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Lifting Up Attendance in Rural Districts: A Multi-Site Trial of a Personalized Messaging Campaign

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Abstract

Student absenteeism has remained high following the COVID-19 pandemic and districts need low-cost strategies to improve attendance. In 2020-21, the National Center for Rural Education Research Networks piloted a promising personalized messaging intervention in 8 rural districts in New York and Ohio. We worked with a student information system provider to replicate the intervention in a randomized trial in 47 districts in 16 states between 2022-23 and 2023-24. We find that the personalized messages reduced student absences by between 1.7 ($p<0.05$) and 4.5 percent ($p<0.05$) and cost, on average, $4.07 per student to implement. We report on implementation challenges and heterogeneous effects across student populations. Our findings have practical implications for implementing technology-based interventions in the rural context.

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I. Introduction

Student absenteeism is the result of multiple intersecting underlying causes and co-occurring challenges (constituting what Biddle et al. (2018) describe as a "wicked problem"). Each day a student is out of school is the result of macro-level factors (such as local transportation infrastructure and housing), family-level factors (such as adult work schedules and relationships with teachers and school leaders), school-level factors (such as bus schedules, school climate, and disciplinary policies) and student-level factors (such as feelings of safety and engagement with school). Even before the pandemic, school leaders sought to address high rates of absenteeism, with many states including chronic absenteeism in their ESSA accountability measures (Jordan & Miller, 2017). However, this challenge has been growing in recent years, particularly with the start of the COVID-19 pandemic (Carminucci et al., 2021). Between the 2017-18 and 2021-22 school years, chronic absenteeism increased 47 percent among rural students, 44 percent among students in urban districts, and 46 percent among students in suburban areas (Bay, 2023). Such dramatic increases are concerning given the well-established adverse effects of absenteeism on academic achievement and socioemotional development (Ginsburg et al., 2014; Gottfried, 2014; Rafa, 2017).

District leaders are confronting the challenge of rising student absenteeism even as state and federal pandemic relief dollars are expiring. During the pandemic, the federal government invested $190 billion in Elementary and Secondary School Emergency Relief (ESSER) funds to accelerate student learning following the pandemic. While these investments have led to improvements in math and reading scores (Dewey et al., 2024), educators still need low-cost, sustainable solutions to pressing challenges such as absenteeism. In rural districts, existing challenges around funding and staff capacity further emphasize the need for solutions that are inexpensive and easily integrated into existing school practices (Best & Cohen, 2014). Rural communities are shaped by unique strengths and challenges that demand evidence tailored to inform rural praxis (Azano & Biddle, 2019). In this context, there is a clear need for rigorous causal research establishing the viability of low-cost strategies that can be feasibly implemented by rural educators to reduce student absenteeism.

In urban districts, nudge interventions (those that focus caregiver attention on their children's absences and the importance of regularly attending school) have been shown to improve student attendance (Bergman & Chan, 2019; Heppen et al., 2020; Rogers & Feller, 2018; Rogers et al., 2017). However, research in rural districts is scarce. Further, the rural context may mediate the effect of nudges in different ways. In rural communities, transportation barriers may loom larger than in urban or suburban areas, as rural school districts tend to encompass larger geographic areas (Gottfried et al., 2021). On the other hand, rural districts have the advantage of maintaining close relationships between teachers, their students, and families (Sheldon, 2007; Barley & Beesley, 2007). While these relationships are potentially important for attendance (Smythe-Leistico & Page, 2018), there is limited research on whether nudges are helpful or harmful in maintaining those relationships. The efficacy of these interventions may also be blunted in rural contexts if they do not ultimately provide new information to families that they haven't already heard from their child's teacher.

In the 2020-21 school year, 8 rural districts in New York and Ohio working with the National Center for Rural Education Research Networks (NCRERN) piloted a personalized messaging intervention in which caregivers were sent regular updates via text, email, or phone call about their child's cumulative absences. The messages also asked caregivers to set a goal for attendance, offered encouragement, or provided a comparison to the grade or school, and ended with encouragement to contact the school to strategize for better attendance. Using a classical frequentist hypothesis test, the messages were found to lead to a statistically insignificant decrease in absences. However, using a Bayesian framework with relatively weak priors, we found that that the intervention likely did decrease absences (with a certainty level of 83 percent), with a point estimate of a 2.4 percent decline in absences (Swanson, 2023). Given these promising findings, NCRERN partnered with a student information system that offers a built-in messaging platform to replicate the intervention at scale and across rural contexts. In this paper, we present results from Leveraging Interactions with Families To (LIFT) Up Attendance, a two-year national replication study of this intervention.

LIFT Up Attendance was implemented in 47 rural districts across 16 states in the 2022-23 and 2023-24 school years. All districts already used the same student information system (SIS) with messaging capabilities. The SIS provider, Infinite Campus, integrated the LIFT Up message templates into their platform, allowing districts to send personalized messages to a randomly assigned treatment group of students in grades K-12. Messages were sent every 4-6 weeks and included information about the student's cumulative absences over the prior 4-6 weeks, the importance of attendance, and an invitation to connect with the school. Messages also provided differentiated guidance, providing encouragement for continued high attendance for students with 0-1 absences and offering a goal for reduced absenteeism for students with 2 or more absences.

While LIFT Up Attendance was designed as a low-cost, easy-to-execute intervention, districts faced significant implementation challenges each year. In 2022-23, the launch was delayed due to technical issues integrating the message templates into the SIS. In 2023-24, the filters used to differentiate messages between students who had 0-1 days absent and students with 2 or more days absent in the preceding 4-6 weeks were inconsistently applied by district implementers. In both years, there was some treatment non-compliance, with students assigned to treatment not receiving messages and students assigned to the control condition receiving messages. Despite these implementation challenges, the intent-to-treat (ITT) estimates suggest personalized messaging reduced absences by 1.7 percent, an effect that is statistically significant at the 5 percent level. Treatment-on-treated (TOT) estimates from instrumental variables analysis indicate the effect of LIFT Up Attendance was larger, reducing absences by 4.5 percent, also statistically significant at the 5 percent level. We find evidence of heterogeneity in effects by student gender, race/ethnicity, receipt of free or reduced-price lunch (FRPL), receipt of Special Education services, and whether the student was chronically absent in the prior year. Effects were nominally larger for students receiving FRPL or Special Education services as well as for students who were chronically absent in the prior year. We also see nominally larger effects for Indigenous students and nominally smaller effects for Black students than for White, Asian/Pacific Islander, Hispanic/Latinx, and Multiracial students. Additionally, we see that the effects of personalized messaging were greater when focusing on districts with higher implementation fidelity. Cost analyses suggest that LIFT Up Attendance was a low-cost intervention—on average, the cost to implement was $4.07 per student.

This study provides some of the first nationally representative causal evidence on the impact of caregiver nudges to reduce student absenteeism in rural areas. We discuss the challenges of implementing a new intervention, even one that leverages existing systems and is designed to require minimal effort. These results fill a critical gap in the literature about effective practices for increasing student attendance and offer key design insights for future rural research.

The paper proceeds as follows. Section II discusses the causes of absenteeism, effects on student outcomes, and effective strategies for reducing absences. Section III describes the personalized messaging intervention design and theory of change. Section IV describes the study context and implementation. Section V describes our data, methods, and analytic approach. Section VI presents results from the randomized control trial of personalized messaging. Section VII concludes.

II. Relevant Literature

Student attendance results from an interplay of systems-, student-, and family -level factors. Systems-level barriers include structural impediments to a child's ability to regularly attend school, such as community violence, trauma, or inadequate transportation (Attendance Works, 2022). Given the travel distance to school in many rural communities, transportation barriers are a more prevalent challenge than in urban or suburban areas (Gottfried et al., 2021). Rural communities are constantly evolving, with the pace of demographic and economic changes accelerating in many communities following the pandemic. With increases in remote work, many rural areas are experiencing rapid population growth (Davis et al., 2023). With the changing community, educators must work to build new relationships as their connections with the community are a key strength of rural education (Azano & Biddle, 2019; Sheldon, 2007), and a valuable leverage point for reducing absenteeism (Smythe-Leistico & Page, 2018).

Students' relationships with school also affect their attendance patterns; these relationships are driven by the school environment. Students may avoid school if they have negative perceptions of the climate or feel anxious about their performance or belonging in school (Attendance Works, 2022). On average, student perceptions of school climate are similar in rural and urban districts (Ellis et al., 2022) but are shaped by the unique context of the school (Moritz Rudasill et al., 2017).

Students may also disengage from school if they are not engaged by their classes and lack meaningful relationships with their teachers and others at their school (Attendance Works, 2022). Rural schools may struggle to attract and retain teachers in specialized areas, leading to a narrower range of course offerings, limiting students' options and offering an incomplete match to their interests. For example, rural schools typically offer fewer career and technical education courses than non-rural schools (Arneson et al., 2020). Rural schools also typically leverage dual enrollment rather than Advanced Placement courses as a strategy to provide college-level courses (Anderson et al., 2021). While these courses could offer engaging, rigorous curriculum, students may also be unable to take up the offer of dual enrollment because of transportation or cost barriers.

