Metro Atlanta Policy Lab for Education

Georgia Policy Labs

Using Existing School Messaging Platforms to Inform Parents about Their Child's Attendance

July 2020

Working Paper

Tareena Musaddiq
Georgia State University

Alexa Prettyman
Georgia State University

Jonathan Smith
Georgia State University

ABSTRACT

School attendance is strongly associated with academic success and high school completion, but approximately one in seven students miss nearly one month of school each year. To address chronic absenteeism, we partnered with four public school districts in the metro-Atlanta area and experimentally deployed email and text messages to inform parents about their child's attendance. Parents received personalized monthly messages through the school districts' existing messaging platforms that have zero marginal cost per message. The messages informed parents about their child's number of absences and how that number compares to the absences of their peers (in percentile terms). We find that receiving these messages reduced end-of-year absences by almost one day (5 percent) and reduced the probability of chronic absenteeism by 7.8 percent. However, we also find that parents of students most in need of improved attendance were the hardest to reach.

1. Introduction

School attendance is strongly associated with academic performance and achievement and is one of the strongest predictors of dropping out of high school (Allensworth & Easton, 2007; Balfanz & Byrnes, 2012; Byrnes & Reyna, 2012; Ginsburg et al., 2014). However, in the United States, an estimated 5–8 million students miss nearly a month of school each year; that is one in every seven students (Balfanz et al., 2012; Ginsburg et al., 2014; Chang et al., 2018). Georgia, which is the context of this paper, is no exception with around 13 percent of students missing more than 15 days of school each year (Chang et al., 2018).

Students are chronically absent for a variety of reasons. Lack of transportation, illness, unwillingness to attend, and household burdens are a few of the leading reasons in the literature (Balfanz & Byrnes, 2013; Ehrlich et al., 2014; Chang & Romero, 2008). Barriers and aversion, such as unsafe neighborhood pathways to school and prior negative experiences with the education system, also contribute to poor school attendance (Chang et al., 2018; Symthe-Leistico & Page, 2018). In addition to identifying the sources of absenteeism, there has been considerable effort put into devising practical solutions. Past approaches include offering school breakfast, bus passes, alarm clocks, laundry machines, and one-on-one mentoring (Balfanz & Byrnes, 2013; Rueb, 2019); most of which come at a substantial cost to the school district.

Another explanation for chronic absenteeism that can be addressed with fewer expenditures by districts has recently come to surface—parents' misconceptions related to attendance.[1] Some parents underestimate the number of days their child has been absent, as much as by a factor of two (Rogers & Feller, 2018). Even if parents are aware of the number of absences, they may not know whether the number of absences is relatively high or worrisome. For example, parents may not know how their child's absences compare to the number of absences of the child's peers, or alternatively, parents may not be aware of the relationship between attendance and academic success (Rogers & Feller, 2018; Chang et al., 2018).

In an effort to improve school attendance in four public school districts in the metro-Atlanta area, we implemented an informational experiment during the 2018-19 academic school year wherein the districts sent a series of simple text and email messages to parents of students who were on track to be chronically absent. The personalized messages informed parents about

[1] We use "parent" as a general term to represent a student's caregiver, whether a parent or legal guardian.

their child's year-to-date absences and how the magnitude of their child's absences compared to the absences of the child's peers. This was done by providing the percentile ranking of their child in the distribution of absences within the school district. Because the experiment targeted students who were on track to be chronically absent, the majority of the students were above the 90th percentile in absences, sending a clear message to parents that their children were absent from school relatively more often than their peers. The messages also included a note regarding the urgency of attendance. Specifically, parents of children in grades K-8 were encouraged to make sure their child attends school and parents of high school students were informed how attendance relates to high school graduation. These messages aimed to both inform parents about absences and reduce any misconceptions related to absences.

We begin our study by asking whether districts' messaging platforms reach the parents of chronically absent students. As districts across the United States increasingly invest in education technologies, including school-to-parent communication technologies, it is worthwhile to assess the effectiveness of these technologies in reaching parents as intended, a prerequisite for using the tools effectively. Although over 96 percent of American adults own a cell phone and 90 percent use the internet (Pew Research Center, 2019a; Pew Research Center, 2019b), school districts that adopt educational technologies have relatively low rates of connecting to parents, especially for families experiencing low income and students with lower academic achievement (e.g., Bergman, 2019).

We find that 37-67 percent of parents of students on track to be chronically absent are unreachable through the districtwide messaging platform, depending on the school district.[2] Moreover, there is a negative relationship between a student's number of absences and the likelihood of receiving the first message. Figure 1 shows this relationship and demonstrates that the parents of the very students most in need of outreach to improve attendance are the hardest to reach. We also find that parents of students eligible for free or reduced price lunch (FRL) and students classified as English language learners (ELL) are 11.5 and 22.5 percentage points, respectively, less likely to receive a message. Parents of all other racial groups are also substantially less likely to receive messages than their White peers.

[2] Our study only uses the districtwide messaging platform to contact parents. Parents may be contacted by school administration and teachers through various other ways (e.g., classroom apps) independent of this district-wide system. Our study does not include those means of communication and cannot speak to their effectiveness.

The next part of our study considers whether parents receiving monthly messages improves their child's attendance. We find that messaging parents about their child's absolute and relative absences from school reduces end-of-year absences by almost one day, which is a 5 percent improvement relative to the control group. The messages also reduce the probability of being categorized as chronically absent by 7.8 percent. Subsample analyses reveal similar improvements in attendance for students in grades K-8 (but not high school) and across gender, race, and most other demographic characteristics. However, we do not find a statistically significant improvement for Hispanic students or ELL students, despite the fact that the message was translated into the parents' preferred language in the messaging platform.

Our estimated impacts of the messages on absenteeism are large in magnitude, cost effective, and scalable. First, our estimates are comparable to some of the successful interventions in the "nudge" literature and are larger than "nudge" interventions that find null effects (adding potentially non-published null effects due to publication bias).[3] Second, the school districts used their existing school messaging platforms, which had no marginal costs associated with sending additional messages (other than personnel hours to deploy the messages). Related work relies on two-way messaging systems that (typically) require a school employee on one end (e.g., Symthe-Leistico & Page, 2018). Our low-cost and light-touch experiment simply used an existing technology, typically used for mass and un-personalized communication, to send personalized messages. However, we also demonstrate that the efficacy of such platforms is limited by the accuracy and completeness of the parental contact information.

The rest of the paper is organized as follows. Section 2 provides the overview of existing literature and experiments, section 3 discusses the experimental design, section 4 describes the data and implementation, and section 5 discusses the empirical approach. Results are discussed in section 6, and section 7 concludes with policy implications and avenues for future research.

2. Motivating Literature

The education literature shows a clear relationship between attendance and positive academic outcomes. Students who attend school regularly have higher test scores (Nichols, 2003) and are less likely to drop out or be retained (Neild & Balfanz, 2006; Balfanz & Byrnes, 2013; Bryk

[3] See Appendix Table A1 for a full list of studies and details in recent years.

& Thum, 1989; Rumberger & Thomas, 2000). Moreover, attendance in kindergarten and elementary school strongly predicts student outcomes (Chang & Romero, 2008). Children who start kindergarten on par with their peers but are subsequently chronically absent score lower on standardized tests in third grade than those who attend school regularly (Applied Survey Research, 2011). The positive association between school attendance and desirable student outcomes in elementary school holds across ethnicity, gender, and income levels (Chang & Romero, 2008; Gottfried, 2010) and is even more critical for students at risk to negative educational outcomes due to systemic inequities (Balfanz & Byrnes, 2006, 2012). Attendance patterns in early grades predict absenteeism in higher grades and the likelihood of drop out (Lehr et al., 2004). Similarly, chronic absenteeism predicts dropping out of high school, suspensions, and grade retention better than low test scores (Byrnes & Reyna, 2012).

Why do so many students miss school? Students miss school for a variety of reasons, which is the subject of decades of research and countless policies and programs across the country. Reasons for being absent can be school, family, or community related. While some reasons such as feeling unsafe relate to school climate and policies, many reasons are beyond a school's control. For example, families might lack resources to ensure that their children attend school. Some critical resources include reliable transportation (Balfanz & Byrnes, 2013), healthcare and nutritious food (Ehrlich et al., 2014), and clean suitable clothing and stable housing (Chang & Romero, 2008). Alternatively, parents may allow their children to miss school because of excessive mobility and other household burdens (Balfanz & Byrnes, 2013). These factors are not necessarily under the control of schools.

Informing parents about their child's attendance may be especially helpful in cases where families are unaware of the number of days their child has missed and the adverse impact of this absenteeism. While parents may have some idea of how often their child misses school, many more may not realize the severity of absenteeism (Rogers & Feller, 2018). Missed days here and there may not seem that important or salient as compared to missing several days in a row. Parents often underestimate both the number of days their child is absent from school in a school year (as much as by a factor of two), especially in comparison to their child's peers, as well as the importance of school attendance for academic achievement and graduation (Rogers & Feller, 2018). This lack of information and knowledge may be an important contributing factor to high rates of absenteeism and motivates our experimental design.

