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REDUCING PARENT-SCHOOL INFORMATION GAPS AND IMPROVING EDUCATION OUTCOMES: EVIDENCE FROM HIGH-FREQUENCY TEXT MESSAGES

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Reducing Parent-School Information Gaps and Improving Education Outcomes: Evidence from High-Frequency Text Messages
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ABSTRACT

We conducted an experiment in low-income schools in Chile to test the effects and behavioral changes triggered by a program that sends attendance, grade, and classroom behavior information to parents via weekly and monthly text messages. Our 18-month intervention raised average math GPA by 0.08 of a standard deviation and increased the share of students satisfying attendance requirements for grade promotion by 4.5 percentage points. Treatment effects were larger for students at higher risk of later grade retention and dropout. Leveraging existing school inputs for a light-touch, cost-effective, and scalable information intervention can improve education outcomes in lower-income settings.

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1 Introduction

Grade retention and early dropout are two of the biggest challenges facing education systems in middle-income countries today. In Latin America, only 46% of students graduate from secondary school on time, and only 53% of young people aged 20 to 24 have completed their high school education [IDB, 2017]. These outcomes contribute to persistent education gaps between low- and high-income families. Researchers have identified absenteeism, failing grades, and classroom misbehavior as important early warning signals for grade retention and the likelihood that students will eventually drop out of school [Manacorda, 2012; Wedenoja, 2017]. While schools around the world routinely record these types of student outcomes, families often do not have timely access to this information. In this paper, we examine whether improving the frequency of communication between parents and schools can improve students' academic outcomes, particularly among those who are at higher risk of being retained at a given grade or of later dropout.

We conducted a randomized experiment in Chile to evaluate the effects of using weekly and monthly cellphone text messages to provide parents with information on students' attendance, grades, and classroom behavior. The intervention focuses on students in the last five grades of primary school and lasts for two school years (18 months of school). It targets information towards parents during the years when attendance and grades start to matter, but before the risks of grade repetition or dropout significantly increase. Our main experimental sample includes about 1,000 children enrolled in seven low-income schools in a metropolitan area in Chile. The text message intervention (Papas al Dia) was deliberately designed to be a low-touch intervention. We did not teach parents how to interpret or use the information, nor did we provide any guidance to students, teachers or principals.

Our paper has several distinguishing features. First, we assess an intervention with great potential for scalability in low-capacity school settings.[1] We deliver more than 44,000 text messages over the intervention period, and find positive impacts on several key school outcomes, with particularly large impacts on at-risk students. Second, we exploit aspects of the research design to try to learn more about the ways in which such information interventions work. Using variation in the weekly and monthly frequency of text messages delivered, we examine whether the effects of messages changed over time or with the frequency of the messaging. We also randomly manipulated the share of treated students in each classroom to assess spillover effects within treated students. And we administered several rounds of parent and student surveys to measure whether the intervention changed parent information gaps,

[1]While not all Chilean schools are low capacity, seven out of eight of our schools were designated as requiring additional resources and support ("Emergent" schools) based on Chilean Ministry of Education standards for student performance.

and parent-child interactions. Third, after parents had some exposure to the program, we administered a survey experiment to assess whether parents in treatment and control groups valued the frequent communication with schools differently, and whether stated willingness to pay for the program was affected by a student's baseline educational performance.

We start by documenting fairly sizable gaps that exist between parents' knowledge and school reports of students' attendance and grades. Comparing baseline survey responses to school records, we find that 26 percent of parents were unable to report correct information about their child's grades; while 48 percent could not approximate their child's school attendance in the previous two weeks. Similar information gaps have been found in settings as diverse as the United States [Bergman, 2021], Malawi [Dizon-Ross, 2019] and Colombia [Barrera-Osorio et al., 2020]. Moreover, we document that the parents of at-risk, low-achieving students are more likely to misreport grades and attendance. Narrowing this gap –between parents' understanding of their child's performance and actual performance as documented by the school– is a key target of our text messaging treatment.

Text messaging to parents had positive impacts on grades and attendance. A comparison of the treated and control students shows that the intervention led to an increase in math GPA of 0.08 of a standard deviation; the probability of earning a passing grade in math increased by 2.7 percentage points (relative to a mean of 93%). The intervention also increased school attendance by 1 percentage point, and increased the share of students who satisfied the attendance requirements for grade promotion by 4.5 percentage points.[2] There is important heterogeneity in these treatment effects related to initial academic performance. The effects on grades, attendance, and behavior are two to three times larger for those students with a standard deviation more of our at-risk index.

We find suggestive evidence of positive classroom-level spillovers among treated students. Classes were randomized into groups with a high (75%) or low (25%) share of students whose parents participated in the texting program and then students were randomized to treatment within each classroom. This allowed us to test whether classroom-level spillovers among treated students could play an important role in impacts. Although our design does not allow us to test for spillovers to the control group, the spillover results on treated students suggest that the positive direct effect on individual grades and attendance that we measure are likely underestimates of the impacts of a scaled-up version of this program in which all students would be treated.[3]

[2]These math grade intention-to-treat effects are somewhat smaller than grade effects of other types of interventions in the literature. For example: Kremer et al. [2009] finds an increase of 0.13 of a standard deviation in test scores as the result of offering expensive scholarships for two school years of high school to girls in grade 6 in Kenya. Bergman [2021] finds an increase of 0.19 of a standard deviation in test scores from a program involving communicating with parents of students in low-income schools in the United States.

[3]For budget reasons we do not have pure control classrooms, therefore we are restricted to estimating

Exploring the timing and frequency of text messages through the week and through the school year over the 18 months of the intervention suggests ways that policymakers might consider adjusting the design of these types of information interventions. The patterns in our data indicate that the positive effect on attendance fades out over the week: effects appear somewhat larger immediately after parents receive the text messages and decline as the days go by. This suggests that for outcomes where the student makes daily choices –to attend or not to attend school– high-frequency text messages may be more beneficial than sporadic messages. At the same time, we find that the intervention is effective throughout the school year. Parents do not seem to get used to the information treatment. Although the data do not allow us to precisely estimate all of the patterns of effects related to timing and frequency of messaging, taken together, the results suggest that information treatments like the one studied in this paper may need to be high frequency and sustained over time in maximize effectiveness.

To gain further insight into the channels that induced the intervention to change students' and parents' behaviors, we combined rich administrative data collected from each school with information collected through surveys conducted with parents and students before and after the program. We show that the text message treatment shrinks information gaps about math scores and misbehavior between parents and schools. Parents of at-risk students "correct" their understanding of their child's performance to the greatest degree (although results are not statistically significant at normal levels). And, although the information treatment was designed to deliver information about specific subjects and behaviors, we provide some evidence that it likely directed parents to pay more attention to all aspects of school performance: we show that the treatment group performed better in non-targeted subjects (e.g., language), and that parent misinformation about these non-targeted subjects also improved among the treated group.

Results from our survey data indicate that parents used the new information they obtained about their children to guide interactions with their children at home. The intervention changed student reports of parent behaviors at home. Treated students perceived that they received significantly more family support as a result of the intervention and that their parents were more involved in school matters.

Consistent with these changes in reported parental behavior, we find that some parents are willing to pay for the information program. We rely on a survey experiment to assess willingness to pay for the information. For all parents, demand slopes downward; a larger share of parents are willing to pay for the text messaging service when offered a lower randomized price. Among parents whose children were measured at risk of grade retention

spillovers within treated students.

and dropout to begin with, those in the treatment group –who had already experienced receiving the text messages for several months– have significantly higher willingness to pay for the continued service. This result echoes the findings of Bursztyn and Coffman [2012], who show that Brazilian parents report being willing to pay for receiving regular updates on their child's absenteeism.

Our text message intervention is characterized by low variable cost and a one-time setup cost. Using the intent-to-treat estimates, we find that a 0.01 of a standard deviation increase in math grades has a variable cost of about US$1.18 per student per year at market prices (rising to US$2/year when we include the fixed set up costs). Papas al Dia is cost-effective when compared to other interventions designed to improve learning outcomes and attendance.

There is a large and recent literature studying the effect of sending parents information about their children's activities and performance in school. This literature includes Bursztyn and Coffman [2012], Kraft and Dougherty [2013], Avvisati et al. [2014], Castleman and Page [2015], Kraft and Rogers [2015], De Walque and Valente [2018], Rogers and Feller [2018], Bergman and Chan [2021], Dizon-Ross [2019], Angrist et al. [2020], Barrera-Osorio et al. [2020], Bergman [2021], Bergman et al. [2020], Gallego et al. [2020], and Bettinger et al. [2021] among others.[4] Many of these studies have been conducted in US settings.

We make three key contributions to this literature. First, we present new evidence on a low-cost intervention that is amenable to scale up in a developing-country setting. There is already evidence that low-cost, light-touch and easily scalable programs of information provision can work in developed country settings [Bergman and Chan, 2021].[5] There is also evidence that more intensive higher-cost information interventions can work to improve school outcomes in low capacity settings [Barrera-Osorio et al., 2020], although these would be difficult to scale.[6] Our results suggest that even a relatively inexpensive low-touch information intervention can have positive impacts in low capacity school settings. Interventions like Papas al Dia hold potential for scaling up in settings with limited resources.

Second, our willingness to pay survey experiment shows that parents value the timely, accurate information about their children's school performance (which can contribute to the program scalability). Parents of the most at-risk students value this information to a greater

[4]Appendix A provides a summary of the results in these papers.

[5]Using 22 middle and high schools in West Virginia, Bergman and Chan [2021] find positive impacts of high-frequency text messaging on class attendance but no impacts on test scores. The researchers automated the process of gathering the data by scraping student information systems, but this is possibly unfeasible in low- and middle-income countries where information is almost always collected on paper.

[6]Barrera-Osorio et al. [2020] find that combining a one-time information intervention with targeted advice to parents can achieve similar sized short-term increases in a combined math and reading test score, but at significantly higher cost per student, of USD7.50 per year.

extent. This is consistent with the intervention having larger positive impacts on outcomes for the most at-risk students. These results connect with a growing economics literature that identifies a lack of information as one of the critical constraints on good decision-making.[7]

Third, our work provides input on designing public policies that rely on providing information to improve individual decision-making and social outcomes. Our results suggest that policymakers should give careful consideration to the timing and duration of information provision. In our specific context, parents were more responsive to attendance information sent earlier in the week. A related concern is whether information interventions lose effectiveness over time as individuals get accustomed to receiving text messages. In our setting, this was not the case: parents continued to be responsive to attendance and grade information throughout the intervention.

Our paper is organized as follows: Section 2 describes the experimental setting, and documents the extent of parent-school information gaps at baseline. Section 3 describes the recruitment of participants in the intervention, the intervention itself, and treatment randomization. Section 4 describes the data we collected and used in our analysis, variable definitions, and survey instrument response rates. Section 5 discusses our estimation strategy and analyzes the internal validity of our experiment. Sections 6 discusses the treatment effects on academic outcomes, heterogeneity, and spillovers. Section 7 explores the mechanisms behind those effects. Section 8 discusses whether the program was cost-effective. Section 9 concludes.

2 Setting

School dropout is concentrated among students in lower-income quintiles in Chile. For instance, in 2010, only 65% of students in the lowest-income quintile complete high school, compared with over 96% of students in the highest-income quintile. Attendance, grades, and classroom behavior in elementary school are key factors affecting the risk of grade retention, which, in turn, increases the probability that students will drop out of school when they grow older [e.g. Manacorda, 2012; Wedenoja, 2017].

There are twelve years of mandatory school in Chile: eight of primary school and four of secondary school. To pass each grade students must attend at least 85% of school days in a

[7] See, for example, Nguyen [2008], Jensen [2010], Oreopoulos and Dunn [2013], Dinkelman and Martínez A [2014], for evidence on how educational outcomes improve after parents or students are informed about the returns to, or costs of, educational investments. Dizon-Ross [2019] studies a one-off information intervention with parents in Malawi, showing that the intervention improves what parents know about their children, and causes family educational investments to adjust to match newly revealed abilities of each child. On the other hand, Fryer Jr [2016] provides an example in which information alone was insufficient for improving educational attainment.

school year, and must obtain a passing grade of 4.0 in all subjects (on a scale from one to seven).[8] As a result, there is a strong correlation between attendance, subject grades, and grade retention.[9]

The transition from the final grade of primary school to the beginning of secondary school is a point at which students are at high risk of grade retention or, in the worst case scenario, of dropping out of the school system. Even though grade retention is an outcome of concern during lower grades, it becomes even more of a concern as students progress through their school years. During grades 1-3 about 3% of students repeat their grade. Starting in grade 4 this percentage increases with each grade, finally reaching 5% by the end of primary school. In the first year of secondary school, the grade retention rate surges, reaching 13%. This pattern is observed in our sample, but it is also common in most Latin American countries [Bassi et al., 2015].

Our intervention focuses on students in the last five grades of primary school, where the median child age is 10. It targets information for parents during the years when attendance and grades start to matter, but before the risks of grade repetition or dropout significantly increase.

Many parents do not have good information about their children's school performance. Gaps in the information that schools and parents have about children have been identified in settings as diverse as the United States [Bergman, 2021], Malawi [Dizon-Ross, 2019] and Colombia [Barrera-Osorio et al., 2020]. In general, examples in the literature suggest that most parents tend to overestimate their child's performance in school, and that parents who have less education themselves have worse information about their child's performance in school [Barrera-Osorio et al., 2020; Rogers and Feller, 2018; Bergman and Chan, 2021].

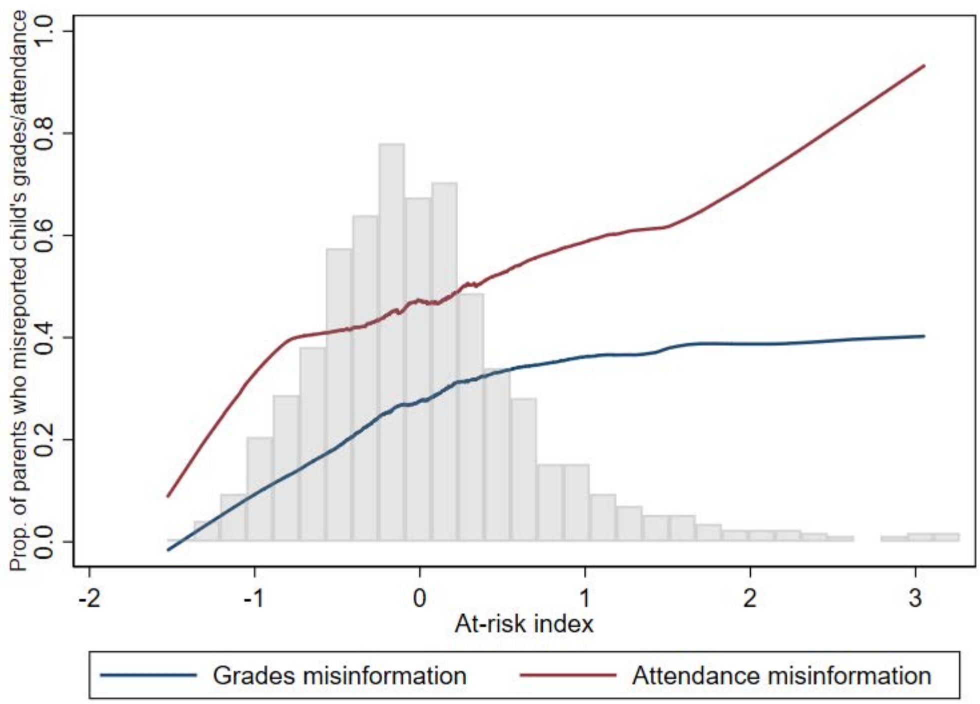
In our setting, we observe similar types of parent-school information gaps regarding the student's actual grades and attendance. Parents are usually provided with information about their child's progress every quarter through a report card that details a student's grades and number of absences. Teachers and principals also communicate with parents on an "as needed" basis for certain cases of misbehavior, regular absenteeism, and repeated low grades. Figure 1, based on data from our baseline survey described in Section 4, plots the

[8]Students who fail one subject can still advance to the next grade if they maintain an average grade of 4.5 for the remaining subjects; students who fail two subjects can also advance if they maintain an average grade above 5.0 in the remaining subjects. In addition, the 85% attendance requirement can be lifted by the school board under special circumstances.

[9]Using administrative data, we examined these same correlations in our sample prior to the start of the intervention. The correlation of average grade was 0.4 with attendance and -0.4 with grade retention. The correlation between school attendance and grade retention was -0.3. Even conditional on age and gender controls, and taking into account grade-level and school fixed effects, the correlations between lower attendance, lower grades, and a higher risk of failing the grade are large and statistically significant at the 5% level.

share of parents whose report of the child's grade/attendance is at odds with the child's actual school performance before the intervention began. We define a grade as being misreported if it deviates more than 0.5 points above or below the actual grade. The share of grade misreports is plotted in blue. We define attendance to be misreported if the parents' report of the child's absence differs by two or more instances from actual absences recorded in the previous two weeks. The share of attendance misreports is plotted in red.[10] These misreports are graphed against a summary measure – the (standardized) at-risk index – of whether a child is considered at-risk of retention or dropping out (because of higher absenteeism, lower grades, or worse behavior in class) before the intervention.[11]

Figure 1: Baseline Share of Misinformed Parents



Note: Y-axis presents the (lowess-smoothed) share of parents misinformed regarding their child's grades (blue line) and attendance (red line) for different levels of the at-risk index –whose histogram is shown in grey. Estimates are based on parent surveys and administrative data at baseline. See notes for columns [2] and [4] of Table 5 for details on the construction of misinformation measures and Section 4 for the index construction.