The potential impact of teacher-student relationships on rural students' attendance is less clear. Teacher turnover is high in high-poverty, remote, and small rural districts (Ingersoll et al., 2018; Lazarev et al., 2017; Monk, 2007), which may prevent the development of sustained, deep student-teacher relationships. However, teachers who stay in rural districts often have deep ties to the community and to their students (Seelig & McCabe, 2016), which may encourage student engagement and consistent attendance.

Family-level factors driving student absences include misconceptions about the school's attendance policies, an underestimation of their child's absences, or a lack of information about the adverse effects of absenteeism (Attendance Works, 2022). Providing information to caregivers about student absenteeism improves attendance (Musaddiq et al., 2023; Bergman & Chan, 2019; Heppen et al., 2020; Rogers & Feller, 2018; Rogers et al., 2017), but these initiatives have only been evaluated in urban settings. As caregivers tend to have stronger existing relationships with schools in rural areas (Azano & Biddle, 2019; Sheldon, 2007), this type of intervention may present less of a contrast with and represent a smaller value-add to existing practice in rural schools.

The resources available to schools when attempting to address challenges to student attendance vary by locale. In rural areas, staff often already feel overburdened with responsibilities, with this driving the exits of many rural teachers (Hammer et al., 2005; Lazarev et al., 2017). Rural districts also often confront shrinking budgets and high fixed costs for transportation and other student services impacted by geography (Biddle & Azano, 2016). There is also a gap in the research literature about effective strategies for reducing absenteeism in rural areas and how they might be sustainably implemented. Much of the existing literature about the factors contributing to absenteeism was conducted in urban areas, while studies aimed at understanding how these factors manifest in rural contexts focus on a specific rural community. While this analytic approach allows for a rich and nuanced exploration of that community, there is a need for broader analysis that probes the root causes of rural student absenteeism across contexts. With this understanding of the factors driving student attendance, we turn to the consequences of student absenteeism.

Prior research finds that absenteeism adversely affects students' academic achievement across subjects and grade levels (Ginsburg et al., 2014; Gershenson et al., 2017; Gottfried, 2009, 2014, 2019; Kirksey, 2019; Romero & Lee, 2007; Spradlin et al., 2012; Rafa, 2017). The detrimental effects of missing school exacerbate inequities across student populations, with larger estimated impacts on students who started the year below grade-level, students from low-income households, and students receiving English Language Learner services (Aucejo &

Romano, 2016; Gershenson et al., 2017). Research suggests that the relationship between absences and achievement gains is linear, with each additional absence associated with less academic progress, as measured by standardized tests (see for example Kieninger et al., 2022).

The effects of missing school can be seen on other outcomes as well. Students who are chronically absent, particularly in early grades, are less likely to graduate high school or enroll in college (Liu et al., 2021; Romero & Lee, 2007; Schoeneberger, 2012). Further, the negative effects of absenteeism are not limited to students who have missed school. There are spillover effects for absent students' peers, including reduced math and reading test scores, and these deleterious effects are again differentially large for already disadvantaged students (Gottfried, 2011, 2014).

While the bulk of the research on the consequences of absenteeism on student outcomes has been conducted in urban areas, descriptive work in rural settings shows a similar negative correlation (Hunt & Hopko, 2009; Kieninger et al., 2022). However, additional work is needed to further examine the impacts of absenteeism on rural students' educational outcomes.

Although student absenteeism is rooted in multiple complex, interlocking causes, prior research has found that low-cost, low-touch interventions can yield modest gains in attendance. Behavioral nudges offer support through mechanisms such as information availability and goal setting, with the aim of encouraging individuals to make positive behavioral changes (Damgaard & Nielsen, 2018).

As students form their early perceptions about the importance of school and being present in the classroom, families play a critical role in ensuring students develop positive behaviors toward school attendance and academic achievement (Houtenville & Conway, 2008). However, families often hold misconceptions about their child's attendance relative to their peers: twothirds of caregivers of students with above-average absences reported that their child had an absence rate lower than their fellow students (Rogers & Feller, 2018). Informational nudges integrated into schools' existing communications systems have the potential to influence the behavior of students and families in a low-cost, low-effort way.

The appeal of low-cost interventions with flexible options for delivery has yielded a growing literature on the effectiveness of nudges in urban educational settings. In an evaluation of a program that sent personalized postcards home to families, Himmelsbach et al. (2022) found a reduction in absences of 8.3 percent for students in primary grades. High-frequency, information-based interventions that provide caregivers with messages containing information on their child's academic performance and attendance, such as those studied by Bergman and Chan (2019), have increased students' presence at school by 12 percent. Similar interventions have decreased rates of chronic absenteeism for students of caregivers who receive periodic mailings about their child's school attendance (Rogers & Feller, 2018; Rogers et al., 2017). Across studies, interventions that provide regular, accurate information about students' cumulative absences and the importance of attendance reduce student absences (Kurki et al., 2021; Musaddiq et al., 2023; Robinson et al., 2018).

Only one study has evaluated the impact of personalized messaging in rural districts (Swanson, 2023). In this trial, personalized messaging was estimated to lead to a smaller estimated decrease in absenteeism than had been previously documented, about a two percent decrease and not statistically significant. However, that trial was conducted in the 2021-22 school year, when schools were facing the acute challenges of the COVID-19 pandemic, including finding ways to safely return to in-person learning. The consistent success of personalized messaging in urban settings and the promise of personalized messaging in rural districts suggest that further evidence is needed on the efficacy of such an intervention in rural districts.

We fill this gap in the literature through a national evaluation of a personalized messaging intervention in a rural setting. We also add to the literature by estimating the costs of the intervention, including the dedication of staff time to implementation. Finally, we provide detailed implementation data highlighting the challenges of starting any new initiative, even one designed to be low effort. Together, this study makes a significant contribution to the literature about how rural districts can reduce student absenteeism in an educational landscape still recovering from the COVID-19 pandemic and facing down a perilous financial outlook.

III. Leveraging Interactions with Families To (LIFT) Up Attendance

The personalized messaging intervention evaluated here is an informational nudge aimed at caregivers/family members of students in grades K-12. Three message templates were included as part of the intervention. First, an initial welcome message personalized with the caregiver's name, providing an overview of the study and its objectives, and saying that their student (personalized with the student's name) had been randomly selected to participate. The welcome message was sent at the beginning of the school year. Next, recurring messages were sent to caregivers every four to six weeks with the exact cadence chosen by implementing districts. There were two recurring message templates. If the student had been absent zero or one days, the caregiver received a message congratulating the student on their attendance and encouraging them to maintain their attendance in the coming period. If the student had been absent two or more days, caregivers received a message with five core components: 1) the student's name; 2) the number of days the student had been absent in the preceding 4-6 weeks; 3) a reminder of the importance of attendance; 4) a goal for attendance in the next 4-6 weeks (intended to be realistic and attainable, based on the number of days the student had been absent); and 5) encouragement and contact information to connect with the school to discuss the student's attendance further (see Online Supplementary Materials for the message templates used in LIFT Up Attendance.)

The standard message templates were available through Infinite Campus' messaging platform. Districts could personalize the templates with the name of the person sending the message, a reference to a school mascot or slogan, or with additional information. The templates automatically pulled in the student's name, school/district name, number of absences in the preceding period, and the goal for absences in upcoming period (one day if the student had been absent two to four days; two days if the student had been absent five to seven days; or three days if the student had been absent eight or more days).

Districts could send the messages by manually pressing 'send' in the messaging platform or by scheduling the messages in advance for the entire school year. Importantly, for the recurring messages, districts needed to select the appropriate filters associated with the message templates to ensure that caregivers received either the message congratulating the student for missing zero or one days or the message informing them of the number of days the student had been absent and setting a goal for the upcoming month. Districts could send messages as emails, texts, or robocalls; in the implementation data we see that all districts sent the messages via email, with some adding other modalities.

We theorized that the messages would reduce absenteeism through four key mechanisms. First, by providing cumulative absence data, caregivers would have an accurate, holistic picture of their student's attendance. This would go beyond typical school communications around absences, which tend to inform caregivers of an absence the day it occurs or when the student is nearing the threshold for truancy, rather than providing proactive, cumulative information. Cumulative information helps reinforce the magnitude of the student's absenteeism, potentially making the issue more salient for caregivers. Second, by reinforcing the importance of attendance, the messages could increase caregivers' motivation to encourage students to attend. Third, by setting a goal for the next month, caregivers may be prompted to formulate clear action steps (such as adjusting bedtime and morning routines or creating contingency transportation plans if their child misses the bus). Fourth, by explicitly welcoming the caregiver to connect with the school, the messages would help strengthen trusting relationships between caregivers and the school. Together, these three mechanisms were intended to make the problem of absenteeism more salient to caregivers, drive action, and make it easier for caregivers to request and receive additional support from the school to address barriers to attendance. Figure 1 illustrates the theory of change of personalized messaging.