In many cases, parents receive automated messages or phone calls on the day their child is absent. These messages inform parents that their child is not present on a particular day, as opposed to providing context of the year-to-date absences. These messaging systems are ubiquitous and have substantial fixed costs but low marginal costs. Alternatively, schools have taken more personalized approaches with larger time and monetary costs. For example, schools focus on tracking attendance and contacting parents when troubling patterns of absences begin to ensure students miss as few days as possible (Chang & Romero, 2008; Epstein & Sheldon, 2002). Other forms of parental outreach include educating parents about attendance, informing parents of the district's attendance policies, and sharing strategies to ensure regular attendance. This information is often shared through school orientation nights and parent workshops. Parent leaders are also trained and given class roll lists from teachers to call and check in with the parents of all absent students (Chang et al., 2018). Although influential, these approaches are costly one-time interventions or require significant hours to carry out. Our experiment uses systems that are already in place and ensures that the outreach remains personalized while keeping the cost low.

We approach the problem using insights from behavioral economics, which suggest that unobtrusive nudges can be used to promote desired behavior through encouragement (Thaler & Sunstein, 2008). There is a growing body of literature that identifies lack of correct and timely information as one of the critical constraints on good decision-making.[4] Notable and related interventions include nudging or messaging parents to enroll their children in preschool (Weixler et al., 2018), to prepare kids for kindergarten (York & Loeb, 2018), and to opt in versus opting out for updates about child's performance (Bergman & Rogers, 2017). Interventions have also found favorable effects of nudging college students regarding student loans (Marx & Turner, 2017) and FAFSA forms (Page et al., 2018).[5] Most recently Bergman & Chan (2019) used weekly, automated alerts to inform parents about their child's missed assignments, grades, and class absences. These alerts reduced course failures by 28 percent, increased class attendance by 12 percent, and increased student retention with larger effects for students with below-median GPA and high school students. We build on these studies not only by informing parents about student absences

[4] See Nguyen (2008), Jensen (2010), Oreopolous & Dunn (2013), Dinkelman & Martinez (2014) for evidence on how education outcomes improve after parents or students are informed about the returns to, or costs of, educational investments. Bettinger et al., (2012) is an example in which information alone was insufficient for improving educational attainment.

[5] For a more detailed review on nudges in education please see Damgaard & Nielsen (2018).

but also by relying on behavioral insights so that the information is presented in a way that may incentivize parental response.

Recent attendance messaging studies in Chicago, Philadelphia, Pittsburgh, and California have targeted parents of students in all grades via mail and text. Most similar to our experiment, interventions that target parents' misbeliefs, such as receiving text messages or postcards that highlight the importance of attendance or report their child's attendance, reduce chronic absenteeism by 10-15 percent (Robinson et al., 2017; Rogers & Feller, 2018) and decrease absences by 2.4-7.7 percent (Robinson et al., 2017; Rogers & Feller, 2018; Rogers et al., 2017) across all grade levels from pre-kindergarten to high school.[6] These interventions are also cost-effective, only costing about $6-7 per student (Rogers & Feller, 2018; Bergman & Chan, 2019).

Our experiment builds on previous work with some notable differences. First, we used existing messaging platforms, so the marginal cost of additional messages was zero. Second, we attempted to be impactful, so we incorporated personalized information on the number of absences, the relative number of absences compared to peers and the importance of attendance. The message sent out in our study informed parents of the absolute number of absences of their child as well as how it ranks relative to their peers. Most existing studies, with the exception of Rogers & Feller (2018), do not provide a peer comparison in their messaging. Rogers & Feller (2018) find no differential effect between their total absences and relative absences treatments. We are not able to disentangle the two treatments because our messages included both pieces of information to ensure maximum impact. As such, we also separately messaged all available contacts, potentially including multiple parents and multiple modes (e.g., text and email). Third, the messaging platforms allow us to analyze which parents have valid contact information, something previously unexplored, but which is likely to impact the efficacy of messaging parents.

3. Experiment Details

Our intervention was a light-touch, low-cost message sent to parents of randomly selected students on track to be chronically absent. We conducted the experiment in four large school districts in the metro-Atlanta area during the 2018-19 school year. The four districts combined have 425,000 students across 430 schools, making up about one-fourth of the student body across

[6] See Appendix Table A1 for details about the location, timing, target population, intervention, and results for recent studies that have used nudge theory to influence attendance behavior.

the state. Approximately 13 percent of the students (or 57,000) were chronically absent during the 2015-16 school year.[7] Between 44-74 percent of the students are eligible for free or reduced price lunch, depending on the district. Finally, per pupil expenditures for the schools in these districts ranges from $8,500 to $15,000 per annum compared to the state average of $10,205 and the national average of $11,392.[8]

The four districts in our experiment have existing procedures in place for contacting parents when their child is absent. For example, in District B, teachers are expected to call or email parents the day their child is absent. District D gives discretion to the schools to employ best practices to improve student attendance. Across all districts, once there have been three unexcused absences, a letter is mailed to the parents explaining attendance expectations. At five, eight, and ten unexcused absences, letters are mailed home with additional information, such as the potential consequences of failing to comply with the compulsory attendance law. Our experiment does not change the existing protocols, so students assigned to the control group still received the usual outreach.

3.1 Messaging Platforms

We used the districts' existing communication platform to send text messages and emails to parents regarding their child's absences from school. These communication platforms are used to send important messages regarding inclement weather and school closings and details about upcoming standardized testing procedures. Once a broadcast is made, messages can be created, personalized, and sent to a specific subgroup of students. The messaging platform contains contact information for parents, such as phone numbers and email addresses. Parents can select a preferred language in which messages are translated by the communication platform, but the default language is English.

The districts used either SchoolMessenger or Blackboard.[9] The School Notification system within these platforms allows districts to send out mass notifications related to inclement weather, emergencies, districtwide events, and so on. Important to our experiment, the system also allows

[7] Authors' calculation based on the interactive data visualization tool for chronic absences across the United States, which is available at: www.hamiltonproject.org/charts/chronic_absence_across_the_united_states.
[8] U.S. Census. patch.com/georgia/atlanta/how-georgia-education-spending-ranks-nationwide-census-bureau. census.gov/library/visualizations/2017/comm/cb17-97-public-education-finance.html
[9] SchoolMessenger offers a variety of services to the school districts including mobile apps, student emails, and school websites. For more information, see schoolmessenger.com. Blackboard is a Learning Management System that allows students and teachers to access learning resources online, view course contents and grades, and participate in online discussion forums. For more information, see blackboard.com/k12/index.html.

the districts to send out personalized notifications to parents through text messages, emails, and robocalls. Only the districts' communication team has the ability to send out these messages and notifications. We used this feature and partnership to send individualized messages to parents in the treatment group.

3.2 Intervention

Our intervention targeted students who had a high number of absences in the first few months of the school year and were projected to be chronically absent by the end of the year by missing 15 or more school days.[10] Based on the absences in late fall, we linearly projected the expected number of absences by the end of the school year for each student. We then restricted our experimental sample to students who were on track to be chronically absent with more than 50 percent of the absences being unexcused to avoid messaging parents of students with chronic medical conditions.[11] Within the eligible sample, we randomly assigned students to treatment and control, separately for each district and in proportion to district size.[12]

All messages were sent by the districts' communication teams through their messaging platforms; parents had received messages from these systems in the past. However, parents of students who were randomly assigned to treatment were still sent an initial opt-out message prior to receiving the attendance messages.[13] Parents were allowed to opt-out at any point during the course of the experiment as well. Across all districts, less than 1 percent of parents opted out. Those who opted out no longer received messages.

In the late fall semester, parents who did not opt-out received personalized messages similar to the examples below, depending on whether their child was in grades K-8 or 9-12:[14]

---

[10] Chronically absent is defined as missing 15 days of school regardless of being excused or unexcused.

[11] In one district where the randomization process varied slightly, additional students identified as medically fragile were removed from the experimental sample.

[12] Moreover, to reduce burden on the districts' communication teams, we assigned the minimum number of students needed to detect modest effect sizes to the treatment, as opposed to splitting the experimental group evenly. This approach results in a larger control group than the treatment group.

[13] One district's opt-out message read: "Thank you for agreeing to participate in our study to improve school attendance at <<Your District>>. If you'd like to stop receiving messages about your child's absences or you are receiving this in error, please fill out the information below. You will not receive any further communications about this study, but you will still receive other district related communications (weather closings, school/district announcements, meal balances, etc.). Please be sure to include the email and/or phone number to which you received this initial message."

[14] The messages varied slightly across districts due to district-specific needs and preferences. The timing of the first message also varied across districts. Appendix Table A2 provides details of the differences across districts. Of particular note, District D, which sees the biggest effect, sent a text message that reminds parents to check their email, which contains the above details.

> **K-8 Message**: "John missed 5 school days so far this year – more absences than 90% of his peers. Please make sure John gets to school."

> **9-12 Message:** "John missed 5 school days so far this year – more absences than 90% of his peers. Students with fewer absences are more likely to graduate."

