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Alejandro J. Ganimian
New York University

Lindsay Page
Brown University

Joshua Childs
The University of Texas at Austin

Verónica Mesalles
New York University

Berta Bartoli
New York University

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Pervasive, Predictable, and (Partly) Preventable: Student Absenteeism in a Middle-Income Country*

Alejandro J. Ganimian[†] NYU

Lindsay Page[‡] Brown/NBER

Joshua Childs[§] UT Austin

Verónica Mesalles[¶] NYU

Berta Bartoli[‖] NYU

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Abstract

We combine descriptive, correlational, experimental, qualitative, and quasi-experimental evidence from 2018 to 2025 from a province in Argentina, to present one of the most comprehensive analyses of students' attendance at school outside the United States. Absences in this setting are pervasive: two-thirds of students miss 10% or more of the school year—about 4 times the U.S. rate and 1.5-2 times those of neighboring countries. Yet they are also predictable: school records enable us to identify 80% of eventual chronic absentees just four months into the year. Students who miss more school learn less, but these differences largely reflect selection, and the causal effects of weather-induced absences are mixed. Text messages were cost effective at preventing absences, and those informing parents of their children's absences had longer-term effects than those reminding them of the importance of school attendance. By contrast, a school-based support approach in which teachers were paid to identify and support high-absence students led to no clear improvements in attendance, school performance, or achievement.

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[†]Associate Professor of Applied Psychology and Economics, Steinhardt School of Culture, Education, and Human Development, New York University. alejandro_ganimian@gse.harvard.edu.

[‡]Annenberg Professor of Education Policy, Brown University. Faculty Research Fellow, National Bureau of Economic Research. lindsay_page@brown.edu.

[§]Associate Professor, Department of Educational Leadership and Policy, University of Texas at Austin. joshuachilds@austin.utexas.edu.

[¶]Doctoral student, Psychology and Social Intervention, Steinhardt School of Culture, Education, and Human Development, New York University. veronica.mesalles@nyu.edu.

[‖]Doctoral student, Psychology and Social Intervention, Steinhardt School of Culture, Education, and Human Development, New York University. berta.bartoli@nyu.edu.

1 Introduction

A large body of evidence—mainly from the United States—indicates that students who are absent from school often are more likely to face adverse outcomes during and after school. Absences are inversely related to multiple indicators of school performance, including grades, the probability of passing a subject, and the probability of graduating from secondary school (Allensworth and Easton, 2007; Balfanz et al., 2007). They are also negatively correlated with students' academic (Chang and Romero, 2008; Ready, 2010; Balfanz and Byrnes, 2012) and social-emotional skills (Gottfried, 2014). Several studies have provided suggestive evidence that this relationship may be causal, using strategies such as accounting for student, family, school, teacher, or classroom characteristics (Gottfried, 2009, 2011; Aucejo and Romano, 2016; Gershenson et al., 2017); leveraging plausibly exogenous variation in attendance from illnesses and weather disruptions (Gottfried, 2010; Goodman, 2014); and exploiting within-student, across-subject variation in absences relative to standardized testing windows (Liu et al., 2021). More recent studies have also found that students with more absences are less likely to enroll in college and earn less once they enter the labor market (Goldman and Gracie, 2024).

We know far less about the frequency, predictors, and consequences of student absences, or efforts to reduce them, in low- and middle-income countries (LMICs). Most countries record attendance on paper registers, but few aggregate and digitize daily, student-level data, so they cannot calculate absence rates (UNESCO-UIS, 2020). Efforts to measure attendance often focus on non-representative samples, rely on surveys (which understate absences), and capture snapshots at specific points (instead of tracking over time) (Evans and Mendez Acosta, 2023). These data are helpful for impact evaluations, but they cannot substitute for the system-level information needed to design policies to reduce absences. We do not know the extent to which the patterns in the U.S., or the interventions to address them, apply to developing settings.

In this paper, we present a suite of studies that together offer descriptive, correlational, experimental, qualitative, and quasi-experimental evidence on students' attendance at school in a middle-income country. Each addresses a different gap in global evidence on attendance; all were conducted in public primary schools in Mendoza—a province that resembles the rest of Argentina in terms of demographics and achievement. In study 1, we document how often students miss school, which are most likely to do so, and when; we also explore whether school registers can help us predict which students will be absent most frequently early in the year. In study 2, we examine whether students who miss more schooldays fare less well in school and standardized tests. In study 3, we experimentally evaluate two text-messaging interventions that informed parents of their children's absences or reminded them of the importance of school attendance.[1] In study 4, we quasi-experimentally evaluate a government initiative that

[1]To interpret the results of study 3, we also conducted focus groups with parents about attendance and the text messages evaluated in the study. We describe our results in detail in Appendix B.

paid one teacher per school to identify and support students with high absences. To our knowledge, this is the most comprehensive study on student attendance in an LMIC.

We report four main sets of results. First, students' absences are pervasive but predictable. The average absence rate in public primary schools in 2025 was 15% and 65% of students were "chronically absent," which means that they missed 10% or more of the school year.[2] The absence rate has come down since spiking right after the COVID-19 pandemic (25%), but it remains above its pre-pandemic level (13%), suggesting it may represent a new equilibrium. Self-reports—a widely used approach to diagnose absence—vastly underestimate absences: the chronic-absence rate according to school registers was *13 times* that from student surveys. Daily attendance data from school registers, however, reveal two clear and actionable patterns: absence rates are highest among students from low-income households enrolled in grades 1-2 and they tend to increase around interruptions in schooling: weekends, holidays, and vacations. In fact, four months into the year, they can already predict 80% of eventual chronic absentees. They could be leveraged to support students before they lose too much instructional time.

Second, students who miss more school learn less, but not necessarily due to their absences. In 2022-2025, the 10% of students with the most absences had grades in school that were nearly a standard deviation (SD) below those of the 10% with the fewest absences; they were 20-22 pp. more likely to fail these subjects; 19-26 pp. more likely to score in the lowest level of a reading fluency test; and they scored 0.66 and 0.52 SDs lower in tests of math and language, respectively. Yet, these associations are between *4 and 15 times* weaker when we compare the same student over time, suggesting that high-absence students differ from their peers beyond their attendance. Further, when we estimate the causal effect of rainfall-induced absences, we find mixed results: a 10 pp. increase in the absence rate lowers math and average grades by 0.24 and 0.21 SDs, respectively, with no clear effects on national tests or school progression.

Third, some absences—particularly, those around weekends and holidays—are preventable. Bi-weekly text messages informing parents of their children's absences or reminding them of the value of attendance had similar effects in the short run (over a three-month experiment).[3] Information (T1) and reminders (T2) reduced the absence rate by 0.5 and 0.3 pp., over a control mean of 17%. T1 also reduced the chronic-absence rate by 3 pp. from a base of 68%.[4] Yet, after messages ended, information continued to reduce absences, and reminders did not. T1 reduced the absence rate by 0.4 pp. in 2023 and the chronic absence rate by 3.7 pp. and 3.1 pp. in 2023 and 2024, respectively. T2 had null effects in all three years. This suggests

[2]This share is much higher than that of neighboring Uruguay (46%) and Chile (30%) and four times that of the U.S. (16%) (MINEDUC, 2020; Attendance Works, 2022; INEEd, 2024).

[3]Information messages were sent only if the child had missed school during the previous 15 days; reminders were sent every 15 days. Most parents assigned to either intervention received at least one message (82% in T1 and 88% in T2; some did not due to outdated phone numbers, connectivity or coverage, or opting out).

[4]Among parents who received at least one message, T1 (T2) reduced the absence rate by 0.7 (0.5) pp. and chronic absenteeism by 3.4 (1.6) pp. Each T1 (T2) message reduced the absence rate by 0.16 (0.08) pp.

that information did more than raise the salience of attendance, making it more cost-effective at reducing absences: each 1 pp. decline cost USD 0.38 for the absence rate and USD 0.06 for the chronic absence rate with T1, compared to USD 0.87 for the absence rate with T2.[5]

Fourth, more intensive, school-based approaches do not necessarily achieve better results. A government initiative that paid teachers to identify and support high-absence students had precisely estimated null effects on attendance and the share of students with high absences. We can rule out reductions above 0.6 pp. in the absence rate and 2 pp. in "critical attendance" (students who missed more than 25% of schooldays per year) across all three follow-up years. It also had mostly null effects on school performance, which allow us to rule out improvements larger than 1.3 pp. in passing or repetition, 0.03 pp. in dropout and 2.4 pp. on graduation.[6] We find almost no evidence that it improved scores on national or sub-national assessments. We can rule out gains larger than 0.05 SDs in language in the national assessment and than 0.04 SDs in reading fluency in the sub-national assessment in the first follow-up year.

Together, these studies meaningfully advance our current understanding of why students in LMICs are absent from school and of what works to reduce their absences. We are among the first to document absence in an entire school system (instead of samples) over the school year (rather than a snapshot in time) using school registers (not surveys) to show that, even in an upper-middle income country, absences are much higher than in high-income nations. We also show that school registers are a valuable resource to identify, early in the year, who will be absent and when, suggesting LMICs would benefit considerably from leveraging them. Further, we offer a more nuanced account of the pandemic's impact on student attendance, distinguishing its well-documented short-term effects (USDoE, 2025; Attendance Works, 2022) from its potential long-term impact on the equilibrium absence rate over subsequent years. In the same context and period, we provide causal evidence on low-touch approaches most frequently tested by researchers (text messages) and high-touch interventions championed by advocates (designated teacher roles), allowing for direct comparisons of their cost-effectiveness.

Relatedly, we also contribute to the broader literature on nudges in behavioral economics. Early field experiments using intensive parent outreach (e.g., daily teacher communications and principal-led meetings) offered promising evidence that engaging parents could improve attendance and related student outcomes (Kraft and Dougherty, 2013; Avvisati et al., 2014). Less intensive but more scalable approaches (e.g., text messages and letters) have generally had more modest impacts on attendance (Rogers and Feller, 2018; Robinson et al., 2018; Musaddiq et al., 2024; Berlinski et al., 2025; Lichand et al., 2026), tempering the initial enthusiasm.[7] By embedding the nudge within the education ministry and leveraging its existing data and

[5]T1 and T2 also reduced the percentage of subjects failed by 7-9% and raised language scores on the national assessment by 0.06 SDs in 2023, but had mostly null effects on other student outcomes.

[6]We find no improvements in school grades or number of subjects failed under either design (Table A.21).

[7]We review prior impact evaluations of interventions to reduce student absences in Appendix C.

personnel, however, we show that even governments in middle-income countries can implement these approaches at scale and at very low cost, shifting the relevant cost-benefit calculation. By tracking post-intervention impacts, we show that short-term evaluations can miss medium-term effects, obscuring important differences between informational and salience-based nudges.

Lastly, we also speak to ongoing debates in economics about how research informs policy. Prior research has found that policymakers demand evidence (Hjort et al., 2021) and update their beliefs based on it (Crawfurd et al., 2025; Vivalt and Coville, 2023; Vivalt et al., 2025). Yet bureaucratic inattention (Agte et al., 2026), weak state capacity (Andrews et al., 2017), and political resistance (Banerjee et al., 2008; Bold et al., 2018) impede delivery, motivating at-scale evaluation (Muralidharan and Niehaus, 2017) and adaptation (Banerjee et al., 2017). Research-use studies also note that evidence fails to inform policy when disconnected from policymakers' problems and institutions (Weiss, 1979, 1982; Tseng, 2012; Crowley et al., 2021). Research-practice partnerships can address this challenge by sustaining collaboration between researchers and practitioners around shared problems of practice (Coburn and Penuel, 2016).

2 Context

2.1 Education in Argentina

All studies take place in Argentina, a federal upper-middle-income country with a USD 13,858 per-capita income (World Bank, 2025b). Its 24 provinces provide pre-primary to secondary education and the federal government oversees higher education and supports provinces. Schooling is compulsory from age 4 through grade 12 (*Ley de Educación Nacional*, 2006). In 12 provinces including Mendoza, primary school covers grades 1-7 (DiNIECE, 2013).

All studies focus on primary school, where enrollment is nearly universal (World Bank, 2025a). Argentina has the world's 28th-largest primary-school system, serving 4.7 million students (World Bank, 2025a; MdCH, 2025a). Learning levels are low: in the latest national assessment, 36% of sixth-graders scored in the bottom two (of four) levels in reading and 49% did so in math, with little change since 2016 (Ganimian and Mesalles, 2025).

Whether students receive enough instructional time has long been a matter of public debate in Argentina, but the focus has been on the formal length of the school year and day rather than on actual attendance. Provinces set their own school calendars, but they must meet national minimums for school days: 180 since 2003 and 190 since 2021 (Ley 25.864, 2003; *Resolución N° 405/21*, 2021; *Resolución N° 431/22*, 2022; *Resolución N° 451/23*, 2023). Yet these targets are often missed. In 2025, 11 of the 24 provinces, enrolling 42% of the country's primary-school students, failed to meet the 190-day requirement (Zorzoli et al., 2025).

Debates about the school day likewise center on non-compliance with legal targets. Argentine primary schools operate on a simple, extended, or full schedule, corresponding to

four, more than four but fewer than eight, and eight hours per day, respectively. Laws in 2005 and 2006 envisioned a broad shift toward extended or full schedules (*Ley de Financiamiento Educativo*, 2005; *Ley de Educación Nacional*, 2006), yet by 2024 only 33% of primary-school students attended schools of either type (MdCH, 2025a). The Federal Council of Education adopted a program to add one hour to simple-schedule schools (*Resolución N° 426/22*, 2022), though its uneven implementation across provinces remains a topic of policy debate.

Given the attention that instructional time has received, it is striking that Argentina does not federally mandate the collection and reporting of student-attendance information. Provinces set their attendance rules, and schools use paper records that are not digitized. The only nationwide attendance measure is from a student survey in the national assessment, but recall error, coarse response options, and changes in wording over time limit its usefulness.

In recent years, school attendance has received growing attention. In 2022, we published a report on attendance in Mendoza's public and private primary and secondary schools (Ganimian, 2022). This was the first time a province publicly released its attendance statistics. We found absences were higher in primary (10%) than in secondary (7%), and within primary, in public (13%) than in private (8%) schools. This motivated the focus of the present study. In 2025, the City of Buenos Aires published its absence rates for public pre-primary (24%), primary (15%), and secondary (16%) schools (UEICEE, 2025). Later that year, the national education ministry analyzed attendance data from public secondary schools in nine provinces (MdCH, 2025b). Yet, because those provinces remained anonymous and inclusion required relatively high data coverage, the generalizability of those findings remains unclear.

2.1.1 The Province of Mendoza

We conducted all studies in Mendoza, a province that closely resembles Argentina as a whole and is thus well suited to pilot policies with broader relevance. Its median per-capita household income is ARS 250,000 (USD 192) per month, compared with ARS 290,000 (USD 223) nationally, and its Gini coefficient (0.396) is close to the national figure (0.431) (INDEC, 2025). Mendoza also has the country's fifth-largest primary-school system, with 230,870 students, and its share of sixth-graders in the bottom two performance levels in reading (34%) and math (50%) is similar to the national average (MdCH, 2025a; Ganimian and Mesalles, 2025).

Mendoza is also unusually well suited for evaluating education policies. It is one of only eight provinces that assign all primary-school students unique identifiers (Ferrari Inchauspe et al., 2024), which allow us to distinguish transfers, dropouts, and new entrants. Since 2018, teachers have been required to upload administrative data on students' demographics, enrollment, attendance, and grades to a centralized online platform,[8] which has replaced paper

[8]Originally *Gestión Educativa Mendoza* (GEM); renamed *Gestión Educativa Integral* (GEI) in 2025.

records since 2019 (DGE, 2018, 2019). The platform also feeds into GEM PAD, a website and app through which students, parents, and teachers can access student records.

Mendoza is also well suited to deepen our understanding of student absences in LMICs. Its attendance data are student-level, daily, longitudinal, and linked to rich information on potential correlates (section 3.2), a level of detail that remains rare in LMICs. Among 27 LMICs, only eight collect any data on student attendance (Evans and Mendez Acosta, 2023).

3 Study 1: Frequency and predictors of absences

We begin by describing the level, distribution, evolution, and predictors of absence rates in Mendoza's public primary schools. We compare the two pre-pandemic years (2018-2019) with the first four post-pandemic years (2022-2025) to assess whether attendance returned to pre-pandemic levels or stabilized at a new equilibrium.[9] To our knowledge, this is among the first systemwide LMIC studies of attendance and its correlates before and after the pandemic.

3.1 Sample

The sample includes 719 of Mendoza's 726 public primary schools. We exclude six boarding schools because students reside in them and thus exhibit very different attendance patterns. We also exclude one rural frontier school without standard attendance records.

3.2 Data

For each school, we observe its geographic area (rural or urban and whether it is high-poverty), department, enrollment, and daily schedule. For each student, we see demographics, schooling trajectories, and disability status and type. For their mother, father, or guardian, we observe education and occupation. Lastly, for each school day in 2018-2019 and 2022-2025, we observe whether each student attended school, arrived late, or left early.

3.3 Results

3.3.1 How often did students miss school before the pandemic?

Students' absences from school in Mendoza were already high before the COVID-19 pandemic. In 2019, the last year without pandemic-induced school closures, the average public primary school student had a 13% absence rate (Table 1).[10] Absences were heavily right-skewed:

[9] We omit 2020-2021 because schools were closed for much of those years and attendance records differ.

[10] When Mendoza began recording attendance digitally in 2018, 13% of students had no recorded absences, likely reflecting uneven compliance. This share fell to 4% in 2019, making that year's figures more reliable.

the median student missed 12% of the school year, while the top 5% missed at least 32% (Figure 1A). Over half of students (57%) were "chronically absent," meaning that they missed at least 10% of the school year (Balfanz and Byrnes, 2012). This share is higher than those of Uruguay (46%) and Chile (30%) for primary and four times that of the U.S. (16%) for K-12 (MINEDUC, 2020; Attendance Works, 2022; INEEd, 2024).[11] Mendoza categorizes students who miss more than 25% of the school year as "critically absent" and those who miss 15-25% as "regularly absent." In 2019, 12% and 24% of students fell into these categories, respectively.

Absences resulted in considerable loss of instructional time. The average student missed 24 of the 182 school days (13%) in 2019. This corresponds to 108 missed hours of instruction. To gauge this magnitude, it helps to compare it to efforts to expand the school day: if Mendoza had added two hours to the school day in 2019 (as it did in 2021; see Ganimian et al. 2026), the average student would have missed 30% of the lesson time added by the reform.

Our results, based on schools' attendance records, illustrate the extent to which self-reports underestimate absences from school. According to the student surveys administered alongside the national student assessment in 2017 (the closest year to 2019 with a question on attendance), 15% of students in grade 6 (the only primary-school grade assessed) in Mendoza reported never missing a schoolday, 66% 1-14 days, 14% 15-24 days, and only 5% more than 24 days (SICDIE, 2025). School registers for 2019 indicate that only 3% of sixth-graders in Mendoza never missed a schoolday, 32% 1-14 days, 26% 15-24 days, and 38% more than 24 days (Figure A.1, panel A). This is consistent with a recent review of studies in LMICs measuring attendance, which found that surveys understate absence (Evans and Mendez Acosta, 2023).[12]

3.3.2 How often did students miss school after the pandemic?

Absences surged right after the pandemic. In 2022, the first year without pandemic-induced school closures, the average public primary-school student had an absence rate of 25%.[13] The absence distribution remained right-skewed, so the median student had an absence rate of 23%, while the top 5% missed 47% or more of the school year (Figure 1A). Ninety-two percent of students were chronically absent—nearly three times the U.S. rate (USDoE, 2025). This resulted in more time lost. In 2022, the average student missed 38 days, which is 19% of Mendoza's school year or 172 instructional hours—60% more than in 2019.

Self-reports increasingly understated absences. In 2023, 13% of sixth-graders in Mendoza reported never missing a schoolday, 42% reported missing 1-5 days, 20% 6-9 days, 13% 10-15 days, 6% 16-20 days, and 6% more than 20 days (SICDIE, 2025). Based on the 2022 registers,

[11] In these comparisons, we only include other register-based figures for entire school systems.