[Figure 1 here]

While we cannot explicitly test the mechanisms by which LIFT Up Attendance affects student absences, we evaluate here the impact of personalized messaging on our distal outcome of interest, the number of days a student is absent in the treatment period. Next, we discuss the context in which LIFT Up Attendance was implemented.

IV. Study Context

In 2019, the federally funded National Center for Rural Education Research Networks (NCRERN) launched its first rural research network with 49 districts in New York and Ohio with a focus on understanding and reducing student absenteeism. Partner districts in the rural research network engage in a data-driven continuous improvement process, through which researchers and practitioners identify potential areas of improvement, design an intervention based on prior literature, test the intervention, and adjust successive interventions based on findings. Through this model, districts receive coaching and collaboratively problem-solve to design, implement, and evaluate rural-specific strategies. Eight districts in the network piloted the original personalized messaging intervention in the 2021-22 school year, with support from NCRERN staff. In 2022, NCRERN launched its national replication network with 21 districts in 5 states, adding 42 districts in 2023-24. Unlike the original districts in New York and Ohio, replication network districts received minimal ongoing support from the NCRERN team.

To scale the personalized messaging intervention, NCRERN partnered with Infinite Campus, a SIS with an integrated messaging platform. We recruited rural districts (as defined by NCES locale code) that were already Infinite Campus messenger users. We did so to facilitate data access (a formidable barrier given the number of rural districts needed) and to reduce implementation challenges, as districts would already be familiar with the messaging platform. When the replication network was launched, Infinite Campus had contracts with over 2,000 rural districts in all 50 states, representing about a quarter of the almost 8,100 districts classified as 'rural' by the National Center for Education Statistics (2023).

District recruitment was led by the study team. Study team members reached out to all rural districts that had active contracts with Infinite Campus via email and set up calls with district leaders who expressed interest in the intervention. The study team also held informational webinars and publicized the study through national channels, including the NCRERN newsletter and the National Forum to Advance Rural Education. While all data was provided by Infinite Campus, this project was done with the written consent of the districts involved, each of which signed a data use agreement with the study team. Sixty-three districts initially agreed to participate in the personalized messaging study; this study is restricted to the 47 districts in 16 states that ultimately launched the intervention. These 16 states represent diverse rural contexts, including the Midwest, South, West, and Northeastern regions of the United States. Districts range in size; the average district size is about 2,300 students, with enrollments ranging from under 50 students to almost 6,000 students. Table 1 summarizes the characteristics of participating districts by year and offers a comparison to the universe of rural districts in the United States in 2023-24.

[Table 1 here]

As shown in Table 1, there are a few differences in sample composition across the two cohorts of participating districts. The 2022-23 cohort has a higher average prior-year absence rate, higher prior-year chronic absenteeism rate, and has a higher share of students of color. The 2023-24 cohort is larger and has lower shares of Black and Latinx/Hispanic students, but a higher share of Indigenous students.

Implementation

This study was designed to evaluate personalized messaging under real world conditions, with implementation led largely independently by participating districts. Districts received written guidance about how to implement the intervention from the study team, participated in an initial one-hour training session with the study team, were encouraged to have a one-on-one support call with Infinite Campus to set up the templates, and could request support from either the study team or Infinite Campus (which was part of districts' existing contracts with the provider) at any point during the implementation period. Given this, the results of this study should be understood as the impacts of personalized messaging in rural districts with typical resource constraints and external support.

LIFT Up Attendance was designed to be a low-effort intervention rural districts could incorporate into their existing practices without dedicating significant additional resources. However, launching any new intervention can be a challenge, and personalized messaging was no exception. There were several threats to the fidelity of implementation of the intervention as designed, both on the technical side for the provider and on the logistical side for implementing districts.

The message templates included several new custom fields that had not been previously generated in the Infinite Campus messaging platform, including the calculation of cumulative absences, the targeting filter directing a specific message template based on the student's prior absences, and the adaptive goal based on the student's prior absences. Creating these fields was ultimately a more complex and lengthy process than anticipated, leading to delays in the release of the message templates to districts participating in the 2022-23 school year. The message templates were expected in August 2022, prior to the start of the school year, but were not released until October 2022. In states with some level of review of SIS updates, districts could not access the templates until up to a month later. This led to significant delays in launching the intervention and reduced the treatment period from the full school year to academic quarters two through four of 2022-23. For the 2023-24 cohort, templates were available from the beginning of the school year, and most districts launched between August and October. The delayed release of the templates affected implementation fidelity in 2022-23. The recommended cadence was to send messages every four to six weeks (e.g., between six and nine rounds of messages). On average, districts in 2022-23 sent messages 3.7 times throughout the year, with districts sending messages between 1 and nine times. We classify districts that sent messages at least three times as "high implementers" for 2022-23. Implementation was stronger in the second cohort. In 2023-

24, 30 of 38 districts sent at least six rounds of messages, with all districts sending messages between two and 10 messages throughout the year. We classify districts that sent messages at least six times as "high implementers" for 2023-24.

Along with delays in the release of the message templates, there were coding errors in the message text. Initial messages for the 2022-23 cohort included typos and pulled a student's cumulative absences since the beginning of the school year rather than since the last message had been sent (as was referenced in the text). These errors were corrected by January 2023 and did not affect the spring semester or the second cohort.

On the logistical side, districts encountered two main barriers to high fidelity implementation. First, when sending messages, districts needed to apply the targeting filter, which would ensure caregivers of students who had been absent zero or one day in the prior month received a message recognizing their accomplishment and encouraging continued strong attendance, and that caregivers of students who had been absent two or more days in the prior month received a message informing them of their student's cumulative absences and setting a goal for the coming month. This filter was not consistently turned on, meaning that caregivers sometimes received both messages at the same time. Often, this had to do with the way in which the message templates and filters were released to the districts—the SIS could only push the templates to each participating district's administrator group, and if the staff members responsible for sending the messages was not part of that group, a district administrator needed to copy the message templates and filters into the appropriate user group. If the message templates were copied over without the filters, then both messages would be sent to caregivers. If a staff member tried to send messages without the filter, they would get a warning message but could still push out the messages. This was primarily a challenge in the 2023-24 cohort, with the share of the treatment group affected varying by month from none to 17 percent (in up to 7 districts).

The second logistical challenge faced by districts was lack of contact information for students' caregivers. There were a few causes for this lack of coverage. When districts first purchase Infinite Campus' messaging capabilities, the default is to release the platform to families as an opt-in opportunity to hear from the school. Districts can change the default to opt-out (recommended by Infinite Campus), but if they do not, they can only send messages (including personalized messaging, although not specific to this intervention) to those who have opted-in. Lack of coverage can also stem from having out-of-date contact information or from families having not provided any contact information. The lack of contact information meant that sometimes substantial shares of caregivers whose students were assigned to the treatment group never received personalized messages. In the 2022-23 cohort, in 4 of 9 districts fewer than half of caregivers of treatment group students received messages. In the 2023-24 cohort, less than 50 percent of caregivers of students assigned to treatment received any message in 9 of 38 districts.

These implementation challenges may dilute the treatment effect we estimate in this study but offer important lessons for districts and researchers looking to evaluate the efficacy of new interventions. Regardless of how straightforward and low effort the intervention is designed to be, there are significant barriers to start-up that need to be proactively mitigated.

V. Data, Methods, and Analytic Approach

We evaluate LIFT Up Attendance through a student-level randomization. Here, we describe our analytic sample, randomization procedure, and approach to impact estimation.

Sample description

We began with 41,990 K-12 students in standard learning environments (excluding those in alternative learning environments, homeschool students, etc.) across the 47 districts that participated in the LIFT Up Attendance trial. We had minimal student-level attrition from students exiting the districts: 317 students (less than one percent) had zero days enrolled in a participating district during the treatment period. An additional 30 students were dropped because they did not have any attendance data for the treatment period. Finally, we dropped 175 students (less than half a percent) who had more absences recorded than days enrolled. This limits our analytic sample to 41,468 students across 47 districts.

Students are evenly distributed across grades, with about seven to eight percent of the sample in each grade Kindergarten through 12th grade; this means that when we look at schooling levels (elementary grades K-5; middle grades 6-8; and high 9-12), we have a larger share of elementary students (45 percent) than middle school students (24 percent) or high school students (31 percent). On average, students missed about seven percent of days in the year prior the intervention launch, and there was an 18 percent chronic absenteeism rate across participating districts. Just over 40 percent of students receive free- or reduced-price lunch (FRPL), 16 percent have an Individual Education Plan, and six percent have received English Language Learner services. About 66 percent of students in the analytic sample are White, 15 percent are Latinx/Hispanic, nine percent are Black, five percent are Indigenous, five percent are multiracial, and one percent are Asian, Native Hawaiian, or Pacific Islander.