We find that in our sample, on average, 26 percent of parents were unable to report correct information about their child's grade while 48 percent could not correctly report their child's school attendance in the previous two weeks. Moreover, Figure 1 shows that

[10] Parents who did not respond to either question were also classified as misinformed. See notes on columns [2] and [4] of Table 5 for details.

[11] We discuss how we construct this at-risk index in Section 4.

misinformation is higher among parents of students with higher at-risk index values, and that a larger share of parents misreport attendance, relative to grades, for students at all levels of risk. About 40% percent of parents of students with a baseline math grade below 4.5 did not accurately know their children's test scores. Similarly, 70% percent of parents of students with an attendance rate of lower than 85 percent, did not know how many days their children had missed school in the previous two weeks. This is despite 79% of parents in our survey declaring that they almost always check their children's report. These are the types of information gaps our intervention is designed to address. The patterns in Figure 1 suggest that our intervention should be particularly relevant for those children who are the most at-risk of grade retention or dropping out.

3 Experimental Design

In this section we outline the basic elements of our experiment: the recruitment of schools and parents, the randomization of students and classrooms, and the intervention.

Recruitment of participants. We worked with the Secretary of Education of two low-income municipalities of Santiago (Chile) to recruit schools to join our study.[12] In these schools, we held a series of meetings, inviting parents of all students in grade 4 or above to join the experiment.[13] Over 50% percent of parents consented to participate. Consent rates by grade-level were similar. Younger students, those not new to the school, and those with better baseline attendance and grades were somewhat more likely to consent.[14]

Randomization. We assigned students to treatment in two steps. First, we stratified by school grade-level, and randomly allocated classrooms (sections) to include a high or low share of students whose parents would receive text messages. In high-share classrooms, 75% of students whose parents had consented to participate were treated; in low-share classrooms, 25% of students whose parents had consented were treated.[15] Second, within each classroom, we randomized students whose parents had consented into treatment or control

[12]Our main sample has seven schools and a total of 63 classrooms.

[13]Initially, students whose parents consented to participation in the experiment were in grades 4 to 8 in the eight schools that participated in the study. The composition changed in the second year. Students in grade 8 participated during the first year of the experiment, but these students could not be treated or followed into secondary school. In addition, one school decided not to continue during the second academic year because it chose to allocate internal resources to other school goals. Because randomization was done at the individual level, stratifying by classroom, the main analysis does not include either the school that dropped out of the program, or the students who were in grade 8 at baseline. In the Online Appendix, we show the main results when using this "full" sample as a robustness check.

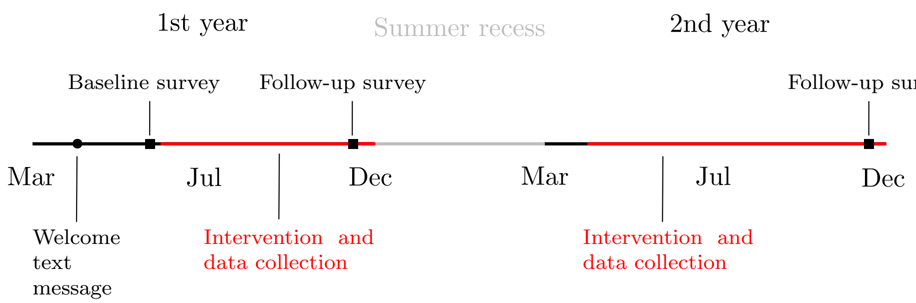
[14]See Appendix B for more details regarding the sample and the characteristics of students whose parents consented to participate in the experiment and those whose parents did not consent.

[15]For budgeting reasons we did not have a pure control group in which no student was treated. We discuss the implication of this in section 5.1.

status, according to the shares allocated in the first-step randomization. Students retained their individual and classroom-level randomization status for the duration of the intervention.

Intervention. Figure 2 shows the timeline of the Papas al Dia intervention and the data collection. The school year in Chile runs from March to December, with two weeks of winter vacation in July. A first welcoming message was sent to all participants in May of 2014. The intervention started before the winter break and lasted until December 2015. The summer break happened from mid-December to early March.

Figure 2: Timeline



Note: The figure shows the timeline of the intervention and data collection implemented in 2014 and 2015.

Parents in the treatment group received weekly messages on attendance, and monthly messages on classroom behavior and math test scores (separately). We told parents how many days the child had attended school out of the previous school week (usually five days), and we provided parents with the number of positive, neutral, and negative classroom behaviors that teachers had recorded in the classroom notebook over the prior month. We provided monthly updates on the record of all math test scores in the semester, the average of these scores, and the classroom average score for the same tests. Hence, parents learned information about their own child's math performance, as well as how their child performed relative to the classroom average. In addition, parents in both the treatment and the control group received text messages about school meetings, holidays, and other general school matters throughout the year. We refer to these as "general" messages.[16] Parents of students in the control group continued learning about their child's academic performance through report cards that were sent home every quarter.

We collected data on attendance, grades, and behavior from school classroom books. Our research team scanned and entered these data into a digital platform, which then automated the sending of messages each week. We sent more than $44,000$ text messages over

[16]Appendix C explains in detail the intervention: production of messages, timeline, and delivery. Appendix Table C.1 provides a script of each type of message sent to parents.

16 months: 68% provided information on attendance, 16% on math grades, and 16% on classroom behavior.[17]

4 Data

Data Sources. We use information from four data sources. First, we collected data on all students' math grades, daily attendance, and all behavior notes from classroom books for the years 2014 and 2015. These are daily-, weekly- and monthly-frequency data that we aggregate to an annual level. Second, we use student-level records provided by the central Ministry of Education of Chile. These records contain information on students' end-of-year school performance, including test scores, annual attendance rate, and grade retention, as well as basic demographic information. They are available for our sample of schools for the period from 2013 to 2015 and are used for allocating funding/subsidies across school. We use the 2013 data as pre-treatment controls and 2014 and 2015 data to validate our main results. Third, we recorded all text messages' information such as day and time stamps, the messages' content, the name of the recipient parent, and the delivery status of the text message (i.e., whether the phone number received the message). Fourth, we administered several surveys to all parents and children participating in the experiment. Surveys were administered before the intervention took place (baseline), at the end of the first academic year (midline), and at the end of the second academic year (endline). Student surveys were conducted in class; parent surveys were administered during an initial parent meeting or sent home with children, who were encouraged to ask their parents to complete and return the surveys.[18]

Outcome Variables.[19] We use data recorded by teachers in classroom books to measure our primary student outcomes: math grades, attendance rates and classroom behavior, which we aggregate at the annual level. Using administrative school records, we also measure outcome variables (i.e., grades, attendance rates, and an indicator for whether the student passed the grade) at an annual frequency at the end of each school year to validate our main sources.[20] Using classroom books we also constructed monthly math grades, attendance

[17] Behavior data were difficult to collect. In Chile, each classroom has a notebook in which teachers can make comments about particularly good or bad behaviors of specific students. For example, the teacher might write, "Samuel concentrated well in reading," or "Taryn hit her friend during math class." We developed a system for categorizing such behavior "notes" as positive or negative, and followed these definitions in all classrooms.

[18] Appendix Section D provides more details and information on these data sources.

[19] Appendix E describes in detail each of the outcome and control variables used in this paper. It shows the specific data sources and provides a description of how the variables were constructed.

[20] We relegate most of the results using these data to the Online Appendix.

rates, and behavioral notes. All math grades were standardized using the corresponding grade-year control mean and standard deviation.[21] In addition, we built two indicator variables for meaningful thresholds required to pass the grade: 85% of annual attendance for passing the grade, and the 4.0 math grade for passing the subject. Using classroom books, we also measured negative behavior by adding all the behavioral entries during the school year (post-treatment) and then standardized the sum using the grade-year control distribution.

Our secondary outcome variables were designed to capture information gaps and certain behavioral responses to the treatment among students and parents. First, we built measures of information gaps by comparing survey questions that asked parents about their children's recent grades, absences, and behavior. We then compared parents' responses to students' responses and administrative records. Second, we asked parents and children a series of questions to compute pre-specified measures (i.e., several items that are aggregated into one variable usually referred to as a "scale") of study habits, academic efficiency, parental support, parental supervision, parental school involvement, and parental positive reinforcement. These were intended to capture any changes in home behaviors and parent-child or parent-school relationships that might result from the intervention. We administered a set of survey items from three sources: the University of Chicago Consortium on Chicago School Research; the Manual for the Patterns of Adaptive Learning Scales (PALS) developed by the University of Michigan; and scales on positive parenting developed by the Prevention Group at Arizona State University. We aggregated categorical answers into scales using a maximum likelihood principal components estimator. We then standardized answers using the mean and standard deviation of the control group. Overall, we find that each scale has good psychometric properties.[22] We asked parents and their children a similar set of questions. Scales are highly correlated both across survey waves and between children and parents –further suggesting that the quality of these scales is high (See Tables E.5 and E.6).

Finally, to assess how much parents value the information provided through our intervention, follow-up surveys asked parents about their willingness to pay for the text messages.[23] Parents were randomly assigned a value $V of (low) $500 Chilean pesos, (medium) $1000 and (high) $1500 price (where $ is Chilean pesos per month, and where $1,000 is about USD

[21]In computing the control mean and standard deviations we only use information of the students that consented to participate in the study.

[22]Appendix E.1 describes how the scales were built. For both parents and students, we show the eigenvalue of each latent factor, the loading associated with each variable, and the Cronbach's alpha for each survey wave.

[23]We asked: "It is possible that next year your daughter's/son's school can send you regular text messages with information about their school performance (attendance, grades, and classroom behavior) four times a month. However, there might not be enough funds to provide this service free of charge. Thinking about how valuable this service would be for you, please tell us whether you will be willing to pay $V pesos a month to receive four text messages a month, from April to December."

1.50).

At-risk index. We build an index to measure each student's risk of failing classes or dropping out later in life. Specifically, we rely on three variables measured before the intervention began: standardized attendance ($Z_i^{attendance}$), math grades (Z_i^{grades}), and negative behavioral notes ($Z_i^{behavior}$).[24] The at-risk index is then defined as a simple average of these measures ($at-risk\ index_i = (-Z_i^{attendance} - Z_i^{grades} + Z_i^{behavior})/3$) which we standardize to the control group. The higher the value of this index, the worse grades, worse attendance, and worse classroom behavior the student has at baseline. Throughout the analysis, we rely on this index to assess the differential impact of the intervention on the primary and secondary outcomes for students with different values of the index.

In our setting, low attendance and low grades are predictive of future grade retention and dropout. To explore this empirically, we used data from the Ministry of Education to look at the complete educational trajectory of almost 1.3 million students who were in grades 8-12 in the period 2006-2013 attending schools in the metropolitan area of Santiago. We estimated a simple model in which the dependent variable was an indicator for having being retained in the same grade or having dropped out of school and the independent variables were the attendance and GPA in the previous three years (two of three components of the at-risk index that we observe for the whole population). We find that all coefficients are negative and most are statistically significant at normal levels.[25]

Response rates. Baseline data from administrative sources are available for all students in the experimental sample (except for a handful of students who joined the schools mid-year in 2014). Administrative data are also complete for the first year of the experiment. During the second year of the experiment, due to the normal churn of students changing schools, we have information for 90% of the students. This attrition rate is similar for treated and control students. Regarding survey data, students' response rates were between 91%, 89% and 80% across baseline, midline, and endline. More data were missing for parents, particularly from follow-up surveys. Parental response rates were 73%, 57%, and 54% at baseline, midline, and endline. For all survey waves, response rates were similar across treated and control students and parents.[26]

[24]We use final attendance and math grades from the academic year prior to the beginning of the intervention and accumulated negative behavioral marks during the month prior to the start of the intervention.

[25]See Appendix Table 1.

[26]Appendix F shows the response rates for the different samples, years, and data sources. It also describes attrition from and entry into the sample, and the characteristics of those students in terms of their treatment status.

5 Estimation and Experimental Validity

5.1 Empirical strategy

Intention-to-treat effects (ITT). To identify the effect of sending parents high-frequency academic information on students' and parents' outcomes we use the two school years of the intervention and estimate individual-level regressions of the form:

$$Y_{icjgt} = \alpha + \beta T_{icjg} + \psi X^0_{icjg} + \gamma_{cjg} + \pi_t + \theta_g + \epsilon_{icjgt} \tag{1}$$

where Y_{icjgt} is the outcome of student (or parent) i in classroom c of school j, in grade-level g, and year t; T_{icjg} is an indicator for whether a child's parents were part of the randomized group that received the information treatment, and it is constant over time; θ_g are grade-level fixed effects; and π_t are year fixed effects.[27] X^0_{icjg} are the baseline standardized math grade and attendance rate.[28] Finally, γ_{cjg} are classroom-level fixed effects (strata in the experimental design). Despite the main randomized variation being at the student level, to be conservative, we cluster standard errors at the classroom level.[29] β captures the intention-to-treat effect. Because we include classroom-level fixed effects (γ_{cjg}), β is identified through differences in individual-level treatment status within each classroom.

Classroom-level spillover effects. We exploit the differential exposure to treatment to estimate spillover effects of the intervention on the treated. Let E_{cjg} be an indicator variable equal to one if classroom c of grade-level g in school j was randomized to have 75% of students treated and is equal to zero if it was randomized to have 25% of students treated instead. We estimate the parameters of the following model:

$$Y_{icjgt} = \alpha + \beta T_{icjg} + \eta T_{icjg} \times E_{cjg} + \psi X^0_{icjg} + \gamma_{cjg} + \pi_t + \theta_g + \varepsilon_{icjgt} \tag{2}$$

The coefficient η measures the differential treatment effect of the text-message intervention in classrooms where a larger proportion of students was treated. Because of randomization, this coefficient's estimate allows us to quantify the size of the spillover effect *on the treated students*. In our experimental design E_{cjg} is collinear with γ_{cjg}, so we cannot estimate differential spillovers among non-treated student.[30] If there are also spillover effects to the

[27] θ_g and π_t are not all collinear because there are 25 students who repeated a grade-level. Results are robust to the exclusion of these grade-level dummies.

[28] For a handful of students baseline values are missing. In those cases, we impute the control baseline variables using the classroom-level mean. We add an indicator variable in the regression model equal to one for these observations.

[29] A classroom is a unique combination of school, grade-level, and section in the first year of the intervention.

[30] Estimating model (2) without classroom fixed effects would not respect the research design, and would

control group such as those found by Bettinger et al. [2021], our treatment effect estimates would be a lower bound of the effect of text messages on all students' outcomes.

5.2 Balance on Pre-Treatment Observable Characteristics

We compare the observable characteristics of students and parents assigned to the treatment and control groups before the intervention began.

Table 1 shows total observations with available data (column 1); the average of each variable for the treatment group (column 2) and the control group (column 3); and the p-value of the null hypothesis that, conditioning on classroom (strata) fixed effects, the differences between treatment and control averages are zero (column 4).[31]

In our sample, 45% of students are female. The median age is 9.8 years. Students in treatment and control groups have similar grades at baseline, with math and language scores around 5.1 (on a 1-7 scale), similar attendance rates (89 percent), and similar levels of the at-risk index. About 95% passed their grade in the year prior to the experiment. Panels B and C show parents' and students' scales from the baseline surveys.[32] Before the intervention began, students in the treatment and control groups reporting putting in similar effort when studying at home, received the same family support and parental supervision. Their parents seemed to be equally involved in their school life. Finally, we built an indicator variable of whether parents graduated from high school using the highest level of completed education among all listed guardians in the household (mother, father, or other guardian, who is often a grandmother). We find that 70% of parents had completed high school, with no difference between treated and control groups.

5.3 Delivery of Text Messages

All text messages were sent to parents as planned. However, not all text messages were actually received.[33] Several factors contributed to reception failure. A message was more likely to fail if the network was very busy, if some technical problem surfaced within the

not allow us to control for variations in class size (in our sample, classes vary from 20 to 44), consent rates across classrooms (mean consent rate is 54%), and possibly other classroom characteristics not observable in the data. This could affect the estimated treatment effect if the number of treated students has an additive impact.

[31] Appendix Figure 1a shows that observable characteristics are similar between treatment and control students when the full sample is used or in the sample of respondents to the parent's and student's baseline surveys. Additionally, Appendix Figure 1b reports a similar balance table to that shown in Table 1; it includes an additional variable to indicate whether the classroom was randomized to receive a high or low share of treatment, and the interaction with T_{icjg}.

[32] The survey items used to build these scales can be found in Appendix Tables E.2 and E.3.

[33] After sending a text message, cellphone companies mark that message as received or failed to be sent.