[12] In Mendoza, arriving late to school or leaving early counts as 0.5 of an absence if it happens more than 10 minutes after the start or more than 10 minutes before the end of the school day, respectively, and both arriving late and leaving early on the same day counts as 0.75 of an absence. However, 74% of students in our sample had no late arrivals or early exits, suggesting that these are either uncommon or infrequently reported.

[13] The share of students without late arrivals or early exits remained at 74%.

however, 0% of grade-6 students never missed a day, 1% missed 1-5 days, 2% 6-9 days, 7% 10-15 days, 10% 16-20 days, and 79% more than 20 days (Figure A.1, panel B). Put differently, the share of chronically absent students was *13 times* the figure from self-report data.

Absences have declined since their post-pandemic peak. The average absence rate fell to 17% in 2023 and 2024 and to 15% in 2025, compared with 13% in 2019. The share of chronically absent students declined to 70% and then to 65% over the same period, but remained above its pre-pandemic level of 57% (Table 1). These improvements indicate that the initial surge has partly receded, although the continued decline raises the question of whether attendance will return to its earlier level or stabilize with students missing more school.

3.3.3 Where are absences more frequent?

Absences differed more by school location than by enrollment. Across 2022-2025, students in high-poverty areas had an average absence rate of 24%, compared with 18% elsewhere (Table A.1). The corresponding figures in urban marginal areas were 21% and 18%. Rates were lower in rural areas (16% versus 19% elsewhere). The comparison for rural frontier locations was 14% versus 18%. By contrast, average absence rates ranged from 18-19% across four groups of schools ranked by enrollment. Even the smallest institutions, with no more than 277 students, had similar attendance to the largest, with at least 583, suggesting little association between size and the share of scheduled instructional days missed.

3.3.4 Who is more likely to be absent?

Students' demographic characteristics predicted little variation in absences. Across 2022-2025, younger students had higher absence rates (20%) than older students (17%; Table A.2). Female students had slightly lower absence rates (18%) than their male peers (19%). In both cases, however, the differences between groups were small. Argentine students had higher absence rates (18%) than foreign students (16%). Because the former accounted for nearly all students in the province, however, nationality explained little of the variation in absences.

Socio-economic disadvantage consistently predicted higher absence rates. Students whose parents had less education generally had higher absence rates than those whose parents had more education (Table A.2); the same pattern is visible in each year (Figure 1B). Parental occupation also displayed a consistent socio-economic gradient (Figure 1C). Across 2022-2025, absence rates ranged from 15-17% among students whose parents held blue- or white-collar jobs to 20-22% among those from households with no income or receiving public assistance.

Schooling characteristics predicted variation in absence rates. Students in grades 1-2 had higher absence rates (21%) than those in grades 3-4 (18%) or grades 5-7 (17%). This pattern was present in 2018 and 2019 and persisted in 2023-2025, though at lower absence levels than in 2022 and with a smaller gap between grades 1-2 and the upper grades (Figure 1D). Students

who were older than the expected age for their grade (because they started school later and/or repeated a grade) also had higher absence rates (28%) than those who were not (18%). Other schooling variables, including school shift and diagnosed disability status, predicted smaller differences than the 9 pp. gap between overage students and their appropriately aged peers.

3.3.5 When do most absences occur?

Absences increased as interruptions in schooling approached. In Mendoza, the school year starts in February and ends in December. The absence rate rose in the months leading up to and immediately following the winter break (in July), then declined and rose again as the summer recess approached, shooting up as the year ended (in December). It was also higher around weekends, on Mondays and Fridays, and spiked right before or after holidays (Figure 2). The consistency in this pattern at the week, month, and year levels suggests that absences may be partly explained by how families respond to interruptions in schooling.

Yet, chronic absentees can be identified early. If we compute each student's cumulative absence rate each month and flag those meeting the 10% absence threshold, 73-81% of eventual chronic absentees in 2019 and 2022-2025 had already met it by May, halfway through the year, and 87-93% had met it by July (Figure A.2), giving schools ample time to intervene.[14]

4 Study 2: Effect of absences on student learning

Next, we examine how students' absences relate to their school performance and achievement. We compare both outcomes across the absence-rate distribution, compare the same students across periods in which their absences differ, and estimate the causal effect of weather-induced absences. To our knowledge, no prior study in an LMIC has linked student absences to school performance and achievement and estimated their causal effect in an entire school system.

4.1 Sample

The sample for this study includes the same 719 public primary schools from study 1.

4.2 Data

This study combines attendance records with other datasets.[15] We see each student's grades in language and math—and other subjects, which vary by grade and year—in 2019 and 2022-2025.[16] In 2022-2025, we also know whether each student passed, repeated a grade,

[14] Identification was slower in 2018 because attendance records begin in April.

[15] We exclude December because schools are open but attendance is very low (see study 1).

[16] Grades are on a 1-10 scale, with 7 as the passing grade. Graduation is defined as passing grade 7.

dropped out, or graduated. We also have their scores on two provincial tests: a 2022 reading-comprehension test of 1,770 grade-4 students in 65 schools halfway through the school year (DGE, 2022b);[17] and a 2022-2025 reading-fluency test of all grade 2-7 students at least twice per year (DGE, 2022a,c).[18] We obtained each school's geolocation (Ministerio de Educación, 2022), mapped it onto daily precipitation (Funk et al., 2015), and use these data to construct the rainy-day instruments for the instrumental-variables analyses described below.

4.3 Empirical strategy

4.3.1 Descriptive comparisons

We begin by examining how students' performance in school and achievement vary across the distribution of absences. We group students by absence-rate decile and compare outcomes across deciles. This approach is descriptive: it documents correlations between absences and performance, but it cannot separate causal effects from selection into higher absence rates.

4.3.2 Within-student estimates

We next exploit the panel structure of the data to estimate within-student models with student and period fixed effects (following Aucejo and Romano, 2016; Liu et al., 2021). [19] We estimate:

$$Y_{it} = \alpha_i + \delta_t + \beta A_{it} + \varepsilon_{it} \tag{1}$$

where Y_{it} is the outcome for student i in period t, α_i and δ_t are student and period fixed effects, and A_{it} is the absence rate of student i in the period preceding t. We cluster standard errors at the school level. β is identified from within-student variation in absences across periods. This specification removes bias from time-invariant differences across students, but it does not address time-varying confounders that may affect absences and performance within a year.

4.3.3 Instrumental-variables estimates

Finally, we instrument absences with local rainy weekdays, assuming they affect outcomes only through attendance (following Goodman, 2014; Goldman and Gracie, 2024). For fluency, we count rainy weekdays in the seven calendar days before each school's assessment window. For grades and end-of-year outcomes, we count them over each grading period or school year.

[17] It used 20 multiple-choice questions to classify reading comprehension as below basic, basic, satisfactory, or advanced on the province's performance scale.

[18] It records the number of words students can read per minute and classifies their performance as critical, basic, medium, or advanced. There were three waves in 2022 and two in 2023-2025.

[19] We observe each student's grades in each period within a year: three trimesters in 2019 and two semesters per year in 2022-2025. For reading fluency, we observe scores in multiple waves across 2022-2025 (section 4.2).

For panel outcomes, the first stage is:

$$A_{it} = \alpha_i + \delta_t + \pi Z_{it} + \eta_{it} \tag{2}$$

where t indexes test waves or grading periods, α_i and δ_t are student and period fixed effects, and Z_{it} is the relevant rainy-days instrument. We assess instrument strength using first-stage F-statistics, which we report alongside the 2SLS estimates. The second stage is:

$$Y_{it} = \alpha_i + \delta_t + \beta \hat{A}_{it} + \varepsilon_{it} \tag{3}$$

where $\hat{A}_{it}$ is the absence rate predicted by weather and Y_{it} is grades or reading fluency. We cluster standard errors at the weather-data-grid level for fluency and at the school level for grades. β identifies the local average treatment effect for weather-responsive students.[20]

4.4 Results

4.4.1 Do students with more absences perform worse in school?

Students with more absences have lower grades. We standardized grades within school and grade and grouped students by their annual absence-rate decile, making grades comparable across subjects. Grade differences between deciles 1 and 8 were 0.50-0.53 SD, and the gradient became markedly steeper in the top two deciles. The differences between deciles 1 and 10 were 0.96 SD in language, 0.98 SD in math, and 1 SD across both (Figure 3A and Table A.3).[21]

Absences also predict students' probability of repeating the grade, especially among those who miss the most school. Repetition rates were 1% in deciles 1-5 of the annual absence rate and 3% in decile 9, but they jumped to 8% in decile 10 (Table A.4). Dropout rates rounded to 0% in every decile, indicating no meaningful gradient across the absence-rate distribution.

4.4.2 Do students with more absences score lower on tests?

Students with more absences read with lower fluency. Across annual absence-rate deciles, students in higher deciles read fewer words per minute in every year, particularly in the two highest deciles: compared with those in decile 1, those in decile 10 read 33 fewer words per minute in 2022, 36 fewer in 2023, 34 fewer in 2024, and 24 fewer in 2025. These differences were 0.63, 0.69, 0.74, and 0.50 SDs, respectively (Figure 3D and Table A.6).[22]

[20]For end-of-year outcomes, we instrument annual absences with annual rainy weekdays and include year and grade fixed effects (except in the graduation model, which is only for grade 7). For the national assessments, we matched attendance at the school-level because they are not linked to student IDs.

[21]The average uses math and language, which are available for all grades in every year, and requires both subjects to be observed for each student.

[22]Pooled national assessments for 2023 and 2025 yield a similar pattern, although attendance and achievement can be matched only at the school level. Compared with students in schools in the lowest absence-

Reading comprehension was lower only among students who missed the most school. The share scoring below level 1 was 19-24% in deciles 1-7, compared with 32%, 36%, and 37% in deciles 8, 9, and 10—a 15 pp. difference between deciles 7 and 10 (Figure 3C and Table A.7).

4.4.3 When the same student misses more days, do they perform worse?

The relationship between absences and grades mostly reflects differences across students. If we compare the same student across grading periods, a 10 pp. higher absence rate was associated with average math and language grades that were 0.04-0.05 SDs lower in every year—six to eight times smaller than the corresponding cross-sectional differences (Table A.8).[23]

Reading fluency followed a similar pattern. Across 2022-2025, the same student read 0.52 fewer words per minute in assessment periods with a 10 pp. higher absence rate, compared with a cross-sectional difference of 6.3 words per minute (Table A.9). The within-student difference was 0.20 fewer words per minute in 2022, 0.45 fewer in 2023, 0.72 fewer in 2024, and 0.30 fewer in 2025. It was concentrated in the early grades in 2022: 0.33 fewer words per minute in grade 2 and 0.25 fewer in grade 3, with no detectable relationship in grades 4-7.[24]

4.4.4 Do weather-induced absences impact achievement and school performance?

Student assessments yielded little evidence that rain-induced absences reduced achievement. For national assessments, across 2023-2025, effects on math and language scores and the share of students at the lowest performance level were small but imprecise (Table 2, panel A). For provincial assessments, across 2022-2025, effects on words per minute and the share of students in the lowest performance level, were also imprecise (panel B).

Rain-induced absences had some adverse effects on grades. Across 2019 and 2022-2025, a 10 pp. higher absence rate during the grading period reduced math grades by 0.24 SD and the average across the two subjects by 0.21 SD (panel C). Yet, across 2022-2025, these absences had imprecise effects on passing, repetition, dropout, and graduation rates (panel D).

5 Study 3: Impact of text messages to parents

We evaluate two text-message interventions for parents, co-designed and fully implemented by the government. In 2022, we randomly assigned 520 primary schools to information about children's absences, reminders about the importance of attending school, or no messages. We estimate effects on attendance, school performance, and achievement through 2025. This is

rate decile, those in schools in the highest decile scored 0.66 SD lower in mathematics and 0.52 SD lower in language; they were also 19.6 pp. and 6.71 pp. more likely to score below basic, respectively (Table A.5).

[23] We also estimated within-student peer effects following Goldman and Gracie (2024), instrumenting peer absences with school-level weather. The first stage was too weak ($F \approx 7$), so we do not report the estimates.

[24] We also replaced student fixed effects with the lagged outcomes. Results were qualitatively similar.

the largest such randomized evaluation in an LMIC, and it builds on similar studies (Ajzenman et al., 2022; Berlinski et al., 2025; Lichand et al., 2026) by estimating long-term effects.

5.1 Sample

The sample includes 520 of Mendoza's 726 public primary schools, which enroll 85% of students in this level and sector.[25] Within sampled schools, we included all students in grades 1-7. In-sample schools differed little from out-of-sample schools in their demographics or prior attendance, but their students were 9.7 pp. more likely to attend the afternoon shift, read eight more words per minute, and were 7-9 pp. less likely to perform at the critical level, suggesting that they may have been slightly higher performing before the intervention (Table A.10).

5.2 Data

In addition to the data in sections 3.2 and 4.2, this study includes two more datasets.[26] For each round of messages, we observe whether and when a message was sent. For messages reporting children's absences, we also see the number of absences that was reported to parents. For each student in grade 6, we have their scores on the census-based national assessments of math and language in 2016, 2018, 2021, 2023, and 2025. We also know the performance level in which they were categorized (below basic, basic, satisfactory, or advanced) on each subject.

5.3 Intervention

The interventions sent parents text messages every two weeks from September to November 2022. T1 (information) messages reported the number of days that the child had missed in the two preceding weeks and so far in the year; parents received them only if their child was absent that fortnight. T2 (reminder) messages reminded parents of the benefits of school attendance; parents received them regardless of whether their child was absent. Both messages directed parents to the ministry's online portal to track their child's attendance (Table A.11).

Parents in treatment schools were automatically enrolled in the text messages, but they could opt out at any time.[27] Mothers were the default recipients because schools were most likely to have their contact information; if their phone number was missing, messages were sent to fathers or guardians. Messages were sent on Thursdays, the day before students were most likely to miss school, to shorten the time between their delivery and attendance decisions. The education ministry used an online platform to download absence data from its own system and send messages to parents. In this platform, messages were limited to 160 characters.

[25] We excluded 36 schools without complete attendance records, 161 without enough cell-phone numbers for parents, and 9 boarding schools, where students reside throughout the school year.

[26] For attendance, we leave out December for the same reasons as in study 2.

[27] Only 28 of 106,539 parents (0.03%) opted out.

5.4 Randomization

As stated above, we randomly assigned schools to T1, T2, or a business-as-usual condition. Within T2, schools were randomized to different message orders to mitigate order effects and compare the effects of the reminder messages. We stratified all randomizations by department. This design allows us to estimate the causal effect of each intervention (by comparing T1 and T2 with the control group) and the added value of information beyond raising the salience of attendance (by comparing T1 to T2). Because few Argentine provinces have daily attendance data linked to student IDs, T2 would be easier to scale nationally if it were as effective as T1.

Random assignment created comparable groups at baseline. In the average control school, 48% of students were female, 99% were Argentine, and 1.8% had a disability (Table A.12). Fifty-seven percent attended school in the morning, and 1.5% were at least a year older than expected for their grade. Through August 2022, the average absence rate was 17.6%, the rates around weekends and holidays were 7.1% and 1.3%, and 78.4% of students were chronically absent. Among students in grades 2-7, the average number of words read per minute rose from 76 in April to 91 in August, while the share at the critical level fell from 31% to 18%.

5.5 Empirical strategy

5.5.1 Intent-to-treat estimates

We estimate the intent-to-treat (ITT) effect of being offered each intervention by fitting:

$$Y_{ist} = \alpha_{r(s)} + X'_{is,t=0}\gamma + T'_s\beta + \varepsilon_{ist} \tag{4}$$

where Y_{ist} is the outcome for student i in school s at time t, $\alpha_{r(s)}$ is a randomization-stratum fixed effect, $X_{is,t=0}$ is a vector of baseline covariates selected separately for each outcome using LASSO (Belloni et al., 2014), T_s is a vector of treatment indicators, and ε_{ist} is the error term. β_1 and β_2 capture the causal effects of being offered T1 and T2, respectively. We estimate equation (4) by OLS with standard errors clustered at the school level.

5.5.2 Treatment-on-the-treated estimates

We also estimate the effect of receiving the intervention by instrumenting message receipt with random assignment. For each treatment arm $k \in \{T1, T2\}$, we restrict the sample to students in arm k and the control group. In the first stage, we regress an indicator for whether the parent received at least one message on assignment to arm k:

$$D_{is} = \alpha_{r(s)} + X'_{is,t=0}\delta + \pi T_{sk} + \eta_{is} \tag{5}$$

where D_{is} indicates whether the parent of student i in school s received at least one message and T_{sk} indicates whether school s was assigned to arm k. In the second stage, we estimate:

$$Y_{ist} = \alpha_{r(s)} + X'_{is,t=0}\gamma + \beta \widehat{D}_{is} + \varepsilon_{ist} \tag{6}$$

where $\widehat{D}_{is}$ is message receipt predicted by random assignment. β captures the treatment-on-the-treated effect among parents who received messages because of assignment to arm k.

5.5.3 Dose-response estimates

The ITT and TOT estimates capture the effect of being assigned to or receiving any message, but not how effects vary with the number of messages received. Therefore, we also estimate:

$$Y_{ist} = \alpha_{r(s)} + X'_{is,t=0}\gamma + \mu M_{is} + \varepsilon_{ist} \tag{7}$$

where $M_{is} \in \{0, 1, \ldots, 7\}$ is the number of messages received by the parent of student i in school s, instrumented with assignment to the relevant arm. The coefficient μ captures the average causal effect of one additional message for students whose receipt was affected by assignment (Angrist and Imbens, 1995). Under constant effects across compliers and a linear dose-response, μ can be scaled to the effect of receiving all seven messages. Because OLS estimates of equation (7) may be biased by selection into receipt, we rely on IV for causal inference and report OLS estimates only for comparison, following Muralidharan et al. (2019).

5.6 Results

Our analyses largely follow a pre-analysis plan (PAP) we wrote a year before the study.[28] Because we did not know at that time the full extent of the data we would receive, or the variables each dataset would include, we have expanded our analyses considerably. We see this use of pre-registration as consistent with Banerjee et al. (2020), who urge that a PAP be treated as "a record of initial intentions... not a binding contract."

5.6.1 Did text messages reduce absences from school?

Text messages modestly reduced students' absence rate. Over three months, T1 and T2 reduced it by 0.5 pp. ($p < 0.05$) and 0.3 pp. ($p < 0.10$), respectively, from a control mean of 17% (Figure 4A and Table 3).[29] T1 also reduced chronic absenteeism by 3 pp. ($p < 0.01$) from a control mean of 68%, a 4.4% reduction; T2 had a smaller and statistically insignificant

[28] See: `http://bit.ly/4pmkEdK`.

[29] Among T2 parents who received the first message, the three templates produced average absence rates of 15.0%, 14.9%, and 14.3% over the following 14 days. A joint test cannot reject equality across templates ($p = 0.101$), and differences across templates were only marginally significant.

effect. These magnitudes are consistent with prior randomized evaluations in South America, where effects on attendance have ranged from null (Ajzenman et al., 2022; Berlinski et al., 2025) to reductions of 2 pp. (Lichand et al., 2026; see Table C.1). Because the latter measures math-class rather than full-day attendance, it is not directly comparable to our estimates.[30]

During the experiment, the effects of T1 and T2 on the absence rate were indistinguishable from each other (Table 3). This is consistent with what Lichand et al. (2026) found in Sao Paulo, Brazil, which led them to conclude that the effect of messages was driven by salience. Yet, after the interventions ended, their effects diverged. From February to November 2023, T1 reduced the absence rate by 0.4 pp., while T2 had no statistically significant effect.[31] The divergence is even starker for chronic absenteeism: T1 reduced it by 3.7 pp. in 2023 and 3.1 pp. in 2024, while T2 had statistically insignificant effects. The T1-T2 difference in chronic absenteeism was statistically significant from 2022 ($p = 0.061$) to 2024 ($p = 0.012$). This pattern indicates that while information and salience had similar impacts on absence rates in the short term, information has larger and longer-lasting effects on chronic absenteeism.

