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The Impact of Nudge Letters on Improving Attendance in an Urban District

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Abstract

This study evaluates a "nudge letter" to parents intervention designed to reduce chronic absenteeism among students in one urban district. Using a regression discontinuity design (RDD), it estimates the impact of the intervention on improving student attendance. The forcing variable for the RDD was 2016–2017 attendance rate, with a "threshold" of a 0.90 attendance rate (missing 10% of days). Analyses established demographic equivalence of students in the 0.88 to 0.92 baseline attendance bandwidth. Although the overall impact of the intervention on attendance change between Fall 2016 and Fall 2017 (first-quarter attendance) was small and non-significant (ES 0.09, $p=.20$), the effect size for middle school students (0.34, $p=.044$) was "substantively important" by What Works Clearinghouse standards. The effect of the intervention on the full year's attendance rate was not significant.

Keywords

chronic absence, attendance, family engagement

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Common sense suggests that learning growth should be positively related to exposure to learning opportunities. For many if not most students, particularly among those whose out-of-school learning opportunities are more limited, this means that school attendance rates should be good predictors of achievement. It is only in the past decade or so, however, that researchers have paid much attention to this important relationship (e.g., Balfanz & Byrnes, 2012, 2013; Chang & Romero, 2008). Policy organizations such as Attendance Works have garnered national attention and mobilized education policymakers on this issue over the past decade. Recent estimates indicate that 15% of students nationwide are chronically absent (miss more than 10% of school days), and that the percentage is much higher in many states and districts (Chang et al., 2018). Chronic absence is a particular problem in many urban districts that serve large populations of low income students (Balfanz & Byrnes, 2018). Policy briefs from the Education Commission of the States emphasize that chronic absenteeism is a key indicator of student success (e.g., Rafa, 2017). In response to the Every Student Succeeds Act of 2015, which requires states to submit plans that include a measure of student success or school quality, three-quarters of the states now use a measure of chronic absenteeism among other measures in their accountability or improvement systems (Kostyo et al., 2018).

Numerous studies have reported a positive association between school attendance rates and academic achievement (Ansari & Purtell, 2018; Chang & Romero, 2008; Fitzpatrick et al., 2011; Fuhs et al., 2018; Gershenson et al., 2017), high school graduation (Allensworth & Easton, 2007; Balfanz et al., 2007; Mac Iver & Messel, 2013; Neild & Balfanz, 2006a, 2006b), and success in college (e.g., Credé et al., 2010). Evidence of a causal effect of school attendance on achievement has been much more difficult to obtain. It is not generally possible to randomize attendance levels in a meaningful way (beyond short term laboratory experiments on learning specific tasks or content material). It is possible, however, to separate the effects of attendance itself from the other factors associated with it, such as family characteristics and levels of motivation associated with one's experience within a family. Analyses using instrumental variables that are related strongly to attendance but not to the achievement outcome variable (such as the number of nurses in the school or the distance of student's home from the school) allowed Gottfried (2010, 2013) to make a stronger case for the potentially causal impact of attendance on achievement. In another study, Gottfried (2011a) used sibling data to separate family fixed effects from attendance effects on achievement. There is also evidence of a negative effect of having absent classmates on students' academic achievement, which is likely related to a "strain on classroom resources"

(Gottfried, 2011b) when teachers are confronted with the needs of students who have missed instruction. Another recent study concluded that absences have an equally negative effect on student achievement across the entire distribution of prior achievement levels (Gershenson et al., 2019).

Studies have also explored underlying factors associated with poor student attendance or chronic absence. Family income status is a key factor predicting attendance rates (e.g., Morrissey et al., 2014), and there is a clear link between low income status and factors like access to transportation and health care and housing instability that help to explain the relationship (e.g., Desmond, 2015; Khullar & Chokshi, 2018). Unpacking the dimensions of poverty helps us to understand the underlying reasons for the relationships that are observed with outcomes like attendance and student achievement. While other factors besides poverty (particularly student health and mental health) are also associated with attendance, the relationship with social class is particularly strong. At the same time, school factors explain some of the variation in attendance rates among students with the same low-income status. A study in Detroit schools found strong negative relationships between chronic absenteeism and survey measures of the "Five Essential Supports" in effective schools (Bryk et al., 2010): "effective leadership, collaborative teachers, ambitious instruction, supportive environment, and involved families" (Lenhoff & Pogodzinski, 2018, p. 158).