The personalization included the student's name, the number of absences year-to-date, and the percentile in the distribution of absences in the district, calculated separately for grades K-8 and grades 9-12. The messages were sent to all email addresses and cell phone numbers on record for students in the treatment group. This implies that some parents might have received multiple messages and for some students, multiple parents might have received these messages. The goal was to make sure parents received the message.

Across the four districts, messages were sent in November, December, February, March, April, and May of the 2018-19 school year.[15] Messages were sent at the beginning of each month with the updated year-to-date absences and the percentile of absences in the district distribution.[16] We did not send messages to parents in January due to winter break. As such, the treatment should be considered to be monthly messages to parents regarding their child's absolute and relative absences.

Two districts faced issues related to message content and implementation. For example, in one district, the message was personalized with the student's school ID number as opposed to the student's name, and in another district, the messages were not sent in the early months of the experiment.[17] The other two districts only faced minor issues and thus implemented the experiment

[15] There was variability in the timing of the messages across districts. Refer to Appendix Table A3 for more details about the timing of the messages sent.

[16] After the first month of messages, we did not send messages the following month if a student's year-to-date absences decreased relative to their previous month or if their percentile rank was less than 50 percent. These 1.5 percent of treatment students were likely a result of updated administrative records, and we wanted to avoid sending inconsistent or inaccurate messages.

[17] Refer to Appendix Table A3 for more details on fidelity of implementation.

with fidelity.[18] We provide results across all districts but focus on the results in the districts that implemented the experiment with fidelity.[19]

4. Data

The data for this study come from two main sources: administrative records from the districts and delivery reports from the communication platform.

4.1 Administrative Records

The data on student demographics and schools come from the Metro Atlanta Policy Lab for Education (MAPLE) database. Districts share administrative data with MAPLE as part of their broader research-practice partnership with the lab. The MAPLE database provides us with information on student demographics, such as race, gender, FRL status, and whether a student is classified as an ELL or has a disability.

Table 1 shows that the experimental group consists of parents of boys (52 percent) and girls (48 percent), White (19 percent), Black (72 percent), Asian (3 percent), and Hispanic (16 percent) students across four districts in the metro-Atlanta area in elementary, middle, and high school.[20] Almost three-fourths (73 percent) are FRL-eligible students, 9 percent are ELL students, and 16 percent are students with disabilities. On average, these students were absent just over 10 days at the start of the experiment and 24 days by the end of the school year. Finally, 70 percent were chronically absent, meaning they missed at least 15 days over the school year. Our main analytical sample is restricted to the two districts that implemented the experiment with fidelity. Overall, these two districts are similar to the two districts that did not implement the experiment with fidelity, aside from having more White and more Hispanic (and fewer Black) students, fewer FRL-eligible students, and fewer initial absences when assigned treatment.

In total, the treatment group consists of 7,880 students, and the control group consists of 15,525 students. The experimental group makes up 3-12 percent of the district student body, depending on the district. The demographic characteristics of the students in the non-experimental, treatment, and control groups, broken down by district, are presented in Appendix Table A4.

[18] An example of a minor issue is sending the message via email but not text for one month in grades 9-12.
[19] We report both sets of results to demonstrate how implementation impacts the efficacy of the experiment. As other districts and researchers try to replicate these findings, they might face similar implementation challenges. Null effects do not necessarily mean the message did not work, but instead, implementation may have been less than ideal.
[20] Race/ethnicity are not mutually exclusive.

Students in the treatment and control group were, on average, absent five times as much as the non-experimental students. Across all districts, Black students, FRL-eligible students, and students with a disability are overrepresented in the experimental group, compared to the non-experimental group. Appendix Table A5 provides results from a balance check analysis and verifies that randomization was successful among most dimensions.

4.2 Delivery Reports

For each student, the districts' communication platform is able to provide information on whether a text message or email is successfully sent to the intended recipient. We utilized this feature to obtain the delivery status report from the communication platforms after the messages were sent each month. We use these monthly delivery reports to determine the success of the implementation. The delivery reports indicate whether valid contact information for students' parents exist in the districts' communication platform and whether messages were received on a per parent-contact mode basis. That is, we know whether each parent listed has valid email or text capabilities or both and whether messages were successfully received. We learn whether a text message was sent, failed to send, or ineligible to send.[21] We say a text was received if the delivery report indicates sent, and an email was received if the delivery report indicates that the email was sent, delivered, or opened.[22]

5. Empirical Model

To answer the first research question (Who receives the messages?), we estimate the following equation using a linear probability model for those assigned to the treatment group:

$$R_{id} = \beta_0 + \beta_1 A_{id} + \boldsymbol{\beta X_{id}} + \gamma_m + \mu_d + \varepsilon_{id} \qquad (1)$$

[21] One district did not send texts and instead made robocalls. See Appendix Table A3 for more details about implementation. We interpret the results from a robocall similar to a text since the communication is via phone. The delivery status for a robocall is either answered, answering machine, or invalid phone number. A robocall was considered received if the delivery status was answered or answering machine.

[22] Per the SchoolMessenger Communicate user guide, "sent" indicates that the message was sent, but SchoolMessenger has not received verification from the recipient's email server; "delivered" indicates that the message was sent and SchoolMessenger has received confirmation that the recipient's email server successfully queued the message for delivery; and "opened" indicates the message was opened by the recipient. We do not differentiate between "sent," "delivered," and "opened" because some of this classification is a function of when the delivery report was pulled. In districts that pulled the delivery report immediately after sending the message, there are fewer "opened" messages than in districts that pulled the delivery report later.

Where R_{id} indicates whether the parent of student i in district d received the first message; A_{id} is the number of initial absences when assigned treatment for student i in district d, $\boldsymbol{X}_{id}$ is a vector of demographic characteristics (gender, race, FRL, ELL, and disability status) for student i in district d, γ_m are fixed effects for whether the message was for grades K-8 or 9-12 (We refer to this as message-level.), μ_d are district-level fixed effects, and ε_{id} is the error term. The message-level fixed effect accounts for differences among the message wording and across school types, such as elementary/middle and high school. We include district fixed effects to account for differences among districts' students, parents, and messaging platforms. We are primarily interested in the estimates of β_1 and β, which indicate how initial absences and demographic characteristics, respectively, effect the likelihood of receiving the first message.

Our second research question (Does messaging parents about their child's absences reduce absenteeism?) is answered by estimating a model with the following intent-to-treat equation:

$$Y_{id} = \theta_0 + \theta_1 T_{id} + \theta_2 A_{id} + \gamma_m + \mu_d + \varepsilon_{id} \qquad (2)$$

Where Y_{id} indicates final absences for student i in district d, T_{id} is an indicator for student i in district d being assigned treatment, and the remaining variables are the same as in Equation 1. We control for initial absences in our main specification. In this equation, the coefficient of interest, θ_1, provides an estimate of the intent-to-treat effect of the messages. A statistically significant negative coefficient indicates that the treatment effectively reduces absences.

Because we know who receives messages from the delivery reports, we also estimate the treatment-on-treated effect using a two-stage-least-squares model, where we use assignment to treatment as an instrument for receiving a message. More specifically, we estimate the following models:

$$R_{id} = \beta_0 + \beta_1 T_{id} + \beta_2 A_{id} + \gamma_m + \mu_d + \varepsilon_{id} \qquad (3)$$

$$Y_{id} = \theta_0 + \theta_1 \hat{R}_{id} + \theta_2 A_{id} + \gamma_m + \mu_d + \varepsilon_{id} \qquad (4)$$

Where the first stage, Equation 3, predicts the probability of receiving the message based on assignment to the treatment group, and the second stage, Equation 4 estimates the effect of receiving the messages on final absences.

We use robust standard errors in all analyses. In our main analysis, we exclude students who are clear outliers that have been absent for months on end, putting them well into the 99th percentile of absences. These are likely students who left the district or had extreme medical or family conditions. Results do not substantially change when these students are included.

6. Findings

6.1 Research Question 1: Who Receives Messages?

We begin by discussing findings on who receives the messages in districts A, B, and C. District D first identified all students with validated contact information and then randomized among that set of students, so they are excluded from this analysis.

Email was more commonly received than a text message, although many students had parents who were unreachable through the districtwide messaging platform. Between 37-67 percent of parents in the treatment group did not receive text or email messages, depending on the district. In other words, in the district with the highest success of message receipt, two out of three parents were reached, and in the district with the lowest success of message receipt, only one out of three parents was reached. On average, 10-59 percent of email messages were received, depending on the district. On average, only 18-27 percent of the text messages were successfully sent; the remaining 73-82 percent failed to send or were ineligible to send.

We plot the relationship between absences and likelihood of receiving the first message via any mode in Figure 1. Without controls, 70 percent of the students with four to five absences received the first message, whereas only 37 percent of the students with more than 20 absences received the first message. These results show that students with more initial absences were less likely to have valid contact information because they were not receiving messages.

