one. Given the wide variation in the size of schools participating and the numbers of mentors available in each school, there was considerable variation across the task force schools in 2012–13 in the percent of eligible students who received Success Mentors. In the top quarter of schools, 71% or more of eligible students received a Success Mentor, compared to 19% or less in the bottom quarter of schools. Because of differences in school size, it is also not surprising that elementary schools were overrepresented in the top quartile of schools with the greatest coverage of chronically absent students, and high schools were over-represented in the lowest quartile with the least coverage. In terms of the number of students mentored, in the top quarter of schools in 2012–13, 81 or more chronically absent students per school received mentors compared to 22 or fewer in the bottom quarter of schools. Overall, across the 100 schools participating in the task force's efforts in 2012–13, 43% of students chronically absent in 2011–12 received the supports of either an internal or external Success Mentor. Thus, the above estimated impacts of the campaign's efforts to reduce chronic absenteeism are in light of an implementation, or penetration, of one of the campaign's key components that reached less than half of the targeted student population. When replacing the categorical variable for program participation in our school level models with a continuous measure of the percent of students within each cohort/school that had mentors, overall impact estimates were identical. That program impact results follow the pattern of mentoring rates provides further evidence of a causal relationship between program implementation and a decrease in the odds of being chronically absent. It also suggests that the mentoring program is one of the main drivers of the Campaign against Chronic Absenteeism's impacts.

Apart from our evaluation of the NYC Task Force's campaign against chronic absenteeism and its mentoring model, a separate and more general, but very important, result to come from our analyses of New York City student data is that students who exit chronic absenteeism return to an on-track path to graduation. Of students from our sample who were chronically absent in 2009–10, but exited chronic absentee status in 2010–11, 82% were still enrolled in a NYC school two years later in 2012–

13. This rate is equivalent to the 80% re-enrollment rate of students who were never chronically absent in 2009–10 or 2010–11. Conversely, only 62% of students who were not chronically absent in 2009–10 but entered that status in 2010–11 were still enrolled in 2012–13, a 20 percent difference. Students who excited chronic absentee status also saw statistically significant increases in their GPA and mathematics and reading achievement levels. In our sample, we saw that many chronically absent students are severely so and far from reaching an attendance rate of 90%. However, even for these students, a substantial improvement in their attendance rates, by 10 or more days, led to significant improvements in the odds of being proficient in math and ELA, their high school credits earned, cumulative high school GPA, and end-of-year exams passing rates. Thus, while chronic absenteeism has a clear negative effect on several student outcomes and is a correlate of dropping out of high school, it is an important finding that the negative academic effects are reversible or can be attenuated, once students start to attend school again on a more regular basis.

Discussion

Knowing that students who stop being chronically absent see academic improvements across the board, contradicts the far-too-often-held belief that “off-track” students cannot recover or improve academic performance. The impact of the NYC chronic absenteeism prevention and intervention programs also shows us that a statistically significant and educationally meaningful impact on chronic absenteeism levels, student attendance and other academic outcomes, are achievable, even in our communities with the greatest needs. The campaign efforts led to significant decreases in the chronic absence levels at task force pilot schools and even greater improvements on the attendance rates of individually mentored students. Impacts were even stronger for low-income, overage, and homeless students, those groups most at-risk and who stand to gain the most from being in school every day. From a practical perspective, the programs were implemented using cost-efficient methods that any school district can replicate, repurposing existing resources in more strategic, and targeted ways. Just as important in term of policy and implementation, is that the Interagency Task Force was able to rapidly expand and institutionalize its efforts on a large scale. A recent report by the New School’s Center for New York City Affairs (Nauer et al., 2014) found that in 2012–13 the chronic absence rates in NYC elementary schools had decreased since 2008 and their initial report which first documented the extent of chronic absenteeism in NYC schools and which spurred the campaign’s initial efforts.

Regarding the success mentor model, the fact that both the internal and external mentor models had equivalent impacts on students’ attendance rates is an important practical and policy point for other districts seeking to replicate such an effort. The use of internal school staff (teachers during service periods, administrators, coaches, non-teaching staff, etc.) is typically a cheaper option for schools and districts as it does not represent the incorporation of any new staff or resources. In addition, it is often a more flexible option for schools and districts, giving them greater control in decision making and the assignment of staff and resources. Thus, the equal performance of the internal model gives futures schools and districts the confidence of using it over the external model without the concern of lessening the impact. However, the specific situations and financial formulas for each district will vary, and for some districts it may be the case that the use of external community partners (national service corps members, social work students, retired professionals, etc.) is in fact the cheaper resource and the more desirable model. But again, with equal outcomes for both mentor models, districts can select their preferred model without fear of reduced impact. The critical factor is that whatever mentoring model is used, it needs to replicate the intensity and focus exhibited by both the internal and external models in NYC, i.e. being in schools at least 3 days/15 hours a week, working with a defined and manageable caseload of students, having direct access to the attendance data of the students they mentor, being able to link students with pressing out-of-school issues with professional supports, and having a voice in weekly principal-led student success meetings.

While mentoring was a key component of the NYC campaign efforts and its impact, attempts at replication must recall that the mentor program was one part in a wider set of intervention and prevention strategies that included a) close, often weekly, measurement and tracking of absenteeism, b) the development of a diagnostic capacity to understand why students are missing school, c) a problem-solving capacity to help address those reasons, d) building and sustaining relationships with the students who are experiencing absenteeism, and often their families, e) the development of a multi-sector and community response that often involves a second shift of adults in the schools with the highest levels of chronic absenteeism to meet the scale of the challenge, f) efforts to recognize and reward good attendance, and g) a commitment to learn what works, and then to replicate and expand effective programs to modify what is not working. These efforts required only a modest financial investment and thus further showed that through artful re-organization and coordination of existing assets and functions, large impacts are possible in high-poverty and high-minority schools with above-average rates of chronic absenteeism.

Those seeking to replicate the NYC campaign efforts and its results must also consider that by design the results represent a case study of NYC alone, and cannot be assumed to be generalizable to other school districts. However, given the large scale of the program's implementation in the context of New York city's size and context, it can be hoped that the program and its impacts would be replicable in other large urban districts serving high-minority and high-poverty student populations, and those are also the types of school districts where chronic absence rates tend to be the most problematic.

In the final years of the Obama administration as part of its My Brother's Keeper campaign, the White House and the U.S. Department of Education undertook to spread the Success Mentor Initiative as a national response to the challenge of chronic absenteeism. The MBK initiative was based largely on the NYC Success Mentor pilot program and sought to scale up the mentor model based upon the NYC evidence. It shared many of the same elements, such as pairing chronically absent students with school based mentors, a partnership with the Ad Council to increase public awareness, data-driven decision making, and the linking of local community resources to schools. The Success Mentor Initiative is now supported by the US Department of Education's Office of Safe and Healthy Students remains active in 25 large, high poverty and largely urban communities at the end of 2017 and is currently engaging in a randomized control trial, which will test the impact of the mentor model on reducing chronic absenteeism at a national level.

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