If information rather than salience drove the T1 effect, absences should drop in the days right after each T1 message and not for T2, which sent only reminders. We regress a daily absence indicator on treatment-by-event-day interactions in a ±6-day window around each message date, with student and day fixed effects (Figure A.4). T1 absences dropped 0.6 pp. one day after the message ($p = 0.15$) and 0.8 pp. two days after ($p = 0.14$); the corresponding T2 coefficients were -0.1 and 0.4 pp. The differences between T1 and T2 are not statistically significant, but their direction is consistent with information driving the T1 effect.[32]

Consistent with the results of study 1, most reductions in the absence rate were due to decreases in absences around weekends and holidays.[33] In 2022, T1 reduced the weekend absence rate by 0.67 pp. and the holiday absence rate by 1.45 pp. (both $p < 0.01$). Together, these reductions account for 56% of the 0.5 pp. effect on the absence rate (Table 3).[34] T2 followed a similar pattern in 2022, reducing absences near weekends by 0.52 pp. ($p < 0.05$). From 2023 onward, however, the two treatments diverged, partly because their impacts on weekend absences differed significantly in 2023 ($p = 0.038$) and 2024 ($p = 0.055$).

[30]The modest effects are consistent with parents' focus-group reports that, because schools uploaded attendance data with irregular frequency, messages sometimes arrived days or weeks after an absence, and they often flagged absences they viewed as outside their control (e.g., school closures; see Appendix B).

[31]In fact, T1's effect on the absence rate was larger than that of T2 in nearly every month in 2023 and 2024, although the differences were statistically insignificant; the two effects converged in 2025 (Figure A.3).

[32]The interventions did not increase parents' propensity to log into the ministry's online portal (Table A.13). This suggests T1 captures the information effect from the SMS itself, not its complementarity with the portal. Appendix B reports that focus-group participants similarly described low and uneven portal use because of connectivity and login problems, as well as delayed and incomplete attendance information.

[33]In the focus groups, some parents acknowledged extending long weekends by keeping children home on an adjacent school day, consistent with the interventions reducing these absences (Appendix B).

[34]We calculate this share by dividing the sum of the weekend and holiday effects by the overall effect, expressing all three outcomes as proportions of all recorded schooldays and using the same sample and controls.

These estimates reflect the effect of being assigned to receive text messages, but not all parents in treatment schools received them. In T1 and T2, 82% and 88% of parents, respectively, received at least one message.[35] The TOT estimates scale up accordingly (Table 3): in 2022, receiving T1 messages reduced the absence rate by 0.7 pp. and chronic absenteeism by 3.4 pp. Receiving T2 messages reduced the absence rate by 0.5 pp. and chronic absenteeism by 1.6 pp. The T1 effects on chronic absenteeism persisted in 2023 and 2024, with reductions of 4.2 pp. and 3.7 pp., respectively, while T2 effects were near zero.[36]

5.6.2 Did more messages lead to fewer absences?

More messages reduced absences during the intervention. Each T1 message reduced the 2022 absence rate by 0.16 pp. ($p < 0.01$) and each T2 message by 0.08 pp. ($p < 0.05$; Table A.14). Extrapolating to all seven messages implies reductions of 1.1 and 0.6 pp., respectively. Parents received an average of 3.3 T1 messages and 5 T2 messages (Table 3).

The per-message effects differed between T1 and T2 immediately after the intervention. In 2023, each T1 message reduced the absence rate by 0.12 pp. ($p < 0.10$), while T2 had a near-zero effect; the difference between arms was statistically significant ($p = 0.035$). In 2024 and 2025, the T1 coefficients remained negative (-0.07 and -0.02 pp.) and the corresponding T2 values remained near zero (0.01 and -0.02 pp.), but neither the arm-specific effects nor the between-arm differences were statistically significant ($p = 0.147$ and $p = 0.911$, respectively). Thus, only the 2023 estimates indicate an informational advantage for T1 over T2.

Students who did not receive messages may also have benefited. Some students had parents without cell phones on file, so they could not be reached, but their classmates' parents were. Among these students (between 6,800 and 13,400, depending on the year), T1 caused a marginally significant reduction in chronic absence by 2.7 pp. in 2022; later estimates were inconclusive (Table A.15). In 2023 and 2024, T1's absence-rate estimates rule out reductions larger than 1 pp. T2 had statistically insignificant effects for all outcomes and years.

5.6.3 Did the messages help some students more than others?

We find little evidence of heterogeneity by students' characteristics. If we regress post-intervention absences from 2022 to 2025 on indicator variables for T1 and T2, demographic and schooling variables, and interactions between them, only 4 of 56 interactions are statistically significant, roughly the number expected by chance. Estimates rule out small-to-moderate heterogeneity by sex and school shift but are less precise for other characteristics (Table A.16).

[35] Focus-group parents linked missed messages to changed phone numbers and coverage gaps (Appendix B).

[36] We also tested for within-household cross-school spillovers using parents' information to link siblings. Among 973 control-school students with at least one cross-school sibling in a T1 or T2 school, the sibling's treatment had no detectable effect on the focal student's absence rate in 2022-2024.

We see little heterogeneity by prior attendance, school performance, or achievement. The coefficients on the interactions between absences and the interventions are around zero (Table A.17). If we plot the average treatment effects by pre-intervention absences (Figure A.5) and quantile treatment effects (Figure A.6), the distributions of post-intervention absences are nearly identical across experimental groups. Interactions between the interventions and provincial achievement measures are mostly null, and for reading fluency, precisely estimated.[37]

5.6.4 Did text messages improve students' performance in school?

Text messages had little effect on students' performance in school. Across 2022-2025, T1 and T2 had mostly null effects on grades and passing, repetition, and dropout, and graduation rates (Table 4).[38] For the intervention year, we can rule out positive effects for either intervention larger than 0.03 SD on grades and than 0.4 pp. on passing, repetition, and dropout rates.

The interventions reduced the percentage of subjects that students failed. The effects were small in *absolute* terms: 0.63 pp. for T1 ($p < 0.10$) and 0.75 pp. for T2 ($p < 0.05$). Yet, given that the average control student only failed 8.59% of subjects, they were non-trivial in *relative* terms, representing reductions of 7% and 9%, respectively (panel A).

5.6.5 Did text messages improve students' achievement?

Both interventions had short-lived impacts on achievement. In the national assessments, T1 and T2 raised average language scores by 0.06 SDs in 2023. T1 also reduced the share of students at the lowest performance level by 2.62 pp., while T2 reduced it by 1.63 pp. and reduced the share at the second-lowest level by 1.48 pp. Yet, neither changed any math outcome in 2023 or any national-assessment outcome in 2025 (Table 5). In the provincial assessments, neither had effects on reading fluency from 2022 to 2025 (Table A.19).

5.6.6 Were text messages cost-effective at increasing attendance?

The text messages were inexpensive. The online platform used to deliver them charged ARS 5 per message (USD 0.042 at the time). The ministry sent about 449,000 messages across both treatment groups, so the total cost of messaging was USD 18,900. Three staffers were collectively paid USD 5,640 for the additional time required to implement both interventions. T1 parents were meant to receive messages only if their child had missed school in the two prior weeks, while T2 parents were supposed to receive them regardless of their child's attendance, so

[37] We also use machine learning to detect treatment-effect heterogeneity across combinations of covariates (Athey et al., 2019; Wager and Athey, 2018). The omnibus tests find no evidence of heterogeneity for T1 ($p = 0.999$) or T2 ($p = 0.18$; Table A.18), reinforcing the conclusion from the parametric analyses.

[38] In 2025, T1 reduced repetition by 0.26 pp. and, counter to the intervention's aims, graduation by 1.07 pp.; both effects were marginally significant. Neither intervention had statistically significant effects on these outcomes in 2022-2024, and T2 also had no detectable effects on repetition or graduation in 2025.

the ministry ultimately sent 187,000 and 262,000 messages to T1 and T2 parents, respectively. Thus, delivering T1 cost a quarter less (USD 0.19 per assigned student) than T2 (USD 0.26).[39]

Both interventions were highly cost-effective at increasing attendance. Applying the average T1 effect of 0.5 pp. on the absence rate to the 62 schooldays from September to November 2022, each assigned student gained about 0.31 additional days of attendance, at a cost of USD 0.61 per day. The corresponding figure for T2 (0.3 pp. on the absence rate, 0.19 additional days per student) was USD 1.40 per day. The cost of reducing chronic absenteeism by 1 pp. per assigned student was USD 0.06 for T1. These magnitudes remained favorable in the post-intervention years for T1, whose effects on chronic absenteeism persisted through 2024, effectively amortizing the one-time messaging cost over multiple school years.

Our interventions compare favorably on cost-effectiveness with other interventions seeking to reduce student absences. We compare costs across interventions described in Table C.1. Of the 11 studies, only six report costs and five of them include cost-effectiveness estimates.[40] The closest comparator, an SMS-based program in Chile, cost USD 10.86 per student per year (Berlinski et al., 2025). At USD 0.61-1.40 per additional attendance day, our interventions cost 4-18 times less than U.S. mailing programs, which cost USD 5.68-6.60 per student and USD 6-10.69 per additional attendance day (Rogers and Feller, 2018; Robinson et al., 2018).[41]

6 Study 4: Impact of attendance facilitators

Lastly, we evaluate a government initiative that paid one teacher per school to identify and support students with high absences. In 2023, it launched with 184 public primary schools. We use difference-in-differences and difference-in-discontinuities to estimate effects on student attendance, school performance, and achievement for schools that entered the program in 2023.[42] To our knowledge, this is one of the first longitudinal quasi-experimental evaluations in an LMIC of a government initiative devoted exclusively to reducing student absence rates.

[39] We add messaging and personnel costs, allocating the latter equally across arms (Dhaliwal et al., 2013). Given that T1 was data driven, it was likely more costly from a staff perspective. If two-thirds of personnel costs are assigned to T1, total costs are approximately USD 0.21 per T1 student and USD 0.24 per T2 student. Yet, T1 becomes more expensive only if 85% of all personnel costs are attributed to it, which seems unlikely.

[40] Avvisati et al. (2014) report EUR 1,000 per school but no cost-effectiveness ratio. Bergman (2021) and Kraft and Rogers (2015) report ratios for achievement and course credits. Musaddiq et al. (2024) report zero marginal messaging costs but do not value staff time; Bursztyn and Coffman (2012); Kraft and Dougherty (2013); Dizon-Ross (2019); Lichand et al. (2026) do not report implementation costs.

[41] The remaining studies report cost-effectiveness for other outcomes: USD 200 per additional course credit (Kraft and Rogers, 2015) and USD 156 per 0.10 SD increase in GPA or math scores (Bergman, 2021).

[42] We exclude December attendance for the same reasons as in studies 2-3.

6.1 Intervention

We evaluated an initiative called *Líderes de Asistencia*, which since 2023 paid one teacher per public primary school to serve as a facilitator to reduce student absences. To be eligible, a school had to be part of a broader initiative that since 2021 offered two additional hours of instruction to students with low achievement (DGE, 2021). To be selected, a school had to have a mean attendance rate below 85%, but this criterion was not consistently enforced. The program began in 184 schools in 2023 (DGE, 2023), expanded to 224 schools in 2024 (DGE, 2024), and reached 301 schools across all departments in the province in 2025 (DGE, 2025).

Teachers hired under the program were paid at a substitute-teacher rate for 10 additional hours of work per week. The role was first offered to the vice-principal, and then to the teacher-secretary, a support teacher, and the most senior teacher (DGE, 2023). Selected teachers (called attendance leaders) had to design and implement a plan to improve attendance. This entailed identifying students with critical attendance (who attended less than 75% of schooldays) and regular attendance (who attended 75-85% of schooldays), understanding their situations, meeting with their parents, coordinating with other authorities, monitoring progress, and documenting actions taken. They also attended training sessions (DGE, 2023).

6.2 Sample

The sample comprises eligible public primary schools across Mendoza. It includes 507 of the province's 726 public primary schools, which enroll 92% of students in this level and sector.[43] We included all students in grades 1-7. In-sample schools differed little from out-of-sample schools in their demographics or prior attendance, but their students were 4.3 pp. more likely to attend the afternoon shift, read seven more words per minute, and were 3-8 pp. less likely to perform at the critical level, suggesting that they may have been slightly higher performing (Table A.20). We estimate the first-, second-, and third-year effects for the 184 schools that entered the program in 2023. We compare them with 284 eligible schools that did not enter in 2023 or 2024 and exclude those that entered in 2025 from that year's comparison group.

6.3 Data

In addition to the data in sections 3.2- 5.2, this study uses information on program eligibility and receipt. We observe which schools were eligible and received the program in 2023-2025.

[43] We excluded 219 schools that were not eligible for the program.

6.4 Empirical strategy

6.4.1 Difference-in-differences

We begin by comparing changes in student outcomes before and after the program at participating schools with those at eligible but non-participating schools. We estimate:

$$Y_{ist} = \alpha_s + \lambda_t + \sum_{\tau \neq 2022} \beta_\tau D_s \mathbf{1}\{t = \tau\} + \sum_{\tau \neq 2022} \boldsymbol{\delta}'_\tau \boldsymbol{B}_s \mathbf{1}\{t = \tau\} + \varepsilon_{ist}, \tag{8}$$

where Y_{ist} is the outcome for student i in school s and year t, D_s indicates program entry in 2023, and α_s and λ_t are school and year fixed effects. The vector $\boldsymbol{B}_s$ includes baseline attendance and critical reading fluency, each interacted with year. The parameters β_τ capture year-specific differential changes at treated schools, with standard errors clustered by school.

For this difference-in-differences (DID) to identify the causal effect of the program, treated and comparison schools have to follow parallel trends in student outcomes before the program. We assess this assumption using event-study estimates for 2018, 2019, and 2022. Pre-program estimates support parallel trends for the absence rate and the share of students with critical attendance, but not for the shares with regular attendance or chronic absenteeism (Figure A.7). We therefore only interpret estimates on these first two outcomes as causal.[44]

6.4.2 Difference-in-discontinuities

We next compare changes in discontinuities in student outcomes. We fit student-level local linear regressions at the original 85% school-attendance cutoff among eligible schools, comparing outcomes in follow-up year $k \in \{2023, 2024, 2025\}$ with 2022:[45]

$$Y_{ist} = \alpha + \gamma L_s + \lambda P_t + \tau L_s P_t + X_s \left(\beta_0 + \beta_1 L_s + \beta_2 P_t + \beta_3 L_s P_t\right) + \varepsilon_{ist}, \tag{9}$$

where X_s is the school's 2022 attendance rate centered at the selection threshold, $L_s = \mathbf{1}\{X_s < 0\}$ indicates a value below this cutoff, and $P_t = \mathbf{1}\{t = k\}$ identifies the follow-up year. In each regression, τ captures the change from 2022 to year k in the difference in outcomes just below and above the threshold. We allow slopes to differ across sides and years.[46]

[44] We estimated a staggered DID design that incorporated the 39 schools first treated in 2024, but it failed all parallel-trends tests, so we restrict the DID to the 2023 cohort in the main analysis. We also re-estimated the DID using a stable comparison group that excluded from every estimation period all comparison schools treated in 2024 or 2025. This alternative provided no robust evidence that facilitators improved attendance in any of the three follow-up years for schools assigned to receive them in 2023.

[45] For the national-assessment outcomes, the baseline year is 2021.

[46] For each outcome, we select a bandwidth using the 2023 data and estimate each regression by unweighted ordinary least squares within that same symmetric window, clustering standard errors by school.

6.5 Results

6.5.1 Did the government initiative reduce absences?

We find no evidence that the government initiative raised average attendance or reduced the share of students with high absences. The DID yielded precisely estimated null effects on the absence rate and critical attendance (<75% attendance) in 2023-2025 (Table 6, panel A). Across all follow-up years, the 95% confidence intervals rule out reductions larger than 0.6 pp. on the absence rate and 2 pp. in critical attendance relative to comparison schools. The difference-in-discontinuities estimates corroborate these results, but the estimated changes in the discontinuity were less precise than the corresponding DID estimates (Table 6, panel B).

6.5.2 Did the initiative improve students' performance in school?

The program did not improve students' school performance. In 2023-2025, the DID estimates show no statistically significant effects on passing, repetition, dropout, or graduation rates (Table 7, panel A). Across all years, the 95% confidence intervals rule out gains above 1.3 pp. in passing or 2.4 pp. in graduation, and reductions above 1.3 pp. in repetition or 0.03 pp. in dropout rates. The difference-in-discontinuities estimates show no significant gains (panel B).

The program did not improve students' grades. In 2025, the DID estimates show a 0.07 SD decline in math and a marginally significant reduction of 0.06 SDs in the average of math and language grades. Other effects, were insignificant in all years (Table A.21, panel A). The difference-in-discontinuities estimates show no significant effects on any outcome (panel B).

6.5.3 Did the initiative improve students' achievement?

The program led to no clear improvement in achievement. In math, the DID pre-trend tests provide evidence against the parallel-trends assumption, so we focus on language. The 95% confidence intervals rule out score gains above 0.05 SDs in 2023 and 0.19 SDs in 2025 (Table 8, panel A). The difference-in-discontinuities shows no gains in language; in 2025, we find a decline in language scores of 0.21 SDs, and increases in the shares of students in the lowest two levels of 4.4 and 7.51 pp. (Table 8, panel B). We observe a similar pattern in the provincial reading fluency test. For students' standardized reading fluency, the 95% confidence intervals rule out gains larger than 0.04 SDs in 2023, 0.1 SDs in 2024, and 0.14 SDs in 2025 (Table A.22).

6.5.4 Was the initiative cost-effective at increasing attendance?

The program was more expensive than the text-messaging interventions evaluated in study 3. Facilitators were paid for 10 hours per week at the substitute-teacher rate from March to November 2023 (DGE, 2023). Using the 2023 minimum monthly salary guarantee for an initial primary-school teaching post (ARS 110,000 in March, rising to ARS 220,000 by November),

we estimate a cost of about ARS 700,000 per facilitator, or USD 1,750 at the 2023 average official exchange rate.[47] Across the 184 schools in the 2023 cohort, this implies a total cost of ARS 129 million (USD 322,000), or about USD 5 per student among the 64,400 students in program schools (Bonelli et al., 2023).[48] Because neither design shows a statistically significant reduction in the absence rate or critical attendance, we do not calculate a cost per additional day of attendance and cannot determine whether the program was cost-effective.

7 Discussion

7.1 Student absenteeism

This study offers possibly the most comprehensive account of student absenteeism in an LMIC. We are among the first to combine systemwide coverage rather than samples, individual records rather than aggregates, full years rather than snapshots, and registers rather than surveys.[49] Our unique data allow us to document how pervasive student absenteeism is in these settings, but also how it is concentrated among early grades and low-income households around specific points in the year, offering concrete guidance on who to target and when for maximal impact.

Our study is also one of the first to estimate the causal effect of absences in an LMIC.[50] Based on studies from the U.S. (Goodman, 2014; Goldman and Gracie, 2024; Liu et al., 2021), we were surprised to find mixed effects of weather-induced absences on school performance and uncertain evidence of achievement losses. Yet, studies in LMICs have found that gains in participation or progression need not improve learning (Miguel and Kremer, 2004; Filmer and Schady, 2014; Barrera-Osorio and Filmer, 2016). This disconnect may help explain our findings, although imprecision and weak instruments limit our conclusions.

Our study is also one of the few to present causal evidence on two contrasting approaches to reducing student absences—one popular among researchers (nudges) and one championed by advocates (school-based)—in the same context during the same period, even beyond LMICs. We know of two randomized evaluations comparing similar low- and high-touch approaches: Heppen et al. (2020) in four urban U.S. districts and Swanson (2023) in Ohio and New York. These two studies reach conflicting conclusions: the first one finds that personalized school-

[47] The salary guarantee is defined for one teaching post, or its equivalent in teaching hours. Mendoza treats 18 teaching hours as one post for this purpose, so we prorate the monthly guarantee by 10/18, sum March-November, and convert at roughly ARS 400/USD.

[48] These cost estimates exclude training, administration, travel, facilitator recruitment, and coordination with other school staff, so they provide a lower bound on the program's total cost.

[49] Our closest analogs are Crawfurd (2016) in South Sudan, Singh (2022) in Delhi, India, and Arbour et al. (2023) in a region of Chile, but the first two use school-by-grade absence counts, which preclude links to student-level outcomes, and the last one focuses on a relatively small sample of only 46 schools.