Table 1: Students and Parents Pre-Treatment Characteristics

	Obs.	Treatment Mean	Control Mean	p-value of adj. dif.
	[1]	[2]	[3]	[4]
Panel A: Administrative records				
Female	1066	0.45	0.47	0.57
Age	1066	9.81	9.79	0.41
New student	1066	0.08	0.07	0.42
Language grade	976	5.10	5.07	0.85
Math grade	976	5.14	5.19	0.37
Final avg. grade	976	5.57	5.59	0.47
Attendance rate	976	0.89	0.89	0.53
Passed grade	1018	0.95	0.96	0.57
Missing grades/attendance/pass data	1066	0.09	0.08	0.41
At-risk index	1066	0.05	0.00	0.35
Panel B: Parents' Survey Data				
Study habits	704	–0.07	0.00	0.51
Academic efficiency	730	–0.09	0.00	0.16
Family Support	739	–0.12	0.00	0.06
Low Family Supervision	709	–0.06	0.00	0.72
Parent School Involvement	716	–0.01	0.00	0.66
Positive reinforcement	738	–0.06	0.00	0.31
Parents completed high school	775	0.71	0.68	0.74
Panel C: Students' Survey Data				
Study habits	909	–0.19	0.00	0.10
Academic efficiency	915	–0.14	0.00	0.15
Family Support	864	–0.15	0.00	0.12
Low Family Supervision	859	0.05	0.00	0.60
Parent School Involvement	858	–0.12	0.00	0.59
Positive reinforcement	868	–0.04	0.00	0.90

Note: Column [1] shows the number of observations with non-missing data, columns [2] and [3] the mean value of each baseline characteristic in the treated and control group, respectively. Column [4] reports the p-value on the treatment coefficient in a regression using each baseline characteristic as the dependent variable. All regressions include classroom fixed effects and robust standard errors are clustered at this level. Observable variables in Panel A correspond to 2013 except for new student variable that refers to 2014.

network, or if a parent had changed their phone number during the experiment. To maximize the chances that text messages reached parents, we sent the messages on Mondays, when the network was not as busy as on other days.[34] At the beginning of the second school year during which the experiment took place, we also recontacted all consenting parents to verify or update their cellphone numbers.

Table 2 shows estimates obtained with equation (1) where the dependent variable is

[34]During the first two months of the experiment, messages were sent on Fridays.

the total number of messages sent (first row) or received (second row) during the course of the experiment. The variables are computed for each type of message (attendance, grades, classroom behavior, general, and all) using information from the digital platform described in Section 3. Each point estimate shows the coefficient β, which estimates the differences in the total number of text messages sent to/received by parents in the treatment group and those in the control group.

Table 2: Compliance by Type of Text Message

	All	Attendance	Behavior	Grades	General
	[1]	[2]	[3]	[4]	[5]
Text messages sent	43.806***	29.877***	6.699***	7.299***	–0.069
	[0.714]	[0.454]	[0.086]	[0.132]	[0.077]
Text messages received	26.338***	17.653***	4.505***	4.335***	–0.155
	[0.774]	[0.452]	[0.122]	[0.127]	[0.122]
Observations	2011	2011	2011	2011	2011
Control mean messages sent	5.520	0.00	0.00	0.00	5.520
Control mean messages received	3.740	0.00	0.00	0.00	3.740

Note: "Text messages sent" refers to the cumulative number of text messages sent to student's parents. "Text messages received" refers to the cumulative number of text messages with a confirmed delivery status. Columns [2]-[5] report the T_{icjg} coefficient of equation (1) with the annual number of each type of text message as the dependent variable. Column [1] adds all types of text messages. Attendance, grades, and classroom behavior text messages were sent only to the treatment group. General text messages were sent to all treatment and control individuals. All models include the baseline math grade, attendance rate as control variables, classroom (randomization strata), year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

By the end of 2015, when the experiment had run for one and a half school years, an average of 44 more text messages per year had been sent to parents in the treatment group than to parents in the control group. Over the same period, an average of 26 messages per year had been received by parents in the treatment group. This implies that almost 60% of sent text messages were successfully received by the end of the intervention, a success rate similar to those reported in the literature. Bergman and Chan [2021], for instance, report that about a third of treated parents never received messages that were sent.

Most of the messages were about attendance, because these were sent weekly, while classroom behavior and grade messages were sent monthly. These treatment messages were only sent to, and received by, parents assigned to the treatment group. By contrast, parents of students in the control group were sent (and received) general text messages at largely the same rate as those in the treatment group (column 5).[35]

The data suggest that the probability of receiving text messages is unlikely to be correlated with family-level characteristics that also affect child outcomes of interest. We might worry, for instance, that parents who have low attachment to the labor market and unstable incomes are also more likely to switch cell numbers. They would then be less likely to receive text messages about their children's academic performance. Children in these families may also have worse school outcomes. To assess this possibility, we estimated a model in which the dependent variable was the total share of successfully delivered text messages (total received/total sent) on baseline attendance and math grades, age, gender and classroom fixed effects. Students with higher baseline grades or attendance are no more (or less) likely to receive text messages (see Appendix C.3 for further discussion).

Beyond the matter of whether parents received text messages that were sent, there is also the question of whether parents read the text of the messages that they received. In the follow-up surveys we asked parents if they had received text messages with information on their children's school outcomes. We found that parents in the treatment group were more likely to answer that they had received text messages regarding their child's attendance, grades, and classroom behavior.[36]

6 Results

6.1 Main Results: Improved Students' Academic outcomes

Table 3 presents the main results of our paper. We show the estimates of the intention-to-treat effects (using equation 1) of the intervention on our primary students' outcomes measured using classroom books: math-grade outcomes at the end of each year (column 1), an indicator for whether the annual math grade was a passing grade (above 4.0) (column 2), yearly attendance rate (column 3) for each year, an indicator for whether attendance was above the 85% cutoff required for the student to pass the grade (column 4), and standardized total annual negative behavioral notes (column 5).

The ITT estimates show positive and significant effects on students' school performance. Math grades improved by 0.083 of a standard deviation. This positive impact on math grades pushed more students over the 4.0 cutoff for passing the subject by increasing this

[35] Panels A and B of Appendix Table 2 reports the treatment compliance in each year of the intervention (2014 and 2015). More messages were sent in 2015, when the intervention was implemented for a full school year, than in 2014 when the intervention was implemented during the second half of the school year. Panel C presents the compliance for the full sample.

[36] See Panel D of Appendix Table 2.

probability by 2.7 percentage points. The treatment also improved attendance by almost 1 percentage point leading to a 4.5 percentage point increase in the number of students who met the 85% attendance rate threshold needed to pass the grade. On average, the treatment did not have an impact on the occurrence of negative classroom behaviors.

Table 3: Treatment Effects on Grades, Attendance and Classroom Behavior

	Math grade	Math grade >4.0	Attendance rate	Cumulative attendance >85%	# negative beh. notes
	[1]	[2]	[3]	[4]	[5]
Panel A: Treatment Effects					
T	0.083*	0.027**	0.009*	0.045*	0.009
	[0.044]	[0.013]	[0.005]	[0.024]	[0.076]
Panel B: Heterogeneity					
T	0.084*	0.026*	0.009*	0.045*	–0.016
	[0.043]	[0.013]	[0.005]	[0.024]	[0.068]
T x at-risk index	0.138*	0.024	0.013*	0.072**	–0.200**
	[0.070]	[0.019]	[0.007]	[0.028]	[0.094]
Observations	2011	2011	2011	2011	2011
Control mean	0.00	0.934	0.871	0.723	0.00

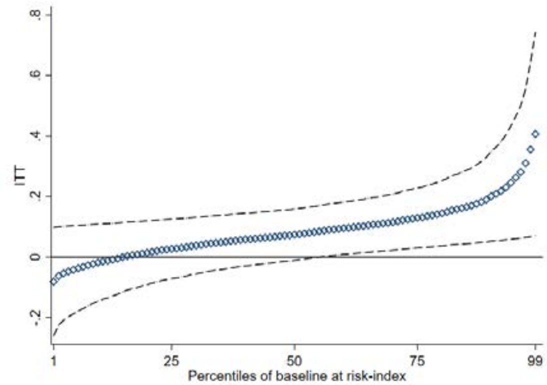
Note: Panel A shows the intention-to-treat (T) estimates and its corresponding standard error estimated using equation (1) using OLS. Panel B adds the interaction with the student-level at risk index. At-risk index is a simple average of standardized baseline attendance, math grades and negative behavioral notes. All models include the baseline math grade, attendance rate as control variables, classroom (randomization strata), year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Models in Panel B additionally include the at-risk index variable as control. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

Our main results are robust across a range of different specifications, sample choices, and data sources. Appendix Figure 2 presents results from estimating the effects of the treatment on grades, attendance, and behavior for specifications that include and exclude baseline controls; that separate out the midline and endline samples; for samples that include students who leave the study in year two (either because they are in grade 8 in the first year or attend the one school that dropped out of our study at the end of year one); and that use outcomes data from the national ministry rather than the administrative data collected by our research team directly from schools. While the effects on math grades are larger in 2014, the impact on attendance rates appears to be stronger in the the second year of the intervention. Overall, while the confidence intervals move around somewhat with different choices of samples and outcomes, the point estimates for the impacts of the treatment on grades and attendance are uniformly positive. The main results in our Table 3 are in the middle of the range of estimates in Appendix Figure 2. And, for each outcome, we could not reject the hypothesis that the point estimates are the same across different samples, specifications, and source of outcomes data, and the same as in Table 3. The fact that the treatment produces stable positive impacts on our main grade and attendance outcomes is reassuring.

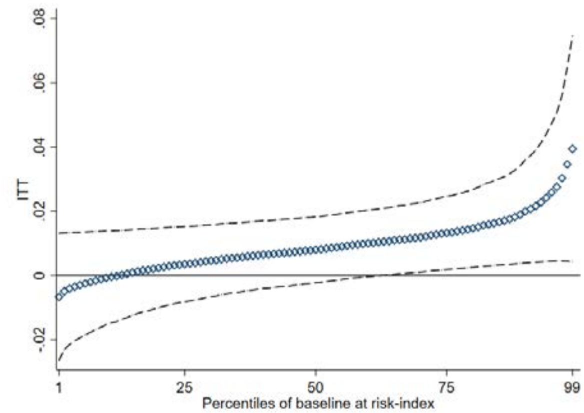
Panel B of Table 3 shows estimates for students with different pre-treatment risk of failing grades. To estimate these effects, we interacted the at-risk index described in Section 4 with the randomized treatment indicator variable (in equation 1) and controlled for the at-risk index. The intervention had the largest impacts on math grades, attendance and improvements in behavior for students who were more at risk before the intervention started. The treatment effects are two to three times larger for students with an at-risk index one standard deviation larger than the mean (which by construction of the index is zero for the control group). Figure 3 explores this result in more detail by plotting the linear prediction of the treatment effects on math grades (Panel A), attendance rates (Panel B), and classroom behavior (Panel C) for students with different levels of the at-risk index. We find that effects for attendance and math grades are larger and statically significant only for students at higher risk. The pattern of behavioral effects by the at-risk index also suggest larger improvements (less negative behavior notes) for students most at-risk, although the confidence intervals in Figure 3 Panel C cannot reject zero. Note that the results in Table 3 Panel B are consistent with the treatment increasing the probability of the most at-risk students achieving the attendance and math grades thresholds for passing the grade and subject; precisely for the population of students who have a higher probability of dropping out in later years.

Figure 3: Predicted Treatment Effect by baseline at-risk index

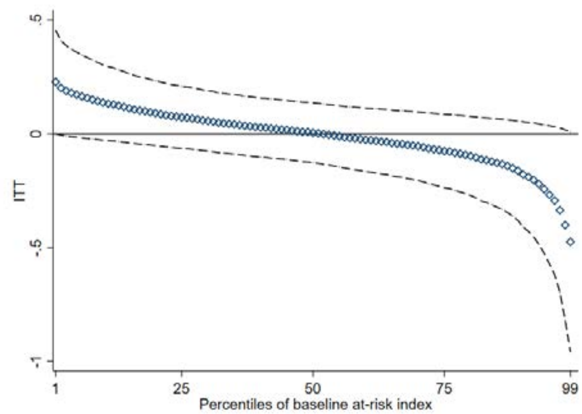
(a) Math score



(b) Attendance rate



(c) Negative behavior



Note: Figure shows linear predictions and 95% confidence intervals of the intention-to-treat (ITT) estimates on math grades, attendance rate and negative behavior. Computed based on coefficients from columns [1], [3] and [5] of Table 3 panel B, respectively. The standard error for estimate at each percentile p is constructed as $\sqrt{Var(\hat{\delta} + \hat{\beta}_Z \times \overline{Z}_p)}$, where $\overline{Z}_p$ is the mean of at-risk index in percentile p.

6.2 Classroom-Level Spillovers on the Treated

In the presence of treatment spillovers among the treated, the treatment effect would vary with the share of other treated students in the classroom. This could happen, for example, if the value of skipping school falls when friends are no longer truant [Bennett and Bergman, 2021]. Alternatively, if a student's friends are working harder to improve their grades, that student's own effort to earn better grades may increase (if, for instance, there are ranking concerns [Tincani, 2018]). To estimate these indirect effects of the intervention, we exploit the randomization of the different shares of students who were part of the treatment group in each classroom.

Table 4: Spillover Effects

	Math grade	Math grade >4.0	Attendance rate	Cumulative attendance >85%	# negative beh. notes
	[1]	[2]	[3]	[4]	[5]
T	0.071	0.005	0.005	0.009	0.114
	[0.054]	[0.015]	[0.007]	[0.035]	[0.095]
T x High-Share	0.030	0.051*	0.010	0.087*	–0.250
	[0.092]	[0.027]	[0.010]	[0.047]	[0.151]
Observations	2011	2011	2011	2011	2011
Control mean	0.00	0.934	0.871	0.723	0.00
p-value $H_0 : T + T \times H = 0$	0.18	0.01	0.06	0.00	0.25

Note: Each row shows the intention-to-treat estimates and its corresponding standard error estimated using equation (2) using OLS. T refers to the randomized individual-level treatment (equal to 1 if parents were sent text messages and zero otherwise). $High - Share$ refers to the randomized classroom-level treatment (equal to 1 for high-share classrooms and zero for low-share classrooms). All models include the baseline math grade, attendance rate as control variables, classroom (randomization strata), year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

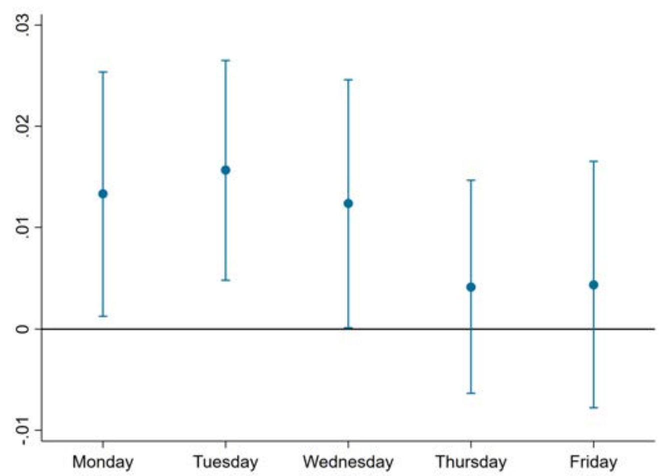
Table 4 presents the results of the ITT spillovers for the same set of outcomes as in Table 3. Note that the interaction coefficient captures the *differential* effect of the spillovers by comparing classrooms with high and low shares of treated students; in other words, it examines whether there is extra value evident in being in the text messaging program when many more classmates are also in the program. Such spillovers could be important, especially if such parent-school communication programs scale up to cover all enrolled students (rather than just a randomly selected treatment group), where by definition there would be no control group. In all cases, the *differential* effect of being assigned to treatment in a high-share classroom improves educational outcomes of treated students –it is larger than the main effect of the treatment in low-share classrooms. The null hypothesis that the treatment effect was zero in high-share classrooms is rejected at the 10% level in columns 2, 3 and 4. This suggests positive spillovers of the intervention among treated students. A greater presence of treated peers in the classroom increases math grades and attendance and reduces misbehavior. With a higher share of treated peers, students are significantly more likely to meet the 4.0 passing grade cutoff, to reach the 85% attendance cutoff, and significantly decrease the number of negative notes.

The spillover results in Table 4 suggest that we would not expect any negative impacts of scaling up this intervention to cover all students. If anything, we should expect even larger impacts (and larger for students most at risk) if everyone is treated.

6.3 Do Parents Forget about Information in the Text Messages?

Parents who receive text messages might forget about the content of the messages after some time, and this could affect their decisions about whether to allow their children to miss a day of school. The majority of the weekly attendance text messages were sent on Mondays. We use daily attendance data to explore whether the effectiveness of the SMS messages fades within the week.[37] Figure 4 depicts point estimates and confidence intervals for models similar to that of equation (1), which was modified to include an interaction of the share of text messages received with days-of-the-week indicator variables. We find a pattern suggestive of fade out over the week. Attendance by students in the treated group is significantly higher than attendance of students in the control group on Mondays, Tuesdays and Wednesdays; by contrast, attendance rates of the two groups are indistinguishable on Thursdays and Fridays.[38] However we cannot reject equality of the coefficient estimates. Rogers and Feller [2018] find similar results with a larger impact in the week immediately following the delivery of the treatment. This result suggests that the treatment effect of the text messages could be somewhat short-lived. Information treatments may need to be high frequency in order to be effective.

Figure 4: Weekly Fade-out of Attendance Treatment Effects



Note: Coefficients are obtained from the daily intention-to-treat estimates of Appendix Table 3. Standard errors clustered at the classroom level. Confidence intervals are at the 90% level.