Other recent studies have evaluated the impact of particular interventions to improve student attendance. Given the strong relationship between attendance and student academic outcomes, such interventions are one step toward addressing causes of low student performance. We can categorize these interventions, discussed more fully below, into whole school early warning and intervention system approaches, targeted personalized interventions such as mentoring, initiatives aimed at increasing student engagement in learning, attempts to directly address transportation or health needs, and interventions aimed at improving family engagement both more generally and through targeted communication interventions like nudge letters or texting initiatives.

Once attendance had been identified as a key early warning indicator for tracking likely graduation outcomes (e.g., Allensworth & Easton, 2007; Balfanz et al., 2007), educators began numerous interventions designed to identify struggling students and intervene with them early enough to get them back on track. Ehrlich and Johnson (2019) tell the story of Chicago Public Schools attempts to create a sense of collective responsibility among school staff to monitor data collaboratively and engage positively with students manifesting attendance problems (as well as with their families). Longitudinal data over the 8 year period of these efforts show notable increase in high school average attendance rates (Ehrlich & Johnson, 2019). Experimental studies of the impact of early warning systems that mobilize school staff to monitor signs of chronic absenteeism and intervene to encourage school attendance have begun to find effects of this intervention in high schools (Faria et al., 2017; Mac Iver et al., 2019) and middle schools (Corrin et al., 2016). Specific efforts to increase student interest in learning with motivating activities such as robotics have also been shown to have a positive effect on student attendance (Mac Iver & Mac Iver, 2019).

Other studies have focused on various types of mentoring interventions with students at risk of chronic absence, with mixed results. A study of a New York City "Success Mentor" initiative (Balfanz & Byrnes, 2013, 2018) found significantly larger increases in attendance rates for intervention students than comparison students. Childs and Grooms (2018) reported on analyses of qualitative data about the strategies employed to facilitate implementation of Success Mentors in a Texas district. Analysis of another mentoring program for middle school students implemented by an external partner in several districts nationwide did not, however, find a significant effect of mentoring on student attendance (Mac Iver et al., 2017), which echoed findings of other national studies in which positive findings did not sustain over time (e.g., Herrera et al., 2011).

There is also evidence that efforts by an educational system to address transportation and health needs could help to reduce absenteeism. A study of New York City students who take city buses arranged by their school leaders, compared to students who do not have such bus services, found significantly lower rates of chronic absence for bus riders (Cordes et al., 2019). Studies also suggest that school based health care centers can help reduce absenteeism for students with chronic conditions like asthma (Guo et al., 2005; Murray et al., 2007; Webber et al., 2003), though more research is needed to determine whether such health centers have a causal effect on attendance more generally (Graves et al., 2019).

School efforts to become more systematic in their efforts to engage families have been shown to be associated with increases in student attendance at the elementary level (Epstein & Sheldon, 2002; Sheldon, 2007; Sheldon & Epstein, 2004). Family interventions with high-risk middle school youth had a positive effect on attendance (Stormshak et al., 2009). One relatively low-cost intervention with promising evidence from randomized studies involves texts or letters sent home by schools or districts to families of chronically absent students. The underlying theory of action in this intervention is that families may need gentle reminders about the importance of attendance or about how many days their child has missed at school. When families receive such a reminder, they are expected to make additional efforts to ensure good attendance for their child. In a randomized study using weekly text messaging to parents of middle and high school students about number of class periods missed and number of missing assignments, as well as monthly alerts if the student fell below a 70% average for the marking period, Bergman and Chen (2017) reported a large positive treatment effect on number of classes attended as well as positive effects on other academic outcomes. Another study (Robinson et al., 2018) sought to address elementary school parental misconceptions about attendance through a randomized study involving "nudge" letters that alerted parents to the number of student absences and emphasized the importance of attendance, finding a decrease in chronic absenteeism of 15% in the treatment group. In a similar study of students at all grade levels in Philadelphia, Rogers and Feller (2018) reported reductions in chronic absenteeism for the treatment group of 10% or more. A randomized study using a single postcard mailing that measured attendance after two and a half months found a decrease in absences of 2.4% (Rogers et al., 2017).