[50] Paredes and Ugarte (2011) in Chile come closest, but ultimately rely on school fixed effects. Rainfall predicts attendance, but their exactly identified model precludes an overidentification test.

staff outreach outperformed automated goal-setting messages among high-absence students, and the second one finds personalized messaging reduced absences while mentoring did not. Our results align with the latter and suggest intensive interventions do not always fare better. Our detailed cost data also show that the light-touch approach is superior in cost-effectiveness.

Lastly, the results from this study invite us to shift the focus of research and policy debates on the effect of the COVID-19 pandemic on the levels of and norms around school attendance. At its height, the global conversation focused on school closures (Azevedo et al., 2021; Kaffenberger, 2021; Schady et al., 2023; Hevia et al., 2022). Fewer studies have examined its effects on absences once schools reopened (Moscoviz and Evans, 2022; Jack et al., 2023; Dee, 2024). And fewer still have asked whether that surge faded or settled into a new normal. In our setting, we find that the pandemic induced a one-time shock and that attendance levels are trending towards pre-pandemic levels, although potentially settling at a higher equilibrium.

7.2 Instructional time

Our study also contributes to research and policy debates on instructional-time expansions. In more than 60% of countries, the school day still spans only half the day (UNESCO, 2007). In light of evidence suggesting that more instructional time leads to better learning outcomes (Lavy, 2015, 2020), many countries recently expanded the school day (Alfaro et al., 2015; Radinger and Boeskens, 2021; Gamberini et al., 2025). These efforts are costly because they require building new schools, buying furniture and equipment, and expanding teaching hours.[51] Yet, their effects in LMICs on learning outcomes span a wide range (Bellei, 2009; Cruz et al., 2017; Cabrera-Hernández, 2020; Agüero et al., 2021; Rosa et al., 2022; Estrada et al., 2025). Our results raise the possibility that such variation may be partly explained by differences in attendance, and that some may be pouring water into a leaky (instructional time) bucket.[52] To our knowledge, no evaluation has explored this source of heterogeneity, which seems like a major oversight given that the students these efforts seek to support are absent most often.

In contexts with high absences, focusing on reducing them would be more cost-effective. The text messages that we evaluated yielded one-off improvements in test scores that overlap with those of school-day expansion, but at a cost that is several orders of magnitude lower. Prior studies suggest that, if messages had gone on for longer and reduced absences by a larger magnitude, our effects could have been even larger (Berlinski et al., 2025; Lichand et al., 2026), which would tip the balance further from expanding required to *effective* instructional time.

[51]The reform in Chile increased public-education operating costs by 25%, excluding investments in infrastructure (Bellei, 2009); the one in Mexico cost about USD 400 per student (Cabrera-Hernández, 2020); and full-day schools in Uruguay cost 60% more than half-day schools (Cerdan-Infantes and Vermeersch, 2007).

[52]Consider Argentina's latest initiative, which adds one hour to every school day (*Resolución N° 426/22*, 2022). It delivers roughly 190 additional instructional hours per year. Yet at Mendoza's 15% absence rate, the average student loses roughly 127 hours of instruction per year—about 67% of the hours the policy adds.

7.3 Behavioral nudges

This study builds on a large literature on nudges to reduce absenteeism, including several studies in South America (Ajzenman et al., 2022; Berlinski et al., 2025; Lichand et al., 2026). Yet ours is the only one in which such nudges were implemented at scale by a government (not researchers), offering a more realistic appraisal of the effect of these nudges as policies. In fact, the Mendoza government has integrated absence notifications into its smartphone app, reaching the parents of nearly half a million students from pre-primary to secondary school.

Our study also advances our understanding of the relative merits of information and reminders in driving the effects of nudges. Lichand et al. (2026) found that reminders in Sao Paulo accounted for 89-126% of the effects of information messages on attendance over a year. Our results highlight the importance of tracking the effects of interventions after they end. In our setting, while information and reminders had nearly identical effects at the end of the intervention period, the former ended up having larger and longer-lasting effects on absences. This insight has key policy implications: information messages require daily, student-level, digitized attendance data, which few LMICs have; reminders require no such infrastructure. Our results suggest that school systems capable of implementing both options would reduce absences more cost-effectively if they favored information and that those systems that cannot would stand to benefit from making the requisite investments to digitize attendance records.

8 Conclusion

We know very little about student absenteeism in LMICs. Existing evidence relies heavily on surveys, small samples, and snapshots that cannot show how the problem unfolds across a school system. Daily administrative records from public primary schools in a middle-income country allow us to examine who misses school, when, and with what consequences, and to evaluate government efforts to improve attendance. Following students over several years also distinguishes temporary changes from persistent patterns and reveals whether intervention effects outlast delivery. Together, these analyses connect the measurement of absences to the design and evaluation of public policies within a shared institutional setting and time period.

Our findings suggest that absenteeism is pervasive, predictable, and partly preventable. School registers reveal far higher absence rates than self-reports and identify most eventual chronic absentees early in the year, while missed days cluster around weekends, holidays, and breaks. Students who miss more school perform worse, but much of this relationship reflects differences between children, and the causal effects of weather-induced absences are mixed. Personalized text messages informing parents of their children's absences reduced chronic absenteeism for years after delivery ended, whereas reminders about the importance of attendance had only short-term effects. Paying teachers to identify and support high-absence

students produced no clear improvements in attendance, school performance, or achievement. These findings suggest that existing daily records can help governments identify students at risk and prevent some missed days through timely, inexpensive communication with parents.

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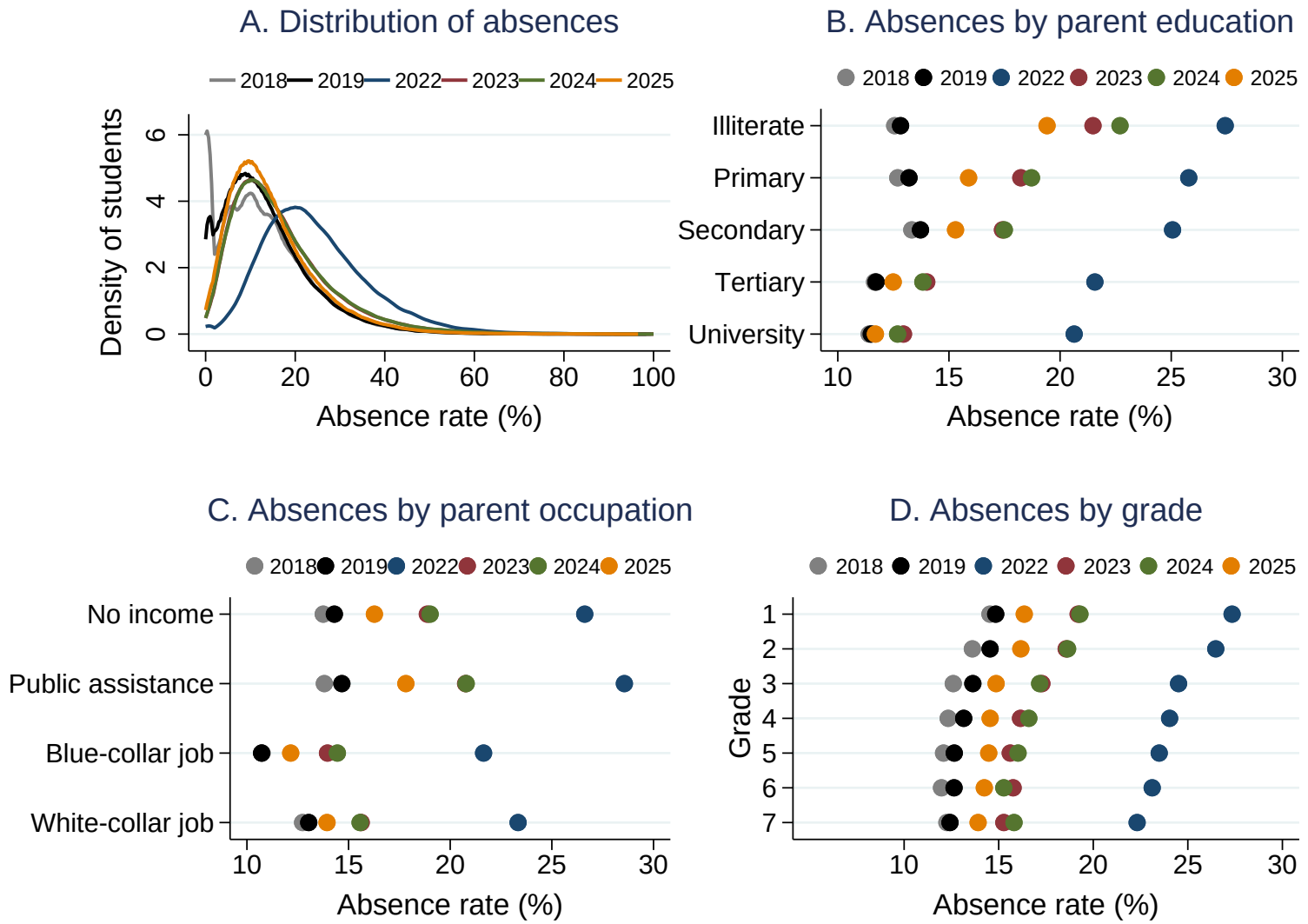
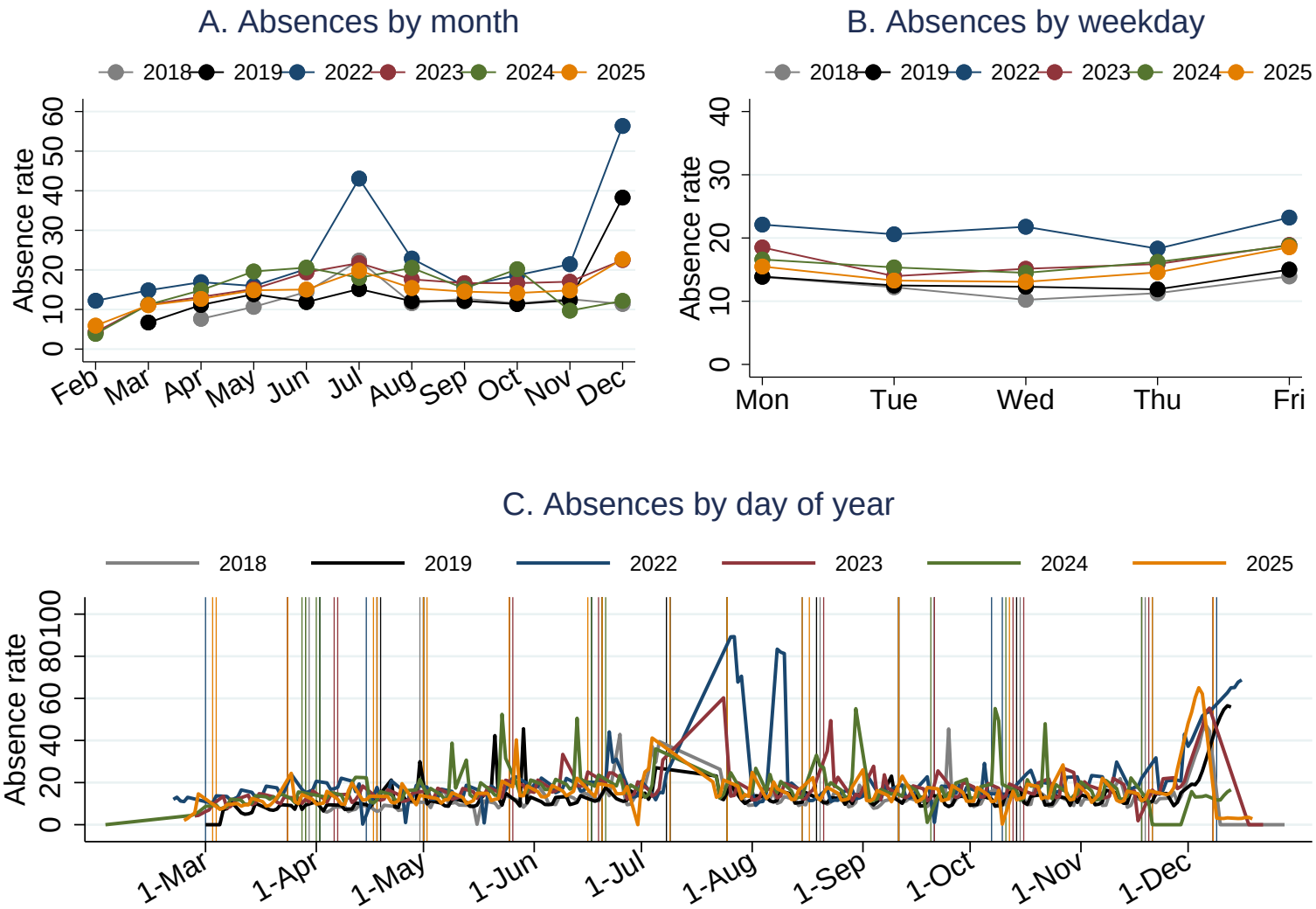
Figure 1: Distribution of absence rates and relationship to student characteristics, 2018, 2019, and 2022-2025



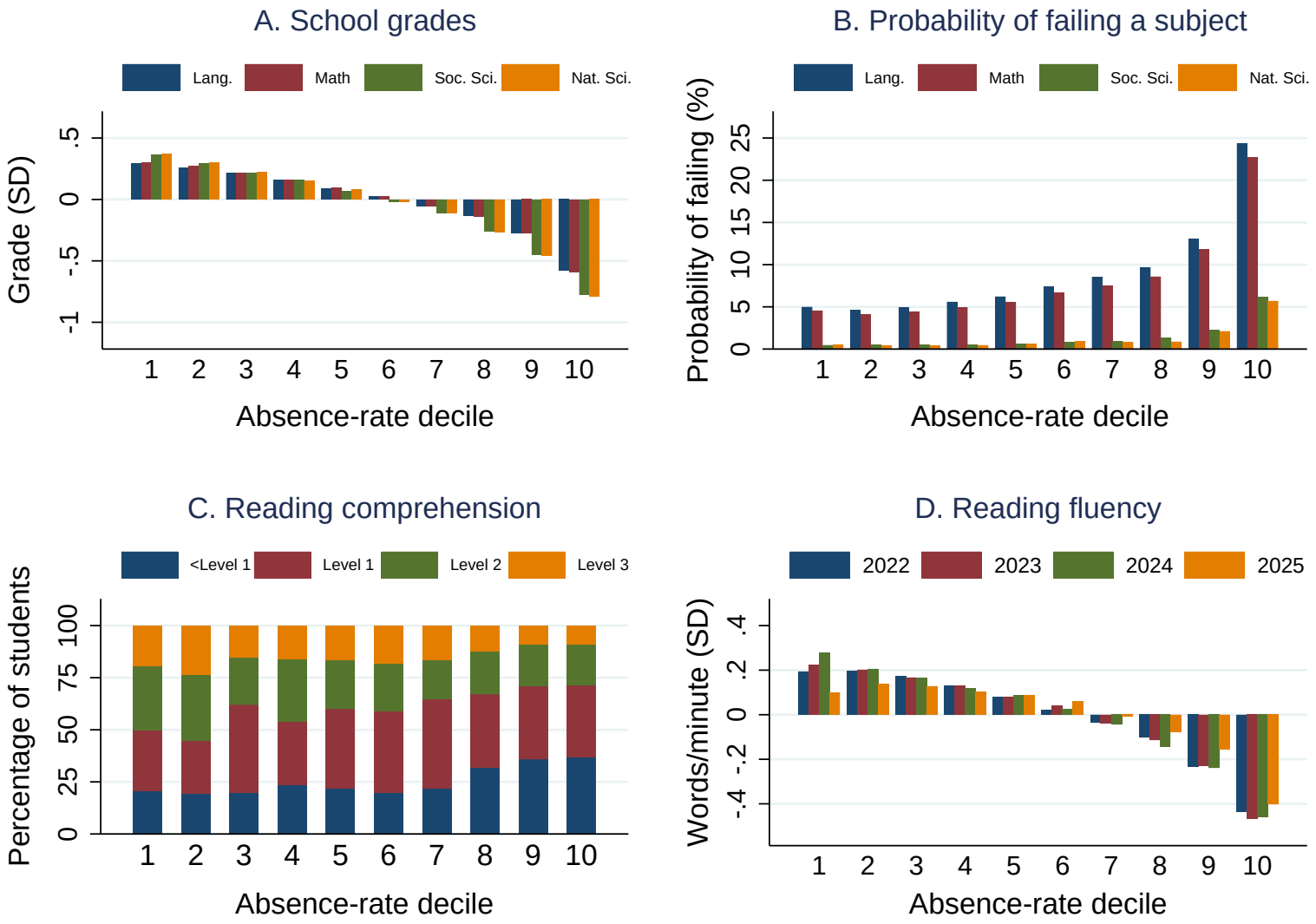
Notes: This figure shows the distribution of student absences and the relationship between absences and students' characteristics. The distribution of absence rates for all public primary-school students in Mendoza is plotted in panel A for 2018, 2019, and 2022-2025. Average absence rates by the highest education and occupation categories across each student's available parents in every year are plotted in panels B and C, respectively. Parent characteristics measured in 2019 are used for 2018-2019; those measured in 2022-2024 are used contemporaneously; and 2024 characteristics are used for 2025. Average absence rates by student grade in every year are plotted in panel D.

Figure 2: Absence rates by month, day of the week, and day of the year, 2018, 2019, and 2022-2025



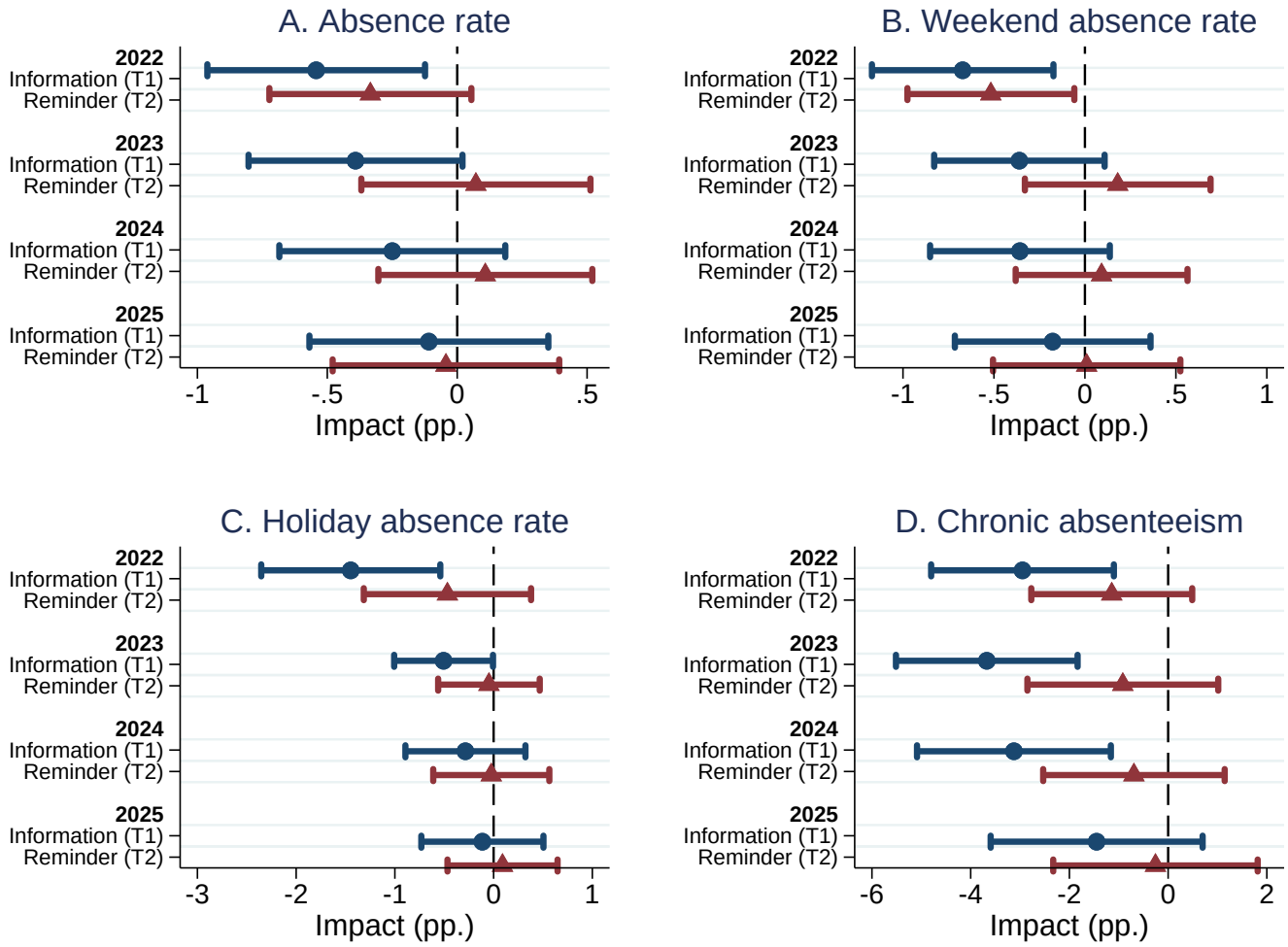
Notes: This figure shows student absences by month, day of the week, and day of the year in the province of Mendoza in 2018, 2019, and 2022-2025. Panels A and B plot the average absence rate by month and day of the week, respectively, and panel C plots the share of absent students by day of the school year. In panel C, the vertical lines mark holidays in Mendoza's school calendar, color-matched to each year.