Randomization

Randomization occurred through a filter connected with the message templates. Students' treatment assignment was based on their ID in the SIS, and school staff did not know which students were assigned to the treatment or control groups. Balance was achieved through randomization, as shown in Table 2.

[Table 2 here]

An omnibus balance test across the two cohorts including student characteristics and district fixed effects confirms balance in our analytic sample, with an F statistic of .64 and a p-value of 0.986.

While randomization was successful, there were threats to compliance with randomization status. As randomization was linked to a filter accompanying the message templates, it had to be consistently turned on with each round of messages sent by the district (the same as the targeting filter discussed above). This was not always the case. In 3 of 9 districts in 2022-23 and in 12 of 38 districts in 2023-24, the randomization filter was not turned on for at least one round of messages, meaning that caregivers of students assigned to the control group also received messages in that round. There is no evidence that districts selectively turned off the randomization filter to make exceptions for specific students they thought would benefit from the intervention, but this does limit the treatment-control contrast in these districts. Table 1 in Appendix A shows compliance by district.

Analytic approach

We estimate the impact of personalized messaging on the number of days a student is absent during the treatment period. We include all absences, whether excused or unexcused, in this count. As days absent is a count variable, we estimate all results using Poisson models.

<u>Intent-to-Treat Effects</u>

We first estimate intent-to-treat (ITT) effects of LIFT Up Attendance[1]. We estimate ITT effects following Equation (1).

$$y_i \sim Poisson(\lambda_i)$$

$$\log(\lambda_{idsg}) = \beta_0 + \beta T_i + \boldsymbol{\alpha X_i} + \varphi \boldsymbol{H_g} + \theta log(\boldsymbol{S_s}) + \boldsymbol{\tau_d} + \log(K_i) + \varepsilon_i \quad (1)$$

Our outcome represents the number of days student *i* was absent during the treatment period. The treatment period varies across the two cohorts given the delays in launching the intervention in 2022-23. We include all absences in quarters two through four for students in the 2022-23 cohort and all absences in the school year for students in the 2023-24 cohort, reflecting the timing of the start of implementation in each year.

The randomized design identifies the effect of T_i, an indicator for whether student *i* was assigned to have messages sent to their caregiver(s). We include additional covariates for added precision in our estimates. Covariates include student characteristics ($\boldsymbol{X_i}$), such as race/ethnicity, FRPL receipt, disability status, gender, and five splines of the student's prior year absence rate[2]. We include grade-level covariates ($\boldsymbol{H_g}$), including grade fixed effects and logged average prior-year days absent for that grade, as well as average school-grade prior days absent ($\boldsymbol{S_s}$) in a logged term. Finally, we include district fixed effects ($\boldsymbol{\tau_d}$). The exposure term is the number of days the student was enrolled in the district during the treatment period. Standard errors are clustered by student, the level of randomization.

We conduct exploratory subgroup analyses by interacting the treatment indicator with an indicator for each subgroup of interest. We show estimated ITT effects by student gender, race/ethnicity, grade level, FRPL receipt, and whether or not the student was chronically absent in the prior year. We include results from post-hoc tests comparing estimated effects by subgroup to each other.

Treatment-on-Treated Effects

Given non-compliance in our sample—both students in control group receiving treatment and students in the treatment group not receiving treatment—we also estimate treatment-on-treated (TOT) estimates. We use the random assignment to instrument for whether or not a caregiver received any personalized message about their student from the school. We use the same model specification as in Equation (1), substituting $\widehat{T}_i$ for the treatment indicator, where $\widehat{T}_i = Z_i\gamma + \mu_i$. We then estimate an instrumental variables Poisson model using generalized method of moments. We present TOT effects for the overall sample, though not for subgroups.

Restricted Samples

Another strategy we use to address randomization noncompliance is to limit our sample to those districts with a valid randomized controlled trial. Since there is not a standard threshold of how much non-compliance is too much, we test the sensitivity of our findings on different samples determined by randomization compliance within districts. Specifically, we estimate ITT and TOT effects as described above on four subsamples of districts:

1. Districts in which no caregivers of students assigned to the control group received messages AND in which at least 50 percent of caregivers of students assigned to the treatment group received messages.
2. Districts in which there is at least a 5-percentage point contrast between the share of caregivers who received messages whose students were assigned to the treatment and control group, respectively.
3. Districts in which there is at least a 25-percentage point contrast between the share of caregivers who received messages whose students were assigned to the treatment and control group, respectively.

4. Districts in which there is at least a 50-percentage point contrast between the share of caregivers who received messages whose students were assigned to the treatment and control group, respectively.

We present below results from the first restricted sample (none of the control group treated and at least half the treatment group treated); results from other three samples are shown in Appendix A.

Cost Analyses

In addition to estimating the efficacy of personalized messaging, we use the ingredients method to estimate the cost of implementing the intervention. We use data on the costs of developing the templates (paid by NCRERN to the SIS and divided across all participating districts), training (time spent by district staff), setting up the messages (time spent by district staff), and sending and responding to messages (time spent by district staff). We collected data through district surveys about the time required as well as which staff were involved. We used staff titles to benchmark compensation against state averages (salaries and a 30 percent fringe rate), adjusted with a national rural scalar. We use contract costs between NCRERN and Infinite Campus for development and training costs. We present total costs per site and per student.

VI. Results

We present four estimates of the effect of personalized messaging on the number of days absent: ITT effects in our full sample, ITT effects in a sample restricted to districts with high randomization compliance, TOT effects in our full sample, and TOT effects in the restricted sample of districts with high randomization compliance. Table 3 summarizes these estimates. Coefficients are from a Poisson specification and can be interpreted as the percent change in days absent (from a base absence rate of about seven percent). Negative coefficients suggest the outcome is moving in the desired direction, reducing absenteeism.

[Table 3 here]

As shown in Table 3, we consistently find estimated decreases in student days absent as a result of LIFT Up Attendance. Our most conservative estimate is the ITT effect of being assigned to have messages sent to a caregiver, which suggests a statistically significant 1.7 percent decrease in absences, saving about .21 days throughout a 180-day school year[3]. This estimated effect is slightly smaller than that estimated in the 2020-21 NCRERN pilot with eight districts in New York and Ohio, as well as some of the effects found for similar interventions in urban settings (e.g., Musaddiq et al., 2023; Bergman & Chan, 2019).

Given the non-compliance observed with LIFT Up Attendance, both with control group caregivers receiving messages and with treatment group caregivers not receiving messages, we also estimate TOT estimates. This analysis suggests that when caregivers did receive at least one message during the treatment period, students' absences decreased by a statistically significant 4.5 percent, representing a little over half a day saved throughout a 180-day school year.

We test the sensitivity of our findings by estimating effects on a restricted sample of districts that met two benchmarks of randomization compliance and implementation fidelity. First, districts in the restricted sample did not send any messages to caregivers of students assigned to the control group. Secondly, districts in the restricted sample sent messages to caregivers for at least half of the students assigned to the treatment group. The estimated ITT effect from this sample is slightly noisier because of the loss of sample, but we still find a statistically significant decrease in absences of 3.1 percent (or .39 days over the course of the year). The estimated TOT effect in this sample is a statistically significant decrease in absences of 3.5 percent (or .44 days over the course of the year). We check the sensitivity of these findings to different sample restrictions, based on the observed contrast between the treatment and control groups rather than external thresholds for treatment status compliance; specifically, we check whether results vary when restricting the sample to districts with at a 5, 25, and 50 percentage point contrast, respectively (shown in Table A2 in Appendix A). All estimated effects are similarly sized, between a 1.5 and 5 percent decrease in absences, and statistically significant.

Subgroup Estimates

We are also interested in examining any potential differential effects of personalized messaging across student populations. We estimate effects of personalized messaging for student populations defined by demographics, services received, grade level, and prior absences. Figure 2 presents the estimated ITT effects by subgroup (point estimates reported in Appendix B).

[Figure 2 here]

As shown in Figure 2, there is some evidence of nominally heterogeneous effects across populations. Starting at the top of the chart, we see estimated treatment effects by student race/ethnicity. Estimated decreases in absences are larger and statistically significant for Indigenous (a 6.6 percent decrease) and White students (a 2.3 percent decrease). There are no significant effects of personalized messaging for Hispanic/Latinx, Asian/Pacific Islander, or Multiracial students. The differences in estimated effects for Indigenous, Hispanic/Latinx, Asian American/Pacific Islander, White, and Multiracial students are not statistically significant.