Next, Table 2 shows the estimates of the determinants of who receives the messages (Equation 1). We use six different outcome variables: received any message (text and/or email), received email, received text, received only email, received only text, and received both text and email. Across the entire treatment group, 54 percent of parents received any message, 47 percent received an email, and 21 percent received a text. Just 33 percent and 8 percent received only an email or only a text, respectively. Very few parents, 14 percent, received both a text and email. On average, being absent one more day when assigned treatment is associated with a 0.8 percentage point decrease in the probability of receiving the first message. In other words, students who were absent 15 days were 8 percentage points less likely to receive the first message than students who were absent 5 days. The magnitude is smaller across the other five outcomes and statistically insignificant for "text only."

We further investigate whether demographic characteristics of students are correlated with the likelihood of receiving the first message. First, parents of Black, Asian, Hispanic, and other non-White students are less likely to receive the first message compared to parents of White students. Among Black and Asian students, it appears that the effect is driven by having invalid email contact information and not by incorrect cell phone numbers. In fact, parents of Black and Asian students are 4.2 and 3.4 percentage points, respectively, more likely to receive the first message as a text only, despite being 8.8 percentage points and 12.7 percentage points less likely to receive the first message as an email or text. Second, parents of FRL-eligible and ELL students are 11.5 and 22.5 percentage points, respectively, less likely to receive the first message. Alternatively, parents of students with disabilities are 3.9 percentage points more likely to receive the first message. There is no evidence of differences across gender or school-level (elementary, middle, and high school).

6.2 Research Question 2: What is the effect of the messages on attendance?

Table 3 reports the results on whether the messages improve attendance. We find evidence that assignment to the treatment group reduces absences by three-fourths of a day (or 4 percent) within the two districts that implemented the experiment with fidelity. The treatment-on-treated effect is larger in magnitude, closer to a one-day reduction in absences. Among all four districts, the effect is smaller and less statistically significant. Appendix Table A6 reports district-specific results, highlighting that most of the effect is being driven by District D.[23]

We test the robustness of our results by adding a combination of controls including school fixed effects, grade fixed effects, and student level controls. Results are shown in Appendix Table A7. Across various specifications, we find similar results: the intent-to-treat effect size ranges from a 0.6-day reduction to a 1.1-day reduction. Additionally, when we include outliers (column 9), the

[23] Not only did District D implement with fidelity, but they provide the most statistical power because nearly all students in the experimental group had valid contact information for their parents.

results are essentially unchanged (-0.722 compared to -0.731). Finally, when we estimate the effect of receiving the last message (row 3), as opposed to the effect of receiving the first message, the results are similar. Practically everyone who receives the first message also receives the last message, so it does not seem like districts, through their centralized contact databases, are updating parents' contact information throughout the year, or are parents' contact information changing over the course of the year, at least among the treatment group.

We further test for heterogenous effects by demographic characteristics and message content. In other words, did certain types of people respond differently or did message content provoke differential response? Results in Table 4 show that the impact of the message is larger for female students, Black students, non-FRL-eligible students, non-ELL students, and students with disabilities. We find no statistical impact of the message among parents of Hispanic students or ELL students, despite the message being translated to their preferred language. Attendance improved for treated students in grades K-8 but not in high school. Two potential explanations for this last result may be the difference in message content or the difference in autonomy between younger and older students. Unfortnately, we cannot definitively detemine which mechanism is working here.

Finally, we consider alternative measures of absences and the impact of messages on each of them. Results in Table 5 show that messages reduce both final excused and unexcused absences by similar amounts—just over one-third of a day. However, because the average number of unexcused absences is more than double the average number of excused absences, the relative impact is larger for excused absences. Informational attendance messages reduce excused absences by 6 percent and unexcused absences by 2.5 percent. Finally, we considered chronic absenteeism as an alternative outcome. Messages reduce chronic absenteeism by 6-7.8 percent for students who were at risk of being chronically absent at the beginning of the school year.

We also conducted an attrition analysis to verify that our treatment did not cause students to leave the district. The results are reported in Appendix Table A8. Students with missing final absences cannot be included in the main analysis and instead are included in the "attrition" sample. Across all four districts and the two districts that implemented the experiment with fidelity, we do not find evidence that assignment to the treatment group leads to attrition. However, district-specific analysis reveals that being assigned treatment in District A and District C increased the likelihood of exit by 18 and 13 percent, respectively. We do not have any clear explanation as to why this may have occurred, and considering District A did not message parents until the end of the year, we argue that this pattern of attrition is unrelated to our intervention.

7. Conclusion

Our results indicate that an attendance message crafted to inform parents about their child's attendance and relative ranking positively impacts student attendance. We have four takeaways. First, we find meaningful impacts of the message that are in line with previous work in the area, despite differences in implementation. A one-day improvement in attendance, on average, likely corresponds to several days of improvement for some students (and no improvement for others), along with potential long-run improvements in academic achievement. Our intervention also substantially reduces the likelihood of being chronically absent (7.8 percent). Chronic absenteeism is linked to reduced student achievement and issues of social-emotional well-being in kids (Gottfried, 2014; Gottfried, 2019). In the long run, chronic absenteeism is correlated with increased rates of high school dropout.

Second, this intervention is light-touch, low-cost, and scalable. Most school districts already pay for a messaging platform and many have the potential to personalize messages. Third, contact information within the districtwide messaging platform for students at risk of being chronically absent was often lacking. The efficacy of the experiment and school districts' efforts to use mass communication rely on valid contact information. Efforts to improve district-wide contact information within the messaging platform may be a good, albeit challenging, investment for districts. Fourth and finally, the efficacy of the experiment also relies on fidelity of implementation; schools or districts that decide to implement will likely face similar initial challenges that some of the districts in this paper experienced.

Our experiment answers several questions but leaves the door open for more research. Teachers and schools have other means of outreach other than the district wide messaging system, which we cannot observe. It is plausible, if not likely, that similar message content from a different source, such as teachers, yields different results. Additionally, it is unclear which part of the message positively altered behavior. The message contained three pieces of information: the number of days absent, the relative rank, and a sentence emphasizing that attendance is important. Finally, although we can see who received texts and emails, due to small sample sizes, we cannot determine which mode of communication was more effective. More broadly, varying the mode of communication, set of students, and message content would provide insight into the mechanisms behind our estimates.

References

Allensworth, E.M. and Easton, J.Q., 2007. What Matters for Staying On-Track and Graduating in Chicago Public High Schools: A Close Look at Course Grades, Failures, and Attendance in the Freshman Year. Research Report. *Consortium on Chicago School Research*.

Applied Survey Research. 2011. Attendance in Early Elementary Grades: Association with Student Characteristics, School Readiness and Third Grade Outcomes. Retrieved from: https://www.attendanceworks.org/wp-content/uploads/2017/06/ASR-Mini-Report-Attendance-Readiness-and-Third-Grade-Outcomes-7-8-11.pdf

Balfanz, R. and Byrnes, V., 2006. Closing the mathematics achievement gap in high-poverty middle schools: enablers and constraints. *Journal of Education for Students Placed at Risk*, 11(2): 143-159.

Balfanz, R. and Byrnes, V., 2012. Chronic absenteeism: Summarizing what we know from nationally available data. *Baltimore: Johns Hopkins University Center for Social Organization of Schools*, pp.1-46.

Balfanz, R., and Byrnes, V., 2013. Meeting the challenge of combating chronic absenteeism: Impact of the NYC Mayor's Interagency Task Force on chronic absenteeism and school attendance and its implications for other cities. *Baltimore, MD: Everyone Graduates Center, Johns Hopkins University School of Education.*

Baltimore Education Research Consortium (BERC) 2011. Destination Graduation: Sixth Grade Early Warning Indicators for Baltimore City Schools: Their Prevalence and Impact BERC: Baltimore MD.

Barge, J., 2011. Student Attendance and Student Achievement. Georgia Department of Education.

Bergman, P., 2019. Nudging Technology Use: Descriptive and Experimental Evidence from School Information Systems. *Education Finance and Policy*. Forthcoming

Bergman, P. and Chan, E.W., 2019. Leveraging parents: The impact of high-frequency information on student achievement. *Poverty Action Lab.*

Bettinger, E.P., Long, B.T., Oreopoulos, P. and Sanbonmatsu, L., 2012. The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment. *The Quarterly Journal of Economics*, *127*(3), pp.1205-1242

Bergman, P. and Rogers, T., 2017. The impact of defaults on technology adoption, and its underappreciation by policymakers.

Bryk, A. S., & Thum, Y. M., 1989. The Effects of High School Organization on Dropping Out: An Exploratory Investigation. *American Educational Research Journal*, *26*(3), 353–383. doi.org/10.3102/00028312026003353

Byrnes, V. and Reyna, R., 2012. Summary of state level analysis of early warning indicators. *Everyone Graduates Center, Baltimore, MD*.

Chang, H.N., Bauer, L. and Byrnes, V., 2018. Data Matters: Using Chronic Absence to Accelerate Action for Student Success. Executive Summary. *Attendance Works*.