Study Background

Inspired directly by the "nudge letter" research described above, district administrative staff in Seattle Public Schools, in partnership with the Seattle Housing Authority, decided to implement a similar intervention for chronically absent students in that district. After identifying students who had been chronically absent during 2016–2017, the district prepared "nudge letters" to send to their parents/guardians of students just after the beginning of the 2017–2018 school year.[1] The short letter, modeled after similar letters from the Rogers et al. (2017) study and signed by the district superintendent, focused on the importance of students' attendance to their learning and the school community (see sample copy in Appendix). The letter included the number of days of school the student had missed in 2016–2017 but did not include any comparisons with "typical" student classmates or graphics. The letter also identified a school contact person with phone number and email address. Letters were translated into the most commonly spoken languages of families listed in district records as speaking languages other than English at home (Spanish, Somali, Vietnamese, Tagalog, Arabic, Oromo, Amharic, Cantonese, Mandarin, and Toishanese). Although the district continued to send nudge letters to parents of chronically absent students after each quarter throughout the 2017–2018 year (see Procedures section below for more details), implementation of the subsequent mailings made interpretation of analytical findings problematic and the current study does not include analyses related to subsequent letters.

Research Questions

Our primary evaluation question was:

> Did the students whose parents/guardians received the nudge letter in September 2017 have a larger increase (or smaller decrease) in attendance during first two months of 2017-18 compared to the same period in 2016-17, compared to similar students whose parents were not sent a nudge letter?

The secondary evaluation question was:

> Did the students whose parents/guardians received the nudge letter in September 2017 have a larger increase (or smaller decrease) in attendance for the full year 2017-18 compared to 2016-17, compared to similar students whose parents were not sent a nudge letter?

Method

Research Design

We used regression discontinuity (RD) analysis to estimate the change in attendance rate associated with receiving the September nudge letter. RD is a particularly appropriate statistical technique for analyzing the impact of an intervention when the decision to include or exclude subjects in the treatment group depends on a sharp threshold in a continuous variable, called a "forcing variable" (e.g., Murnane & Willett, 2011). The groups in a small bandwidth to either side of the threshold are typically very similar to each other, so RD treats them as quasi-experimental treatment and control groups. RD analysis estimates separate local regressions for the groups on either side of the cut point. A significantly large difference between those local regressions at the cut point can be interpreted as an effect of the treatment on the outcome variable.

Data

The district's student administrative records were the source of data for this study. Attendance data from 2016–2017 were used to identify students to receive the nudge letters and data from both 2016–2017 and 2017–2018 (attendance, demographic, and school status indicators) were used in impact analyses.

Procedure

Students were selected for the intervention at the beginning of the 2017–2018 school year based on attendance data from the 2016–2017 school year. As a result, only students in Kindergarten through grade 11 in 2016–2017 who were also enrolled in 2017–2018 (in grades 1–12),[2] were eligible for the intervention. Chronic absence was calculated on a "segment" basis. That is, students who transferred mid-year but were chronically absent (>10% of possible school days) during their time at any one school were flagged. The decision rule for intervention was the flag for chronic absence and at least five absences (as short enrollment times at any school could result in missing 10% of school days but less than 5 days). Schools were also allowed to opt out students from the intervention for known issues (particularly medical conditions and homelessness). The letter was sent out Friday, September 15, 2017 (9 days after the first day of the 2017–2018 school year).[3]

Measures

For Research Question 1, the outcome variable was the change in attendance rate between mid-September and mid-November 2016 and the same period in 2017.[4] The latter period was the 43-day period after the first nudge letter was sent out, as described above. The outcome variable was calculated as the attendance rate in the 2017 period minus the attendance rate in the 2016 period, so that a positive value indicated improved attendance. For Research Question 2, the outcome variable was the change in the student's full year attendance rate between 2016–2017 and 2017–2018.