A related concern is that parents could at some point stop paying attention to the content of the communication, or stop internalizing the information after having received such

[37]After the first two months of the intervention, we started to systematically send all the text messages on Mondays. For this part of the analysis, we restrict the sample to this period.

[38]Appendix Table 3 shows the estimated coefficients used to construct this figure.

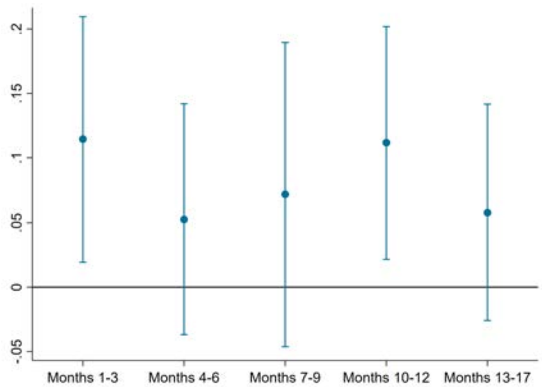
messages over some period of time. Because our intervention lasted for one and a half school years we can explore the treatment effects over the months of the intervention. We estimated effects by month-groups interacting the treatment with month-groups identifying groups of months since the beginning of the intervention. Figure 5 plot the estimates and confidence intervals on the impact on monthly attendance, monthly math grades, and monthly negative behavioral notes.[39]

We find that the impact on attendance is mainly concentrated in the last months of the intervention, although we cannot reject the null that all coefficients are equal. In the case of math grades and behavior, there is no clear pattern in the timing of the effect. This is consistent with students/parents dynamically optimizing attendance behavior. The intervention could have more of an impact on absenteeism than grades by the end of the year because that was when parents/students started to realize that the absences had accumulated enough to matter. From a policy perspective these results suggest that the effect of the intervention does not fade out. Thus, this type of information intervention could be sustained over time in order to increase its effectiveness.

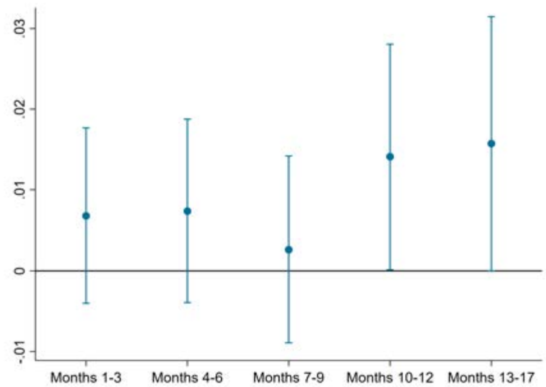
[39] Appendix Table 4 reports the estimated coefficients used to construct this figure.

Figure 5: Treatment Effects Over Time

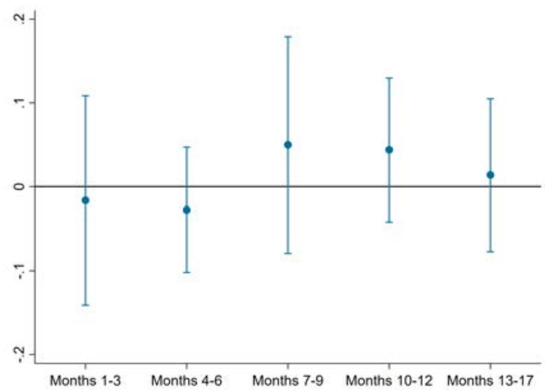
(a) Monthly math grade



(b) Monthly attendance



(c) Monthly behavior



Note: Coefficients are obtained from the respective intention-to-treat estimates of Appendix Table 4. Standard errors are clustered at the classroom level. Confidence intervals are at the 90% level.

7 Why Did Academic Outcomes Improve?

We explore some of the underlying mechanisms that might have contributed to why students' school performance improved after their parents received text messages. We show that the treatment was able to close existing parent-school information gaps about math grades, attendance and behavior while also improving parent attentiveness to other non-targeted aspects of school performance. This new information seemed to have changed the way parents provide support and supervise their children at home.

7.1 Narrowed Parent-School Information Gaps

We study whether the text messages reduced the prevailing parental information gaps regarding students' academic performance; to do this, we compare the accuracy of information among parents in the treated and control groups. We construct different measures of the accuracy of parent's beliefs regarding their child's school performance. Specifically, we contrast parents' responses with student surveys, classroom books, and school records. We then estimate treatment effects using equation (1), in which the outcome variables are the misinformation measures.

Table 5 presents the ITT effects. Columns 1-2 measure parental misinformation regarding a student's attendance. Surveys asked parents about their child's absences with and without permission in the previous two weeks. We contrast parents' responses to students' own responses on total absences (column 1) and to actual absences recorded in classroom books (column 2). Columns 3-4 assess the effect of the intervention on parental information about students' grades. Columns 5-6 capture parental misinformation about students' misbehavior. In both cases we also contrast parents' responses with students' surveys responses (column 3 and 5) and with classroom books (column 4 and 6). In all cases, the outcome variable is an indicator variable that is equal to one if the parent response does not match the student's responses or the administrative records.[40]

Panel A of Table 5 shows that all point estimates are negative. That is, text messages reduced information gaps about student attendance, grades and classroom behavior. Parents' reports got closer both to students' reports and to school administrative records. Because our sample of parents who responded to the follow-up survey is relatively small, these reductions in information gaps are not always precisely estimated; nevertheless, coefficients are large and negative for all outcomes.[41] The ITT estimates, for instance, show that text messages significantly reduced the probability that parents misreported the number of their child's absences; the likelihood of such misreporting fell by more than 7.5 percentage points, in comparison to the results from student surveys. When we compare parents' beliefs with classroom books, the results also show a decline in information gaps, but not to a degree that is statistically significant.

In addition, the information intervention seems to have improved the accuracy of parents' knowledge of their child's grades. Although not statically significant at conventional levels, coefficients are negative and stable across outcomes. We also find a significant improvement

[40] When comparing with classroom books, we allowed for a "mistake" of 1 absence and 0.5 points in the case of grades.

[41] We cannot reject equality of treatment effects on information gaps based on students' reports and those based on administrative records.

Table 5: Treatment Effects on Parental Misinformation

	Attendance Misinformation		Grades Misinformation		Behavior Misinformation	
	All absenteeism (Surveys)	All absenteeism (Admin.)	All grades (Surveys)	All grades (Admin.)	Misbehavior (Surveys)	Misbehavior (Admin.)
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Treatment Effects						
T	–0.076*	–0.016	–0.011	–0.026	–0.080**	–0.083**
	[0.039]	[0.040]	[0.046]	[0.036]	[0.034]	[0.038]
Panel B: Heterogeneity						
T	–0.079*	–0.012	–0.018	–0.027	–0.073**	–0.087**
	[0.040]	[0.039]	[0.048]	[0.037]	[0.033]	[0.038]
T x at-risk index	–0.008	0.036	–0.089	–0.018	0.079	–0.052
	[0.067]	[0.047]	[0.061]	[0.046]	[0.056]	[0.056]
Observations	992	1143	827	1185	1140	1188
Control mean	0.535	0.392	0.398	0.319	0.639	0.470

Note: Panel A shows intention-to-treat (T) estimates and its corresponding standard error estimated using equation (1) using OLS. Panel B adds the interaction with the student-level at risk index. At-risk index is a simple average of standardized baseline attendance, math grades and negative behavioral notes. All models include the baseline math grade, attendance rate as control variables, classroom (randomization strata), year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Models in Panel B additionally include the at-risk index variable as control. Column outcomes are indicator variables constructed by contrasting responses in parent surveys with those of student surveys or administrative records (shown in parentheses). Column [1] measures parental misinformation on all absenteeism (with and without parent permission in the previous two weeks) contrasting the responses of parents with those from students. Parents are classified as misinformed if they do not answer at least one of the questions, or if at least one of the answers (in bracket days) provided by students and parents do not match. Column [2] measures misinformation on all absenteeism (with and without permission) contrasting parent responses with classroom books. The ends of original bracket days in absences with and without permission are added to construct new bracket days. Parents are classified as misinformed if they do not answer at least one of the questions, or if classroom books' records of absences over the previous two weeks do not fall in the range. Column [3] contrasts parent and student responses and parents are classified as misinformed if they do not answer, or if reported grades' brackets do not match. Column [4] measures parental misinformation regarding all grades by contrasting parent responses about the student's last end-of-year grades with school records. Parents are treated as misinformed if they do not answer, or if the absolute difference between reported and actual grades is greater than 0.5. Columns [5] and [6] measure misinformation about student misbehavior by contrasting parent answers with student answers, and with information from classroom books, respectively. Using a four-value scale, parents and students were asked about the degree of agreement with the student's misbehavior statements. For column [5], parents are classified as misinformed if they do not answer at least one of the questions, or if the average absolute difference between parent and student answers are larger than the median (0.8). For column [6] parents are treated as misinformed if they do not answer; if the parent's average answer is equal to or larger than the median (2), and student did not misbehave according to classroom books; or if the parent's average answer is less than the median answer and student misbehaved in class according to books. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

in the precision of parents' assessment of their child's misbehavior at school. Overall, these results suggest that treated parents had more accurate information about their child's grades, attendance and classroom behavior after the treatment.

Panel B of Table 5 tests whether treatment effects on information gaps vary for students with different baseline values of the at-risk index. The intervention seems to have improved the accuracy of parents' beliefs about their child's grades and behavior for students with a higher at-risk index (although results are not statistically significant).

7.2 Effects on other subjects, and parent misinformation about those subjects

In Table 6 we estimate effects of the treatment on other, non-targeted subjects using outcomes data reported by the schools to the national ministry. We see that language scores increased by a significant 0.1 of a standard deviation, and scores on natural science and history also increased by 0.05-0.09 of a standard deviation (not significant). This positive impact of the treatment on non-math subjects could have occurred through the channel of increased attendance (i.e. a positive downstream impact of the treatment). However, it might have also increased parental attention to school in general, thus leading to improvement in non-targeted academic subjects.

Table 6: Treatment effects on Other Subjects' grades and misinformation

	Language	Natural science	History
	[1]	[2]	[3]
Panel A: Grades			
T	0.108*	0.095	0.054
	[0.059]	[0.058]	[0.044]
Observations	1946	1916	1916
Control mean	0.00	0.00	0.00
Panel B: Misinformation			
T	–0.078**	–0.046	–0.050
	[0.032]	[0.044]	[0.042]
Observations	1142	973	972
Control mean	0.499	0.534	0.493

Note: Panel A and Panel B show intention-to-treat (T) estimates on subjects not targeted by the intervention. Panel A shows the effect on grades and Panel B on parental misinformation regarding those grades. Point estimates and standard error were estimated using equation (1) using OLS. All models include the baseline math grade, attendance rate as control variables, classroom (randomization strata), year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Columns [1]-[3] of Panel B measure parental misinformation each subject grade. Parents are treated as misinformed if they do not answer or if the answered grade bracket does not match to the actual grade from administrative data. Standard errors are clustered at the classroom level (shown in parentheses). * significant at 10%; ** significant at 5%; *** significant at 1%.

In Panel B of the same table, we show some suggestive evidence that the treatment may have improved parent attention in general. We estimate the impact of the treatment on parental misinformation about other subjects not specifically targeted by the intervention. Across the board, parent misinformation relative to the administrative records shrinks; the coefficients for parent information gaps about languages, social studies, and history are all negative. Interestingly, parent information gaps in languages shrink to about the same extent as they shrink for math grades (Table 5 column (1)). The results in Table 6 suggest that, in addition to reducing information gaps on the specific topics on which parents received information, the text message intervention seems to make parents pay more attention to how their children are doing in other (non-math) subjects.

7.3 Increased Parental Involvement at Home

By providing parents with information, the intervention led students and parents to respond with changes in behaviors at home – which, in turn, might then have resulted in better outcomes at school. To examine this, in Table 7 we analyze the responses to survey questions that were put to both parents (Panel A) and students (Panel B) in an identical manner. Columns 1 and 2 measure students' academic responses. Columns 3-6 looks at parents' behavioral responses, in terms of providing family support, providing supervision, involving themselves with school matters, and offering positive reinforcement.[42]

Table 7: Treatment Effects on Parental Behavior at Home

	Study habits	Academic efficiency	Family Support	Low Family Supervision	Parent School Involvement	Positive reinforcement
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Parent scales						
T	–0.092	0.085	–0.001	0.019	0.030	–0.048
	[0.079]	[0.063]	[0.083]	[0.064]	[0.063]	[0.079]
Observations	1042	1090	1108	1096	1116	1098
Panel B: Student scales						
T	0.053	0.001	0.116*	–0.079	0.113**	0.017
	[0.059]	[0.059]	[0.060]	[0.050]	[0.056]	[0.056]
Observations	1726	1728	1686	1693	1700	1692

Note: Panel A and Panel B shows intention-to-treat (T) estimates on parent and student scales, respectively, and its corresponding standard error estimated using equation (1) using OLS. Outcomes are scales built with answers to surveys (see Tables E.2 and E.3 for details). All models include the baseline math grade, attendance rate and outcome scales as control variables, and classroom (randomization strata), year and grade-level fixed effects. If baseline values of baseline math grade/attendance or baseline outcomes were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

We do not find a clear pattern or statistically significant results for the information provided by parents in terms of how the treatment affected their self-reported behaviors. By contrast, however, treated students perceived that they received significantly more family support as a result of the intervention (0.116 of a standard deviation). This scale incorporated

[42]See Section E.1 in the Data Appendix for details on how the scales were built, as well as the psychometric properties of each of them.

the students' answers to questions such as whether parents checked the child's homework, or provided motivation to them, or talked to them when needed. Moreover, the treatment also increased students' perception of their parents' level of school involvement. This perception was reflected in students' answers to questions about whether their parents contacted the school director or teachers, or whether their parents attended school meetings. These results are consistent with those from Bergman [2021] and Bergman and Chan [2021], who find that the additional information provided to parents increased their contact with the school.[43]

7.4 Parents Valued the Information

In our follow-up surveys, we asked both treatment and control parents to tell us whether they would be willing to pay for a text message service that provided them with four monthly messages from schools about their child's performance and behavior in school. We implemented a survey experiment in which we randomized the price at which parents were given a "take it or leave it" offer: a high price of 1,500 CLP (Chilean pesos, or 2.2 USD) per month, a medium price of 1,000 CLP (or 1.5 USD) per month, or a low price of 500 CLP (0.74 USD) per month.

Parents seem to value the information provided in the text messages. Table 8 uses the survey experiment to estimate parents' demand curves for the complete sample in column 1. On average, 71 percent of parents said that they were willing to pay at least the minimum amount to receive text messages from the school. In column 2 we allow each experimental group to have a different response to the randomized price by including price assignment by treatment assignment interaction terms. In column 3 we explore whether the valuation of the information is different for parents of students with higher levels of risk of failing grades.

Overall, the demand curve for a service like the one we offered in our intervention is downward sloped. Column 1 shows that the share of parents willing to pay for the service falls by more than 15 percentage points as the price increases from low to medium levels, and by an additional 8.7 percentage points when the price increases from a medium to a high level (the coefficient on High price is -0.238). We then analyze whether the treatment induced parents to value the text messages program differently (column 2). We do not find that treated parents value the information differently than control parents.

[43] To further assess whether parenting styles were a constraint to improve students' outcomes, we implemented a complementary randomized control trial to evaluate the effect of providing parents with tools to relate to their children more positively. The intervention followed an established "positive parenting" approach and was developed jointly with educational psychologists at Arizona State University. It was delivered to parents using a set of videos. The estimated coefficients were, in general, positive and large. However, we lack statistical power to reject the null of no differential treatment effect. Results are shown and discussed in Appendix G.