Chang, H., and Romero, M., 2008. Present, engaged, and accounted for: The critical importance of addressing chronic absence in early grades. *Columbia University: National Center for Children in Poverty.*

Damgaard, M.T. and Nielsen, H.S., 2018. Nudging in education. *Economics of Education Review*, *64*, pp.313-342.

Dinkelman, T. and Martínez A, C., 2014. Investing in schooling in Chile: The role of information about financial aid for higher education. *Review of Economics and Statistics*, *96*(2), pp.244-257.

Ehrlich, S., Gwynne, J., Pareja, A., and Allensworth, E., 2014. Preschool Attendance in Chicago Public Schools: Relationship with Learning Outcomes and Reasons for Absences: Research Summary. *Chicago: University of Chicago Consortium on Chicago School Research*.

Epstein, J.L. and Sheldon, S.B., 2002. Present and accounted for: Improving student attendance through family and community involvement. *The Journal of Educational Research*, *95*(5), pp.308-318.

Ginsburg, A., Jordan, P. and Chang, H., 2014. Absences Add Up: How School Attendance Influences Student Success. *Attendance Works*.

Gottfried, M.A., 2010. Evaluating the relationship between student attendance and achievement in urban elementary and middle schools: An instrumental variables approach. *American Educational Research Journal*, *47*(2), pp.434-465.

Gottfried, M.A., 2014. Chronic absenteeism and its effects on students' academic and socio-emotional outcomes. *Journal of Education for Students Placed at Risk (JESPAR)*, *19*(2), pp.53-75.

Gottfried, M.A., 2019. Chronic absenteeism in the classroom context: Effects on achievement. *Urban Education*, *54*(1), pp.3-34.

Kalil, A. and Mayer, S. 2017. Understanding how behavioral tools can influence preschool attendance. *Association for Public Policy Analysis and Management Conference.*

Lehr, C., Johnson, D., Bremer, C., Cosio, A., and Thompson, M., 2004. Essential Tools: Increasing rates of school completion: moving from policy and research to practice. *A Manual for Policymakers, Administrators, and Educators.*

Marx, B.M. and Turner, L.J., 2019. Student loan nudges: Experimental evidence on borrowing and educational attainment. *American Economic Journal: Economic Policy*, *11*(2), pp.108-41.

Musser, M. 2011. Taking attendance seriously: how school absences undermine student and school performance in New York City. *Campaign for Fiscal Equity.*

Neild, R. C., & Balfanz, R. 2006. Unfulfilled promise: The dimensions and characteristics of Philadelphia's dropout crisis, 2000–2005.

Nguyen, T., 2008. Information, role models and perceived returns to education: Experimental evidence from Madagascar. *Unpublished manuscript*.

Olsen, L.S., 2014. Why September Matters: Improving Student Attendance. Policy Brief. *Baltimore Education Research Consortium*.

Oreopoulos, P. and Dunn, R., 2013. Information and college access: Evidence from a randomized field experiment. *The Scandinavian Journal of Economics*, *115*(1), pp.3-26.

Page, L.C., Castleman, B.L. and Meyer, K., 2020. Customized nudging to improve FAFSA completion and income verification. *Educational Evaluation and Policy Analysis*, *42*(1), pp.3-21.

Pew Research Center. 2019a. Mobile Fact Sheet. *Internet and Technology.* https://www.pewresearch.org/internet/fact-sheet/mobile/. Accessed March 24, 2020.

Pew Research Center. 2019b. Internet/Broadband Fact Sheet. *Internet and Technology.* https://www.pewresearch.org/internet/fact-sheet/internet-broadband/. Accessed March 24, 2020.

Robinson, C.D., Lee, M.G., Dearing, E. and Rogers, T., 2017. Reducing student absenteeism in the early grades by targeting parental beliefs. *American Educational Research Journal*, DOI: 10.3102/0002831218772274

Rogers, T. and Feller, A., 2018. Reducing Student Absences at Scale by Targeting Parents' Misbeliefs. *Nature Human Behaviour,*2(5), pp. 335-342

Rogers, T., Duncan, T., Wolford, T., Ternovski, J., Subramanyam, S. and Reitano, A., 2017. A Randomized Experiment Using Absenteeism Information to "Nudge" Attendance. REL 2017-252. *Regional Educational Laboratory Mid-Atlantic*.

Rueb, E. 2019. Schools Find a New Way to Combat Student Absences: Washing Machines. *New York Times.* https://www.nytimes.com/2019/03/13/us/schools-laundry-rooms.html. Accessed March 10, 2020.

Rumberger, R. W., & Thomas, S. L. (2000). The distribution of dropout and turnover rates among urban and suburban high schools. *Sociology of Education, 73*(1), 39–67. doi.org/10.2307/2673198

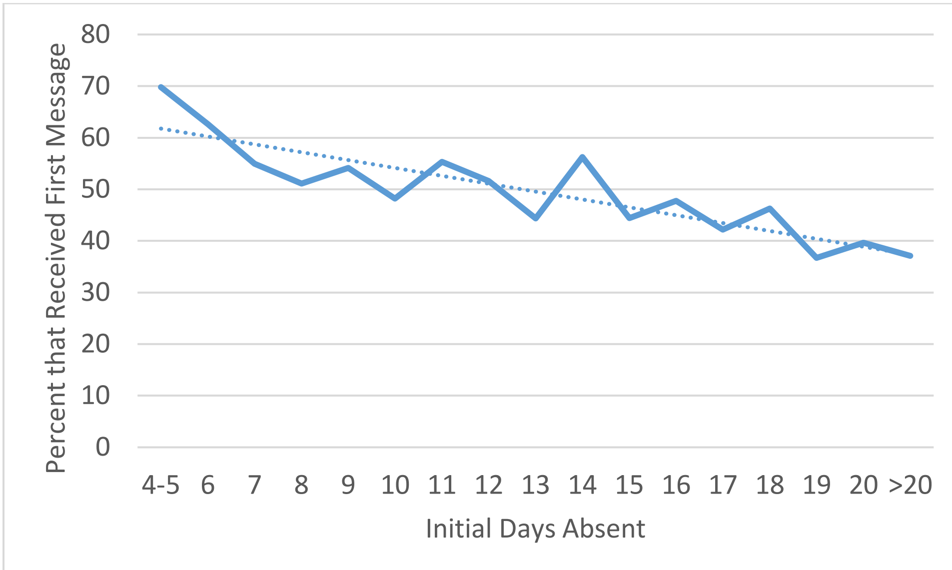
Smythe-Leistico, K. and Page, L. 2018. Connect-text: Leveraging text-message communication to mitigate chronic absenteeism and improve parental engagement in the earliest years of schooling. *Journal of Education for Student Placed at Risk,* 23(1): 139-152.

Thaler, R. and Sunstein, C., 2008. Nudge: The gentle power of choice architecture. *New Haven, Conn.: Yale*.

Weixler, L., Valant, J., Bassok, D., Doromal, J.B. and Gerry, A., 2019. Helping Parents Navigate the Early Childhood Enrollment Process: Experimental Evidence from New Orleans.

Figures

Figure 1: Probability of Having Valid Contact Information Based on Number of Days Absent when Assigned Treatment



The figure includes students from districts A, B, and C. Initial days absent was measured in November of the 2018-19 school year and includes excused and unexcused absences. The solid line plots the percent of parents that received the first message by days absent, and the dashed line plots the trendline. The downward sloping line indicates a negative relationship between days absent and receiving the first message. In other words, those most absent are the hardest to reach. We say a parent has "valid contact information" if they were successfully messaged.

Tables

Table 1: Summary Statistics

	Non-experimental Group		Experimental Group				
	Districts A, B, and C (N=197,317)		All Districts (N=23,405)			Districts that Implemented with Fidelity (N=8,790)	
	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.
Male	51%	0.5	52%	0.499		52%	0.5
White	30%	0.458	19%	0.394		41%	0.491
Black	55%	0.497	72%	0.452		53%	0.499
Asian	9%	0.283	3%	0.178		5%	0.211
Other Race	6%	0.233	6%	0.238		2%	0.138
Hispanic	15%	0.359	16%	0.369		22%	0.416
Free or Reduced Price Lunch	54%	0.499	73%	0.445		65%	0.476
English Language Learner	12%	0.319	9%	0.287		9%	0.284
Student with Disability	11%	0.31	16%	0.37		17%	0.378
District A	21%	0.407	27%	0.442		0%	0
District B	37%	0.483	36%	0.479		0%	0
District C	42%	0.493	21%	0.406		55%	0.497
District D	0%	0	17%	0.374		45%	0.497
Elementary School	47%	0.499	39%	0.487		44%	0.496
Middle School	24%	0.429	20%	0.401		21%	0.41
High School	29%	0.453	41%	0.492		35%	0.476
Absences when Assigned Treatment	2.07	2.479	10.44	5.862		8.115	3.958
End-of-year Absences	7.64	7.572	24.39	15.2		19.55	12.23
Chronically Absent - National	13%	0.335	70%	0.458		58%	0.494

Summary statistics are provided for the non-experimental group for Districts A, B, and C. District D is excluded due to data limitations. The summary statistics for the experimental group in all districts and the two districts that implemented the experiment with fidelity are also included.