Student level covariates included sex, ethnicity,[5] English language learner status, special education status, and a dichotomous variable indicating whether the student lived in Seattle Housing Authority (SHA) housing. Student grade level was converted to a categorical variable for elementary grades (1–5), middle grades (6–8), and high school (grades 9–12).

The district data included a flag indicating that the student's parent/guardian was sent the September nudge letter ($n = 6{,}363$). Letters sent, but returned to the district as undeliverable, were also flagged ($n = 308$). The remaining students' families were assumed to have received the letter ($n = 6{,}055$).

Analytic Approach

Functional form and bandwidth. We used the R package rdd (Dimmery, 2013) to estimate the effect at the treatment cutoff of minimum segment attendance rate equal to 0.9 (90% attendance rate). The package performs local linear regressions at either side of the cutoff to estimate the size of the discontinuity ("break") between the regressions. The rdd package uses the Imbens-Kalyanaraman procedure (Imbens & Kalyanaraman, 2012) to calculate optimal bandwidth. We investigated the distribution of covariates in several different

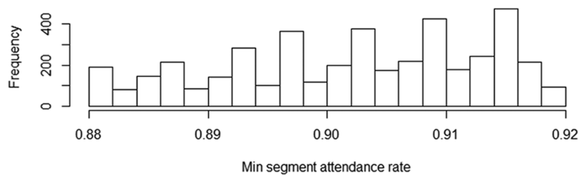

Figure 1. Histogram of the forcing variable.

bandwidths. To investigate functional form, we compared results from local regression (R package rdd) with ordinary linear regressions including a quadratic term for the forcing variable and using observations within the same bandwidth as the rdd analysis; the results were very similar.

Integrity of the forcing variable. This standard involves whether there was systematic manipulation of the forcing variable or assignment to the intervention. As described above, the assignment to the intervention included some planned deviation from strict adherence to the 0.90 attendance level for assignment to the intervention. Students had to have more than five absences as well as an attendance rate below 0.90. The decision rule also allowed schools with students flagged for meeting these criteria to opt students out of the treatment (generally because of known issues including medical conditions and homelessness). Although students with similar conditions could have been part of the control group, the size of this group was less than 1% of the full treatment sample.

Figure 1 provides a histogram of the distribution of students around the 0.90 level of the forcing variable. The histogram indicates no "strong evidence of a discontinuity at the cutoff that is obviously larger than discontinuities in the density at other points" (What Works Clearinghouse, 2017, p. 61).

Continuity of the relationship between the outcome and the forcing variable. To address this standard, we investigated baseline equivalence of key covariates at the forcing variable cutoff of 0.9. Table 1 shows covariate distributions in several different bandwidths around the 0.9 cutoff. There were substantive differences in the treatment and control groups within the full bandwidth, especially in race/ethnicity categories. Narrowing the bandwidth reduced the discrepancies (except for gender). The quarter bandwidth (students with attendance rates between 0.88 and 0.92) was determined to be optimal.

Table 2 reports demographics of students on both sides of the optimal analysis bandwidth (attendance rates of 88–90% and attendance rates of just

Table 1. Distribution of Key Covariates in Analysis Bandwidths.