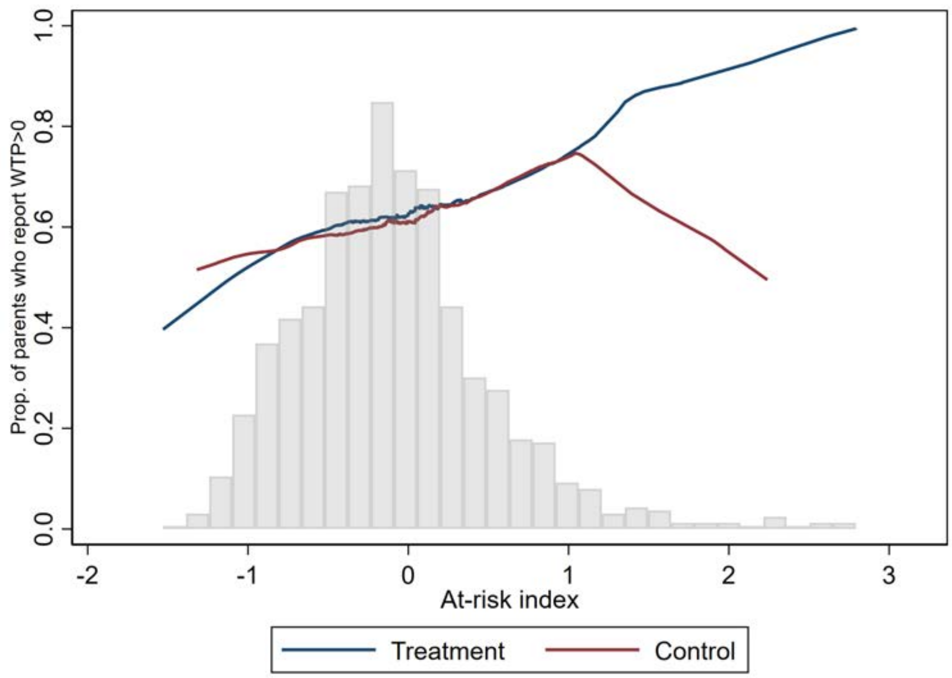
Table 8: Parental Willingness to Pay

Sample:	Complete sample		Students at-risk
	[1]	[2]	[3]
Medium Price	–0.151***	–0.086	–0.005
	[0.043]	[0.063]	[0.125]
High Price	–0.238***	–0.256***	–0.289***
	[0.039]	[0.059]	[0.100]
T x Low Price		0.029	0.036
		[0.063]	[0.096]
T x Medium Price		–0.095	–0.134
		[0.060]	[0.132]
T x High Price		0.070	0.236**
		[0.069]	[0.111]
Constant	0.706**	0.700**	0.578
	[0.292]	[0.295]	[0.457]
Observations	1,124	1,124	421

Note: Outcome is an indicator variable for whether the parent reports being willing to pay for continued text message service (4 text messages per month from the school) after the end of the year. Column [1] reports estimates of being assigned a particular randomized priced (1,500 CLP, 1,000 CLP or 500 CLP, the omitted category). Column [2] shows intention-to-treat estimates by interacting these randomized prices with the randomized treatment (equal to 1 if parents were sent text-messages and zero otherwise). Column [3] shows the same intention-to-treat effects estimates but restricting the sample to those students with high at-risk index (>mean). At-risk index is a simple average of standardized baseline attendance, math grades and negative behavioral notes. Coefficients estimated using OLS. All models include the baseline math grade, attendance rate as control variables, classroom (randomization strata), year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

It is likely, however, that not all families experienced the same "returns" to the text messages program. For example, the value of such a service may be relatively low for parents who have children who do well in school. In column 3 of Table 8, we present results that emerge when we restrict to the sample of parents whose children have an at-risk index above the mean. At the highest price, parents in the treatment group –who had already experienced receiving the text messages for several months– and whose children had not been not as successful in school to begin with are significantly more likely to say they are willing to pay the highest price for the continued service relative to control parents. At the low and medium price levels, there are no statistical differences on the willingness to pay between the treatment and control group. Figure 6 shows the proportion of parents who are willing to pay a positive amount to receive information about their children who are at different levels of risk (of failing classes). More parents of at-risk students are willing to pay for the text message service, especially among those who have experienced the service before (i.e., those who were treated). Note that if we think that parents who most valued

Figure 6: Share of Parents Willing to Pay for Text Messages



Note: Y-axis presents the (lowess-smoothed) share of parents who report willing to pay for continued text message service by at-risk index –whose histogram is shown in gray– and treatment status. Based on parents follow-up surveys.

the program were also the most willing to participate in the survey experiment, then these WTP estimates are likely upper bound estimates on the value of the program.

8 Cost-Effectiveness

Our intervention led to 0.08 standard deviations gains in math grades and a 1 percentage point increase in attendance, with larger effects for at-risk students. These effect sizes are slightly smaller than those found in the rest of the literature. A recent literature review (Escueta et al. [2020]) that focuses on technology in education in developed countries finds 13 experiments where information is sent to parents about student performance (e.g., attendance, behavior, or grades) through text messages and emails. For example, in Bergman [2021] parents receive automated texts about missing assignments and grades. In a sample of 462 students in grades 6-11 in Los Angeles, he finds that the intervention decreases missed assignments by 28% and leads to a gain of 0.21 standard deviations in mathematics grades. We expect a smaller impact for our intervention, as in the United States the GPA depends on assignment submission, whereas in Chile grades are based only on performance on class exams.

Regarding our intervention cost, as pointed out by Bergman and Chan [2021], these types of interventions leveraging technology to bridge parent-school communications gaps are characterized by low variable costs and a one-time setup cost. In their study, the variable cost per text message was negligible. The fixed setup cost included a per student training cost of US$7 if schools did not already have an electronic gradebook. In our Chilean context, the initial fixed cost of setting up the digital platform was US$1.63 per student.[44] The cost of maintaining the digital platform that automated message sending was US$0.77 per month per student, and the market value of sending text messages was US$0.05 per message, with 6 text messages sent per month during our intervention, for 10 months in a school year. This results in a total variable cost per student of US$10.70 per year. Therefore, the variable cost of a 0.01 standard deviation increase in math grade was US$1.18 per student per year at market prices (US$2 per year if we include the fixed setup cost for the two year program: 0.5*US$1.63 + US$1.18).[45] Our willingness to pay experiment suggested that about 71 percent of parents were willing to pay at least US$0.75 per month for the program, thus covering more than twice the monthly cost of sending messages.[46]

A program like Papas al Dia is cost-effective when compared to other interventions designed to improve learning outcomes. IDB [2017] provides information on 21 low-cost interventions designated to improve student learning in primary schools. Strategies include tracking, funding for materials, lesson plans, non-monetary incentives and guided technology. The authors of that study calculate the implementation cost of each intervention implemented in Colombia. The average cost per student for a 0.01 standard deviation gain in learning is US$4.42, and the median cost is US$2.00.[47] In terms of cost, our intervention compares very favorably to these other approaches.

[44]The setup cost for the platform was US$613.4 per school in our intervention. Considering the average primary school size has 377 students, the cost per student is US$1.63.

[45]The costs of putting the experiment into the field were higher. The text message cost per treated child was US$6.5 per year. Once we included platform maintenance costs, a field team coordinator and web domain costs, the total cost per student comes to US$27 per year.

[46]Sending 6 messages per month at 0.05 cents per message is 30 cents per month.

[47]IDB [2017] also provides information for 52 evaluations designed to improve student learning in secondary schools around the world. The strategies for which they find evidence of success include: i) monetary incentives to students, ii) "no excuses" models, iii) extended school day, and iv) vouchers, subsidies or scholarships for students. The weighted averages of the effect-sizes on test scores are respectively 0.16SD, 0.14SD, 0.08SD and 0.03SD. Although this study does not include intervention costs for these alternative strategies, it is likely that our text message intervention used fewer resources than any of these four programs, and therefore was cheaper on a per student basis. McEwan [2015] provides a meta-analysis of randomized experiments of school-based interventions on learning in primary schools and finds seven experiments that involve informational treatments. The mean effect size of these interventions is 0.049 (p-value=0.240). Andrabi et al. [2017] find that providing report cards to parents in Pakistan leads to a closing in informational gaps and a 0.11SD gain in student outcomes.

9 Conclusions

We present the results of a simple, effective, and low-cost intervention that uses existing data regularly collected by schools to improve the accuracy and timeliness of information parents have about their children' attendance, grades and classroom behavior.

We show that sending weekly text messages with attendance information and monthly text messages with math grades and classroom behavior outcomes decreases the prevailing information gap between what parents believe about their children's progress in school, and what schools report is the case. We also provide suggestive evidence that treated students report more family support (parents checked the child's homework, or provided motivation to them, or talked to them when needed) and more school involvement by their parents (parents contacted the school director or teachers, or whether their parents attended school meetings). We find that parents in both treated and control groups valued receiving information via text message and were willing to pay for it, especially those parents of initially low-achieving children. Treated parents of at-risk students had the highest willingness to pay for the program.

Providing parents with this information led to better student academic outcomes. First, the intervention led to an increase in math GPA of 0.08 of a standard deviation. Second, the probability of earning a passing grade in math increased by 2.7 percentage points (relative to a mean of 87%). Third, the intervention reduced school absenteeism by 1 percentage point. Finally, the intervention increased the share of students who satisfied the attendance requirements for grade promotion by 4.5 percentage points. Moreover, we find that at-risk students benefit the most from the intervention: these students exhibit even larger gains in math and in attendance, and have a much lower chance of notable negative in-class behavior. At a broad level, these findings suggest that efforts to reduce grade retention and school dropout in later grades may be supported by early interventions like Papas al Dia that have large benefits for those most at risk of grade retention and dropout.

Our results generate further important insights for policy design. We find evidence that program effectiveness is higher when a larger share of parents receive the text messages. These positive spillover effects among the treated suggest that our impact are underestimates of the effects of a scaled-up version of this program in which all students would be treated. Furthermore, our suggestive evidence on differential treatment effects by day of the week and month of the year imply that the choices about the timing and duration of information delivery are important aspects of program design. Policy makers should pay attention to choices of when and how often to send messages (which day of the week, month of the year and on an on-going basis) to maximize the its effectiveness of such programs.

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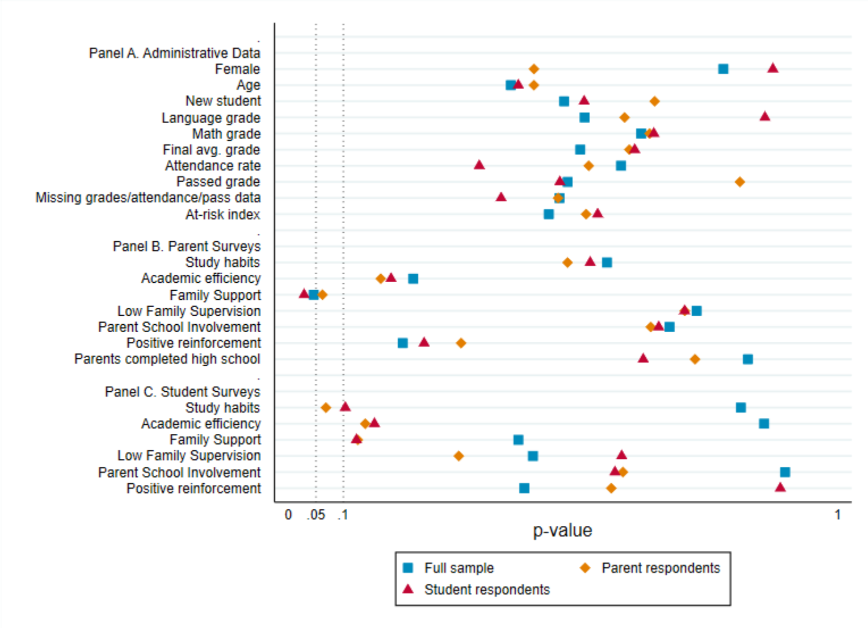
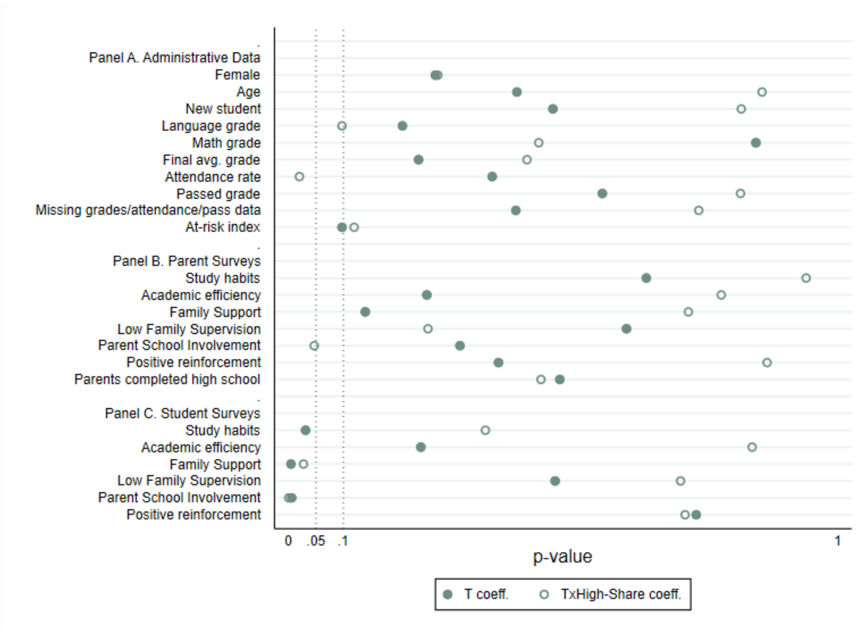
Appendix Figures

Figure 1: Balance in alternative samples and specification

(a) Alternative samples



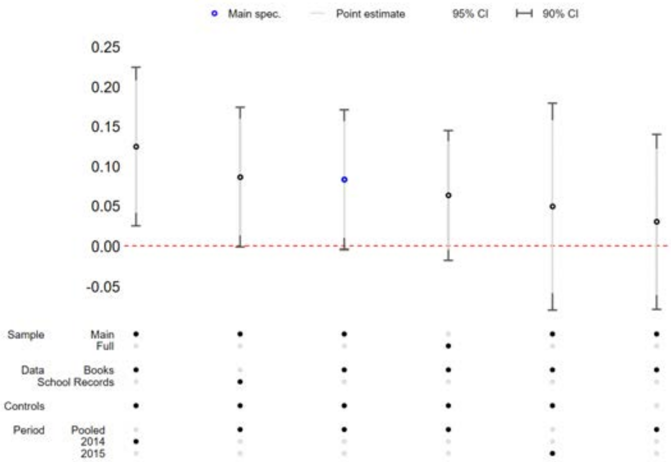
(b) High-share specification



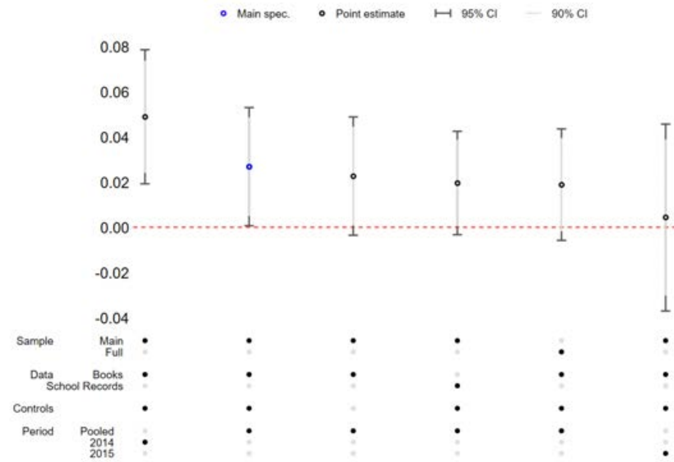
Note: Panel A plots the p-value on the treatment coefficient in a regression using each baseline characteristic as the dependent variable for alternative samples (full sample, surveys' parent and student respondents). Panel B plots p-values on the treatment coefficient and on the interaction between treatment and high-share classrooms in regressions using each baseline characteristic as the dependent variable. All regressions include classroom fixed effects and robust standard errors are clustered at this level. Observable variables correspond to 2013 except for new student variable that refers to 2014.

Figure 2: Robustness

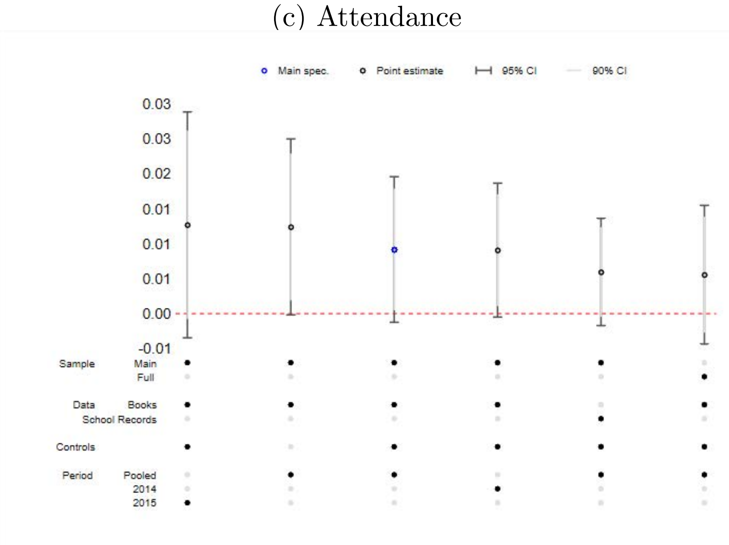
(a) Math grade



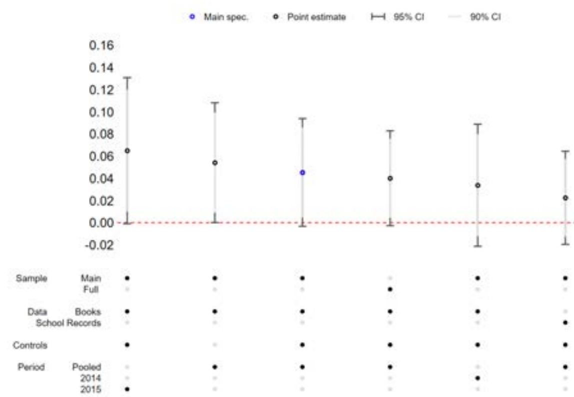
(b) Math grade > 4



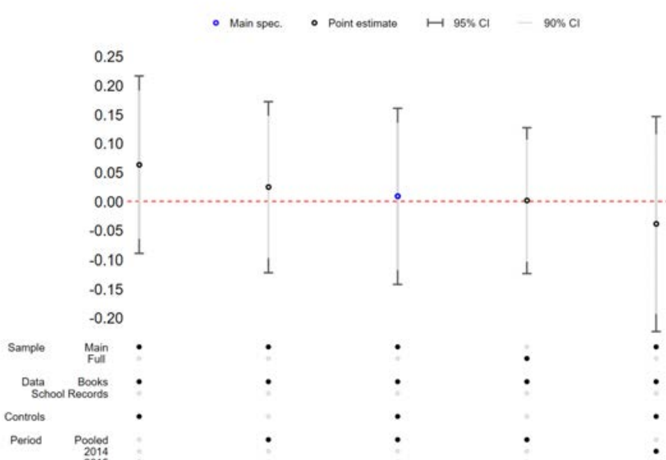
(c) Attendance



(d) High attendance



(e) Behavior



Note: Figure plots the treatment coefficients (and 90% and 95% confidence intervals) for each panel outcome using different specifications (with and without baseline controls), different samples (with and without the students who leave the sample due to being in grade 8 in the first year, or being in one school that left our sample in the second year; using the pooled sample versus separating the midline and endline samples), and different data sources for outcomes (using administrative data from the national ministry or administrative data from the school records collected by our research team). Each combination is represented by black/white dots in the bottom of each subfigure.