Table 2: Who Receives the Messages?

	Received First Message (Text and/or Email)	Received First Email	Received First Text	Received First Message (Email Only)	Received First Message (Text Only)	Received First Message(Both Email and Text)
Absences when Assigned Treatment	-0.008***	-0.008***	-0.002*	-0.006***	0.000	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Male	0.011	0.016	-0.002	0.013	-0.005	0.003
	(0.014)	(0.013)	(0.012)	(0.013)	(0.007)	(0.010)
Comparison Group: White						
Black	-0.088***	-0.130***	-0.086***	-0.001	0.042***	-0.129***
	(0.024)	(0.024)	(0.026)	(0.027)	(0.010)	(0.025)
Asian	-0.127***	-0.161***	-0.054	-0.073	0.034*	-0.088**
	(0.041)	(0.042)	(0.041)	(0.046)	(0.019)	(0.038)
Hispanic	-0.122***	-0.124***	-0.128***	0.006	0.002	-0.130***
	(0.029)	(0.030)	(0.027)	(0.030)	(0.010)	(0.026)
Other Race	-0.176***	-0.187***	-0.002	-0.174***	0.011	-0.013
	(0.037)	(0.036)	(0.024)	(0.033)	(0.014)	(0.020)
Free or Reduced Price Lunch	-0.115***	-0.122***	-0.085***	-0.030*	0.008	-0.092***
	(0.017)	(0.017)	(0.016)	(0.017)	(0.009)	(0.014)
English Language Learner	-0.225***	-0.236***	-0.107***	-0.118***	0.010	-0.117***
	(0.029)	(0.028)	(0.019)	(0.027)	(0.010)	(0.017)
Student with Disability	0.039**	0.019	0.021	0.018	0.020*	0.001
	(0.018)	(0.017)	(0.016)	(0.018)	(0.010)	(0.013)
Comparison Group: District A						
District B	0.268***	0.456***	-0.076***	0.344***	-0.188***	0.112***
	(0.020)	(0.015)	(0.018)	(0.014)	(0.015)	(0.011)
District C	0.286***	0.458***	-0.050***	0.336***	-0.172***	0.122***
	(0.021)	(0.017)	(0.019)	(0.017)	(0.015)	(0.012)
Comparison Group: Elementary School						
Middle School	0.005	0.014	-0.005	0.010	-0.010	0.005
	(0.017)	(0.016)	(0.015)	(0.016)	(0.009)	(0.012)
High School	0.009	0.016	-0.017	0.027*	-0.006	-0.011
	(0.017)	(0.016)	(0.014)	(0.016)	(0.009)	(0.012)
Observations	4,749	4,749	4,749	4,749	4,749	4,749

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Each regression controls for initial absences and includes district and message-level fixed effects. Excluding initial absences yields similar coefficients on the remaining variables. District D is excluded from this analysis due to differences in their random assignment process. They randomly assigned students to treatment and control after knowing who has valid contact information. The columns identify the mode in which the first message was received. Received First Message (Text and/or Email) means parents received message either as a text or email or both. Received First Email means parents received email and may or may not have received a text. Received First Text means parents received text and may or may not have received email. Received First Message (Email Only) means parents received only email and not text. Received First Message (Text Only) means

parents received only text and not email. Received First Message (Both Email and Text) means parents received both email and text. District A made robocalls instead of sending texts, and so “text” refers to “robocall” in this district.

Table 3: The Effect of Messages on End-of-year Absences

	All Districts		Districts that Implemented with Fidelity		Districts with Implementation Issues
Intent-to-Treat					
Treated	-0.388**		-0.731***		-0.113
	(0.163)		(0.182)		(0.255)
Mean End-of-year Absences for the Control Group	25.48		20.34		27.56
Percent Change in End-of-year Absences	-2%		-4%		0%
Treatment-on-Treated					
Received First Message	-0.626**		-0.928***		-0.234
	(0.263)		(0.231)		(0.530)
Mean End-of-year Absences for the Control Group	25.48		20.34		27.56
Percent Change in End-of-year Absences	-2%		-5%		-1%
First Stage					
Treated	0.621***		0.788***		0.481***
	(0.006)		(0.006)		(0.008)
Observations	23,405		8,790		14,615

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Each regression controls for initial absences and includes district and message-level fixed effects. The first column includes all four districts, the second column includes district C and D, and the third column includes district A and B.

Table 4: Heterogeneous Effects of Receiving Messages by Demographic Characteristics

	Male	Female	White	Black	Hispanic	Elementary & Middle School	High School	Free or Reduced Price Lunch	Non-FRL	English Language Learners	Non-ELL	Students with Disability	Students w/o Disability	Initial Absences less than the Median	Initial Absences more than the Median
Intent-to-Treat															
Treated	-0.741***	-0.922***	-0.675**	-1.065***	-0.106	-0.696***	-0.523	-0.787***	-0.902***	-0.183	-0.878***	-1.209**	-0.762***	-0.606***	-1.060**
	(0.286)	(0.285)	(0.291)	(0.298)	(0.422)	(0.187)	(0.402)	(0.267)	(0.280)	(0.635)	(0.213)	(0.545)	(0.216)	(0.183)	(0.496)
Treatment-on-Treated															
Received First Message	-0.940***	-1.165***	-0.806**	-1.445***	-0.146	-0.871***	-0.682	-1.099***	-0.969***	-0.248	-1.103***	-1.499**	-0.969***	-0.772***	-1.327**
	(0.362)	(0.358)	(0.347)	(0.404)	(0.582)	(0.234)	(0.523)	(0.372)	(0.301)	(0.860)	(0.267)	(0.673)	(0.273)	(0.233)	(0.620)
Observations	3,808	3,505	2,977	3,854	1,630	5,730	3,060	4,779	2,534	649	6,664	1,265	6,048	6,751	2,039
Mean End-of-Year Absences for the Control Group	20.44	20.71	19.36	21.94	21.06	17.17	25.37	22.10	17.43	18.52	20.76	22.48	20.17	17.06	31.97

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Each regression applies to students that fall within the specific sub group identified by the column heading.
Each regression controls for initial absences and includes district and message-level fixed effects.
Only the districts that implemented the experiment with fidelity (districts C and D) are included in this analysis.

Table 5: The Effect of Messages on Alternative Outcomes

	End-of-year Absences	Total Excused Absences	Total Unexcused Absences	Chronically Absent - National Definition
	Intent-to-Treat			
Treated	-0.731***	-0.371***	-0.360**	-0.0375***
	(0.182)	(0.120)	(0.182)	(0.00927)
	Treatment-on-Treated			
Received First Message	-0.928***	-0.472***	-0.456**	-0.0476***
	(0.231)	(0.153)	(0.231)	(0.0117)
Observations	8,790	8,790	8,790	8,790
Mean of Control Group	20.34	6.10	14.23	61%

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Each regression controls for initial absences and includes district and message-level fixed effects.
Only the districts that implemented the experiment with fidelity (districts C and D) are included in this analysis.

Appendix

Table A1: Previous Attendance Messaging Studies

Study	Location & School Year	Target Population	Treatment and Control Groups	Intervention Details	Findings
Authors: Smythe-Leisyico & Page (2018)	Pittsburgh Public Schools (F2015-S2016)	- Kindergarten students	- Treatment: students in one elementary school with low-income and high Kindergarten chronic absenteeism - Control: Synthetically constructed	**Message Type: Text** - Pilot - Two-way messaging - Three types of messages: utility (even/activity sharing), individualization, support (resource provision) - Technology partner: Signal Vine	- 11.1 pp (45%) reduction in chronic absenteeism
Authors: Kalil & Mayer (2017) Sponsor: Behavioral Insights and Parenting Lab (BIP Lab)	Chicago (S2016-S2017)	- Head Start (Pre-school)	- 780 families across 9 schools	**Message Type: Text** - Three separate rounds of messages sent 3-5x per week for 18 weeks. - Four types of messages: reminders, feedback, loss aversion, and planning prompts	- 1.8 pp increase in attendance rate - 7.4 pp reduction in number of children chronically absent - Higher effects towards the end of the school year
Authors: Robinson, Lee, Dearing, and Rogers (2017)	California (F2015-S2016)	- Grades K-5 - Students in bottom 60th of attendance distribution	- Treatment A: 3,307 - Treatment B: 3,272 - Control: 4,388 - Excluded extreme absences, inconsistent records, and small school by grade combinations	**Message Type: Mail** - 6 rounds - Treatment A: emphasized importance of attendance, reported year-to-date absences - Treatment B: Treatment A plus encouragement to reach out to people who can help with attendance	- 7.7% reduction in absences (Reduced number of days absent by 0.53) - 14.9% reduction in chronic absenteeism - Equally effective across all grades - No significant differences between Treatment A & Treatment B
Authors: Rogers,	Philadelphia	- Grades 1-12	- Treatment A: 14,190	**Message Type: Mail**	- 2.4% reduction in absences