	Full bandwidth (0.819–0.981)	Half bandwidth (0.860–0.940)	Quarter bandwidth (0.88–0.92)
	N (treatment) = 3,824	*N* (treatment) = 2,701	*N* (treatment) = 1,655
% Male			
Control	50.7	48.8	47.1
Treatment	51.9	52.0	52.4
% Bilingual			
Control	10.7	11.7	12.4
Treatment	14.4	13.7	12.6
% Special ed			
Control	13.9	15.6	16.8
Treatment	19.8	18.4	18.1
% Black			
Control	13.9	16.5	18.6
Treatment	22.1	20.6	20.4
% White			
Control	51.6	48.5	46.0
Treatment	38.3	41.1	43.4
% Hispanic			
Control	11.5	13.2	12.8
Treatment	16.7	15.0	13.5

over 90% to 92%). Table 2 demonstrates that the treatment and control groups are reasonably comparable based on their demographics. The last column of Table 2 is the Cox index, a statistic that measures baseline differences between treatment and control groups for binary variables. Following What Works Clearinghouse (2017) requirements that baseline differences be no larger than 0.25 and that variables with differences greater than 0.05 be included as control variables in the model, we included gender, race/ethnicity, special education status, and whether students lived in Seattle Housing Authority residences as control variables in the RDD models.

Attrition. A total of 6,363 students met the decision rules for inclusion in the study. An additional 107 met inclusion rules for being chronically absent but were excluded from the "intent to treat" group because of having fewer than five absences, being opted out by their schools (for medical conditions or homelessness), or being found to have inaccurate district enrollment records

Table 2. Demographics in Analysis Bandwidth 0.88 to 0.92.

	Control (0.90–0.92)		Treatment (0.88–>0.90)		Baseline difference
	n	%	*n*	%	(Cox index)
Gender					
Male	1,200	47.1	867	52.4	0.129
Female	1,347	52.9	788	47.6	
Race/ethnicity					
American Indian	20	0.8	18	1.1	
Asian	285	11.2	175	10.6	
Black	474	18.6	338	20.4	
Caucasian	1,172	46.0	718	43.4	
Hispanic	326	12.8	223	13.5	
Multiracial	255	10.0	171	10.3	
Pacific Islander	15	0.6	12	0.7	
Historically Underserved					
Historically Underserved	835	32.8	591	35.7	0.078
English language learners					
No	2,231	87.6	1,446	87.4	−0.011
Yes	316	12.4	209	12.6	
Special education					
No	2,119	83.2	1,355	81.9	−0.055
Yes	428	16.8	300	18.1	
Seattle Housing Authority residents					
No	2,216	87.0	1,413	85.4	−0.082
Yes	331	13.0	242	14.6	
All students	2,547		1,655		

for 2017–2018 that affected their original inclusion. All these conditions were part of the district's original decision rule for treatment. An additional 56 students mistakenly received the treatment without meeting the decision rule for enrollment status and were excluded from the analyses.

Of the 6,363 letters sent to families in the "intent to treat" group, a total of 308 were returned to the district as undeliverable. These students were included in the "intent-to-treat" analyses.

Because the decision rule for the intervention required enrollment in the district for 2017–2018, there was no attrition due to missing attendance outcome data. The treatment group did, however, include 326 students (5.1%) who had entered the district after the first quarter in 2016–2017 and were

Table 3. Students with Attendance Measures Based on Less Than Full Enrollment.

	Treatment		Control	
	n	%	*n*	%
Q1 2016–2017	222	3.9	370	1.0
Q1 2017–2018	314	5.5	373	1.0
2016–2017 school year	1,099	18.2	5,461	13.8
2017–2018 school year	847	14.0	1,481	3.7

missing data on the baseline variable for the analyses to address Research Question 1. All members of the treatment group had attendance rate outcome measures for the entire year in 2016–2017 and 2017–2018 for the analysis to address Research Question 2. Table 3 summarizes the percentages of the treatment and control group whose attendance measures were based on enrollment less than the entire first quarter and less than the entire year in 2016–2017 and 2017–2018.

Findings

This section begins by summarizing the descriptive findings about chronic absence and its relationship to demographic factors. We then report the findings from regression discontinuity analyses about the impact of the nudge letters on attendance.