Figure 3: Absence rates, school performance, and student achievement in the province of Mendoza, 2022-2025



Notes: This figure shows the relationship between students' absences, their performance in school, and on standardized tests in the province of Mendoza. Subject-specific grades standardized within school and grade in 2022 appear in panel A. The probability of failing each subject in 2022 appears in panel B. Reading comprehension levels in 2022 appear in panel C. Average words per minute, standardized within grade and averaged across available assessment waves, are plotted by absence decile for each year from 2022-2025 in panel D.

Figure 4: ITT effects of information and reminder text messages on school absences, 2022-2025



Notes: This figure shows the intent-to-treat (ITT) effect of each intervention on four outcomes for September-November 2022 (after randomization) and for 2023-2025 excluding December. Each panel displays one outcome, with separate estimates for the information (T1, in navy) and reminder (T2, in maroon) interventions. Impact estimates come from regressions of each variable on treatment indicators, randomization-strata (i.e., department) fixed effects, and covariates determined by the LASSO procedure. Weekend and holiday rates divide absences on the relevant days by recorded Mondays/Fridays and holiday-adjacent days, respectively; dates separated from a holiday by a weekend are excluded. Chronic absenteeism means missing 10% or more of schooldays. Effects are in percentage points; bars show 95% confidence intervals based on school-clustered standard errors.

Table 1: Distribution of absence rates, 2018, 2019, and 2022-2025

	(1) 2018	(2) 2019	(3) 2022	(4) 2023	(5) 2024	(6) 2025
A. Absence rate (%)						
Mean	12.8	13.4	24.5	16.8	16.9	14.9
Standard deviation	10.7	10.1	12.0	11.2	11.4	10.0
5th percentile	0.00	0.54	8.45	3.45	3.45	2.91
25th percentile	4.76	6.21	16.0	8.84	8.84	7.94
Median	11.1	11.5	22.7	14.4	14.4	12.7
75th percentile	18.4	18.3	31.0	22.1	22.3	19.6
95th percentile	32.6	32.4	46.6	38.5	38.8	33.9
B. Absences near weekends (%)						
Mean	14.1	14.5	22.7	18.8	17.8	17.0
Standard deviation	12.3	11.2	13.1	12.8	12.4	11.8
5th percentile	0.00	0.00	5.97	3.03	2.90	2.82
25th percentile	4.55	6.76	13.2	9.23	8.70	8.45
Median	12.1	12.3	20.3	16.1	15.0	14.1
75th percentile	20.5	20.3	29.4	25.4	23.9	22.5
95th percentile	37.5	35.9	47.8	43.8	41.9	39.4
C. Absences near holidays (%)						
Mean	15.1	16.7	23.3	20.9	17.6	17.8
Standard deviation	15.2	14.4	13.5	14.2	15.6	12.4
5th percentile	0.00	0.00	6.67	3.85	0.00	3.57
25th percentile	0.00	9.09	13.3	11.5	7.14	7.14
Median	11.8	13.6	20.7	18.8	14.3	14.3
75th percentile	25.0	27.3	30.0	28.0	26.9	25.0
95th percentile	44.4	45.5	50.0	48.0	50.0	41.1
D. Absence thresholds (%)						
Chronic ($\geq$10% absence)	54.6	57.1	92.4	69.8	69.8	64.6
Regular (15-25% absence)	24.0	24.2	37.0	28.8	28.5	26.5
Critical (>25% absence)	11.9	11.7	41.8	18.7	19.2	13.8
N (students)	149,284	192,077	193,420	189,865	184,877	179,819

Notes: This table reports the distribution of student absence rates in public primary schools in Mendoza in 2018, 2019, and 2022-2025. Panel A reports the mean, standard deviation, and selected percentiles. Panels B and C report absences near weekends and holidays. Panel D reports overlapping benchmarks: chronic absence (at least 10% of schooldays), the U.S. benchmark used in the literature, and Mendoza's regular (15-25%) and critical (more than 25%) absence categories. The final row reports the number of students in each year.

Table 2: Effects of absences on achievement and school performance, 2019 and 2022-2025

	(1)	(2)	(3)	(4)
	Math		Language	
	Score (SD)	Below basic (pp.)	Score (SD)	Below basic (pp.)
A. National assessments				
Absence rate (10 pp.)	-0.06	1.49	0.00	1.24
	(0.07)	(2.88)	(0.07)	(1.67)
First-stage F-statistic	101	102	93.0	85.7
N (students)	43,387	43,387	43,940	43,940
	Reading fluency		Reading comprehension	
	Words per minute	Critical level (pp.)	Below lowest level (pp.)	Highest level (pp.)
B. Provincial assessments				
Absence rate (10 pp.)	-4.19	3.70	2.45	-5.60
	(3.01)	(2.59)	(14.6)	(10.2)
First-stage F-statistic	13.1	13.1	10.5	10.5
N (student-waves)	1,241,613	1,241,613		
N (students)			1,745	1,745
	Language (SD)	Math (SD)	Average grade (SD)	Subjects failed (pp.)
C. School grades				
Absence rate (10 pp.)	-0.15	-0.24**	-0.21**	-6.50
	(0.10)	(0.11)	(0.10)	(4.39)
First-stage F-statistic	18.4	18.3	18.6	18.7
N (student-periods)	1,995,682	1,994,953	1,991,389	1,992,086
	Passing rate (pp.)	Repetition rate (pp.)	Dropout rate (pp.)	Graduation rate (pp.)
D. School performance				
Absence rate (10 pp.)	-0.45	0.46	-0.01	-1.91
	(0.43)	(0.43)	(0.01)	(2.87)
First-stage F-statistic	125	125	125	88.8
N (student-years)	689,371	689,371	689,371	102,863

Notes: This table reports instrumental-variable effects of absences on achievement and school performance. Estimates correspond to a 10 pp. increase in the absence rate. National assessments in panel A use 2023 and 2025 censuses, February-November rainy-weekday instruments, and 2016, 2018, and 2021 achievement controls. Scores are standardized by year; below-basic outcomes are in pp. Provincial assessments in panel B pool 2022-2025 reading fluency with prior-week rainy-weekday instruments and report 2022 grade-4 reading comprehension with rainy-weekday instruments through June. Grades in panel C pool 2019 and 2022-2025 grading periods, excluding December, with within-period rainy-weekday instruments. Grades are standardized within year, subject, school, and grade. Columns 3 and 4 report the average of math and language grades and the percentage below 7, respectively, requiring both subjects to be observed in each period. School performance in panel D pools 2022-2025 passing, repetition, dropout, and graduation rates, using February-November rainy-weekday instruments. Fixed effects are student and assessment-period for fluency and grades, year for national assessments, and year and grade for school performance (year only for graduation). Reading comprehension includes neither fixed effects nor additional covariates. Standard errors are clustered by weather-data grid for fluency and by school otherwise. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: ITT and TOT effects of text messages on school absences, 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Absence rate (pp.)				Weekend absence rate (pp.)				Holiday absence rate (pp.)				Chronic absenteeism (pp.)			
	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025
A. ITT																
Information (T1)	-0.54**	-0.39*	-0.25	-0.11	-0.67***	-0.36	-0.36	-0.18	-1.45***	-0.51**	-0.29	-0.11	-2.95***	-3.67***	-3.12***	-1.45
	(0.21)	(0.21)	(0.22)	(0.23)	(0.25)	(0.24)	(0.25)	(0.27)	(0.46)	(0.25)	(0.31)	(0.31)	(0.94)	(0.94)	(1.00)	(1.09)
Reminder (T2)	-0.33*	0.07	0.11	-0.04	-0.52**	0.18	0.09	0.01	-0.47	-0.05	-0.02	0.09	-1.14	-0.92	-0.69	-0.26
	(0.20)	(0.22)	(0.21)	(0.22)	(0.23)	(0.26)	(0.24)	(0.26)	(0.43)	(0.26)	(0.30)	(0.28)	(0.83)	(0.98)	(0.94)	(1.05)
Control mean	17.0	15.8	16.3	14.1	21.0	18.7	17.5	16.4	21.2	16.9	17.0	16.5	67.8	66.1	70.0	59.7
P-value (T1=T2)	0.31	0.04	0.08	0.75	0.53	0.04	0.05	0.45	0.02	0.08	0.33	0.43	0.06	0.01	0.01	0.26
N (students)	164,777	138,587	113,730	90,572	157,379	138,585	113,730	90,572	157,155	138,442	113,636	90,572	164,836	138,694	113,816	90,581
B. TOT																
Information (T1)	-0.68***	-0.50**	-0.32	-0.13	-0.77**	-0.45	-0.46	-0.21	-1.77***	-0.65**	-0.33	-0.13	-3.41***	-4.18***	-3.66***	-1.34
	(0.26)	(0.25)	(0.26)	(0.28)	(0.30)	(0.28)	(0.30)	(0.33)	(0.55)	(0.30)	(0.37)	(0.38)	(1.14)	(1.09)	(1.17)	(1.25)
Reminder (T2)	-0.47**	0.03	0.08	-0.10	-0.67***	0.15	0.07	-0.03	-0.58	-0.10	-0.11	0.04	-1.61*	-1.20	-0.92	-0.49
	(0.21)	(0.25)	(0.23)	(0.25)	(0.26)	(0.29)	(0.27)	(0.29)	(0.48)	(0.29)	(0.33)	(0.31)	(0.92)	(1.08)	(1.03)	(1.17)
Control mean	17.0	15.8	16.3	14.1	21.0	18.7	17.5	16.4	21.2	16.9	17.0	16.5	67.8	66.1	70.0	59.7
N (students)	164,777	138,587	113,730	90,572	157,379	138,585	113,730	90,572	157,155	138,442	113,636	90,572	164,836	138,694	113,816	90,581

Notes: This table shows the intent-to-treat (ITT) and treatment-on-the-treated (TOT) effects of each intervention on students' absence rate, weekend absence rate (Fridays and Mondays), holiday absence rate (before and after holidays), and chronic absenteeism (missing 10% or more of schooldays) for September-November 2022 (after randomization) and for 2023-2025 excluding December. In every year, weekend and holiday rates divide absences on the relevant days by recorded Mondays/Fridays and holiday-adjacent days, respectively. ITT estimates come from regressions of each variable on treatment indicators, randomization-strata (i.e., department) fixed effects, and covariates determined by the LASSO procedure. TOT estimates are 2SLS: for each treatment arm, we restrict the sample to students in that arm and the control group, and instrument actual message receipt with random assignment. The first-stage compliance rates are 82% for T1 and 88% for T2 ($p < 0.001$ in both arms), and treated parents received an average of 3.3 (T1) and 5.0 (T2) messages out of 7. The reported N (students) refers to the full ITT sample; each TOT estimate uses only students in that arm and the control group, yielding approximately two-thirds of the reported sample. Standard errors are clustered at the school level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: ITT effect of text messages on grades and school performance, 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Language (SD)				Math (SD)				Average grade (SD)				Subjects failed (pp.)			
	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025
A. School grades																
Information (T1)	0.00	-0.01	0.02	0.04*	0.00	0.00	0.01	0.04**	0.00	-0.01	0.02	0.05**	-0.63*	0.05	-0.29	-0.62
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.34)	(0.39)	(0.37)	(0.39)
Reminder (T2)	0.01	0.00	0.01	0.03	0.01	-0.01	0.01	0.03	0.01	-0.01	0.01	0.03	-0.75**	0.22	-0.20	-0.76**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.34)	(0.38)	(0.36)	(0.37)
Control mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.59	7.91	6.87	5.76
P-value (T1=T2)	0.56	0.52	0.46	0.38	0.44	0.45	0.74	0.53	0.45	0.99	0.58	0.44	0.70	0.63	0.79	0.69
N (students)	159,393	135,702	112,140	89,857	159,446	135,686	112,115	89,853	159,298	135,652	112,084	89,845	159,297	135,659	112,096	89,860
	Passing rate (pp.)				Repetition rate (pp.)				Dropout rate (pp.)				Graduation rate (pp.)			
	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025
B. School performance																
Information (T1)	-0.19	-0.28	0.45	0.24	0.19	0.28	-0.45	-0.26*	0.00	0.00	0.00	0.00	-0.72	0.10	-0.54	-1.07*
	(0.20)	(0.25)	(0.30)	(0.16)	(0.20)	(0.25)	(0.30)	(0.16)	(0.00)	(0.00)	(0.00)	(0.01)	(0.70)	(0.69)	(0.64)	(0.65)
Reminder (T2)	-0.05	-0.16	0.28	0.01	0.06	0.16	-0.28	-0.02	0.00	0.00	0.00	0.00	-0.55	-0.02	-0.07	-1.06
	(0.19)	(0.22)	(0.31)	(0.19)	(0.19)	(0.22)	(0.31)	(0.19)	(0.00)	(0.00)	(0.00)	(0.01)	(0.67)	(0.79)	(0.66)	(0.86)
Control mean	97.7	97.5	98.2	98.6	2.28	2.51	1.82	1.44	0.00	0.00	0.00	0.01	92.0	92.5	93.6	93.6
P-value (T1=T2)	0.48	0.63	0.32	0.23	0.50	0.63	0.33	0.19	0.05	0.36	0.12	0.42	0.82	0.88	0.46	1.00
N (students)	152,280	129,244	106,890	85,615	152,280	129,244	106,890	85,615	155,490	132,021	109,363	87,515	22,215	22,511	21,553	21,172

Notes: This table shows the intent-to-treat (ITT) effect of each intervention on students' final grades and school performance over four school years. In panel A, columns 1-4 report language grades, columns 5-8 report math grades, columns 9-12 report average math and language grades, and columns 13-16 report the number of these two subjects failed. In panel B, columns 1-4 report the passing rate, columns 5-8 the repetition rate, columns 9-12 the dropout rate, and columns 13-16 the graduation rate. Within each group, columns correspond to 2022-2025. Grade outcomes are expressed in year-specific control-group standard deviations. School performance outcomes are expressed in percentage points. Impact estimates come from regressions of each variable on treatment indicators, randomization-strata (i.e., department) fixed effects, and covariates determined by the LASSO procedure. School-clustered standard errors are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All outcomes are binary, and significance levels use two-sided tests.

Table 5: ITT effect of text messages on national-assessment achievement, 2023 and 2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Math						Language					
	Score (SDs)		% below basic		% basic		Score (SDs)		% below basic		% basic	
	2023	2025	2023	2025	2023	2025	2023	2025	2023	2025	2023	2025
Information (T1)	0.01	-0.01	0.44	0.68	-1.23	-0.15	0.06**	-0.03	-2.62***	-0.21	-0.46	0.09
	(0.03)	(0.03)	(1.43)	(0.97)	(0.94)	(0.89)	(0.03)	(0.03)	(0.83)	(0.44)	(0.88)	(0.86)
Reminder (T2)	0.03	0.00	-1.13	0.27	0.29	-0.69	0.06**	0.02	-1.63*	-0.47	-1.48*	-0.77
	(0.03)	(0.03)	(1.41)	(0.97)	(1.02)	(0.90)	(0.03)	(0.03)	(0.88)	(0.42)	(0.84)	(0.86)
Control mean	0.00	0.00	27.6	20.9	27.3	28.2	0.00	0.00	14.6	4.49	24.1	19.5
P-value (T1=T2)	0.47	0.54	0.25	0.67	0.12	0.54	0.80	0.07	0.21	0.56	0.25	0.30
N (students)	18,873	19,182	18,873	19,182	18,873	19,182	19,230	19,275	19,230	19,275	19,230	19,275

Notes: This table reports the intent-to-treat (ITT) effect of each intervention on grade-6 national-assessment achievement. Columns 1-6 report mathematics outcomes and columns 7-12 report language outcomes; within each subject, the column groups report average scores, the percentage of students below basic, and the percentage at the basic level, with columns corresponding to 2023 and 2025. Average scores are in control-group standard deviations (SD); performance-level effects are in percentage points (pp.). Impact estimates come from regressions of each outcome on treatment indicators, department fixed effects, and LASSO-selected pre-treatment covariates, including school-level achievement in 2021, changes in school-level achievement from 2016 to 2018 and from 2018 to 2021, performance-level shares, and tested-student counts. School-clustered standard errors are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: DID and difference-in-discontinuities estimates of the impact of the government initiative on student attendance, 2023-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Absence rate (pp.)			Critical attendance (pp.) < 75%			Regular attendance (pp.) 75-85%			Chronic absenteeism (pp.) < 90%		
	2023	2024	2025	2023	2024	2025	2023	2024	2025	2023	2024	2025
A. Difference-in-differences												
Program effect	-0.11	-0.05	0.27	-0.74	-0.09	-0.08	1.03	0.31	2.04	0.73	0.21	2.54
	(0.24)	(0.26)	(0.43)	(0.57)	(0.69)	(0.96)	(0.69)	(0.68)	(1.11)	(1.06)	(1.10)	(1.83)
Comparison mean	13.8	14.7	12.2	11.8	12.6	9.14	24.0	27.2	19.9	58.6	64.4	50.6
N (students)	160,035	155,803	73,321	160,035	155,803	73,321	160,035	155,803	73,321	160,035	155,803	73,321
P-value (parallel trends)		0.39			0.68			0.01			0.04	
B. Difference-in-discontinuities												
Program effect	-0.33	-0.40	0.22	0.22	0.21	2.09	-0.71	-1.76	-0.22	-3.80	-4.23	0.45
	(0.41)	(0.49)	(0.62)	(0.97)	(1.29)	(1.32)	(1.25)	(1.32)	(1.53)	(2.49)	(2.83)	(3.48)
N (student-year observations)	149,490	147,655	146,221	141,344	139,557	138,332	188,764	186,417	184,471	140,366	138,595	137,385

Notes: This table reports student-level DID and difference-in-discontinuities estimates of the impact of the government initiative on the absence rate, the shares of students in the province's critical and regular attendance categories, and chronic absenteeism. Attendance excludes December. Critical attendance means attending less than 75% of schooldays, regular attendance means attending 75-85%, and chronic absenteeism means attending less than 90%. Columns 1-3 report the absence rate, columns 4-6 report critical attendance, columns 7-9 report regular attendance, and columns 10-12 report chronic absenteeism; within each outcome group, columns correspond to 2023-2025. The DID estimates for 2023 and 2024 compare 184 schools first treated in 2023 with 284 eligible schools not treated in either year; the 2025 estimates also exclude comparison schools that received a facilitator in 2025. DID specifications include school and year fixed effects and interact year indicators with schools' baseline attendance rate and share of students with critical reading fluency. The parallel-trends row reports joint tests of the 2018 and 2019 treatment-group interactions, relative to 2022. Because these tests reject parallel trends for regular attendance and chronic absenteeism, we interpret those DID estimates as descriptive. The difference-in-discontinuities estimates compare each follow-up year with 2022 at the original 85% selection cutoff among eligible schools. Separate local linear regressions use the fixed 2022 school attendance rate, unweighted ordinary least squares, and the same outcome-specific symmetric bandwidth selected from the 2023 data. DID counts refer to students in the indicated follow-up year; difference-in-discontinuities counts include student-year observations in both estimation periods within the bandwidth. Standard errors clustered at the school level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: DID and difference-in-discontinuities estimates of effects on school performance, 2023-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Passing rate (pp.)			Repetition rate (pp.)			Dropout rate (pp.)			Graduation rate (pp.)		
	2023	2024	2025	2023	2024	2025	2023	2024	2025	2023	2024	2025
A. Difference-in-differences												
Effect	0.33	-0.02	0.13	-0.33	0.02	-0.13	0.01	0.01	0.00	0.79	0.22	-0.94
	(0.31)	(0.26)	(0.59)	(0.31)	(0.26)	(0.59)	(0.00)	(0.01)	(0.01)	(0.82)	(0.81)	(1.20)
Comparison mean	98.2	98.3	97.5	1.82	1.70	2.54	0.00	0.00	0.01	92.7	93.6	95.3
N (students)	150,665	147,056	68,441	150,665	147,056	68,441	150,665	147,056	68,441	22,862	22,090	10,413
B. Difference-in-discontinuities												
Effect	0.26	-0.81	-0.33	-0.28	0.81	0.32	0.02	0.00	0.01	2.81	2.04	-0.31
	(0.52)	(0.59)	(0.67)	(0.52)	(0.59)	(0.67)	(0.01)	(0.01)	(0.01)	(2.09)	(2.02)	(2.44)
N (student-years)	133,857	132,338	130,543	133,857	132,338	130,543	148,109	146,428	144,387	25,198	24,915	24,816
Bandwidth (pp.)	2.13	2.13	2.13	2.13	2.13	2.13	2.41	2.41	2.41	2.84	2.84	2.84

Notes: This table reports student-level DID and difference-in-discontinuities estimates of the impact of the government initiative on school performance. Outcomes include passing, repetition, dropout, and grade 7 graduation rates, with columns for 2023-2025 within each group. All estimates are in percentage points. The DID estimates in panel A compare schools first treated in 2023 with eligible schools not treated in either that year or 2024; the 2025 comparison also excludes those that received a facilitator in the final follow-up. Specifications include school and year fixed effects and interact annual indicators with baseline attendance and critical reading fluency. The passing, repetition, and dropout regressions also include grade fixed effects. Outcomes are unavailable before 2022, preventing pre-intervention parallel-trends tests. The difference-in-discontinuities estimates in panel B compare each follow-up with 2022 at the original 85% attendance cutoff among eligible schools, retaining those that received facilitators later. The running variable is the school's 2022 attendance rate in every regression. Local linear specifications allow slopes to differ across sides and periods, using unweighted ordinary least squares within the same outcome-specific symmetric bandwidth selected from the 2023 data. Bandwidths are reported in percentage points of the baseline attendance rate. DID counts refer to students in the indicated follow-up; difference-in-discontinuities counts include observations from both estimation periods within the bandwidth. Standard errors clustered at the school level appear in parentheses. * 10%; ** 5%; *** 1%.