Appendix Tables

Table 1: Rention and drop-out

	Retention	Drop-out	Retention	Drop-out
	[1]	[2]	[3]	[4]
GPA_{t-1}	–0.034***	–0.005***		
	[0.000]	[0.000]		
GPA_{t-2}	–0.019***	–0.001***		
	[0.000]	[0.000]		
GPA_{t-3}	–0.039***	0.000		
	[0.000]	[0.000]		
$Attendance_{t-1}$	–0.003***	–0.001***		
	[0.000]	[0.000]		
$Attendance_{t-2}$	–0.001***	–0.001***		
	[0.000]	[0.000]		
$Attendance_{t-3}$	–0.000	–0.001***		
	[0.000]	[0.000]		
$At-risk\,index_{t-1}$			0.076***	0.027***
			[0.000]	[0.000]
$At-risk\,index_{t-2}$			0.037***	0.017***
			[0.000]	[0.000]
$At-risk\,index_{t-3}$			0.037***	0.007***
			[0.000]	[0.000]
Observations	6,594,877	6,594,877	6,594,877	6,594,877
Adjusted-R2	0.116	0.0970	0.0944	0.0522

Note: Table shows estimates of a linear probability model with retention or drop-out in year t as dependent variable. Columns 1-2 show standardized GPA attendance $t-k$ years ago ($k = 1, 2, 3$) estimate coefficients. Columns 3-4 estimate the same lags for an at-risk index. At-risk index is the negative of a simple average of standardized attendance and GPA. Based on public data for primary and secondary education level for the period 2002-2020 from the Ministry of Education of Chile. We restrict the sample to educational trajectories of students who were in grades 8-12 between 2006 and 2013 and that ever attended any school in the Santiago metropolitan region. Grades 1-3 are excluded. All models control for student's sex and include municipality fixed effects. Standard errors clustered at the student level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2: Compliance in different samples

	All	Attendance	Behavior	Grades	General
	[1]	[2]	[3]	[4]	[5]
Panel A: 2014					
Text messages sent	29.772***	21.211***	4.544***	4.023***	–0.006
	[0.305]	[0.218]	[0.066]	[0.041]	[0.023]
Text messages received	19.850***	14.137***	3.094***	2.716***	–0.097
	[0.570]	[0.363]	[0.101]	[0.082]	[0.068]
Observations	1433	1433	1433	1433	1433
Panel B: 2015					
Text messages sent	60.238***	40.018***	9.243***	11.071***	–0.094
	[1.334]	[0.865]	[0.156]	[0.252]	[0.155]
Text messages received	33.788***	21.653***	6.180***	6.202***	–0.247
	[1.264]	[0.711]	[0.203]	[0.205]	[0.245]
Observations	1006	1006	1006	1006	1006
Panel C: Full Sample					
Text messages sent	42.030***	28.793***	6.440***	6.863***	–0.066
	[0.729]	[0.456]	[0.098]	[0.150]	[0.065]
Text messages received	25.459***	17.166***	4.341***	4.125***	–0.172*
	[0.721]	[0.423]	[0.119]	[0.125]	[0.103]
Observations	2439	2439	2439	2439	2439
Panel D: Parent Surveys 2015					
Declares to have received text messages	0.359***	0.523***	0.432***	0.443***	-
	[0.049]	[0.042]	[0.042]	[0.047]	-
Observations	549	565	561	567	-

Note: Panel A uses the 2014 data of the intervention. Panel B uses the 2015 data of the intervention. Panel C analyzes compliance in the full sample. Panel D uses 2015 parents' surveys data. Text messages sent/received refers to the cumulative number of text messages sent to/received by student's parents. For Panels A-C columns [2]-[5] report the T_{icjg} coefficient of equation (1) with the annual number of each type of text message as the dependent variable. Column [1] adds all types of text messages. For Panel D columns [1]-[4] report the T_{icjg} of equation (1) using each column parent's self-declared text messages' reception as the dependent variable. Parents answer on a four-value scale the frequency in which they have received each type of text message ("never or almost never" to "always or almost always") in the last month. Outcomes are indicator variables equal to one if parent answer value 4 and zero otherwise. Column [1] outcome equals one if at least one of the attendance, grades and behavior text messages outcomes equals one. Attendance, grades, and classroom behavior text messages were sent only to the treatment group. General text messages were sent to all treatment and control individuals. All models include the baseline math grade and attendance rate as control variables and grade level dummies. If baseline values are missing, we impute them using the classroom-level mean and flag these observations in the regression. Regressions additionally include year and classroom fixed effects and standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Treatment Effects Over the Week (Weekly Fade Out)

	Daily Attendance
T x Monday	0.013*
	[0.007]
T x Tuesday	0.016**
	[0.006]
T x Wednesday	0.012*
	[0.007]
T x Thursday	0.004
	[0.006]
T x Friday	0.004
	[0.007]
Observations	222827
p-value of equall coeff.	0.0370

Note: Table shows intention-to-treat estimates (T) by day of the week estimated using OLS. Attendance outcome is measured at a daily basis. T refers to the randomized treatment (equal to 1 if parents were sent text-messages and zero otherwise) and is interacted with each day-of-the-week indicator variables. All models include the day-of-the-week indicator variables as controls, baseline math grade, attendance rate as control variables, classroom (randomization strata), month, year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Treatment Effects Over Time

	Math grade	Attendance rate	Negative beh. note
	[1]	[2]	[3]
T x months 1–3	0.114**	0.007	–0.016
	[0.057]	[0.006]	[0.075]
T x months 4–6	0.053	0.007	–0.027
	[0.054]	[0.007]	[0.045]
T x months 7–9	0.072	0.003	0.050
	[0.071]	[0.007]	[0.077]
T x months 10–12	0.112**	0.014*	0.044
	[0.054]	[0.008]	[0.051]
T x months 13–17	0.058	0.016	0.014
	[0.050]	[0.009]	[0.055]
Observations	10,391	15,912	15,214
p-value of equal coeff.	0.756	0.721	0.560

Note: Table reports intention-to-treat (T) estimates for each group-of-months estimated using OLS. Outcomes are measured at a monthly basis. T refers to the randomized treatment (equal to 1 if parents were sent text-messages and zero otherwise) and is interacted with each group-of-months indicator variables.. All models include the group-of-months indicator variables as controls, baseline math grade, attendance rate as control variables, classroom (randomization strata), month, year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

A Appendix: Prior Research

Table A.1 presents an overview of the literature studying interventions providing information to children or parents to improve student's school outcomes.

Table A.1: Literature Review

Study	Method	Sample	Information	Intensity	Effect	Explored mechanisms
Kraft and Dougherty [2013]	RCT	140 students, grades 6 and 9, summer school program, Boston	Student's academic progress and class behavior, upcoming homework assignments and tests, and suggestions for student's improvement	Daily teacher-to-parent phone calls and daily written messages for five consecutive days	Increased the odds of completing homework by 40%, decreased in-class misbehavior by 25%, and increased class participation rates by 15%	Teacher–student relationships, parental involvement, student motivation
Avvisati et al. [2014]	RCT	34 middle-schools, 96 classes, 2008-2009 school-year, Paris	Advice on how to support and monitor children with school work	Three parent–school meetings every two-three weeks	Reduced truancy by 25% and the probability of being sanctioned and increased positive behavior (effects-size around 15% of a sd), no test scores improvement	Parent's school-and home-based involvement
Castleman and Page [2015]	RCT	5,753 recent high school graduates identified as college-intending, summer 2012, Dallas, Boston and Philadelphia	Text messages intervention: tasks required by the students' intended college required for successful matriculation + offer of counselor assistance via messages	A series 10 texts messages sent to students and their parents about every five-days	Increased by 3 p.p. the likelihood to enroll at two-year institutions, more effective on students with low access to college-planning supports	-
Kraft and Rogers [2015]	RCT	435 high school students in a summer credit-recovery program in the Northeastern US	Child's performance and behavior in school: on what their students were doing well and should continue doing (Positive treatment), or what their students needed to improve upon (improvement treatment)	Weekly one-sentence individualized messages from teachers to the parents	Decreased the percentage of students who failed to earn course credit by 41%	Parent-child interactions' content
De Walque and Valente [2018]	RCT	Girls in the last two grades of primary school, 173 schools, 2016 school year, Mozambique	Child's attendance (three treatments: (i) "information only"; (ii) (i) + cash transfers to parents conditional on regular attendance; (iii) (i) + cash transfers to girls in form of a voucher conditional on regular attendance)	Weekly attendance information through a report card over the school year	Effect of 4.5 p.p. on attendance (as large as 75% of the effect of the CCT treatment)	Parental monitoring
Rogers and Feller [2018]	RCT	28,080 students, kindergarten to 12th grade; 2014-2015 school-year, School District of Philadelphia	Treatments: (i) reminder on importance of absences, (ii) student's number of absences, and (iii) student's relative absences	Up to five rounds of mail-based messaging throughout the school year	Most effective versions reduced total absences by 6% and chronic absenteeism by 10% or more, spillover effects on untreated cohabiting students, no effect on student performance	Parent's beliefs about total absences and relative absences

York et al. [2019]	RCT	1,031 preschoolers, 2013-14 and 2015-16 school years, San Francisco Unified School District (SFUSD)	Parenting strategies	Three type of text-messages each week during eight months	Effect of 0.15 to 0.29 sd on parental involvement at home and school and of 0.11 SD on child's early literacy	-
Bergman and Chan [2021]	RCT	1,137 students, grades 5 to 11, 22 middle and high schools during 2015-2017, West Virginia	Missed assignments, grades, and class absences	Weekly alerts for assignments and absences and monthly alerts for grades, 32,000 text-messages	Reduced course failures by 28%, increased class attendance by 12%, and increased student retention by 1.5 pp, increased in-class exam scores by 0.1 SD (larger effects for below-median GPA students and high school students)	Accuracy of parents' beliefs about child's performance, parental behavioral responses
Dizon-Ross [2019]	RCT	3,451 households with at least two children enrolled in grades 2–6, 39 schools, Malawi	Student's average performance on school tests (Report Cards)	Once after baseline survey visit	Improved what parents knew about their children and causes family educational investments to adjust	Parent's beliefs
Angrist et al. [2020]	RCT	4,500 families with primary-school-aged children, April-July 2020 (COVID-19 Pandemic), Botswana	Treatments: (i) SMS text messages with basic numeracy "problems of the week", (ii) (i) + phone calls which walk-through of the learning activities sent via text message	Weekly treatment over 4 months	The combined treatment increased the average numerical operation learned by 0.12 SD, the SMS messages only treatment effective when targeted	Children cognitive skills effects vs. effort effects. Parental educational investment.
Barrera-Osorio et al. [2020]	RCT	4,371 students, grades 4 to 6, 31 public schools, Manizales, Colombia	Children's reading and math achievement + suggestions about how parents could engage with their children's education	Information delivered once at the end of the baseline household interview	Effect of 0.09 SD to 0.10 SD in student's performance (math and reading scores) in the first two semesters, effect fades out in year two	Information gap between beliefs and performance, parental behavioral responses.
Bergman [2021]	RCT+ structural modeling	279 students, grades 6 to 11, 2010-2011 school year, low-income communities in Los Angeles	Missed assignments and grades	Emails, text messages and phone calls several times a month over a six-month period	0.19 SD increase in GPA and classes missed by students decreased by 28%	Parent's beliefs about child's efforts and parental monitoring
Bergman et al. [2020]	RCT	7,000 parents, 12 middle- and high-schools, 2015, Washington DC	Missed classes, missed assignments and low-grades	Weekly automated text-message alerts from January to June	Automatically enrolling parents improved student GPA by 0.06 points and reduced course failures by 9%	Enrollment defaults and simplification in technology adoption, decision-makers beliefs on implementation strategies
Gallego et al. [2020]	RCT	7,700 children, grades 7 and 8, 2013, Chile	Children's last week internet use and/or offering assistance with installing parental control software	Weekly SMS messages mainly sent during summer vacation	Information treatment reduced children's internet use by 6–10%, no significant impacts from helping parents directly control their children's internet access	Parenting behavior (punishment and discussions about internet use), substitution for the presence of a parent at home without lowering parental involvement
Bettinger et al. [2021]	RCT	19,300 ninth graders students, 287 schools, Sao Paulo, Brazil	Treatments: (i) text message with information on child's attendance and school effort, and (ii) messages that try to redirect parent's attention without child-specific information	Weekly text messages for 18 weeks	Information treatment increased attendance by 2.1 pp, math GPA and standardized test scores by 0.09 SD, and grade promotion rates by 3.2 pp. The treatment without child-specific information improved outcomes by 89-126% relative to those in the information group.	Salience. Parent's accuracy about changes in children's school effort. Parental behavior.

B Appendix: Sample and Recruitment of parents

B.1 Sample of students

In early 2014, we worked with education leaders in a deprived administrative of Santiago de Chile to recruit schools to join our study. Eight schools consented to work with the program. All students enrolled in grades 4 through 8 in each of these schools were included in the study (a total of 85 classrooms and 1,447 students). Throughout the paper, we call this sample "full sample".

During 2015 one school (with 65 students) decided not to continue during the second academic year. Similarly, students in grade 8 participated during the first part of the experiment (a total of 316 students across the remaining schools). These students could not be treated or followed into secondary school. We also dropped them from the main analysis. Because randomization was done at the individual level stratifying by classroom we drop this school from the main analysis without invalidating the experimental design. Throughout the paper, we call this sample "main sample".

B.2 Recruitment of participants

During a series of school meetings, we invited parents of all children in grades 4-8 to participate in the project and over 50 percent of parents signed consent. Consent rates were very similar across grade-levels (Table B.1). Younger students, those not new to the school, and those with better baseline attendance and math grades were somewhat more likely to consent (see Table B.2).

Table B.1: Consent rate by grade level

Grade level	Full Sample	Main Sample
	[1]	[2]
4	0.57	0.58
5	0.49	0.50
6	0.54	0.55
7	0.52	0.52
8	0.53	
Total	0.53	0.54

Note: N=2,720 for the full sample and N=1,987 for the main sample.

Table B.2: Likelihood to Consent

	Full Sample	Main Sample
	[1]	[2]
Age	-0.013**	-0.017**
	[0.006]	[0.008]
New student in 2014	-0.092***	-0.087**
	[0.035]	[0.039]
Attendance rate in 2013	0.744***	0.743***
	[0.116]	[0.138]
Math grade in 2013	0.013	0.009
	[0.010]	[0.011]
Students	2720	1987

Note: The table shows the estimated coefficients of a regression of an indicator for whether the parent's student consented to participate in the intervention as the dependent variable. Column [1] uses the full sample (i.e. including grade 8 in 2014 and the dropped school). Column [2] uses the main sample.

C Appendix: Intervention

C.1 Text messages: Production

The experiment offered each participating parent the chance to receive high frequency information about their selected child via text message. The specific information covered attendance, behavior and mathematics test scores of their child. In addition to the information text messages, parents of both treatment and control groups received general text messages about school meetings, holidays and other general school matters throughout the year.

Once the intervention began our project teams digitized the classroom books described in Section D.2, which contained information on attendance, behavior, and math score. This information was collected weekly and uploaded to a platform designed for the purpose of this study (called, in Spanish, *Papás al Día*) which turned the information into text messages for the treatment groups. Treated parents received weekly messages on attendance, and monthly messages on behavior and math test scores. In the case of attendance information, we told parents how many days out of the last week (usually five days) the child was in school. In the case of behavior information, we provided parents the number of positive, neutral and negative behavior notes recorded in the classroom books over the prior month. Regarding the math test scores, we provided monthly updates on the record of all math test scores, the average of these scores, and the class average score. Hence, parents learned information about their own child, as well as how their child performed relative to the class mean.

C.2 Timeline of distribution of text messages

The Chilean school year runs from March to December, with two weeks of winter vacation in July. We introduced parents to the intervention at school meetings located at school premises in May, and collected consent forms at these meetings. Since school meetings were not always well attended, we also sent project introduction materials and consent forms home with students and followed up by phone to get verbal and written consent.

In Chile, receiving a text message is free. The cost of text messages was paid by the research team.