Overall, a total of 13.8% of students enrolled in grades 1 to 12 in Seattle Public Schools in 2017–2018 had missed more than 10% of school days the year before and were flagged to receive a nudge letter. The proportion of students chronically absent and flagged for a letter was 8.6% among elementary students, 11.0% among middle grades students, and 24.7% among high school students.

As expected from other research findings, students who were chronically absent and flagged to receive a nudge letter were significantly different demographically from students who were not chronically absent. Chronically absent students were disproportionately Historically Underserved Students of Color (Black, Hispanic, Native American, and Pacific Islander), English Language Leaners (ELL), Special Education, and Seattle Housing Authority (SHA) students. Table 4 shows the detailed demographic breakdown by September nudge letter flags. Roughly half (51.4%) of the students who received the September nudge letter were high school students, 29.6% were elementary and 19% were middle school grade students (see Table 5).

Table 4. Demographic Characteristics of Students by September Nudge Letter Status.

	Received September letter		Sent September letter, did not receive		Not sent September letter		
	n	%	*n*	%	*n*	%	Total
Gender							
Male	3,180	52.5	167	54.2	20,288	51.2	
Female	2,875	47.5	141	45.8	19,356	48.8	
Race/ethnicity							
American Indian	81	1.3	10	3.2	166	0.4	
Asian	632	10.4	22	7.1	5,978	15.1	
Black	1,490	24.6	111	36.0	5,228	13.2	
Caucasian	2,064	34.1	63	20.5	19,692	49.7	
Hispanic	1,123	18.5	63	20.5	4,325	10.9	
Multiracial	598	9.9	35	11.4	4,155	10.5	
Pacific Islander	67	1.1	4	1.3	100	0.3	
Historically Underserved							
Historically Underserved	2,761	45.6	188	61.0	9,819	24.8	
English language learner							
No	5,149	85.0	269	87.3	35,366	89.2	
Yes	906	15.0	39	12.7	4,278	10.8	
Special education							
No	4,629	76.4	234	76.0	34,437	86.9	
Yes	1,426	23.6	74	24.0	5,207	13.1	
Seattle Housing Authority residents							
No	4,870	80.4	244	79.2	36,475	92.0	
Yes	1,185	19.6	64	20.8	3,169	8.0	
All students (grades 1–12)	6,055	13.2	308	0.7	39,644	86.2	46,007

Table 6 shows the impact results of receiving a nudge letter on the first quarter attendance of 2017–2018 (RQ1) for students at all grade levels. The effect estimate—a less than 1% increase in attendance rate—was not statistically significant ($p = .20$). The effect size of 0.09 SD means that the difference between treatment and control groups at the discontinuity was just 0.09 times the standard deviation of the outcome variable (calculated from all students in the analysis).

Figure 2 below graphically represents the RD analysis for students at all grade levels. The left side of the figure (attendance rate between 0.88 and

Table 5. Number and Percent of Students by Grade Level.

	Received September letter		Sent September letter, did not receive		Not sent September letter		
	n	%	*n*	%	*n*	%	Total
Elementary (grades 1–5)	1,790	29.6	100	32.5	20,024	50.5	21,914
Middle school (grades 6–8)	1,151	19.0	35	11.4	9,588	24.2	10,774
High school (grades 9–12)	3,114	51.4	173	56.2	10,032	25.3	13,319
All students (grades 1–12)	6,055		308		39,644		46,007

Table 6. Results of Regression Discontinuity Analysis.

	Overall			In bandwidth				
Analysis	*N* (treatment)	*N* (control)	Band-width	*N* (treatment)	*N* (control)	Effect estimate	*p*	Effect size
Treatment	5,757	38,624	0.88–0.92	1,655	2,547	0.008	.20	0.09

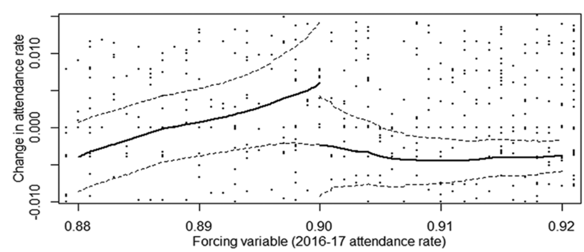

Figure 2. Graphic representation of regression discontinuity (RD) analysis.