Duncan, Wolford, Ternovksi, & Reltano (2017)	(F2013-S2015)		- Treatment B: 22,815 - Control: 14,192 - Stratified by number of absences, grade, and school - Excluded students without reliable addresses	- Treatment A: Encouragement to improve their student's attendance - Treatment B: Treatment A plus specific info about their student's attendance history	(Reduced number of days absent by 0.13) - No significant differences between Treatment A & Treatment B - No significant differences between grade level
Authors: Rogers & Feller (2017)	Philadelphia (Pilot in S2014; F2014-S2015)	- Grades K-12	- Pilot: 3,007 households randomly assigned among Treatment B, Treatment C, and Control - Treatment A: 7,020 - Treatment B: 7,020 - Treatment C: 7,020 - Control: 7,020 - Stratified by number of absences, grade, and school - Excluded students with perfect attendance prior year, extreme absences, IEPs, and more	**Message Type: Mail** - Pilot: 14-week period; 5 rounds - Treatment A: reminder - Treatment B: total absences - Treatment C: relative absences - Cost: $6.60 per household	- Pilot: 6% reduction in absences ((Reduced number of days absent by 0.7) - 5.88% reduction in absences (Reduced number of days absent by 1) - 10% reduction in chronic absenteeism - No differential impact of relative absences compared to total absences - No differences among gender, race, grade level

Appendix Table A2: Message Details

Standard text and email message in three of the four districts:

Message Type	Message
K-8	Jonathan missed 5 school days so far this year – more absences than 90% of his peers. Please make sure Jonathan gets to school.
HS (9-12)	Jonathan missed 5 school days so far this year – more absences than 90% of his peers. Students with fewer absences are more likely to graduate.

In one district, the primary mode of communication was email. A text message was sent to remind parents to check their email. This district altered their main mode of communication and wording in response to concerns heard from some of the other districts that parents were responding a bit negatively to the terseness of the texts they were receiving. The email message in this district read as follows:

Message Type	Message
K-8	Jonathan has missed 5 school days so far this year, which is more absences than 90% of his peers. We realize that some absences cannot be avoided, but did want to make you aware of the number of days your child has missed to date. School attendance is important and we look forward to working with you to make sure your child is at school and doing well academically.
HS (9-12)	Jonathan has missed 5 school days so far this year, which is more absences than 90% of his peers. We realize that some absences cannot be avoided, but did want to make you aware of the number of days your child has missed to date. School attendance is important and can be a key factor in a student's progress toward graduation. We look forward to working with you to make sure your child is at school and doing well academically.

Appendix Table A3: Details of Timing of Messages

	District A	District B	District C	District D
November 2018		X No message sent to HS students	X	
December 2018			X	X
February 2019		X	X HS <u>email</u> messages were <u>not</u> sent	X
March 2019		X	X	X
April 2019	X		X	X
May 2019	X	X No text messages were sent	X	X

We intended for messages to be sent each month (except for January) starting in November 2018 for District B and District C and starting in December 2018 for District A and District D. This table shows which messages actually went out, indicated by the "x". If applicable, implementation issues are noted. District A sent two rounds of messages at the end of the school year and communicated via robocalls instead of text messages. For this district, throughout the paper we treat robocalls the same as text messages since the communication was via phone; however, we recognize there are still considerable differences between these two modes of communication. District B did not send messages in December 2018 and April 2019 and had additional implementation issues in the other months. Overall, in District C and District D, the messages were sent with minor or no implementation issues, so we classify these as the two districts that "implemented the experiment with fidelity."

Appendix Table A4: Summary Statistics by District

	District A						
	Non-experimental Group		Control (N=5,148)		Treatment (N=1,083)		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	P-Value
Male	0.50	0.50	0.51	0.50	0.49	0.50	0.48
White	0.21	0.41	0.05	0.21	0.04	0.20	0.56
Black	0.72	0.45	0.91	0.28	0.93	0.26	0.22
Asian	0.02	0.14	0.01	0.07	0.00	0.07	0.75
Other Race	0.06	0.23	0.04	0.19	0.03	0.17	0.29
Hispanic	0.08	0.27	0.06	0.23	0.04	0.20	0.02
Free or Reduced Price Lunch	0.55	0.50	0.78	0.42	0.80	0.40	0.20
English Language Learner	0.05	0.22	0.02	0.15	0.02	0.14	0.37
Student with Disability	0.11	0.32	0.15	0.36	0.16	0.37	0.50
Elementary School	0.56	0.50	0.41	0.49	0.44	0.50	0.02
Middle School	0.22	0.42	0.20	0.40	0.21	0.41	0.42
High School	0.21	0.41	0.40	0.49	0.35	0.48	0.00
Absences when Assigned Treatment	2.38	2.75	11.81	6.02	11.46	5.82	0.08
End-of-year Absences	6.97	6.84	25.04	14.61	24.22	14.06	0.09
Chronically Absent - National	0.11	0.31	0.77	0.42	0.76	0.43	0.30
Received First Message					0.33	0.47	
Received Last Message					0.45	0.50	
Received First Text					0.27	0.44	
Received First Email					0.10	0.30	
Received Both Email & Text as First Message					0.04	0.19	
	District B						
	Non-experimental Group		Control (N=5,894)		Treatment (N=2,490)		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	P-Value
Male	0.51	0.50	0.54	0.50	0.55	0.50	0.32
White	0.18	0.38	0.09	0.28	0.09	0.28	0.93
Black	0.63	0.48	0.76	0.43	0.75	0.43	0.29
Asian	0.07	0.26	0.04	0.19	0.05	0.21	0.09
Other Race	0.12	0.33	0.12	0.32	0.12	0.33	0.72
Hispanic	0.19	0.39	0.18	0.39	0.18	0.38	0.61
Free or Reduced Price Lunch	0.65	0.48	0.76	0.43	0.77	0.42	0.36
English Language Learner	0.18	0.38	0.13	0.34	0.16	0.37	0.01
Student with Disability	0.11	0.31	0.16	0.36	0.18	0.38	0.02
Elementary School	0.44	0.50	0.26	0.44	0.45	0.50	0.00
Middle School	0.26	0.44	0.16	0.36	0.28	0.45	0.00
High School	0.30	0.46	0.59	0.49	0.28	0.45	0.00
Absences when Assigned Treatment	2.67	2.71	12.00	6.62	11.70	6.61	0.06
End-of-year Absences	9.68	8.73	29.77	16.95	27.45	16.62	0.00
Chronically Absent - National	0.19	0.40	0.80	0.40	0.75	0.43	0.00
Received First Message					0.56	0.50	
Received Last Message					0.92	0.27	

Received First Text					0.18	0.39	
Received First Email					0.53	0.50	
Received Both Email & Text as First Message					0.15	0.36	
	District C						
	Non-experimental Group		Control (N=2,793)		Treatment (N=2,072)		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	P-Value
Male	0.50	0.50	0.53	0.50	0.54	0.50	0.45
White	0.45	0.50	0.34	0.47	0.30	0.46	0.02
Black	0.41	0.49	0.63	0.48	0.66	0.47	0.04
Asian	0.13	0.34	0.02	0.15	0.03	0.17	0.30
Other Race	0.00	0.06	0.00	0.06	0.00	0.06	0.69
Hispanic	0.16	0.36	0.21	0.41	0.21	0.41	0.76
Free or Reduced Price Lunch	0.44	0.50	0.75	0.43	0.77	0.42	0.33
English Language Learner	0.09	0.29	0.08	0.27	0.09	0.29	0.32
Student with Disability	0.10	0.31	0.17	0.37	0.17	0.38	0.74
Elementary School	0.44	0.50	0.35	0.48	0.45	0.50	0.00
Middle School	0.24	0.43	0.19	0.39	0.24	0.43	0.00
High School	0.32	0.47	0.46	0.50	0.31	0.46	0.00
Absences when Assigned Treatment	1.38	1.88	7.51	3.48	7.40	3.45	0.25
End-of-year Absences	6.18	6.31	22.64	13.17	21.41	12.50	0.00
Chronically Absent - National	0.08	0.27	0.70	0.46	0.66	0.47	0.00
Received First Message					0.63	0.48	
Received Last Message					0.64	0.48	
Received First Text					0.22	0.42	
Received First Email					0.59	0.49	
Received Both Email & Text as First Message					0.18	0.38	
	District D						
			Control (N=1,690)		Treatment (N=2,235)		
			Mean	Std. Dev.	Mean	Std. Dev.	P-Value
Male			0.52	0.50	0.49	0.50	0.12
White			0.53	0.50	0.50	0.50	0.11
Black			0.37	0.48	0.37	0.48	0.82
Asian			0.06	0.24	0.08	0.27	0.02
Other Race			0.03	0.18	0.04	0.21	0.08
Hispanic			0.24	0.43	0.24	0.43	0.85
Free or Reduced Price Lunch			0.53	0.50	0.51	0.50	0.32
English Language Learner			0.10	0.30	0.09	0.29	0.60
Student with Disability			0.18	0.38	0.18	0.38	0.83
Elementary School			0.52	0.50	0.47	0.50	0.00
Middle School			0.21	0.41	0.22	0.42	0.60
High School			0.27	0.44	0.31	0.46	0.01
Absences when Assigned Treatment			8.73	4.13	9.07	4.52	0.02
End-of-year Absences			16.53	9.85	16.25	10.98	0.40
Chronically Absent - National			0.47	0.50	0.42	0.49	0.01
Received First Message					0.98	0.16	

Received Last Message					0.97	0.17	
Received First Text					0.00	0.00	
Received First Email					0.98	0.16	
Received Both Email & Text as First Message					0.00	0.00	

Summary statistics are provided for the non-experimental group, treatment group, and control group for each district. District A made robocalls instead of sending texts and so "text" refers to "robocall" in this district. The non-experimental group for District D is not included due to data limitations. The non-experimental group consists of students that remained in the district for the entire school year. The p-value is calculated for the treatment and control group. For the variables with a p-value of 0.05 we are 95 percent confident that the two means are different, and for the variables with a p-value of 0.01, we are 99 percent confident that the means are different. The sample sizes for the districts' non-experimental group are not reported to maintain anonymity.