Table C.1 presents the first day and text of each of the text messages. On May 23rd, we first sent all participants, including those randomized to the control group, in seven out of eight schools a welcome text message to introduce the intervention and let them know they might expect further free messages from their child's school. The child was mentioned by name. This message helped identifying valid phone numbers for caregivers, following up on all undelivered welcome messages to correct phone numbers. After that, we started sending behavior text messages on July 9th, 2014; attendance text messages around June 13th, 2014; and math test scores text messages around July 14th 2014. The 8th school was incorporated into the experiment slightly later. The implementation milestones for this school were as follows: July 28th, 2014 (welcome message); August 1st, 2014 (first attendance message); August 11th 2014 (first math test score message); and August 12th, 2014 (first behavior message). Because winter vacations are taken in July, differential timing of the start of the intervention for the 8th school is of little consequence. The intervention continued for a second year. From April 2015 to December 2015, we continued to send text messages to treated parents in a retained sample of students. We recorded all text message information such as day and time, the message's content, the name of the recipient parent, etc.

Table C.1: Text messages

text message Type	Frequency	Start Date	Text
Behavior	Monthly text message	July 9th, 2014 (August 12th, 2014 for 8th school)	{Name parent}, according the school's record of {month}, {Name student} had {Number} positive notes and {Number} negative notes. Papas al dia
Attendance	Weekly text message	June 13th, 2014 (August 1st, 2014 for 8th school)	{Name parent}, according the school's record, {Name student} attended to school {week attendance days} of {week total days}. Papas al dia.
Mathematics Scores	Monthly text message	July 14th 2014 (August 11th, 2014 for 8th school)	{Name parent}, the math scores of {Name student} are {List of student's grade} and his/her average now is {Current GPA}. The average in the class is {Average class GPA}. Papas al dia

C.3 Text messages: Delivery

All text messages were sent as planned. However, not all text messages sent were delivered or received. Several factors contributed to message failure. A message was more likely to fail if the network was very busy, if there was some technical problem with the network, if parents turned off their phones or if they changed their numbers during the experiment. To maximize the chances of message receipt, we changed the dates of message delivery from Friday to Monday in August 2014, early on in the intervention. We also re-contacted all consenting parents in March 2015 to verify and/or update their cellphone numbers, to minimize the chance of message failure due to new phone numbers. We also gathered these data on the delivery status of the text message (i.e. whether the phone number received the message).

Technical reasons affecting whether a text message is successfully delivered or not (e.g. network overload at certain times of the day/week) are unlikely to be correlated with family-level unobservables that also affect child outcomes. However, we check this possibility by regressing the total share of successful text messages (total received/total sent) of each type (attendance, grades, behavior and general text messages) on baseline attendance and math grades, age, gender and classroom fixed effects. Table C.2 shows that students with higher baseline grades or attendance behaviors were no more (or less) likely to receive text messages that were sent.

Table C.2: Likelihood to receive sent text messages

	Main Sample				Full Sample			
	Attendance	Grades	Behavior	General	Attendance	Grades	Behavior	General
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Attendance in 2013	–0.155	–0.074	–0.101	0.075	–0.100	–0.054	–0.068	0.021
	[0.212]	[0.205]	[0.204]	[0.168]	[0.200]	[0.195]	[0.200]	[0.144]
Math grade in 2013	0.019	0.017	0.016	0.007	0.009	0.007	0.015	0.001
	[0.017]	[0.019]	[0.017]	[0.011]	[0.016]	[0.017]	[0.015]	[0.011]
Students	530	530	530	1066	710	710	710	1447

Note: Table shows the coefficients of a regression of the total share of successful text messages (total received/total sent) of each column type (attendance, grades, behavior and general text messages) on attendance and math grades at baseline. Columns [1]-[4] present results for the main sample and columns [5]-[8] for the full sample. Regressions of columns [1]-[3] and [5]-[7] use the sample of treated students. Regressions of columns [4] and [8] use the sample of treated and control students. All regressions include controls for class fixed-effects, age and gender. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

D Data Sources

D.1 School Records

Our analysis takes advantage of rich administrative data collected from several sources throughout the project. First, before the intervention, we collected basic demographic data (age, gender) and school performance data (e.g. average test scores, annual attendance rate, and grade repetition) from administrative school records (i.e. transcripts, called *Actas* in Spanish) provided by the Ministry of Education of Chile (MINEDUC). After that, to measure the impact of the intervention, we collected administrative school records for our sample schools at midline (end of year 1) and endline (end of year 2) using the same source. For students who left our sample of schools during the experiment, we collected their aggregate data on attendance and scores (subject-specific GPA) from the municipality school records and tried to track the remaining students by phone. This allowed us to fill in the missing midline and endline data.

D.2 Classroom books

Our research team also collected data (attendance, behavior note, and mathematics score) on a weekly basis throughout the duration of the experiment. Table D.1 highlights the sources, frequency, and availability of this information. Once the intervention began, each of our project teams visited their assigned school once per week and collected the administrative data by photographing daily attendance entries, behavior reports, and all recent mathematics test records for all children in treated classrooms. For attendance data, the information was originally reported at a daily frequency (0: absent, 1: attended class, .: not in roster of students). We then aggregated this information at a weekly, monthly and yearly frequencies (as sum of days and percentage of days) to facilitate comparison with other sources of information. These attendance data are available since the school year starts in 2014. In the case of behavior outcomes, we collected all positive and negative notes recorded on a daily basis if they exist. We collected these data since June 2014. For aggregating the number of positive/negative records at the monthly level we considered only the months when the student was in the school. In the case of mathematics score, we collected all test scores recorded for each student on each month. We then aggregated these simple averages into a monthly score. The semester and annual averages were computed in the same way. Math scores data are available since when we started to send text messages in July 2014.

D.3 Surveys

We administered surveys to all participating parents and all children in all grades. Surveys were administered before treatment (baseline, around June 2014), at midline (end of year

Table D.1: Classroom books data

Outcomes	Data Source	Years	Frequency
Attendance	Attendance register pictures	2014 (since March), 2015	Daily
Behavior	Behavior records pictures	2014 (since June), 2015	Daily
Mathematics Test Score	Test records pictures	2014 (since July), 2015	Monthly

1) and endline (end of year 2). Student surveys were administered in class; parent surveys were administered at the first parent meeting or sent home with children and encouraged to be returned to the school.

Baseline and follow-up parent surveys collected information on what parents knew about their child's attendance (questions were for a specific child in our sample), grades and behavior; their level of involvement with the school and the child; demographics and economic characteristics; and any concerns they had with schooling. Some of these questions were later used to form scales on study habits, academic efficiency, parental support, parental supervision, parental school involvement and parental positive reinforcement. We describe the estimation process underlying scales construction in detail in section E.1. Child surveys collected demographics, self-reported performance, engagement in schooling, engagement of parents, and information on their peer networks within the classroom. We also tested them on a few age-appropriate simple math problems.

Follow-up surveys also included specific questions regarding the intervention. For example, we asked parents how much they were willing to pay (WTP) to continue receiving text messages from their school. We randomly assigned one out of three WTP amounts to this question for each parent. In particular, we ask parents: *"It is possible that next year your daughter's/son's school can send you regularly text messages with information about their school performance (attendance, grades, and behavior) four times a month. However, there might not be enough funds to provide this service free of charge. Thinking about how valuable would this service be for you, please tell us whether you will be willing to pay a month to receive four text messages a month, from April to December."* Parents were assigned with equal probability to a value of \$500, \$1000 or \$1500. In addition, we asked if parents were receiving text messages with general school information and student's attendance, behavior and grades.

E Variables' Construction and Description

Table E.1 lists all the variables used in the paper, including details on their construction and sources.

Table E.1: Variable definitions and sources

Variable definition	Variable name	Sources	Description
Baseline characteristics			
Age	age	Administrative school records *(Actas)* provided by the MINEDUC	A student's age is computed based on his/her date of birth
Gender	female		Dummy equal to 1 if female student; 0 if male student
New student	new2014		Dummy equal to 1 if student not in the schools sample in 2013; 0 otherwise
Language grade	language		
Control variables			
Standardized Annual Math Test Score 2013*	math_std2013	Administrative school records *(Actas)* provided by the MINEDUC	Baseline annual average math test raw scores are standardized within grade-cohort by the mean and standard deviation observed in the control group at 2013.
Annual Attendance Rate 2013*	attendance2013		Baseline annual attendance rate recorded at the end of 2013.
Outcomes variables			
Standardized Monthly Math Test Score	A_month_std	Mathematics Test Records Pictures	Monthly average raw scores are computed as a simple average of all the test scores recorded on each month. All these monthly raw scores are standardized within grade-cohort by the mean and standard deviation observed in the control group at the corresponding point of measurement (2014 and 2015).
Standardized Annual Math Test Score	A_annual_std		Annual average scores are computed as a simple average from each semester average. Each semester average is computed from the simple average of all monthly test scores recorded in the semester. All these annual raw scores are standardized within grade-cohort by the mean and standard deviation observed in the control group at the corresponding point of measurement (2014 and 2015).
Annual Math Test Score higher than 4.0	A_month_4_std		Dummy equal to 1 if a student scores above the passing score (4.0); 0 if a student scores below the passing score.

* The baseline data exist for all students that were enrolled in our sample schools in 2013. For about half of the students who joined our sample schools in 2014, we collected their aggregate data on attendance and math scores from the municipality school records. For the remaining new students joining our sample schools in 2014, we assign classroom-level mean attendance and math grades to fill in the missing baseline data.

Variable definition	Variable name	Sources	Description
Monthly Attendance Rate	attendance_month	Daily Attendance Register Pictures	Monthly attendance rate is calculated by dividing the total number of days the student is present by the total number of days of attendance registered in each month.
Annual Attendance Rate	attendance_year		Annual attendance rate is calculated by dividing the total number of days the student is present by the total number of days of attendance registered in each school year.
Annual Attendance Rate higher than 85%	highattendance		Dummy equal to 1 if student's annual attendance rate is higher than 85%; 0 if student's annual attendance rate is below 85%.
Monthly Number of Positive Notes	beh_month_pos	Daily Behavior Records Pictures	Total number of positive notes recorded on each month.
Monthly Number of Negative Notes	beh_month_neg		Total number of negative notes recorded on each month.
Standardized Annual Math Test Score*	math_std	Administrative school records *(Actas)* provided by the MINEDUC	Annual average math test raw scores are standardized within grade-cohort by the mean and standard deviation observed in the control group at the corresponding point of measurement (2014 and 2015).
Annual Attendance Rate*	attendance		Annual attendance rate recorded at the end of each year.
Passing grade	pass		Dummy equal to 1 if a student passes grade; 0 if a student repeats grade.
Treatment variables			
Individual Level Treatment	T	Treatment dataset	Dummy equal to 1 if treated student; 0 if control student.
Strata	strata		Individual level treatment is stratified by school-grade-section level.
Year	year		This variable is used to indicate each year: 2014 and 2015.
Main sample	constant		Dummy equal to 1 if a consenting student remains in our sample school during the two consecutive years; 0 if a consenting student drops our sample school during the intervention.

* Annual math scores and attendance rates are available at *(Actas)* for most students excluding for those who change schools and are no longer observed in our sample schools by the end of the year. In that case, we fill in the missing data on math scores and attendance with the annual data coming from math test records and attendance register for each year.

E.1 Survey Data: Construction of scales

Throughout the questionnaires we asked students and parents a series of questions (items) that we later used to form scales on: study habits, academic efficiency, parental support, parental supervision, parental school involvement and parental positive reinforcement. The survey items were drawn from: The University of Chicago Consortium on Chicago School Research, the Manual for the Patterns of Adaptive Learning Scales (PALS) developed by the University of Michigan, and scales on positive parenting developed by the Prevention Group at Arizona State University. These items were randomly mixed into the student and parents' survey instruments. Students and parents could give categorical answers of the type "strongly agree", "agree", etc. to each statement.

We aggregated student and parent answers into scales (indices) using a maximum likelihood (ML) principal components estimator where only one latent factor was retained to describe all responses to the same category of questions. The models were estimated on the treatment and control groups for baseline scales. For follow-up scales, models were estimated only in the control group and then results were applied to the full sample. After the prediction was computed to produce each scale, we standardized them using the mean and standard deviation of the control group. Each scale was pre-specified and had been previously used and validated in other studies.

In the Tables E.2 and E.3 we describe these scales and their properties at *baseline*. Column 1 states the scale name, the eigenvalue of each latent factor, and the Cronbach's alpha. Column 2 presents the items that belong to each scale. Column 3 shows the loading associated with each item. Rather than repeating the information, Table E.4 summarizes the properties of these scales by the eigenvalue and Cronbach's Alpha for follow-up measures, both for parents and students.

Table E.2: Student Scales — Baseline

Scale	Variable	Loadings
Study Habits	I always study for the exams	0.622
Eigenvalue: 2.134	I spend free time doing homework and study	0.516
Cronbach's Alpha: 0.750	I try to do well my school work even though I do not find interesting	0.448
	If I must study I do not spent time with friends	0.428
	I always know the homework that I must present	0.532
	I organize well my time to do my school work	0.745
	I can organize school tasks and spent time with friends and family	0.507
Academic efficiency	I am sure that I can dominate all the school subjects	0.674
Eigenvalue: 2.279	I am sure that I can understand the hardest things	0.779
Cronbach's Alpha: 0.801	I can do almost all the work or I give up	0.540
	Even though subjects are hard I can learn	0.696
	I can do the hardest homework if I try	0.664
Family support	My parents or guardians checked that I really made my homework	0.454
Eigenvalue: 2.100	My parents or guardians motivated me to work hard at school	0.489
Cronbach's Alpha: 0.753	My parents or guardians supported me in activities outside school	0.565
	My parents or guardians heard me when I needed to talk with them	0.507
	My parents or guardians showed that they were proud of me	0.739
	My parents or guardians helped me to take decisions	0.729
Low family supervision	I went alone to school	0.757
Eigenvalue: 1.490	My parents or guardians checked the behavior and attendance book	-0.187
Cronbach's Alpha: 0.575	I returned to home alone	0.716
	I stayed alone at home without adult supervision	0.347
	I left home without letting know my parents where I went or who I was with	0.367
	I allowed that my parents or guardians spoke with my school friends	-0.042
	I went to school and did not enter or left home saying I will not assist	0.214
	I signed in school but I left before class' end	0.255
Parent school involvement	My parents or guardians met with school's director	0.549
Eigenvalue: 1.782	My parents or guardians met with school teachers	0.529
Cronbach's Alpha: 0.665	My parents or guardians contacted the director through e-mail	0.649
	My parents or guardians contacted teacher through e-mail	0.650
	My parents or guardians went to school meetings	0.106
	My parents or guardians went to school events	0.396
	My parents or guardians volunteered at school	0.435
Positive reinforcement	My parents or guardians thanked me for helping with housework	0.549
Eigenvalue: 3.405	My parents or guardians told me they have fun with me	0.727
Cronbach's Alpha: 0.862	My parents or guardians congratulated me for my effort	0.794
	My parents or guardians told me that I have outstanding qualities	0.578
	My parents or guardians told me that they were proud of me	0.770
	My parents or guardians congratulated me for having done well or having improved	0.721
	My parents or guardians encouraged me when I was doing something hard	0.706

Table E.3: Parent Scales — Baseline

Scale	Variable	Loadings
Study Habits	My child always studies for the exams	0.693
Eigenvalue: 3.187	My child spends free time doing homework and study	0.627
Cronbach's Alpha: 0.846	My child tries to do well my school work even though he/she do not find interesting	0.631
	If my child must study he/she does not spent time with friends	0.450
	My child always knows the homework that he/she must present	0.654
	My child organizes well time to do his school work	0.858
	My child can organize school tasks and spent time with friends and family	0.740
Academic efficiency	I am sure that my child can dominate all the school subjects	0.773
Eigenvalue: 2.854	I am sure that my child can understand the hardest things	0.823
Cronbach's Alpha: 0.860	My child can do almost all the work or he/she gives up	0.504
	Even though subjects are hard my child can learn	0.781
	My child can do the hardest homework if he/she tries	0.845
Family support	I checked that my child really made his homework	0.555
Eigenvalue: 2.156	I motivated my child to work hard at school	0.481
Cronbach's Alpha: 0.747	I supported my child in activities outside school	0.471
	I heard my child when he/she needed to talk with me	0.533
	I showed that I was proud of my child	0.752
	I helped my child to take decisions	0.738
Low family supervision	My child went alone to school	0.715
Eigenvalue: 1.586	I checked the behavior and attendance book	-0.219
Cronbach's Alpha: 0.576	My child returned to home alone	0.872
	My child stayed alone at home without adult supervision	0.377
	My child left home without letting me know where he/she went or with who he/she was	0.235
	My child allowed that I speak with my school friends	-0.130
	My child went to school and did not enter or left home saying he/she will not assist	0.179
	My child signed in school but he/she left before class' end	0.139
Parent school involvement	I met with school's director	0.629
Eigenvalue: 1.874	I met with school teachers	0.481
Cronbach's Alpha: 0.651	I contacted the director through e-mail	0.727
	I contacted teacher through e-mail	0.714
	I went to school meetings	-0.071
	I went to school events	0.301
	I volunteered at school	0.338
Positive reinforcement	I thanked my child for helping with housework	0.440
Eigenvalue: 2.960	I told my child I have fun with me	0.617
Cronbach's Alpha: 0.839	I congratulated my child for his effort	0.756
	I told my child that he/she has outstanding qualities	0.654
	I told my child that I was proud of him	0.732
	I congratulated my child for having done well or having improved	0.638
	I encouraged my child when he/she was doing something hard	0.666

Table E.4: Parent and Student Scales at Follow-Up

Year	Respondent	Scale	Eigenvalue	Cronbach's Alpha
[1]	[2]	[3]	[4]	[5]
2014	Parent	Study habits	2.775	0.809
2014	Parent	Academic efficiency	2.992	0.877
2014	Parent	Family Support	1.974	0.733
2014	Parent	Family Supervision	1.554	0.578
2014	Parent	Parent School Involvement	1.644	0.631
2014	Parent	Positive reinforcement	3.755	0.867
2015	Parent	Study habits	2.895	0.831
2015	Parent	Academic efficiency	2.642	0.840
2015	Parent	Family Support	2.236	0.778
2015	Parent	Family Supervision	1.480	0.537
2015	Parent	Parent School Involvement	1.716	0.666
2015	Parent	Positive reinforcement	3.458	0.858
2015	Parent	Parent feelings	1.080	0.539
2014	Student	Study habits	2.442	0.784
2014	Student	Academic efficiency	2.486	0.826
2014	Student	Family Support	2.412	0.795
2014	Student	Family Supervision	1.514	0.604
2014	Student	Parent School Involvement	1.902	0.685
2014	Student	Positive reinforcement	4.087	0.891
2015	Student	Study habits	2.246	0.760
2015	Student	Academic efficiency	2.623	0.837
2015	Student	Family Support	2.418	0.794
2015	Student	Family Supervision	1.236	0.478
2015	Student	Parent School Involvement	1.832	0.676
2015	Student	Positive reinforcement	4.145	0.890

Note: See Table E.2 and E.3 for details on variables used in each scale. Parent feelings scale was only asked for parents in endline 2015.