0.90) represents the treatment group (those who received a nudge letter), while the right side (attendance rate of just above 0.90 to 0.92) represents the comparison group that is similar to the treatment group on other characteristics. The solid lines are regression lines of the outcome variable (increase in attendance rate) on the forcing variable (whether or not the prior attendance was less than 90% and the student's family received a nudge letter). The dotted lines around each solid line represent the 95%

Table 7. Results of Regression Discontinuity Analysis by Grade Band and Seattle Housing Authority (SHA) Residence.

Analysis	Overall		In bandwidth (0.88–0.92)				
	N (treatment)	*N* (control)	*N* (treatment)	*N* (control)	Effect estimate	*p*	Effect size
Elementary	1,691	19,496	648	1,013	0.004	.449	0.05
Middle	1,105	9,397	372	609	0.025	.044	0.34
High school	2,961	9,731	605	969	0.001	.937	0.01
Seattle Housing Authority residence	1,135	3,047	235	337	0.006	.747	0.05

confidence interval for the regression. The discontinuity ("gap") between the regression lines at the threshold of 0.9 (90% attendance rate) is the estimate of the effect associated with the treatment. While we can clearly see the discontinuity in the figure, note that the y-axis range is very small (the gap is 0.008 or 0.8%, less than 1%).

To investigate the possibility that the effect may have been greater for some subgroups, we also conducted separate analyses for elementary, middle, and high school students. In addition, a separate analysis was conducted for Seattle Housing Authority (SHA) students. The subgroups showed results similar to the overall result (Table 7), with the exception of a larger effect for middle school students. The statistical significance of this effect should be treated with caution, because performing multiple comparisons for multiple subgroups increases Type I error. However, the effect size for middle school students (0.34) is "substantively important" by WCC standards. The effect coefficient estimate of 0.025 indicates that controlling for the demographic variables mentioned above, the nudge letter treatment group middle school students on average had a 2.5% higher change in attendance rate from 2016–2017 to 2017–2018 than students who did not receive the nudge letter. Those not receiving the letter showed essentially no change in the attendance rate between the two school years. The increased attendance rate for the nudge letter students translates into a little over one more day attended during a school calendar quarter of 45 days.

Table 8 reports the impact on the change in full-year attendance rates from 2016–2017 to 2017–2018 of the September nudge letter treatment (RQ2). The effect estimate was not statistically significant ($p = .78$). The effect size of 0.03 SD means that the difference between treatment and control groups at the discontinuity was just 0.03 times the standard deviation of the attendance rate change outcome variable (calculated from all students in the analysis).

Table 8. Results of Regression Discontinuity Analysis for Full Year 2017–2018 Attendance.

Analysis	Overall			In bandwidth				
	N (treatment)	*N* (control)	Band-width	*N* (treatment)	*N* (control)	Effect estimate	*p*	Effect size
Treatment	6,054	39,533	0.88–0.92	1,655	2,661	0.002	.78	0.03

Table 9. Results of Regression Discontinuity Analysis by Grade Band and SHA.

Analysis	Overall		In bandwidth (0.88–0.92)				
	N (treatment)	*N* (control)	*N* (treatment)	*N* (control)	Effect estimate	*p*	Effect size
Elementary	1,789	19,997	655	1,052	0.009	.28	0.12
Middle	1,151	9,564	377	620	0.012	.30	0.15
High school	3,114	9,992	623	989	0.002	.85	0.03
SHA	1,135	3,047	235	337	0.015	.38	0.14

Students whose families received the September nudge letter did not have significantly better attendance rate changes over the entire year than students in the comparison group.