We find a significant adverse effect for Black students (a 6.5 percent increase), which is significantly different from the estimates for Indigenous, Hispanic/Latinx, White, and Multiracial students (and is not different from the estimate for Asian American/Pacific Islander students). This finding is unexpected and concerning, as prior evaluations of similar interventions have not found adverse impacts for certain populations. This estimate is driven by the 2022-23 school year, when the majority of Black students in our sample were enrolled in one district with low rates of contact information for caregivers, meaning most caregivers in the treatment group did not receive messages. The overall estimated effect of the intervention for this district was insignificant but positive, indicating a potential increase in absences and making it difficult to disentangle the mediating effect of unobserved district characteristics from our overall estimated effect of the intervention for Black students. When we estimate results for just the 2023-24 cohort, we no longer find an adverse effect of LIFT Up Attendance for Black students.

We find a larger estimated decrease for male students (about a 2.4 percent decrease) than for female students (an insignificant 0.9 percent decrease), although the difference in estimated effects for male and female students is not significant. Similar to the nominal differences by race/ethnicity, this is driven by the 2022-23 cohort; we do not see any differences in estimated effects by gender when looking at the 2023-24 cohort.

We find there is a significant decrease in absences for students receiving FRPL (a 3.7 percent decrease). This estimate is larger than that found for students not receiving FRPL (a 0.4 percent increase), with a post-hoc F test significant at the 5% level. We also find a significant decrease in absences for students receiving Special Education services (a 4.7 percent decrease), although this is not significantly different from the smaller estimated 1 percent decrease for students not receiving Special Education services.

We also find larger estimated decreases in absences for students who were chronically absent in the prior year (a 3.5 percent decrease) than for students not chronically absent in the preceding year (a .8 percent decrease)[4]. The estimated effects for those previously chronically absent and those not previously chronically absent are not significantly different from each other.

However, the large and statistically significant estimated decrease for students who were previously chronically absent suggests that personalized messaging may be effective at both decreasing absenteeism overall and particularly among students who may be at greatest risk of missing key academic progress because of high absenteeism.

Finally, we see slight nominal differences in estimated effects by grade level. We find that personalized messaging reduced absences by 1.1 percent for students in elementary school, by 1.8 percent for students in middle school, and by 2.4 percent for students in high school. However, none of these estimates are statistically significant or different from each other.

Cost Estimates

Overall, our results suggest that personalized messaging effectively reduced student absenteeism by a small to moderate amount, with effects predictably larger when focusing on students whose caregivers actually received a message from the school. Initial cost analyses suggest that personalized messaging is likely cost effective in most contexts. The average estimated cost per student to implement personalized messaging in the 2022-23 school year was $3.79. Costs were slightly higher in the 2023-24 school year, as districts sent more rounds of messages and received additional support for implementation, but still averaged just $4.20 per student. Table 4 summarizes the implementation costs of the intervention.

[Table 4 here]

Costs varied across sites depending on the number of students served, which staff were responsible for implementation, and how many staff were involved in implementation. The smallest district across the two years had 24 treated students in 2022-23, and had a total cost of $2,090.56 and a per-student cost of $87.11. The largest district across the two years reached almost 3,000 students and had a total site cost of $7,807.14 but a per-student cost of just $2.64.

In the 2023-24 school year, one participating district had three school administrators (dean, vice principal, principal, and/or superintendent) implementing the intervention, which pushed the per-student cost for their roughly 400 treated students to \$9.19—in contrast, a similarly sized district that relied on a guidance counselor and teacher for implementation had a per-student cost of \$2.86 for the year. Fixed per-district costs varied between the two years, as contractual costs for message creation and individual district support were fixed but there were 38 districts in 2023-24 rather than the 9 in the 2022-23 school year.

Using as a benchmark prior estimates that put the value of an additional day in school at \$75, given the relationship between attendance and test scores (Aucejo & Romano, 2016) and expected returns to increased achievement (see Watts, 2020 for a recent review), this would suggest that personalized messaging is cost-effective if the per student cost is between \$15 and \$41.25, depending on the effectiveness estimate we use[5]. These estimates suggest personalized messaging is a cost-effective strategy for most districts but may not be cost-effective for very small districts. However, the costs detailed here reflect the first year of implementation for each district. In subsequent years, districts would not face the fixed costs of message development. Excluding these costs reduces the average per-student cost to \$2.21 across the two years. If the staff member(s) implementing the intervention did not change in subsequent years, training costs would also be a one-time investment, further reducing the cost of the intervention and making personalized messaging a cost-effective strategy even for the smallest districts.

VII. Discussion & Conclusion

We report on a national trial of a personalized messaging intervention designed to reduce student absenteeism in rural areas. The intervention was implemented by 47 rural districts across 16 states in all regions of the United States in the 2022-23 and 2023-24 school years. We evaluated this intervention using student-level randomization. Overall, we find that LIFT Up Attendance did significantly reduce the number of days students were absent. Our most conservative estimate is an intent-to-treat effect across all 47 districts and suggests the intervention reduced absences by 1.7 percent, a decrease that is statistically significant at the 5 percent level. We additionally estimate treatment-on-treated effects given observed non-compliance with random assignment. In our full sample, this suggests that the intervention reduced absences by 4.5 percent, an effect that is again statistically significant at the 5 percent level. We further triangulate our findings by estimating effects in restricted samples, focusing on districts that met minimum benchmarks of randomization compliance and/or implementation fidelity. These estimates consistently suggest that the intervention reduced absences somewhere in the 1.7 to 4.9 percent range and are all statistically significant. Estimates from an initial cost analysis using the ingredients method suggest that this intervention, which on average costs roughly $4 per student for the year, is typically cost-effective, although for small districts the benefits may not exceed the costs until the second year of implementation.

We find minimal heterogeneity in effects across student populations, although certain estimates merit further study. We find that the intervention led to nominally larger-than-average decreases in absences among Indigenous, White, and male students, as well as students receiving FRPL and Special Education services. Estimated effects were also large for students who had missed 10 percent or more of the prior school year. Concerningly, however, we find an estimated adverse impact of the messages among Black students. This estimate is driven by the 2022-23 cohort, and specifically the estimate from one district included in that sample with low treatment compliance due to limited caregiver contact information. The estimated average treatment effect in this district—across all racial/ethnic populations—is positive (increasing absences) and insignificant, meaning that unobserved district characteristics may be contributing to the estimated effect and cannot be fully disentangled from potentially true heterogeneity by student race/ethnicity. The 2022-23 cohort also showed differential effects by gender, which was not replicated in the 2023-24 cohort or found in earlier studies, suggesting this cohort may have been unique in unmeasured ways. While there is reason to be cautious in our interpretation of the estimated adverse effect for Black students, it should not be ignored by decision-makers when deciding whether to implement a similar intervention in their context. Additional research is needed to study the effects of personalized messaging across contexts and student populations, to better identify mediators and moderators of the effect of this type of intervention for reducing student absenteeism. An initial line of inquiry would be to explore the reactions of caregivers to these messages and the impact of the messages on relationships between caregivers and the school. Understanding how the messages may be interpreted by caregivers and the enabling contextual factors that facilitate the hypothesized mechanisms for change may help to clarify the LIFT Up Attendance theory of action. Such qualitative and localized research can point to changes in the intervention design needed to more consistently and equitably support student attendance.

There were significant implementation challenges to LIFT Up Attendance. There were unexpected technical delays in creating the message templates and releasing them to partner districts. The use of filters to differentiate message templates for students with different patterns of recent attendance increased the complexity of the message set up and of sending the messages in ways that led to some caregivers receiving conflicting messages about their student's attendance. Districts' prior decisions about sending messages through the platform on an opt-in or opt-out process had consequences for how many caregivers received the treatment messages.

These implementation challenges were unanticipated, as the study was designed to leverage existing infrastructure; for example, all districts already had the messaging platform and the SIS provided other messaging templates. Some of these challenges were mitigated following the first year of the study, when the study team identified critical areas for district support, but challenges related to the use of message filters persisted and affected both implementation fidelity and randomization compliance. These implementation challenges offer valuable lessons to researchers and district leaders alike. Launching any new intervention, however seemingly incremental and low effort, is challenging, given that schools are complex organizations in which staff members already face numerous competing priorities. Researchers and district leaders alike need to meaningfully plan for implementation of any new intervention, anticipating challenges, identifying what responsibilities can be removed from implementing staff's portfolio to free capacity for the new intervention, and continually monitor implementation to intervene and adjust as needed.

There are a few limitations to this study. First, while we have a large sample overall, particularly for the rural setting, sample sizes get sparse when looking at effects for specific subgroups. Given the differences we see in estimated effects across student populations, districts should consider their student population and the nature of their existing relationships with families. It is possible that if relationships are currently contentious or negative, these personalized messages may feel accusatory or punitive rather than welcoming and supportive. Further research is needed to understand how the nature of current school-family relationships moderates the effectiveness of personalized messaging. Districts should begin by implementing such an intervention on a small scale and gathering feedback from families to better understand the potential benefits or unintended consequences of personalized messaging before adopting at scale. Relatedly, while the 47 rural districts in our sample represent 16 states and all geographic regions of the state, they are all districts that were already using a specific SIS and messaging platform prior to the start of the intervention. They also represent a small share of the total number of recruited districts (47 out of about 2,000). These districts may differ from other rural districts in ways that are moderating the effect of the intervention. Additional evidence is needed about the efficacy of personalized messaging interventions in rural contexts to better understand the generalizability of our findings here.