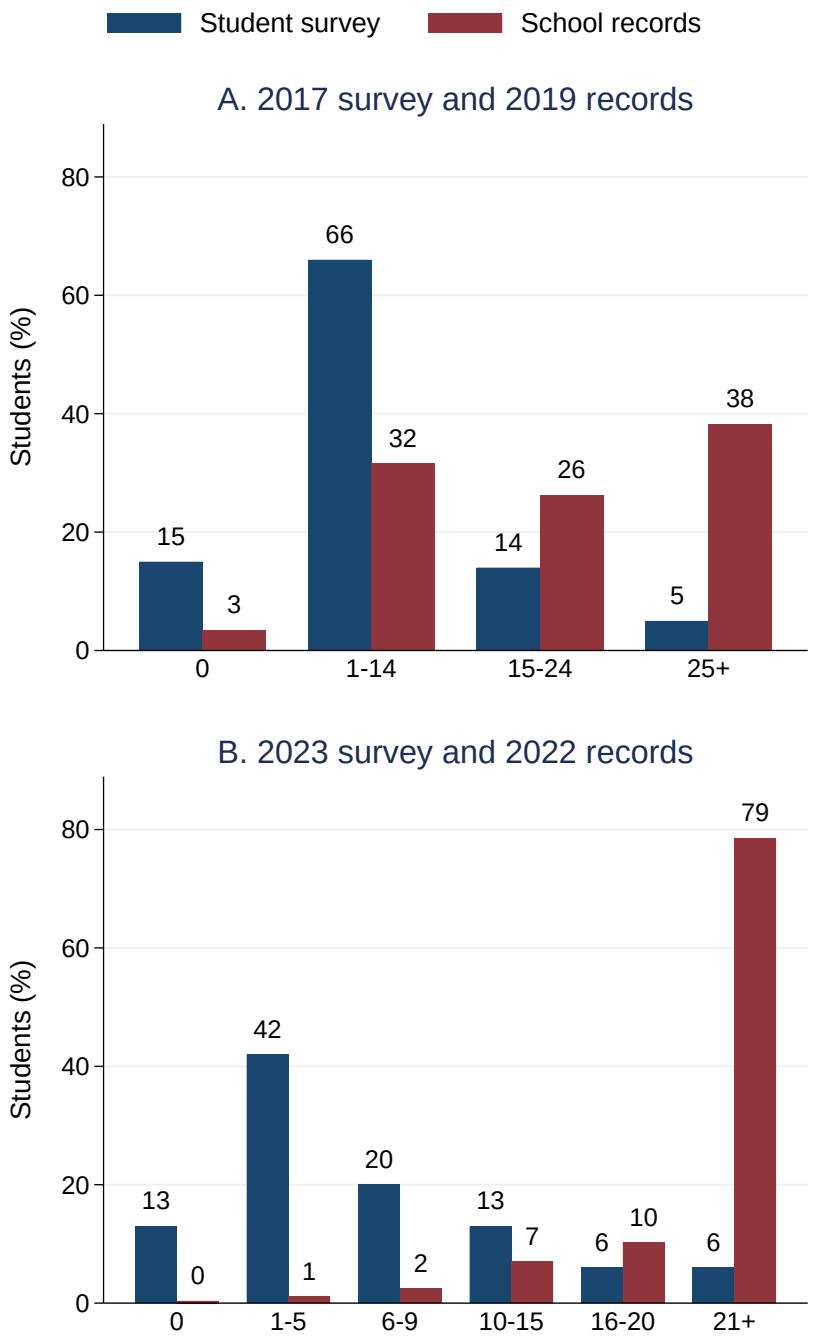
Table 8: DID and difference-in-discontinuities estimates of effects on grade 6 national-assessment achievement, 2023 and 2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Math						Language					
	Score (SDs)		Below basic (pp.)		Basic (pp.)		Score (SDs)		Below basic (pp.)		Basic (pp.)	
	2023	2025	2023	2025	2023	2025	2023	2025	2023	2025	2023	2025
A. Difference-in-differences												
Effect	0.10*	0.12	-3.44	-3.63	0.20	-1.19	-0.04	0.02	1.83	2.12	0.56	-3.41
	(0.06)	(0.10)	(2.19)	(3.24)	(1.58)	(2.43)	(0.04)	(0.08)	(1.18)	(1.62)	(1.48)	(2.71)
Comparison mean	0.00	0.00	24.1	23.1	25.9	28.5	0.00	0.00	11.0	5.14	21.4	21.7
N (students)	18,625	8,766	18,625	8,766	18,625	8,766	19,007	8,813	19,007	8,813	19,007	8,813
P-value (parallel trends)	0.06	0.07	0.09	0.11	0.46	0.19	0.54	0.12	0.42	0.09	0.25	0.82
B. Difference-in-discontinuities												
Effect	0.00	-0.10	-4.40	1.08	-0.50	1.87	-0.05	-0.21**	-1.47	4.40**	1.88	7.51***
	(0.10)	(0.10)	(3.85)	(3.21)	(4.35)	(4.28)	(0.08)	(0.09)	(2.45)	(1.80)	(2.69)	(2.68)
N (student-year observations)	22,135	22,263	19,023	19,150	13,711	13,887	21,137	21,116	17,905	18,039	17,905	18,039
Bandwidth (pp.)	3.22	3.22	2.58	2.58	1.67	1.67	2.86	2.86	2.22	2.22	2.29	2.29

Notes: This table reports student-level DID and difference-in-discontinuities estimates of the impact of the government initiative on national-assessment achievement. Outcomes cover grade 6 mathematics in columns 1-6 and language in columns 7-12. Within each subject, columns report average scores, the share scoring below basic, and the share scoring basic for 2023 and 2025. Scores are in comparison-group standard deviations; all other estimates are in percentage points. The DID estimates in panel A compare schools first treated in 2023 with eligible schools not treated in 2023 or 2024; the 2025 estimates also exclude comparison schools treated in 2025. Specifications include school and year fixed effects and interact annual indicators with baseline attendance and critical reading fluency. The pre-trend tests jointly assess the 2016 and 2018 treatment-group interactions, relative to 2021. The difference-in-discontinuities estimates in panel B compare each follow-up with 2021 at the original 85% attendance cutoff among eligible schools, retaining those that received facilitators later. The running variable is the school's 2022 attendance rate in every regression. Local linear specifications allow slopes to differ across sides and periods, using unweighted ordinary least squares within the same outcome-specific symmetric bandwidth selected from the 2023 data. DID scores use the comparison group for the relevant follow-up. For difference-in-discontinuities, the original comparison group provides each year's mean and standard deviation. DID counts refer to students in the indicated follow-up; difference-in-discontinuities counts include observations from both estimation periods within the bandwidth. Standard errors clustered at the school level appear in parentheses. * 10%; ** 5%; *** 1%.

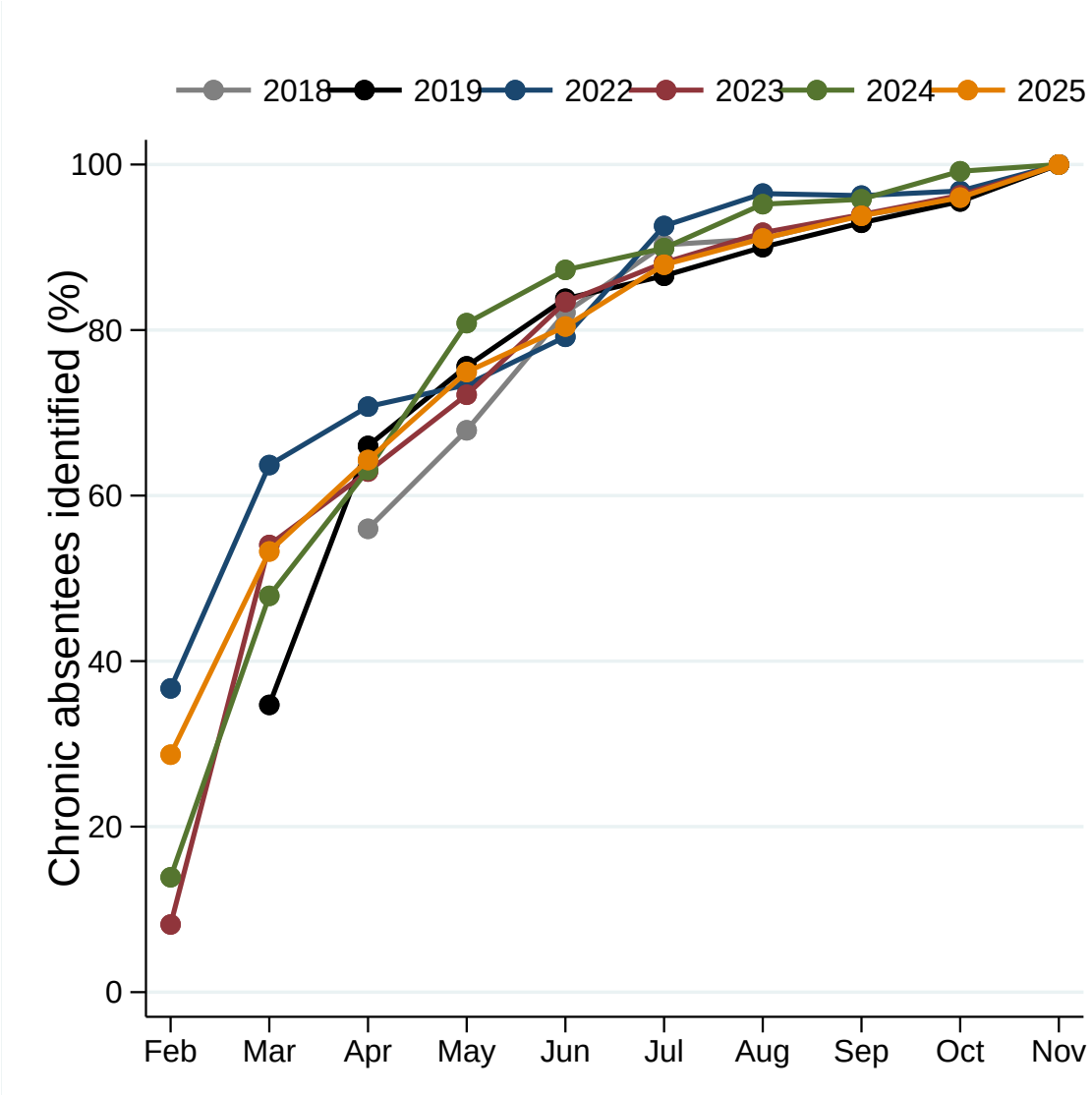
Appendix A Additional figures and tables

Figure A.1: Student-reported and recorded absences among sixth-grade students



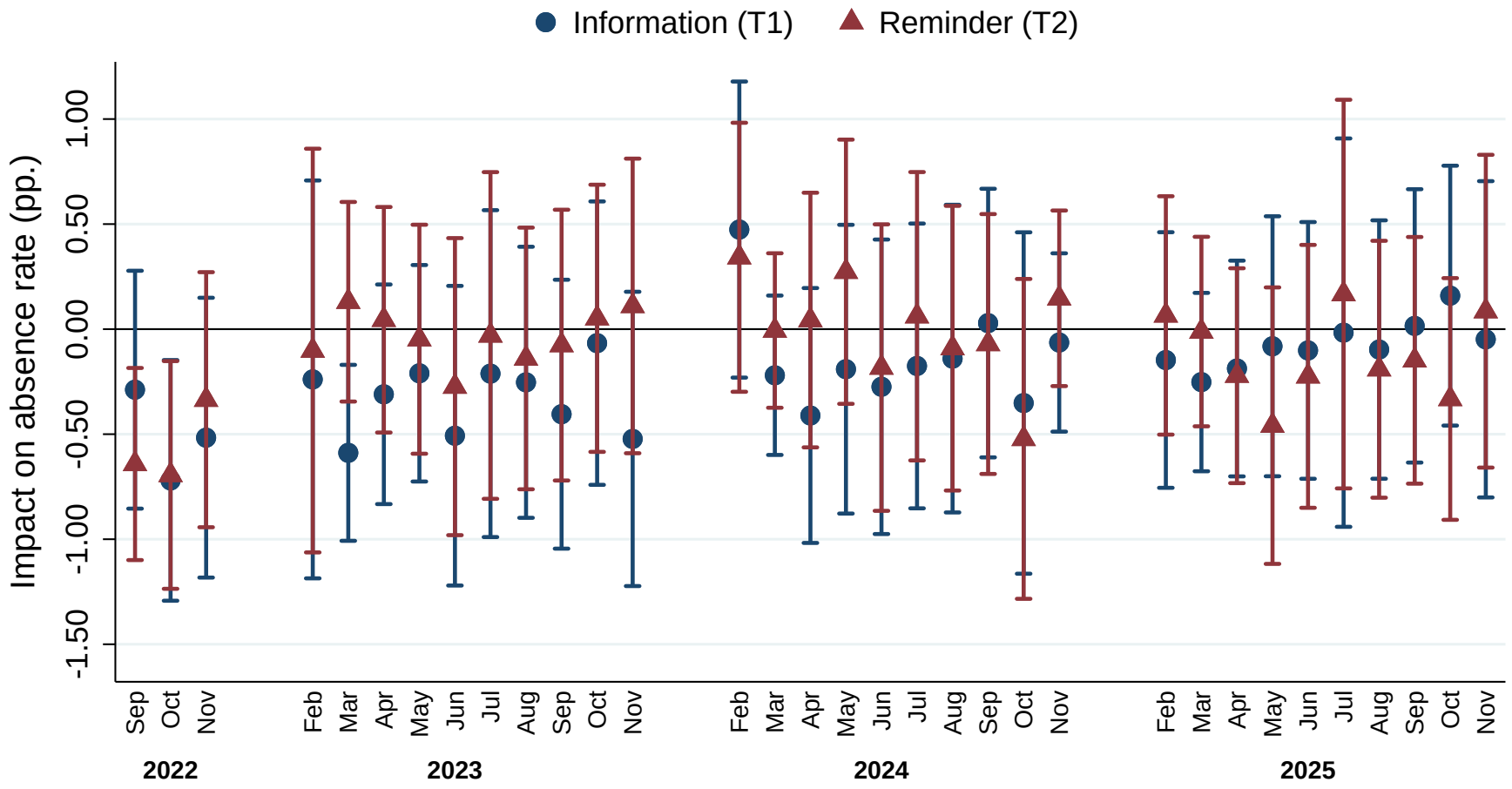
Notes: This figure compares students' self-reported absences with absences recorded by schools. Panel A compares the 2017 student survey with 2019 school records. Panel B compares the 2023 student survey with 2022 school records. The samples include sixth-grade students in public primary schools in Mendoza. Categories follow those reported in each student survey.

Figure A.2: Identification of eventual chronic absentees, 2018-2025



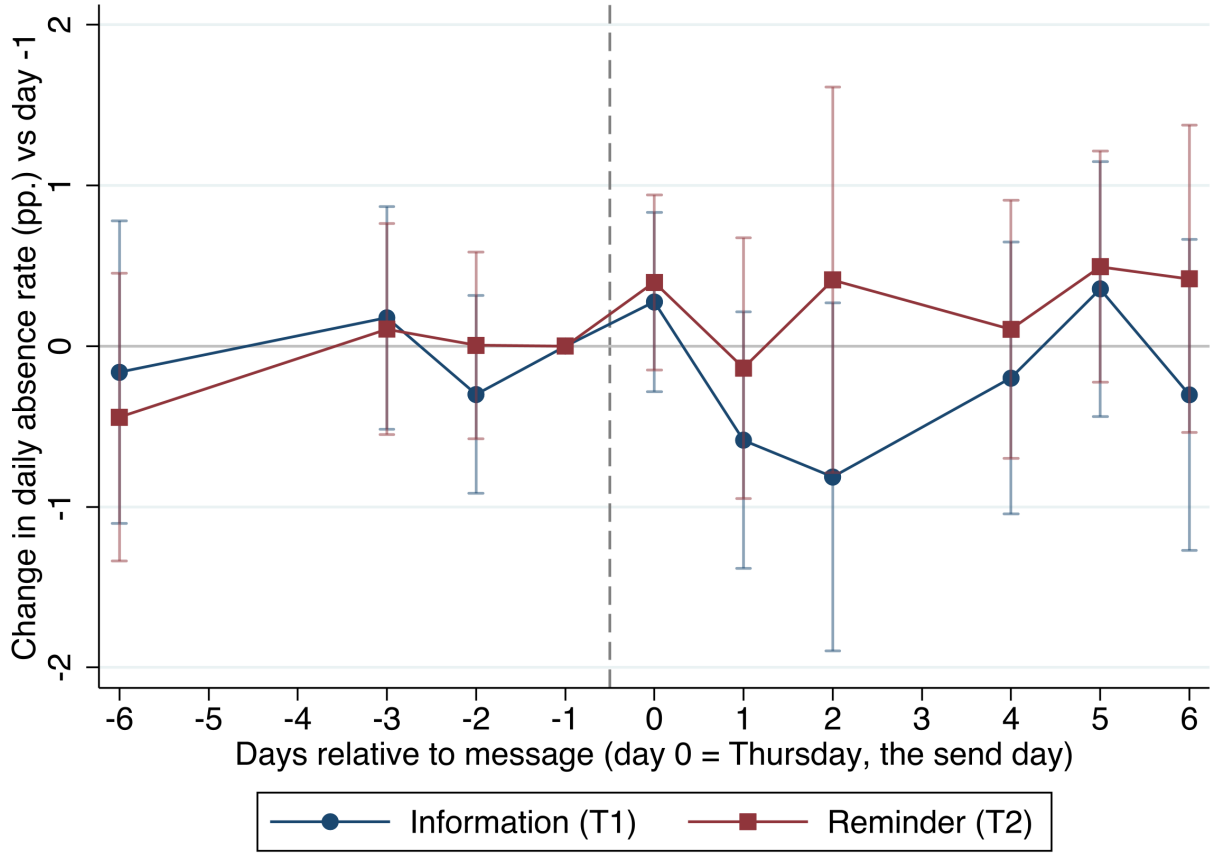
Notes: This figure plots, for each year, the share of students who were chronically absent by the end of November and met the cumulative 10% threshold by the end of each month. Chronic absence is defined as missing 10% or more of schooldays.