To investigate the possibility that the effect of the nudge letters on the change in full-year attendance rates may have been greater for some age groups, separate analyses were conducted for elementary, middle, and high school students. The subgroups showed results similar to the overall result (Table 9). None of the effects were statistically significant.

Discussion

This study contributes to the growing literature on the effectiveness of attendance improvement initiatives such as the nudge letter approach. The finding of a notable short-term effect on middle school students, but not an overall effect on all grade levels of students, suggests the need for further research in other contexts to explore specific grade level effects. If these findings are replicated in other studies, there may be evidence for a more targeted intervention approach.

It is possible that this study did not find the same positive effects of nudge letters on student attendance as previous randomized studies found (e.g., Rogers et al., 2017) because the study design could not include students with lower levels of attendance (below 0.88) and effects could be much more pronounced on students with lower attendance rates. It is also possible that the statistically significant effects found in randomized studies were due to large sample sizes (over 50,000 students). The effect sizes reported in the Rogers et al. (2017) study (0.03) were the same or lower than those found in the current study with a smaller sample. It is also possible that this RD analysis was underpowered.

The fact that we found some evidence of a short-term effect of nudge letters on middle school student attendance, but not a longer-term effect on attendance rates over the full year, suggests that the intervention may need to be sustained over time. As noted, implementation issues related to the sending of quarterly nudge letters throughout the year made interpretation and inferences from analyses of the more sustained intervention problematic in this study. If such implementation issues can be addressed in future studies, it will be useful to examine impacts from more sustained delivery of the nudge letter intervention.

Given findings of a positive effect in previous randomized studies, the district in this study sought to intervene with all chronically absent students and not just a random sample of them. This study's use of a regression discontinuity design makes a methodological contribution to the nudge letter research and models the type of analyses that will be needed going forward as districts seek to intervene with all students falling below a certain level in attendance.

Interventions that help improve student attendance are important to the extent that they also help to improve student performance. Building the habit of good attendance is critical for success in postsecondary education and employment as well. Interventions such as nudge letters cost only a fraction per incremental school day generated compared to more intensive whole school personalized interventions (Mac Iver et al., 2019; Robinson et al., 2018; Rogers & Feller, 2018). Whether they can lead to the lasting changes that will translate into improved student outcomes is a question that future studies should continue to explore.

Appendix

Text of September Nudge Letter

Dear Parent/Guardian of [NAME]:

Last year, [NAME] missed [X] days of school.

We miss [NAME] when they are gone and value their contributions to our school community. Excused and unexcused absences affect [NAME's] learning.

We know there are a wide variety of reasons that students are absent from school, however, we know that improving attendance for all students improves student learning.

Please reach out to [NAME] at [SCHOOL NAME] at [PHONE NUMBER] or [EMAIL] if you have questions about your student's attendance.

Because attendance matters, we promise to keep you informed of your child's attendance throughout this school year. Thank you for partnering with us to help [NAME] attend school as much as possible.

Warm regards,

SUPERINTENDENT SIGNATURE

Declaration of Conflicting Interests

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Notes

1. See Procedures section below for a more precise description of how students were included in the study.
2. Retention in grade rates for grades K-11 in Seattle Public Schools are nearly zero.
3. Letters were also sent in November, February, and April after the end of each quarter. Those students who improved their attendance so as to be no longer chronically absent for the quarter were sent a reinforcement letter acknowledging their attendance improvement. Students who continued to be chronically absent received another nudge letter. Students who were newly chronically absent (and did not receive the September nudge letter) also were flagged to receive letters throughout the year. The November and February mailings excluded students who were absent for more than 1 day due to medical and other reasons. The substantial deviations from the original intervention assignment criteria for

subsequent nudge letters throughout the year made it difficult to conduct rigorous analyses of their effect.

4. Specifically, the periods ranged from September 19 to November 18, 2016 and from September 18 to November 17, 2017.
5. A dichotomous "historically underserved" variable was also created, coding as Black, Hispanic, American Indian and Pacific Islander students as 1.

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