Finally, our identification is threatened by the randomization non-compliance observed in our sample. This non-compliance seems to have been driven by technical challenges associated with message (and randomization filter) setup as well as prior coverage of caregiver contact information rather than intentional compliance based on perceptions of which students would benefit from the intervention but does extend to a substantial portion of our sample. We address this by estimating TOT effects through an instrumental variables approach as well as by restricting our sample to districts with evidence of a valid treatment-control contrast. All estimates from these robustness checks suggest the same conclusion: personalized messaging significantly reduced student absenteeism by a small to moderate amount.

Despite these limitations, this study makes a major contribution to the literature by evaluating a low-cost nudge intervention in a national sample of rural districts. Our findings suggest that adopting such a strategy is likely a cost-effective way for rural districts to improve student attendance. Future adaptations should consider providing additional support for setting up the intervention and reducing complexity as much as possible by, for example, considering using one message template instead of differentiating based on the student's recent attendance pattern. As districts, rural and non-rural alike, continue to grapple with worsened attendance following the COVID-19 pandemic and contracting budgets, personalized messaging offers a promising and cost-effective strategy that can meet immediate needs to reduce absenteeism as districts and researchers continue to seek solutions that address other root causes of absenteeism, particularly systems-level barriers.

Endnotes

[1] Our plan to estimate ITT effects was pre-registered on the Registry of Efficacy and Effectiveness Study under Registry ID 14780.

[2] Absences have a roughly linear relationship year over year; we split absence rate into splines to match this relationship in the Poisson model.

[3] ITT effects are larger when estimated by treatment fidelity. Districts with high fidelity (sending 3 or more messages) in 2022-23 had a 5 percent decrease in absences ($p<.05$), with no significant impact in low-fidelity districts. Districts with high fidelity (6 or more messages) in 2023-24 had 2.1 percent decrease in absences ($p<0.5$), with no significant decrease in absences in low-fidelity districts.

[4] We also examined whether the intervention led to a decrease in students' likelihood of being chronically absent. We find nominally negative (ranging from a 0.30 to a 4.0 percentage point decrease in a student's likelihood of being chronically absent, depending on sample and ITT vs. TOT estimates) but imprecise effects.

[5] A $15 per-student cost is based on our ITT estimate from the full sample, which found a 1.7 percent decrease in absences, or .21 days in a 180-day school year. A $41.25 per-student cost is based on our TOT estimate from the full sample, which found a 4.4 percent decreases in absences, or .55 days in a 180-day school year.

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Tables

Table 1. District Characteristics, by Year of Participation

Characteristic	2022-23 Mean (SD)	2023-24 Mean (SD)	Pooled Mean (SD)	National- Rural Mean (SD)
Race/Ethnicity				
Asian/Pacific Islander	0.01	0.01	0.01	0.03
	(0.11)	(0.10)	(0.10)	(0.07)
Black	0.23	0.03	0.09	0.10
	(0.42)	(0.16)	(0.28)	(0.16)
Indigenous	0.02	0.06	0.05	0.02
	(0.12)	(0.24)	(0.21)	(0.09)
Latinx/Hispanic	0.21	0.12	0.15	0.18
	(0.41)	(0.33)	(0.35)	(0.21)
Multiracial	0.05	0.04	0.05	0.05
	(0.22)	(0.20)	(0.21)	(0.03)
White	0.48	0.74	0.66	0.64
	(0.50)	(0.44)	(0.47)	(0.28)
Grade Level				
Elementary (K-5)	0.45	0.45	0.45	0.48
	(0.50)	(0.50)	(0.50)	(0.50)
Middle (6-8)	0.24	0.23	0.23	0.34
	(0.42)	(0.42)	(0.42)	(0.47)
High (9-12)	0.31	0.31	0.31	0.18
	(0.46)	(0.46)	(0.46	(0.39)
Gender				
Male	0.51	0.52	0.52	0.51
	(0.50)	(0.50)	(0.50)	(0.04)
Services Received				
Free- or Reduced- Price Lunch	0.46	0.43	0.44	0.39
	(0.50)	(0.49)	(0.50)	(.15)
Students with Disabilities	0.13	0.17	0.16	0.15
	(0.34)	(0.37)	(0.37)	
English Language Learner		0.06	0.06	0.04
		(0.24)	(0.24)	
Engagement in School				
Prior Absence Rate	0.09	0.06	0.07	.09
	(0.08)	(0.06)	(0.07)	(.50)
Missing Prior Absence Rate	0.18	0.17	0.17	
	(0.38)	(0.37)	(0.38)	
Prior Chronic Absence	0.26	0.15	0.18	.11
	(0.44)	(0.36)	(0.39)	(.50)
Prior Days Enrolled	167.24	170.20	169.40	
	(25.65)	(36.98)	(34.32)	
N Students	12,699	29,291	41,990	9,602,555
N Districts	9	38	47	10,182

Note. The share of English Language Learner students was not available for the 2022-23 study cohort. Sample includes all students included in randomization. National rural absence and chronic absence rate are from the June 2024 School Pulse Panel survey administered by the National Center for Education Statistics. National rural school level, race/ethnicity, and gender are from the Common Core of Data for the 2023-24 school year, with schools restricted to regular public schools coded as 'elementary, middle, high, or secondary schools.' National statistics represent all students in a rural school (NCES locale codes 41, 42, and 43), with the number of districts representing the number of unique LEAs with at least one rural school. National rural statistics for students with disabilities and English Language Learner students reflect shares of students in rural districts (not schools) in 2019, as reported by the National Center for Education Statistics (2023)- standard deviations not available.

Table 2. Balance in analytic sample

	Characteristic	**Control Mean**	**Treatment Mean**	**Difference**	**P-Value**
Demographics	Latinx/Hispanic	0.15	0.144	-0.006	0.087
	Indigenous	0.046	0.045	-0.001	0.651
	Black	0.088	0.086	-0.002	0.39
	White	0.659	0.669	0.01	0.037
	Multiracial	0.047	0.044	-0.003	0.201
	Asian/Pacific Islander	0.009	0.011	0.002	0.027
	Male	0.456	0.453	-0.003	0.549
Grade level	Elementary	0.234	0.236	0.001	0.735
	Middle	0.309	0.311	0.002	0.738
	High	0.519	0.521	0.002	0.746
Services received	English Language Learner	0.061	0.062	0.001	0.797
	Free- or Reduced- Price Lunch	0.433	0.44	0.006	0.184
	Students with Disabilities	0.158	0.159	0.001	0.716
Engagement	Prior absence rate	0.069	0.07	0	0.686
	Mi prior abs rate	0.167	0.169	0.001	0.727
	Prior chronic abs	0.18	0.179	0	0.949
	Prior days enrolled	169.422	169.574	0.152	0.657
Omnibus test	N				41,648
	Joint test (p-value)				.986

Note. District fixed effects included in the joint omnibus test

Table 3. Estimated impacts of personalized messaging on total number of days absent

	Intent-To-Treat		Treatment-on-Treated	
	(1) Full Sample	(2) Restricted Sample	(3) Full Sample	(4) Restricted Sample
Assigned to Treatment	**-0.017****	**-0.031****		
	(0.008)	**(0.015)**		
Received Treatment			**-0.045****	**-0.035****
			(0.022)	**(0.017)**
Latinx/Hispanic	0.005	0.065**	0.005	0.065**
	(0.013)	(0.030)	(0.013)	(0.030)
Indigenous	0.139***	0.172***	0.138***	0.173***
	(0.030)	(0.045)	(0.030)	(0.045)
Asian, Pacific Islander, or Native Hawaiian	-0.194***	-0.203**	-0.195***	-0.202**
	(0.050)	(0.090)	(0.050)	(0.090)
Black	-0.035	0.081	-0.036	0.080
	(0.025)	(0.096)	(0.025)	(0.096)
Multiracial	0.050***	0.067*	0.049**	0.067*
	(0.019)	(0.037)	(0.019)	(0.037)
Male	-0.014*	0.013	-0.014*	0.0130
	(0.008)	(0.016)	(0.008)	(0.016)
FRPL	0.171***	0.121***	0.171***	0.122***
	(0.009)	(0.018)	(0.009)	(0.018)
Has IEP	0.041***	0.070***	0.040***	0.070***
	(0.012)	(0.023)	(0.012)	(0.023)
Logged Prior-Year School Avg Days Absent	0.834***	0.364***	0.848***	0.349***
	(0.033)	(0.082)	(0.034)	(0.083)
Logged Prior-Year School-Grade Avg Days Absent	-0.127***	-0.175***	-0.127***	-0.176***
	(0.025)	(0.046)	(0.025)	(0.046)
Constant	-4.794***	-3.785***	-4.819***	-3.762***
	(0.053)	(0.139)	(0.054)	(0.14)
Observations	41,468	9,341	41,468	9,341