Figure A.3: ITT effect of text messages on absence rate by month, 2022-2025



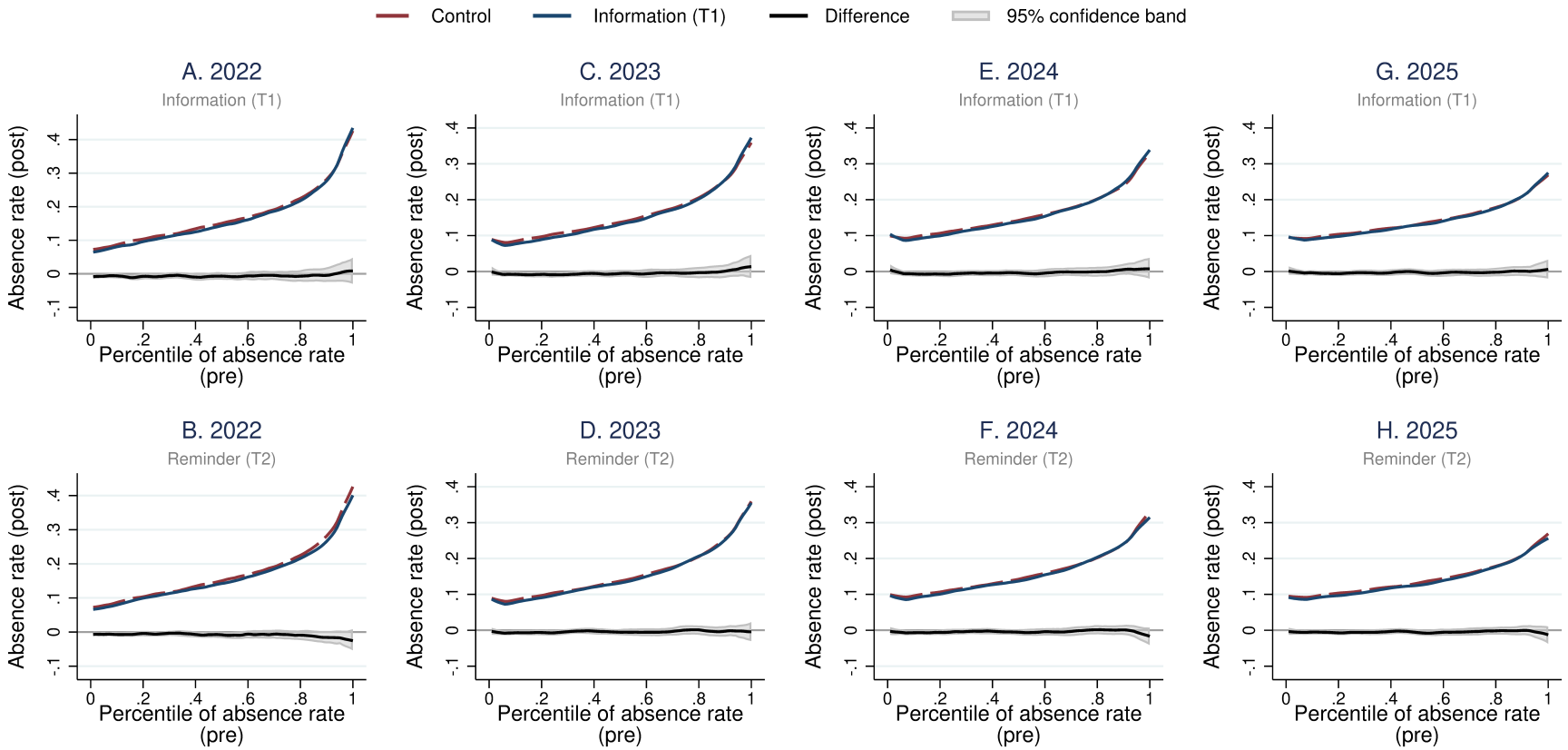
Notes: This figure shows the intent-to-treat (ITT) effect of each intervention on the monthly absence rate from September 2022 to November 2025. Each dot represents the coefficient from a separate regression of the monthly absence rate (absences in that month divided by school days in that month) on treatment indicators, randomization-strata (i.e., department) fixed effects, and controls for pre-intervention absences. Vertical lines display 95% confidence intervals. Standard errors are clustered at the school level. The intervention was delivered from September to November 2022.

Figure A.4: Event-study of daily absences around each message send date, 2022



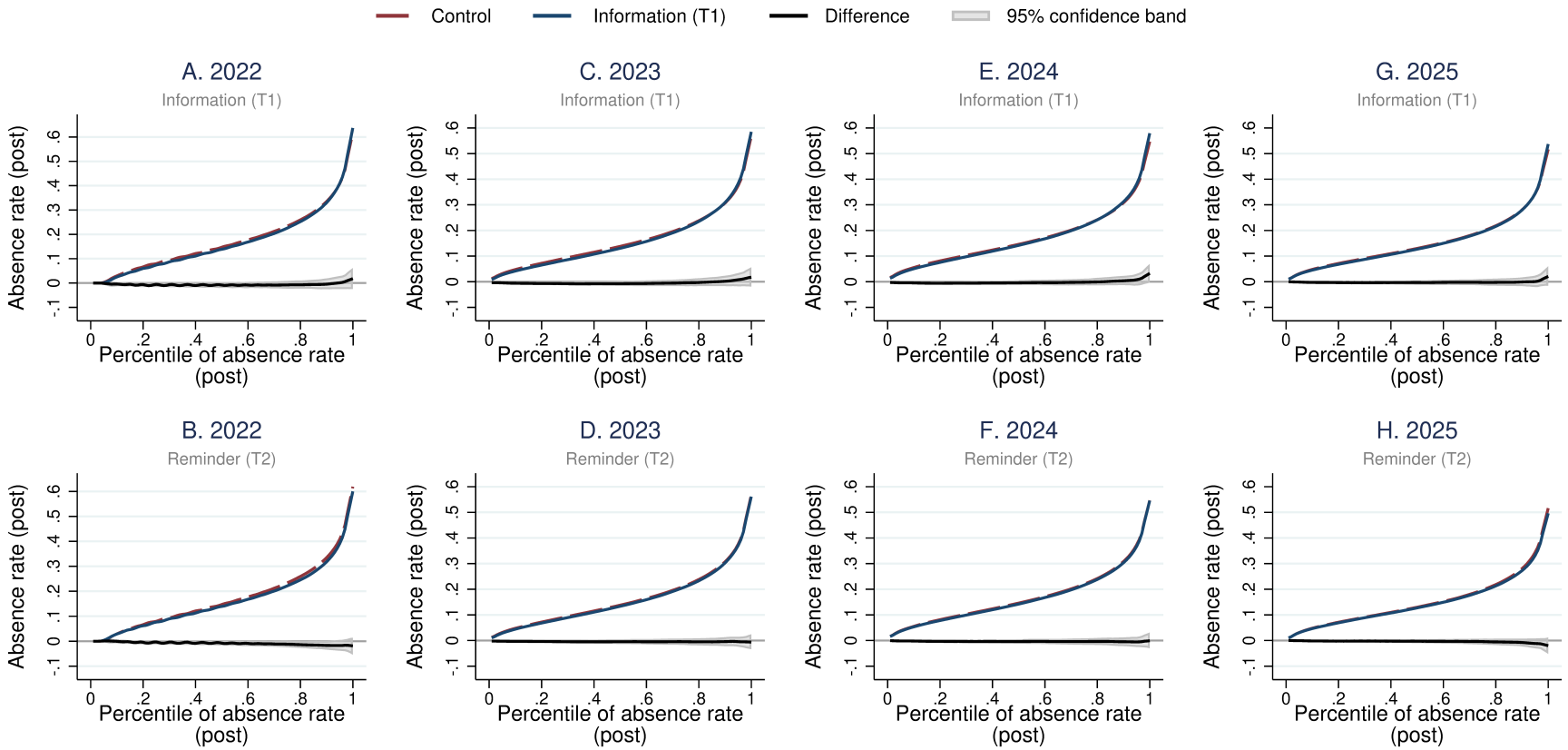
Notes: This figure plots coefficients from a student-day event-study regression of daily absence indicators on treatment-by-event-day interactions, with student and calendar-day fixed effects. The sample stacks all students in the randomized sample across ±6-day windows around each of the seven biweekly message send dates in September-November 2022 (all Thursdays). Event day 0 is the send date (Thursday, after school hours); event day −1 (Wednesday, the last pre-message school day) is the omitted reference. Markers are intention-to-treat coefficients relative to the control group, vertical bars are 95% confidence intervals (standard errors clustered at the school level), and the dashed vertical line separates the pre- and post-message windows.

Figure A.5: ITT effect on absences by pre-intervention absences, 2022-2025



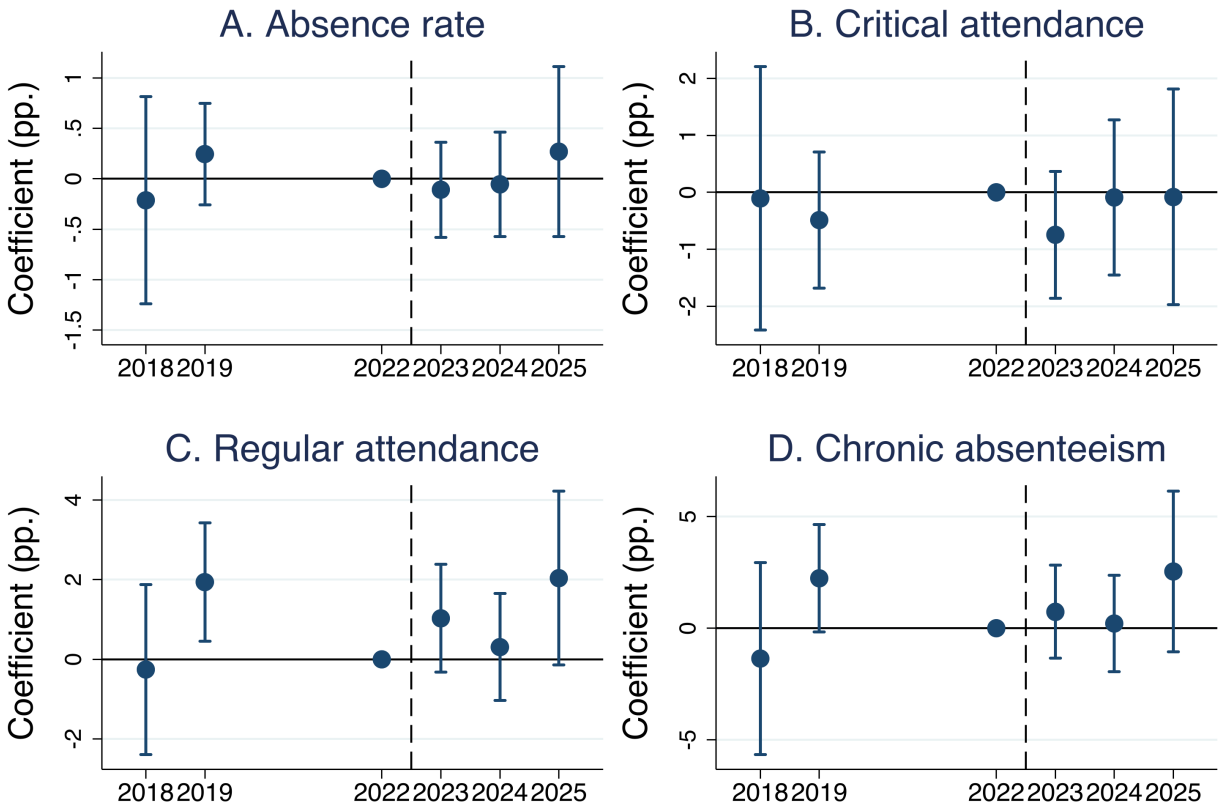
Notes: This figure shows average absences and treatment effects in 2022-2025 at each percentile of the pre-intervention absence rate, estimated separately by experimental group using local polynomial regressions. Solid black lines show treatment-control differences, and gray bands show bootstrapped 95% confidence intervals.

Figure A.6: Quantile ITT effects on absences, 2022-2025



Notes: This figure shows average absences and treatment effects in 2022-2025 by percentile of the post-intervention absence rate within each experimental group, estimated using local polynomial regressions. Solid black lines show differences between the smoothed treatment and control distributions, and gray bands show bootstrapped 95% confidence intervals.

Figure A.7: Conditional DID event study of the government initiative, 2018-2025



Notes: This figure plots coefficients from student-level event-study regressions for the absence rate, the shares of students in the province's critical (attendance below 75%) and regular (75-85% attendance) categories, and chronic absenteeism (attendance below 90%) from 2018 through 2025. The 2023 and 2024 estimates compare 184 schools first treated in 2023 with 284 eligible schools not treated in either year; the 2025 estimates also exclude comparison schools that received a facilitator in 2025. The regressions include school and year fixed effects and interact year indicators with schools' baseline attendance rate and share of students with critical reading fluency. The omitted year is 2022. Markers show coefficients in pp., vertical bars show 95% confidence intervals based on standard errors clustered by school, and the dashed line separates the pre- and post-treatment periods.

Table A.1: Average absence rates by school characteristics in Mendoza, 2022-2025

	(1) Yes/ ≥ median	(2) No/ < median	(3) Col. (1)-(2)	(4) N (student-years)
A. Area type				
High-poverty	23.8	18.1	5.75***	747,981
	[14.4]	[11.6]	(1.04)	
Rural	15.9	19.2	-3.31***	747,981
	[10.5]	[12.1]	(0.34)	
Rural frontier	14.3	18.4	-4.11***	747,981
	[9.83]	[11.8]	(1.00)	
Rural marginal	19.5	18.3	1.21	747,981
	[12.9]	[11.7]	(1.24)	
Urban	17.6	18.8	-1.14***	747,981
	[10.8]	[12.3]	(0.37)	
Urban marginal	20.6	17.5	3.12***	747,981
	[12.7]	[11.3]	(0.40)	
B. Region				
Metropolitan	20.4	15.7	4.69***	747,981
	[12.5]	[10.2]	(0.32)	
East	17.7	18.5	-0.77**	747,981
	[10.8]	[11.9]	(0.39)	
Northeast	14.3	18.6	-4.37***	747,981
	[9.75]	[11.9]	(0.42)	
Center-West	16.4	18.6	-2.15***	747,981
	[10.4]	[11.9]	(0.56)	
South	14.5	19.1	-4.58***	747,981
	[9.62]	[12.0]	(0.36)	
C. Enrollment				
Quartile 1 (≤ 277 students)	17.7	18.6	-0.91**	747,981
	[12.2]	[11.6]	(0.39)	
Quartile 2 (278-411 students)	18.8	18.2	0.51	747,981
	[11.8]	[11.8]	(0.41)	
Quartile 3 (412-582 students)	19.2	18.1	1.06**	747,981
	[12.0]	[11.7]	(0.50)	
Quartile 4 (≥ 583 students)	17.9	18.5	-0.65	747,981
	[11.0]	[12.0]	(0.47)	

Notes: This table reports student-level absence rates in 2022-2025 by school characteristics in public primary schools in Mendoza. For dichotomous characteristics, schools are grouped by whether they have the characteristic; for enrollment, each quartile is compared with the other three quartiles. Columns (1) and (2) report means and standard deviations for student-years in schools with and without each characteristic, respectively. Column (3) reports the difference in average absence rates between the groups. * 10%; ** 5%; *** 1%. Column (4) reports the number of student-years in the estimation sample, and standard errors are clustered at the school level, the level of the characteristics reported in the table.

Table A.2: Average absence rates by student characteristics in Mendoza, 2022-2025

	(1) Yes/ ≥ median	(2) No/ < median	(3) Col. (1)-(2)	(4) N (student-years)
A. Demographics				
Age	17.4	19.5	-2.04***	723,049
	[11.5]	[12.1]	(0.07)	
Female	18.0	18.9	-0.90***	723,160
	[11.6]	[12.0]	(0.06)	
Argentine	18.4	16.0	2.42***	713,769
	[11.8]	[11.8]	(0.25)	
B. Parents				
Illiterate	22.7	18.1	4.60***	668,813
	[18.0]	[11.6]	(1.46)	
Primary	19.8	17.7	2.10***	668,813
	[13.1]	[11.1]	(0.21)	
Secondary	18.7	17.5	1.22***	668,813
	[11.5]	[11.8]	(0.11)	
Tertiary	15.4	18.7	-3.21***	668,813
	[9.62]	[11.9]	(0.17)	
University	14.3	18.4	-4.09***	668,813
	[9.39]	[11.7]	(0.20)	
No income	20.2	17.1	3.10***	626,955
	[12.7]	[10.9]	(0.16)	
Social protection	22.0	17.9	4.04***	626,955
	[13.5]	[11.5]	(0.41)	
Blue-collar job	15.4	18.5	-3.09***	626,955
	[10.4]	[11.7]	(0.26)	
White-collar job	17.1	19.2	-2.10***	626,955
	[10.6]	[12.4]	(0.19)	
C. Schooling				
Grades 1-2	21.0	17.6	3.46***	724,006
	[12.7]	[11.4]	(0.08)	
Grades 3-4	18.2	18.6	-0.38***	724,006
	[11.5]	[11.9]	(0.06)	
Grades 5-7	17.2	19.5	-2.35***	724,006
	[11.2]	[12.2]	(0.07)	
Attends morning shift	18.2	18.6	-0.40***	692,713
	[11.7]	[11.9]	(0.15)	
Attends afternoon shift	18.8	18.1	0.72***	692,713
	[11.9]	[11.7]	(0.15)	
Has disability	20.6	18.4	2.25***	723,232
	[13.1]	[11.8]	(0.17)	
Is overage	27.7	18.3	9.40***	723,232
	[17.8]	[11.6]	(0.39)	

Notes: This table reports student-level absence rates in 2022-2025 by student characteristics in public primary schools in Mendoza. Parent education and occupation are the highest categories across the student's mother and father, as in Figure 1. For dichotomous characteristics, student-years are grouped by whether they have the characteristic; for age, by whether they are above or below the pooled median; and for parent education, parent occupation, and grade, by whether they are in each category. Columns (1) and (2) report means and standard deviations for student-years in and outside each group, respectively. Column (3) reports the difference in average absence rates between the groups. Column (4) reports the number of student-years in the estimation sample. Standard errors are clustered at the school level. Significance levels are * 10%; ** 5%; *** 1%.