E.2 Correlations between parental and student's scales

Table E.5 shows, for each scale, the cross-sectional correlation between parents and students values. We find that there is a stable positive correlation between parent and student scales across the different survey waves (baseline, midline and endline).

Table E.6 analyzes the correlation of each scale over time (baseline-midline and baseline-endline), both for parents (Panel A) and students (Panel B). This correlation appears to be positive and stable in all cases.

Taken as a whole, this information suggests that scales seem to be capturing constructs that are similar across the different survey waves.

Table E.5: Parents and Students' Scales Correlation

	Baseline	Follow-Up 1	Follow-Up 2
	[1]	[2]	[3]
Study habits	0.34	0.40	0.34
Academic efficiency	0.25	0.28	0.18
Family Support	0.23	0.31	0.27
Low Family Supervision	0.65	0.66	0.69
Parent School Involvement	0.22	0.26	0.29
Positive reinforcement	0.29	0.29	0.32

Note: Columns [1], [2] and [3] show the Pearson's correlation coefficient between parent and student scales at baseline (mid-2014), midline (end 2014) and endline (end 2015), respectively. Correlation figures are calculated with the main sample (excluding grade 8 in 2014 and dropped school).

Table E.6: Scales' Correlation Over Time

	Baseline - FU1	Baseline - FU2
	[1]	[2]
Panel A: Parents' Scales		
Study habits	0.56	0.51
Academic efficiency	0.46	0.39
Family Support	0.56	0.51
Low Family Supervision	0.73	0.57
Parent School Involvement	0.43	0.42
Positive reinforcement	0.54	0.53
Panel B: Students' Scales		
Study habits	0.49	0.38
Academic efficiency	0.39	0.33
Family Support	0.59	0.46
Low Family Supervision	0.69	0.56
Parent School Involvement	0.44	0.35
Positive reinforcement	0.63	0.50

Note: Columns [1] and [2] show the Pearson's correlation coefficient between scales at baseline and midline (end 2014) and between scales at baseline and endline (end 2015), respectively. Panel A focus on scales constructed with parent answers. Panel B focus on scales constructed with student answers. All correlation figures are calculated with the main sample (excluding grade 8 in 2014 and dropped school).

F Data Quality

F.1 Response rates

Table F.1 summarizes the response rates of consenting students for the data sources described in Section D. Columns 1 and 2 present the response rate of all consenting students in our experiment with non-missing data for each year (i.e., full sample). Columns 3 and 4 show the statistics of consenting individuals in our main sample.

Table F.1: Response Rates

	Full sample		Main sample	
	Total sought	Found(%)	Total sought	Found(%)
Consent	1447	1.000	1066	1.000
Panel A: Administrative Data				
Student outcomes				
2013	1334	0.922	976	0.916
2014	1439	0.994	1063	0.997
2015	1090	0.753	955	0.896
Panel B: Survey Data				
Student surveys				
Baseline 2014	1332	0.921	970	0.910
Endline 2014	1283	0.887	947	0.888
Endline 2015	906	0.626	854	0.801
Parent surveys				
Baseline 2014	1045	0.722	782	0.734
Endline 2014	775	0.536	609	0.571
Endline 2015	612	0.423	578	0.542

Note: Column [2] presents the response of consenting individuals with non-missing data. Column [4] presents the response rate of consenting individuals in the main sample (excluding all students enrolled in Grade 8 at the baseline and those from dropped school) who have non-missing data. Administrative data is considered available for a student if an individual has data on grades, attendance, and pass/fail/exited school status at the end of the year.

Administrative data is considered available for a student if an individual has data on math scores, attendance, and pass/fail/exited school status at the administrative school records (*actas*) by the end of the year. These data is available for most students excluding those who withdraw before the end of the school year. We use the administrative data of the last school in case students change schools during the school year to one of the schools in our sample.[48]

Panel A of Table F.1 shows that we have baseline data for 92.2% of the full sample, and 91.6% of the main sample. The baseline data exist for all students enrolled in our sample schools in 2013, and for about half of the students who joined the school in 2014.[49] For these

[48] In very few cases, we further use classroom books to impute missing data on math scores and attendance with the annual data coming from math test records and attendance register, respectively.

[49] We collected their aggregate data on attendance and math scores (subject-specific GPA) from the municipality school records.

students who joined our sample schools in 2014, we assign classroom-level mean attendance and math grades to fill in missing baseline data. In all regressions, we use these imputed values and include an indicator variable denoting that the attendance/math grade baseline data are imputed. Focusing on the main sample, in 2014, these administrative data exist for 99.7% and in 2015 for 89.6% of the sample.

Most of the students who drop out of the full sample between 2014 and 2015 are those enrolled in grade 8 in 2014. As mentioned above, when they pass to grade 9, many of them change schools. Other students who left our sample include those who repeated grade 4 and those who left the schools and move out of the municipality. Section F.2 discusses these issues in detail.

Panel B shows the response rates for parents and student surveys. Whereas students present high response rates (90% in baseline and end of 2014, and 80% in 2015 for the main sample), parents have more missing data, specially in follow-up surveys.

F.2 Attrition and entry

Table F.2 describes the possible data status a student can have according to different data dimensions. Specifically, we analyze whether students change school or not, their final academic status in 2014, whether and when they were sent general text messages, and data availability (school records and classroom books). For each of these dimensions, we classify students into mutually exclusive categories. About 90% of the students are always in the same school and the majority of the attrition happens after the change of academic years.

General observations by panel:

- School status. Change of school can be to an in-sample or to an out-of-sample schools (out of the municipalities participating in the study). Students that drop out of the sample are very likely moving to other municipalities (and changing school as a consequence).

- Final status 2014. We asses the final students that changed school during 2014 from the end of the year school records at their new school. However, there might be students for which we do not have information (those that in panel A appear as not found or to have changed to schools).

- Text message status. Those students with never sent general text messages are mainly students retired in 2014 and not found in 2015 (12 out of 18 in the main sample). From those 18, most of the treated students did not received either treatment text messages in 2014. 6 students never appear in text messages data.

- Data Availability (school records). 4 students were *not found* in the school records (*actas*) for which school, grades, and **final status** were imputed using classroom books.

Table F.2: Data Classification

Dimension	Category	Main Sample	Full Sample
School status	Same school always	942	991
	Change school during 2014	5	5
	Change school between 2014 and 2015	17	59
	Change school during 2015	5	6
	Not found between 2014 and 2015	97	321
Final status 2014	Passed	1011	1312
	Failed	28	38
	Retired	27	32
Text messages status	Sent messages in 2014 and 2015	907	958
	Sent messages only in 2014	139	399
	Sent messages only in 2015	2	2
	Never sent	18	23
Data availability status			
School records	Available 2014 and 2015	955	1041
	Available 2014 and missing 2015	108	335
	Missing 2014 and 2015	3	6
Classroom books	Available 2014 and 2015	948	1004
	Available 2014 and missing 2015	115	371
	Missing 2014 and 2015	3	7

Note: Table presents the frequency distribution of students in the main and full samples for different dimensions and their categories. For all dimensions, N=1,066 for main sample and N=1,382 for full sample. The full sample does not include the school not participating in the study in year 2.

- Data Availability (classroom books). We use annual (rather than high frequency) attendance and grades. Data is considered not missing when *both* attendance and grades are available. There are a few cases (15) in which the student withdrew early in the year and attendance takes very low values (more than half of the observations are zeros) and there are no available grades.

Minor observations:

- We found two students in the main sample who only receive text messages in 2015. They have complete administrative data. It is likely that we did not have their correct phone number.
- Students with missing data in 2014 and 2015 (school records and classroom books) drop out of their schools before treatment (April/May/June of 2014).
- Within students that changed school during 2014 there is one that also changes school between 2014 and 2015 returning to the original one.

Table F.3 presents how students are distributed when we consider the combination of the defined categories of Table F.2. We find that almost 90% of the sample passed 2014, and either remain in the same school and we have data for both years, or we do not find them in 2015 and, consequently, we only have data for 2014.

Table F.3: Data classification: Combined Categories

School status	Final status 2014	text messages status	Data Actas	Data Books	Freq.
Same school always	Passed	Sent messages in 2014 and 2015	Available 2014 and 2015	Available 2014 and 2015	873
Not found between 2014 and 2015	Passed	Sent messages only in 2014	Available 2014 and missing 2015	Available 2014 and missing 2015	69
Same school always	Passed	Sent messages only in 2014	Available 2014 and 2015	Available 2014 and 2015	26
Same school always	Failed	Sent messages in 2014 and 2015	Available 2014 and 2015	Available 2014 and 2015	18
Not found between 2014 and 2015	Retired	Sent messages only in 2014	Available 2014 and missing 2015	Available 2014 and missing 2015	11
Not found between 2014 and 2015	Retired	Never sent	Available 2014 and missing 2015	Available 2014 and missing 2015	9
Same school always	Passed	Sent messages only in 2014	Available 2014 and missing 2015	Available 2014 and missing 2015	8
		Other combinations			52
		Total			1066

Note: Table shows the frequency distribution for the main sample of the combination of categories in Table F.2.

F.3 Administrative records: no differential attrition

We next estimate an OLS regression model where the dependent variable is an indicator variable for each possible status and the independent variable is the treatment binary variable. Table F.4 shows that there are no systematic differences between treatment and control students regarding all possible status of each dimension.

F.4 Survey data: no differential response rates

Table F.5 shows that there are no significance differences in the surveys' response rate between the treatment and control group. This is true for all survey waves (baseline and the two follow-up) and both for students and parents.

Table F.4: Differential attrition of administrative records

Dep. var	Treatment coeff. Main Sample	Full Sample
School status		
Same school always	0.001	-0.005
	[0.025]	[0.020]
Change school during 2014	-0.002	-0.001
	[0.005]	[0.004]
Change school between 2014 and 2015	-0.008	-0.003
	[0.012]	[0.015]
Change school during 2015	-0.005	-0.005
	[0.006]	[0.004]
Not found between 2014 and 2015	0.014	0.015
	[0.022]	[0.022]
Final status 2014		
Passed	0.032*	0.031**
	[0.016]	[0.013]
Failed	-0.020	-0.018
	[0.014]	[0.011]
Retired	-0.012	-0.012
	[0.012]	[0.009]
Text messages status		
Sent messages in 2014 and 2015	-0.033	-0.040
	[0.029]	[0.024]
Sent messages only in 2014	0.031	0.041*
	[0.028]	[0.024]
Sent messages only in 2015	0.002	0.002
	[0.002]	[0.001]
Never sent	-0.000	-0.003
	[0.009]	[0.007]
Data availability status		
School records		
Available 2014 and 2015	-0.010	-0.011
	[0.023]	[0.022]
Available 2014 and missing 2015	0.011	0.015
	[0.023]	[0.021]
Missing 2014 and 2015	-0.002	-0.004*
	[0.002]	[0.002]
Classroom books		
Available 2014 and 2015	-0.000	-0.017
	[0.024]	[0.021]
Available 2014 and missing 2015	0.002	0.022
	[0.024]	[0.022]
Missing 2014 and 2015	-0.002	-0.005*
	[0.002]	[0.003]
Students	1066	1382

Note: Column [1] shows the dependent variable of a regression of each category dummy on the treatment variable. The coefficients for the main sample and full sample are presented in column [2] and [3], respectively. text messages status relates to general text messages. All regressions are estimated by OLS including classroom fixed-effects (strata). Robust standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table F.5: Surveys Differential Response Rate

	Obs.	Treatment Mean	Control Mean	p-value
	[1]	[2]	[3]	[4]
Panel B: Parents' Survey Data				
Baseline 2014	1066	0.74	0.73	0.59
Endline 2014	1066	0.58	0.57	0.36
Endline 2015	1066	0.55	0.54	0.70
Panel C: Students' Survey Data				
Baseline 2014	1066	0.92	0.91	0.84
Endline 2014	1066	0.90	0.88	0.38
Endline 2015	1066	0.80	0.80	0.95

Note: Column [1] shows the number of observations with non-missing data, column [2] and [3] the average response rate for treatment and control group, respectively, for the estimating sample (excluding grade 8 and dorpped school). Column [4] reports the p-value on the treatment coefficient in a regression using a dummy indicating response as the dependent variable. All regressions include controls for classroom fixed-effects (randomization strata) and standard errors clustered at the classroom level.* significant at 10%; ** significant at 5%; *** significant at 1%.

G Information and parenting styles

The effects of information interventions such as the one analyzed in this paper could be mediated by parenting styles (generally understood as the strategies parents use in raising their children). To examine this issue, we implemented a complementary randomized control trial to evaluate the effect of providing parents with tools to relate to their children more positively using an established "positive parenting" intervention.

We worked with educational psychologists at Arizona State University to adapt videos of their successful parenting intervention, "Family Check-up", which has been delivered to hundreds of low-income schools in the US (Lim et al. [2005]). These training videos provided parents with specific guidance about how to use the school-provided information on attendance, grades, and classroom behavior. The videos were distributed in DVD format. We stratified by school grade-level, and randomly allocated *classrooms* to receive or not receive the informational videos. Hence, this video-intervention was orthogonal to the text message intervention. Control classrooms received a placebo DVD with music. The video distribution was implemented in the fall of 2014. Let V_{cjg} be an indicator variable equal to one if a parent of student i in classroom c of school j, grade-level g received the video.

We are interested in estimating the effects on students of inducing parents to use a more positive parenting style when processing the information received via text message. Thus, we interact the individual-level treatment variable T_{icjg} with the classroom-level video treatment V_{cjg} to estimate an intention-to-treat effect. Table G.1 presents the results for additional effects (beyond the effects of the text message treatment) of receiving the parenting video treatment. Estimated coefficients of additional parent training through the video-delivered parenting intervention are, in general, positive and large. However, we lack statistical power to reject the null of no differential treatment effect for parents who received the parenting treatment. We take this as suggestive evidence that parents could benefit from receiving tools to improve their parenting styles towards a more positive one.

In order to assess if, upon receiving the information from the school, parents knew how to use it to change their children's behavior, we implemented a video-delivered parenting intervention which was randomly assigned to the experimental sample. This complementary intervention was designed to foster a more positive parenting style. We find that those parents that received the text message information treatment and the positive parenting intervention had larger treatment effects than those that did not. However, we lack statistical power to reject the null of no differential treatment. We take this as suggestive evidence that parents could benefit from receiving tools to improve their parenting styles towards a more positive one.

Table G.1: Additional Treatment Effects by Parental Training

	Math grade	Math grade >4.0	Attendance rate	Cumulative attendance >85%	# negative beh. notes
	[1]	[2]	[3]	[4]	[5]
T	0.071	0.034*	0.008	0.028	–0.038
	[0.057]	[0.018]	[0.007]	[0.036]	[0.113]
T x V	0.020	–0.013	0.001	0.033	0.089
	[0.087]	[0.026]	[0.010]	[0.048]	[0.152]
Observations	2,011	2,011	2,011	2,011	2,011

Note:Table shows intention-to-treat effects estimates shown on each column for each outcome. Coefficients were estimated using OLS. T refers to the randomized individual-level treatment (equal to 1 if parents were sent text messages and zero otherwise). V refers to the classroom-level video treatment (equal to 1 for classrooms in which the DVD was distributed and zero otherwise). All models include the baseline math grade, attendance rate as control variables, classroom (randomization strata), year and grade-level fixed effects. If baseline values of baseline math grade/attendance were missing, we imputed them using the classroom-level mean and added an indicator variable for these imputed observations. Standard errors are clustered at the classroom level (shown in brackets). * significant at 10%; ** significant at 5%; *** significant at 1%.