Note. Grade and district fixed effects, absence splines, and missing indicators not shown. The exposure term is the number of days the student was enrolled in the district in the outcome year. Standard errors clustered by student. The restricted sample is comprised of students in districts that did not treat any students assigned to the control group and reached at least half of students assigned to the treatment group. Poisson coefficients shown.
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Average Total Annual Cost of Implementation, by Category and Cohort

Cohort	Avg. Treated N Per Site	Site Total-Personnel	Site Total-Training	Site Total-NCRERN	Total Per Site	Total Per Student
2022-23	778	$1.28	$0.44	$2.06	$2,949.08	$3.79
2023-24	387	$1.73	$0.71	$1.77	$1,625.09	$4.20
Average	462	$1.59	$0.62	$1.86	$1,878.62	$4.07

Note. Personnel costs include time spent setting up messages, sending messaging, and following up with families about the messages. Training costs include the cost to deliver training and time spent by implementing staff in training sessions. NCRERN costs are program fixed costs, including the contractual cost with the SIS to develop the message templates.

Figures

Figure 1. Personalized Messaging Theory of Change.

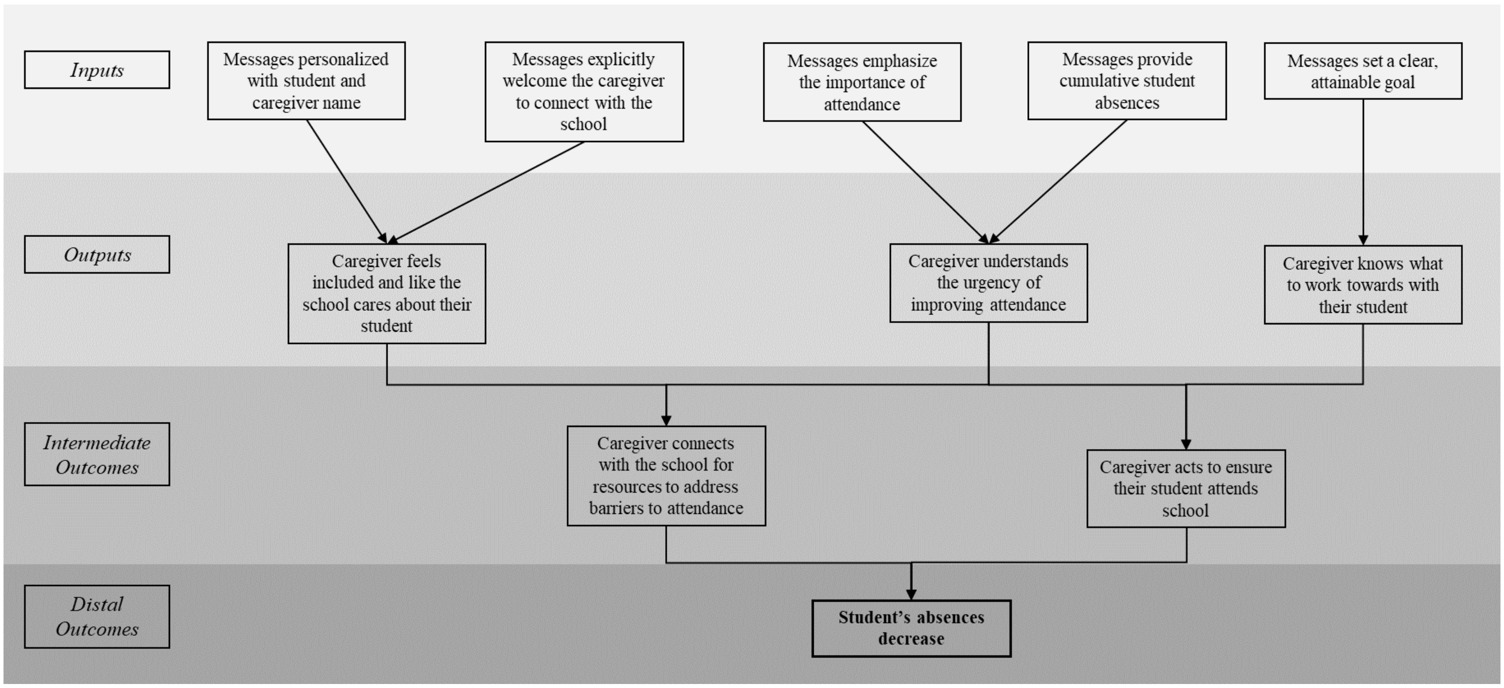
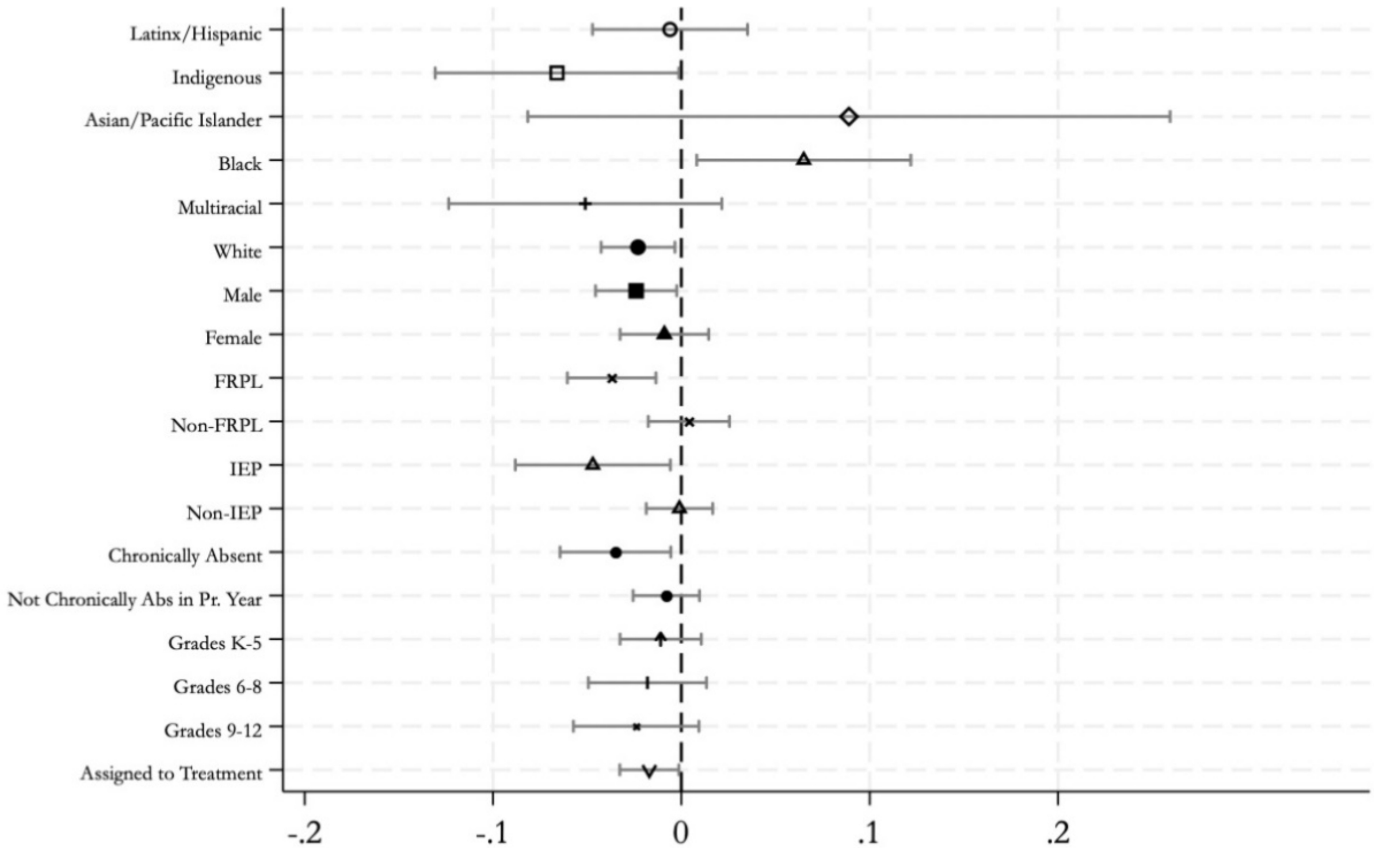


Figure 2. Estimated ITT effects of personalized messaging, by subgroup



Note. Models estimated separately for each subgroup, with the treatment indicator interacted with an indicator for whether or not the student was part of the indicated population. Models include student characteristics, grade and district fixed effects, and missing indicators. All models except those examining differences by chronic absenteeism include splines of prior-year days absent; models looking at effects by prior-year chronic absenteeism control for prior-year absenteeism. The exposure term is the number of days the student was enrolled in the district in the outcome year. Standard errors clustered by student. Poisson coefficients and 95% confidence intervals shown. N = 41,468.