Appendix Table A5: Balance Check of Random Assignment

	Absences when Assigned Treatment	Male	White	Black	Hispanic	Free or Reduced Price Lunch	English Language Learner	Student with Disability
				All Districts				
Treated	0.320***	-0.00545	-0.0152**	0.000743	-0.00149	0.000246	0.00530	0.00832
	(0.0758)	(0.00794)	(0.00597)	(0.00682)	(0.00591)	(0.00694)	(0.00465)	(0.00597)
Observations	23,405	19,923	19,923	19,923	19,923	19,923	19,923	19,923
				Districts that Implemented with Fidelity				
Treated	0.200**	-0.00759	-0.0321***	0.0144	-0.00182	-0.00571	-0.00223	-0.000934
	(0.0819)	(0.0118)	(0.0114)	(0.0114)	(0.00988)	(0.0109)	(0.00672)	(0.00897)
Observations	8,790	7,313	7,313	7,313	7,313	7,313	7,313	7,313

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Each regression includes district and message-level fixed effects.
We randomly assigned eligible students to treatment and control within a district and grades K-8 and 9-12. To reduce messaging burden for our district partners, instead of splitting the eligible sample 50-50, we made the treatment group as small as possible to still detect an effect. The first panel shows the results from the balance check for all four districts and the second panel shows the results from the balance check for the two districts that implemented the experiment with fidelity (districts C & D). Our random assignment is balanced across most races and student-level characteristics, such as FRL status, ELL classification, and disability status. By chance, students assigned to the treatment group have one-fifth to one-third more initial absences and are less likely to be white. We are missing demographic information for Kindergarten and new students, so the sample size decreases from 23,405 to 19,923 when we check balance across demographic characteristics.

Appendix Table A6: The Effect of Messages on End-of-year Absences by District

	All Districts	District A	District B	District C	District D
Intent-to-Treat					
Treated	-0.388**	-0.085	-0.168	-0.303	-1.040***
	(0.163)	(0.376)	(0.342)	(0.293)	(0.190)
Mean of End-of-year Absences for the Control Group	25.48	25.04	29.77	22.64	16.53
Percent Change in End-of-year Absences	-2%	0%	-1%	-1%	-6%
Treatment-on-Treated					
Received First Message	-0.626**	-0.254	-0.301	-0.478	-1.066***
	(0.263)	(1.129)	(0.615)	(0.461)	(0.195)
Mean of End-of-year Absences for the Control Group	25.48	25.04	29.77	22.64	16.53
Percent Change in End-of-year Absences	-2%	-1%	-1%	-2%	-6%
First Stage					
Treated	0.621***	0.333***	0.557***	0.634***	0.976***
	(0.006)	(0.014)	(0.010)	(0.011)	(0.003)
Observations	23,405	6,231	8,384	4,865	3,925

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Each regression controls for initial absences and includes message-level fixed effects.

Appendix Table A7: Robustness Checks on End-of-year Absences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intent-to-Treat									
Treated	-0.731***	-0.688***	-0.608***	-1.124***	-0.914***	-0.884***	-0.770***	-0.759***	-0.722***
	(0.182)	(0.181)	(0.181)	(0.182)	(0.171)	(0.169)	(0.203)	(0.201)	(0.190)
Treatment-on-Treated									
Received First Message	-0.928***	-0.875***	-0.772***	-1.417***	-1.154***	-1.116***	-0.987***	-0.972***	-0.917***
	(0.231)	(0.230)	(0.229)	(0.231)	(0.216)	(0.213)	(0.261)	(0.259)	(0.240)
Received Last Message	-0.930***	-0.877***	-0.774***	-1.421***	-1.157***	-1.119***	-0.989***	-0.974***	-0.920***
	-0.232	-0.23	-0.23	-0.231	-0.217	-0.213	-0.262	-0.26	-0.241
Observations	8,790	8,790	8,790	8,790	8,790	8,790	8,790	8,790	8,829
Number of Grade by School Combinations							1,112	1,112	
Number of Schools				198	198	198			
District Fixed Effects	x	x	x						x
Message-level Fixed Effects	x	x	x						x
Controls for Demographic Characteristics		x	x			x		x	
District by Message-level Fixed Effects			x						
School Fixed Effects				x	x	x			
Grade Fixed Effects					x	x			
School by Grade Fixed Effects							x	x	
Includes Outliers									x

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
All regressions control for initial absences. Column 1 displays the main results again, column 2 adds demographic controls, and column 3 adds in an interaction between the district and message-level. Column 4 includes school fixed effects for 198 schools, column 5 adds in grade fixed effects, and column 6 adds in demographic controls. Column 7 includes school by grade fixed effects for 1,112 combinations, and column 8 adds demographic controls to this specification. Finally, column 9 includes outliers (students with more absences than 99% of the students). Only the districts that implemented the experiment with fidelity (districts C and D) are included in this analysis.

Appendix Table A8: Attrition Analysis

	All Districts	Districts that Implemented with Fidelity	District A	District B	District C	District D
Treated	0.00593	0.00537	0.0233**	0.00592	0.0214**	-0.0117
	(0.00409)	(0.00657)	(0.0106)	(0.00451)	(0.00975)	(0.00820)
Observations	26,140	10,184	7,179	8,777	5,896	4,288
Mean Attrition Rate for the Control Group	0.104	0.141	0.129	0.050	0.171	0.087
Percent Change in Attrition	6%	4%	18%	12%	13%	-13%

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Each regression controls for initial absences and includes district and message-level fixed effects.

ABOUT THE AUTHORS

Tareena Musaddiq was a graduate research assistant with the Georgia Policy Labs and is now a Postdoctoral Research Fellow at the Gerald R. Ford School of Public Policy at the University of Michigan. Her research interests are in education, health, and development economics. Her current work focuses on the impact of policy interventions in K-12 schools on child health and education outcomes and on long-run and intergenerational effects of girls' education in developing countries. She holds a Ph.D. in economics from Georgia State University, a master's in economics and finance from the University of Warwick in the United Kingdom, and a B.Sc. (Hon.) in economics from Lahore University of Management Sciences in Pakistan.

Alexa Prettyman is an economics doctoral student at Georgia State University studying labor, public, and urban/regional economics and a graduate research assistant with the Georgia Policy Labs. Her research evaluates and develops interventions and evidence-based policies that overcome the disparities of educational attainment for vulnerable youth, such as chronically absent students and children in foster care. She is also interested in the short and long-run effects of non-instructional services offered by schools and the community that can improve school quality. Alexa earned her B.S. in mathematical economics from the University of Kentucky.

Jonathan Smith is an assistant professor of economics at Georgia State University and faculty affiliate with the Georgia Policy Labs. His research focuses on the behavioral and institutional factors that determine how students transition from high school to college and the consequences of those decisions. His research is published in leading economics, policy, and education journals including the *Journal of Labor Economics*, *Journal of Human Resources*, and the *Journal of Policy Analysis and Management* and has been featured in numerous media outlets, including *The New York Times*. Prior to joining Georgia State University, he worked as a Policy Research Scientist at the College Board. He received his Ph.D. in economics from Boston University and a B.A. in economics from Tufts University.

ABOUT THE GEORGIA POLICY LABS

The Georgia Policy Labs (GPL) is a collaboration between Georgia State University and a variety of government agencies to promote evidence-based policy development and implementation. Housed in the Andrew Young School of Policy Studies, GPL works to create an environment where policymakers have the information and tools available to improve the effectiveness of existing government policies and programs, try out new ideas for addressing pressing issues, and decide what new initiatives to scale. The goal is to help government entities more effectively use scarce resources and make a positive difference in people's lives. GPL has three components: The Metro Atlanta Policy Lab for Education works to improve K-12 educational outcomes; the Career & Technical Education Policy Exchange focuses on high-school-based career and technical education in multiple U.S. states; and the Child & Family Policy Lab examines how Georgia's state agencies support the whole child and the whole family. In addition to conducting evidence-based policy research, GPL serves as a teaching and learning resource for state officials and policymakers, students, and other constituents. See more at gpl.gsu.edu.