Appendix A.

Table A1. Treatment compliance by district and year

2022-23				2023-24			
District	**N**	**Treatment Compliance**	**Control Non-Compliance**	**District**	**N**	**Treatment Compliance**	**Control Non-Compliance**
1	542	91%	0%	1	1020	52%	0%
2	148	40%	7%	2	391	95%	0%
3	47	0%	0%	3	3145	59%	60%
4	5998	89%	46%	4	321	87%	0%
5	3371	10%	0%	5	843	97%	0%
6	221	72%	0%	6	387	91%	0%
7	2003	45%	0%	7	858	97%	65%
8	217	85%	0%	8	432	43%	0%
9	157	86%	0%	9	380	98%	95%
				10	1016	98%	98%
				11	434	90%	94%
				12	551	95%	0%
				13	1890	33%	28%
				14	479	97%	0%
				15	288	49%	0%
				16	699	97%	0%
				17	194	69%	54%
				18	849	40%	0%
				19	914	43%	0%
				20	575	44%	0%
				21	620	23%	0%
				22	353	51%	0%
				23	337	95%	50%
				24	380	98%	0%
				25	188	90%	92%
				26	277	97%	0%
				27	648	94%	57%
				28	410	95%	93%
				29	1132	93%	0%
				30	3285	93%	86%
				31	195	97%	0%
				32	489	94%	0%
				33	430	88%	82%
				34	1188	23%	0%
				35	306	96%	0%
				36	2944	39%	36%
				37	291	95%	0%
				38	159	89%	0%

Note. Treatment compliance is the share of students assigned to treatment whose caregiver received at least one message. Control non-compliance is the share of students assigned to control whose caregiver received at least one message. Ns at randomization.

Table A2. Estimated effects across samples, restricted by treatment-control contrast

Intent-to-Treat Estimates			
	(1)	(2)	(3)
	5% Contrast	25% Contrast	50% Contrast
Assigned to Treatment	-0.017*	-0.031***	-0.031**
	(0.009)	(0.011)	(0.015)
Observations	32,917	22,024	9,341

Treatment-on-Treated Estimates			
	(1)	(2)	(3)
	5% Contrast	25% Contrast	50% Contrast
Received Treatment	-0.036*	-0.049***	-0.035**
	(0.019)	(0.017)	(0.017)
Observations	32,917	22,024	9,341

Models include race/ethnicity, FRPL receipt, Special Education services receipt, grade level, prior year absence rate in 5 splines, logged school average prior days absent, logged school-grade average prior days absent, and district effects. The exposure term is the number of days the student was enrolled in the district in the outcome year. Standard errors clustered by student. Poisson coefficients shown.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix B.

Table B1. Estimated ITT Effects, by Student Population

Subgroup		Estimated Effect	Standard Error
Race/Ethnicity			
	Asian/Pacific Islander	0.089	0.087
	Black	0.065**	0.029
	Indigenous	-0.066**	0.033
	Latinx/Hispanic	-0.006	0.021
	Multiracial	-0.051	0.037
	White	-0.023**	0.010
Gender			
	Female	-0.009	0.012
	Male	-0.024**	0.011
Services Received			
	Free-Reduced Price Lunch (FRPL)	-0.037***	0.012
	Not FRPL	0.004	0.011
	Has Individualized Education Plan (IEP)	-0.047*	0.021
	Does Not Have IEP	-0.001	0.009
Chronic Absenteeism			
	Chronically absent in prior year	-0.035**	0.015
	Not chronically absent in prior year	-0.008	0.009
Grade Level			
	Elementary	-0.011	0.011
	Middle	-0.018	0.016
	High	-0.024	0.017
Overall		**-0.017****	**0.008**
	N	*41,468*	

Note. Models estimated separately for each subgroup, with the treatment indicator interacted with an indicator for whether or not the student was part of the indicated population. Models include student characteristics, grade and district fixed effects, and missing indicators. All models except those examining differences by chronic absenteeism include splines of prior-year days absent; models looking at effects by prior-year chronic absenteeism control for prior-year absenteeism. The exposure term is the number of days the student was enrolled in the district in the outcome year. Standard errors clustered by student. Poisson coefficients shown.
*** p<0.01, ** p<0.05, * p<0.1

Online Supplementary Material

LIFT Up Attendance- Message Templates

WELCOME MESSAGE (Beginning of school year – Prior to initial message)

Welcome Template

Hello [*CAREGIVER FIRST NAME*], this is [*NAME/ROLE*] from [*SCHOOL/DISTRICT NAME*]. We're excited to share that our district has partnered with Harvard University to test out personalized messaging, a new program designed to improve student attendance. Each month, you'll receive an update about the days of school your student has missed. We know that every day counts for student success, and the program's goal is to provide regular attendance updates and foster collaboration between our school and families. We're trying out this program with a small group of families, and [*STUDENT FIRST NAME*] has been randomly selected to participate. If you have any questions about the program or the updates you receive, please don't hesitate to contact [*CONTACT INFORMATION*].

INITIAL MESSAGE (Approximately 1 month after start of school)

Initial Template: **2 or more absences**

Hello [*CAREGIVER FIRST NAME*], this is [*NAME/ROLE*] from [*SCHOOL/DISTRICT NAME*]. Consistently staying engaged in school is important for your student's learning and future success. Since the beginning of the school year, your student, [*STUDENT FIRST NAME*], has missed [*# OF ABSENCES SINCE START DATE*] days of school. Set a goal for your student to miss no more than [*GOAL # OF DAYS*] in the next [*MESSAGE TIMEFRAME*]. Please contact us at [*CONTACT INFORMATION*] if you would like to discuss your student's attendance.

Initial Template: 0 or 1 absences

Hello [*CAREGIVER FIRST NAME*], this is [*NAME/ROLE*] from [*SCHOOL/DISTRICT NAME*]. I want to personally thank [*STUDENT FIRST NAME*] for attending school every day! We are so proud of [*STUDENT FIRST NAME*] for working so hard and participating in learning. As we know, staying engaged in school is important for your child's learning and future success. Thank you for supporting and encouraging [*STUDENT FIRST NAME*].

RECURRING MONTHLY MESSAGES (Sent every 4-6 weeks on schedule determined by district/school)

Recurring Template: **2 or more absences**

Hello [*CAREGIVER FIRST NAME*], this is [*NAME/ROLE*] from [*SCHOOL/DISTRICT NAME*]. In the last [*PREVIOUS MESSAGE TIMEFRAME*], your student, [*STUDENT FIRST NAME*], has missed [*# OF ABSENCES*] days of school. Set a goal for your student to miss no more than [*GOAL # OF DAYS*] in the next [*MESSAGE TIMEFRAME*]. Consistently staying engaged in school is important for your student's learning and future success. Please contact us at [*CONTACT INFORMATION*] if you would like to discuss your student's attendance.

Recurring Template: 0 or 1 absences

Hello [*CAREGIVER FIRST NAME*], this is [*NAME/ROLE*] from [*SCHOOL/DISTRICT NAME*]. I want to personally thank [*STUDENT FIRST NAME*] for attending school every day over the last [*PREVIOUS MESSAGE TIMEFRAME*]! We are so proud of [*STUDENT FIRST NAME*] for working so hard and participating in learning. Thank you for supporting and encouraging [*STUDENT FIRST NAME*].

Message Customization (exact fields determined by message template)

Custom Variable	Data Source	Definition
CAREGIVER FIRST NAME	SIS	First name of individual receiving message
NAME/ROLE	Customized by district/school	Name and role of individual sending the message (e.g., Principal Sarah Jones)
SCHOOL/DISTRICT NAME	SIS	Name of the school or district at which student is enrolled
PREVIOUS MESSAGE TIMEFRAME	Customized by district/school	The amount of time since the most recent message was sent. For example, "…over the last month" or "…over the last six weeks"
STUDENT FIRST NAME	SIS	First name of student
# OF ABSENCES	SIS	Total number of excused and unexcused absences, reported as total days, since the last message was sent.
GOAL # OF DAYS	SIS	Establish goal based on total absences: - If student missed 2-4 days, goal = 1 - If student missed 5-7 days = 2 - If student missed 8+ days = 3
MESSAGE TIMEFRAME	Customized by district/school	Timeframe for when next message will be sent. For example, "…in the next month" or "…in the next 6 weeks."
CONTACT INFORMATION	Customized by district/school	Email/phone number of individual to whom families and caregivers should direct questions.