Table A.3: School grades by decile of absence rate, 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)
	Language		Math		Math and language	
	Grade (SD)	Percent failed	Grade (SD)	Percent failed	Average grade (SD)	Failed subjects
Decile 1	0.34	3.58	0.35	3.15	0.36	0.07
	[0.92]	[18.6]	[0.91]	[17.5]	[0.92]	[0.34]
Decile 2	0.28	3.83	0.28	3.36	0.29	0.07
	[0.92]	[19.2]	[0.91]	[18.0]	[0.92]	[0.35]
Decile 3	0.22	4.39	0.22	3.89	0.23	0.08
	[0.93]	[20.5]	[0.93]	[19.3]	[0.93]	[0.37]
Decile 4	0.16	4.91	0.16	4.39	0.17	0.09
	[0.94]	[21.6]	[0.94]	[20.5]	[0.94]	[0.40]
Decile 5	0.10	5.73	0.10	5.08	0.10	0.11
	[0.95]	[23.2]	[0.94]	[22.0]	[0.94]	[0.43]
Decile 6	0.03	6.65	0.03	5.95	0.03	0.13
	[0.96]	[24.9]	[0.96]	[23.7]	[0.96]	[0.46]
Decile 7	-0.06	8.01	-0.06	7.14	-0.06	0.15
	[0.97]	[27.2]	[0.97]	[25.7]	[0.96]	[0.50]
Decile 8	-0.16	9.78	-0.16	8.77	-0.17	0.19
	[0.97]	[29.7]	[0.97]	[28.3]	[0.97]	[0.55]
Decile 9	-0.31	13.3	-0.31	12.1	-0.32	0.25
	[0.97]	[34.0]	[0.98]	[32.6]	[0.97]	[0.63]
Decile 10	-0.62	25.3	-0.63	23.5	-0.64	0.49
	[0.94]	[43.5]	[0.95]	[42.4]	[0.95]	[0.82]
Decile 1-8	0.50***	-6.20***	0.52***	-5.62***	0.53***	-0.12***
	(0.00)	(0.13)	(0.00)	(0.12)	(0.00)	(0.00)
Decile 9-10	0.31***	-11.9***	0.32***	-11.4***	0.32***	-0.23***
	(0.01)	(0.20)	(0.01)	(0.20)	(0.01)	(0.00)
Decile 1-10	0.96***	-21.7***	0.98***	-20.3***	1.00***	-0.42***
	(0.00)	(0.17)	(0.00)	(0.17)	(0.00)	(0.00)
N (student-years)	729,645	730,701	729,580	730,652	729,382	730,362

Notes: This table shows students' final grade (before exams) on language and math, and students' propensity to fail these subjects, by their decile of absence rate, pooling student-year observations from 2022-2025. Columns 5 and 6 report the average grade and number of failed subjects (0-2), respectively, using math and language only and requiring both to be observed. Grades are standardized within each school and grade level separately by year. The last three rows of the table compare students in deciles 1 and 8, deciles 9 and 10, and deciles 1 and 10 in terms of these outcomes. Absence-rate deciles are defined separately by year before pooling. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.4: School performance by decile of absence rate, 2022-2025

	(1) Passing rate	(2) Repetition rate	(3) Dropout rate	(4) Graduation rate
Decile 1	98.6	1.43	0.01	90.5
	[11.9]	[11.9]	[1.11]	[29.3]
Decile 2	99.0	0.96	0.00	92.9
	[9.75]	[9.75]	[0.00]	[25.6]
Decile 3	98.9	1.12	0.00	93.3
	[10.5]	[10.5]	[0.00]	[25.1]
Decile 4	98.8	1.23	0.00	93.3
	[11.0]	[11.0]	[0.00]	[25.1]
Decile 5	98.6	1.40	0.00	93.6
	[11.8]	[11.8]	[0.38]	[24.4]
Decile 6	98.3	1.67	0.00	94.0
	[12.8]	[12.8]	[0.00]	[23.8]
Decile 7	98.1	1.92	0.00	94.3
	[13.7]	[13.7]	[0.65]	[23.2]
Decile 8	97.5	2.46	0.00	94.6
	[15.5]	[15.5]	[0.54]	[22.7]
Decile 9	96.5	3.49	0.00	93.1
	[18.4]	[18.4]	[0.00]	[25.3]
Decile 10	91.6	8.34	0.01	86.9
	[27.7]	[27.7]	[1.08]	[33.8]
Decile 1-10	6.91***	-6.92***	0.00	3.65***
	(0.12)	(0.12)	(0.01)	(0.44)
N (student-years)	692,592	692,592	692,592	103,876

Notes: This table reports mean passing, repetition, dropout, and graduation rates (percentages) by absence-rate decile, pooling student-year observations across 2022-2025. Graduation applies only to Grade 7. Brackets report standard deviations, and parentheses report standard errors. * 10%; ** 5%; *** 1%. The comparison subtracts the pooled mean for decile 10 from the pooled mean for decile 1 for each outcome (pp.). Absence-rate deciles are defined separately by year before pooling.

Table A.5: National-assessment achievement by school absence-rate decile, 2023 and 2025

	(1)	(2)	(3)	(4)	(5)	(6)
	Math			Language		
	Score (SDs)	Below basic (%)	Basic (%)	Score (SDs)	Below basic (%)	Basic (%)
Decile 1	0.23	15.8	24.3	0.07	7.68	19.4
	[1.02]	[36.5]	[42.9]	[1.02]	[26.6]	[39.5]
Decile 2	0.02	19.9	25.2	-0.02	6.80	19.3
	[0.96]	[39.9]	[43.4]	[0.94]	[25.2]	[39.5]
Decile 3	-0.07	22.8	26.7	-0.14	8.73	22.0
	[0.98]	[42.0]	[44.3]	[0.93]	[28.2]	[41.4]
Decile 4	-0.09	23.6	26.6	-0.08	7.68	20.8
	[0.97]	[42.4]	[44.2]	[0.95]	[26.6]	[40.6]
Decile 5	-0.10	23.9	26.4	-0.07	8.36	20.6
	[0.96]	[42.7]	[44.1]	[0.96]	[27.7]	[40.5]
Decile 6	-0.10	24.5	27.1	-0.09	8.70	20.4
	[0.98]	[43.0]	[44.5]	[0.97]	[28.2]	[40.3]
Decile 7	-0.09	22.8	27.9	-0.06	7.92	19.9
	[0.95]	[41.9]	[44.8]	[0.97]	[27.0]	[39.9]
Decile 8	-0.16	24.8	29.4	-0.16	9.38	22.7
	[0.95]	[43.2]	[45.6]	[0.96]	[29.2]	[41.9]
Decile 9	-0.25	27.1	30.2	-0.24	9.85	24.5
	[0.91]	[44.4]	[45.9]	[0.94]	[29.8]	[43.0]
Decile 10	-0.43	35.4	30.1	-0.45	14.4	30.3
	[0.89]	[47.8]	[45.9]	[0.91]	[35.1]	[45.9]
Decile 1-10	0.66***	-19.6***	-5.71**	0.52***	-6.71***	-10.9***
	(0.10)	(2.60)	(2.55)	(0.11)	(1.81)	(2.36)
N (students)	43,387	43,387	43,387	43,940	43,940	43,940

Notes: This table reports student-level national-assessment outcomes by school absence-rate decile, pooling the 2023 and 2025 censuses. National-assessment records are matched to same-year school-level attendance records using the national school identifier. Scores are standardized within subject and year. Below basic and basic report percentages of tested students in each performance level. Brackets report standard deviations across students, and parentheses report standard errors clustered by school. Absence-rate deciles are defined separately by year before pooling. The comparison subtracts the mean for decile 10 from the mean for decile 1. * significant at 10%; ** significant at 5%; *** significant at 1%, respectively.

Table A.6: Reading fluency by decile of absence rate, 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2022		2023		2024		2025	
	Words per minute	Percent critical	Words per minute	Percent critical	Words per minute	Percent critical	Words per minute	Percent critical
Decile 1	97.4	16.0	102	12.5	104	8.35	95.8	12.6
	[46.6]	[31.3]	[45.0]	[27.5]	[40.5]	[23.0]	[43.5]	[29.3]
Decile 2	96.2	16.0	99.0	13.3	99.1	9.83	95.2	11.8
	[46.5]	[31.5]	[45.3]	[28.1]	[40.7]	[24.7]	[42.9]	[28.2]
Decile 3	94.1	16.8	96.3	14.6	97.2	11.1	94.3	12.1
	[46.1]	[31.8]	[45.7]	[29.6]	[41.5]	[26.3]	[42.8]	[28.7]
Decile 4	91.0	18.4	93.8	15.7	94.6	12.0	93.4	13.0
	[46.2]	[33.1]	[45.8]	[30.4]	[41.7]	[27.2]	[43.1]	[29.6]
Decile 5	88.6	19.8	91.6	17.2	93.0	13.1	92.8	13.4
	[46.6]	[34.2]	[46.0]	[31.8]	[42.1]	[28.4]	[43.3]	[29.9]
Decile 6	85.4	21.9	88.4	18.9	89.9	15.2	91.3	14.4
	[46.2]	[35.6]	[46.3]	[33.1]	[42.7]	[30.5]	[43.9]	[30.9]
Decile 7	82.1	24.2	85.0	21.7	86.8	16.6	88.4	16.4
	[46.7]	[37.0]	[46.6]	[35.2]	[42.6]	[31.5]	[44.0]	[32.8]
Decile 8	78.5	26.8	81.5	24.3	83.3	19.7	85.8	18.1
	[46.4]	[38.4]	[47.2]	[36.8]	[43.1]	[34.3]	[43.9]	[34.1]
Decile 9	72.8	31.9	76.3	28.2	78.6	23.5	82.0	21.4
	[46.4]	[41.0]	[47.0]	[38.9]	[44.1]	[36.9]	[44.5]	[36.6]
Decile 10	63.9	40.5	66.4	38.2	70.1	32.4	72.1	31.9
	[46.2]	[43.6]	[48.0]	[43.4]	[45.5]	[41.8]	[46.6]	[42.6]
Decile 1-10	33.5***	-24.5***	35.7***	-25.7***	33.6***	-24.1***	23.7***	-19.4***
	(0.54)	(0.44)	(0.52)	(0.41)	(0.48)	(0.38)	(0.52)	(0.42)
N (students)	148,353		160,083		156,518		152,092	

Notes: This table shows reading-fluency outcomes by absence decile for 2022-2025, averaging the first and last available assessment rounds within each year. The test was administered to students in grades 2-7. Brackets report standard deviations, and parentheses report standard errors. * 10%; ** 5%; *** 1%.

Table A.7: Reading comprehension by decile of absence rate, 2022

	(1) Below level 1	(2) Level 1	(3) Level 2	(4) Level 3
Decile 1	20.7	29.3	30.8	19.2
	[40.6]	[45.6]	[46.3]	[39.5]
Decile 2	19.4	25.5	31.5	23.6
	[39.7]	[43.7]	[46.6]	[42.6]
Decile 3	19.9	42.1	22.8	15.2
	[40.0]	[49.5]	[42.1]	[36.0]
Decile 4	23.6	30.2	30.2	15.9
	[42.6]	[46.0]	[46.0]	[36.7]
Decile 5	21.8	38.2	23.5	16.5
	[41.4]	[48.7]	[42.5]	[37.2]
Decile 6	20.0	38.9	22.9	18.3
	[40.1]	[48.9]	[42.1]	[38.8]
Decile 7	21.9	42.7	19.1	16.3
	[41.5]	[49.6]	[39.4]	[37.0]
Decile 8	31.8	35.3	20.8	12.1
	[46.7]	[47.9]	[40.7]	[32.8]
Decile 9	35.8	35.2	19.9	9.09
	[48.1]	[47.9]	[40.0]	[28.8]
Decile 10	36.9	34.7	19.3	9.09
	[48.4]	[47.7]	[39.6]	[28.8]
Decile 1-6	0.71	-9.56*	7.95*	0.91
	(4.19)	(4.90)	(4.60)	(4.06)
Decile 7-10	-15.0***	8.04	-0.22	7.20**
	(4.79)	(5.17)	(4.20)	(3.53)
Decile 1-10	-16.2***	-5.37	11.5**	10.1***
	(4.61)	(4.83)	(4.48)	(3.61)
N (students)	1,764	1,764	1,764	1,764

Notes: This table shows the percentage of students classified in each of the four performance levels of the assessment of reading comprehension administered in Mendoza in 2022 by decile of absence rate prior to the test. The test was only administered to grade 4 students. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.8: Within-student estimates of absences on school grades, 2019 and 2022-2025

	(1) 2019	(2) 2022	(3) 2023	(4) 2024	(5) 2025
A. Language grade (SD)					
Cross-sectional (10 pp.)	-0.24***	-0.27***	-0.29***	-0.31***	-0.28***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Within-student (10 pp.)	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
N (student-periods)	555,803	374,436	367,873	358,593	349,028
B. Math grade (SD)					
Cross-sectional (10 pp.)	-0.23***	-0.27***	-0.29***	-0.31***	-0.28***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Within-student (10 pp.)	-0.04***	-0.04***	-0.05***	-0.04***	-0.04***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
N (student-periods)	555,748	374,174	367,614	358,562	348,908
C. Average grade (SD)					
Cross-sectional (10 pp.)	-0.25***	-0.28***	-0.30***	-0.32***	-0.29***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Within-student (10 pp.)	-0.04***	-0.04***	-0.05***	-0.04***	-0.04***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
N (student-periods)	554,707	372,362	367,154	358,110	348,741
D. Failed subjects (SD)					
Cross-sectional (10 pp.)	0.16***	0.21***	0.22***	0.24***	0.20***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Within-student (10 pp.)	0.03***	0.04***	0.04***	0.04***	0.04***
	(<0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N (student-periods)	554,707	372,362	367,154	358,110	348,741

Notes: This table reports cross-sectional and within-student estimates of the relationship between absences and school grades in 2019 and 2022-2025. Columns 1-5 correspond to 2019, 2022, 2023, 2024, and 2025, respectively. Language and math grades appear in panels A and B, average grades in panel C, and the number of subjects failed in panel D. The combined outcomes use only math and language grades, requiring both in each period. All outcomes are standardized within year. The unit is a student-period. The absence rate equals absences divided by recorded schooldays in each period, excluding December. Grades are recorded for three trimesters in 2019 and two semesters per year in 2022-2025. Cross-sectional estimates include grading-period fixed effects; within-student estimates add student fixed effects. Standard errors are clustered by school. * 10%; ** 5%; *** 1%.

Table A.9: Within-student estimates of absences on reading fluency, 2022-2025

	(1)	(2)	(3)	(4)
	Words per minute		Critical level (pp.)	
	Cross-sectional	Within-student	Cross-sectional	Within-student
A. Pooled, 2022-2025				
Absence rate	-63.4***	-5.16***	45.2***	2.82***
	(1.28)	(0.36)	(1.24)	(0.48)
Assessment FE	Yes	Yes	Yes	Yes
Student FE	No	Yes	No	Yes
N (student-assessments)	1,268,749	1,268,749	1,268,749	1,268,749
B. By year				
Assessment FE	Yes	Yes	Yes	Yes
Student FE	No	Yes	No	Yes
2022	-73.8***	-2.03***	54.5***	-0.12
	(1.76)	(0.74)	(1.57)	(1.00)
N (student-assessments)	381,255	381,255	381,255	381,255
2023	-57.7***	-4.54***	37.2***	-10.1***
	(1.71)	(1.15)	(1.44)	(1.67)
N (student-assessments)	300,115	300,115	300,115	300,115
2024	-67.4***	-7.17***	47.4***	-1.70
	(1.64)	(1.12)	(1.47)	(1.56)
N (student-assessments)	297,995	297,995	297,995	297,995
2025	-47.7***	-2.96***	37.0***	-2.92**
	(1.64)	(0.96)	(1.50)	(1.44)
N (student-assessments)	289,384	289,384	289,384	289,384
C. By grade, 2022				
Grade 2		-3.28***		2.96
		(0.97)		(2.27)
Grade 3		-2.55*		-1.73
		(1.49)		(2.47)
Grade 4		-0.56		-2.22
		(1.36)		(2.08)
Grade 5		-2.45		-2.03
		(1.73)		(2.12)
Grade 6		0.18		-0.85
		(1.82)		(1.79)
Grade 7		-1.44		-2.84
		(2.28)		(1.98)

Notes: This table shows cross-sectional and within-student estimates of the relationship between the absence rate and reading fluency. Panel A pools the 2022-2025 assessments, panel B reports estimates by year, and panel C reports within-student estimates by grade in 2022. The unit of observation is a student-assessment. The absence rate is the number of absences divided by the number of school days with attendance data in the instructional period preceding each assessment. Columns 1 and 3 include assessment fixed effects; columns 2 and 4 add student fixed effects. The critical-level outcome is coded 0/1. Standard errors are clustered at the school level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.10: Comparison between in- and out-of-sample schools in study 3, 2022

	(1) All schools	(2) Out-of-sample schools	(3) In-sample schools	(4) Col.(3)-(2)
A. Demographics				
Female	48.8	49.5	48.6	-0.88
	[50.0]	[50.0]	[50.0]	(1.63)
Argentine	99.1	98.8	99.1	0.33*
	[9.68]	[11.0]	[9.46]	(0.20)
Has disability	1.92	1.60	1.97	0.37***
	[13.7]	[12.6]	[13.9]	(0.14)
N (students)	193,605	27,925	165,680	193,605
B. Schooling				
Attends morning shift	58.5	62.9	57.8	-5.11***
	[49.3]	[48.3]	[49.4]	(1.92)
Attends afternoon shift	40.5	32.2	41.9	9.70***
	[49.1]	[46.7]	[49.3]	(2.02)
Is overage	1.72	2.47	1.59	-0.88***
	[13.0]	[15.5]	[12.5]	(0.26)
N (students)	193,605	27,925	165,680	193,605
C. Attendance				
Absence rate pre-intervention	17.5	18.1	17.5	-0.61
	[10.0]	[11.0]	[9.85]	(0.38)
Mon/Fri absence rate pre-intervention	7.03	7.36	6.97	-0.39**
	[4.61]	[5.01]	[4.54]	(0.18)
Holiday absence rate pre-intervention	1.27	1.31	1.26	-0.05
	[1.21]	[1.28]	[1.20]	(0.04)
Chronically absent pre-intervention	77.0	76.1	77.2	1.07
	[42.1]	[42.6]	[42.0]	(1.12)
N (students)	193,420	28,011	165,409	193,420
D. Reading fluency				
Words per minute (Apr 2022)	74.4	67.4	75.5	8.13***
	[47.7]	[47.0]	[47.7]	(1.59)
Words per minute (Aug 2022)	89.6	82.4	90.8	8.44***
	[51.6]	[51.2]	[51.6]	(1.73)
Performs at critical level (Apr 2022)	31.9	39.6	30.6	-9.00***
	[46.6]	[48.9]	[46.1]	(1.67)
Performs at critical level (Aug 2022)	19.4	25.5	18.4	-7.12***
	[39.5]	[43.6]	[38.7]	(1.38)
N (students)	149,149	21,379	127,770	149,149

Notes: This table compares students in schools outside and inside study 3 in 2022. Columns 1-3 report means, with standard deviations in brackets; column 4 reports the difference between in-sample and out-of-sample means, with school-clustered standard errors in parentheses. In study 3, none of the out-of-sample schools had information on mothers' education and fathers' occupation, so we omit those variables. Binary variables and attendance rates are percentages; their differences are percentage points. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.11: Templates for text messages

(1) Experimental group	(2) English text	(3) Spanish text
Information (T1)	Greetings, our records indicate that *[name]* missed *[number]* schooldays this week and *[number]* this year. Visit: `https://bit.ly/2ZsUXg9`. Best, DGE	Estimado/a, nuestros datos indican que *[nombre]* faltó *[número]* días a la escuela esta quincena y *[número]* días en el año. Visite: `https://bit.ly/2ZsUXg9`. Atte., DGE
Reminder (T2)	Academic benefits of attendance: Greetings, it is key that *[name]* goes to school to succeed academically and pass [his/her] courses and grade. Visit: `https://bit.ly/2ZsUXg9`. Best, DGE	Estimado/a, es clave que *[nombre]* vaya a la escuela para sacarse mejores notas y aprobar sus materias y el grado. Visite: `https://bit.ly/2ZsUXg9`. Atte., DGE
	Social benefits of attendance: Greetings, it is key that *[name]* goes to school to learn and interact with their teacher and friends. Visit: https://bit.ly/2ZsUXg9. Best, DGE	Estimado/a, es clave que *[nombre]* vaya a la escuela para aprender e interactuar con su docente y amigos/as. Visite: `https://bit.ly/2ZsUXg9`. Atte., DGE
	Actionable advice to reduce absences: Greetings, it is key that *[name]* goes to school. If you cannot take them, ask a friend or relative to do so. Visit: `https://bit.ly/2ZsUXg9`. Best, DGE	Estimado/a, es clave que *[nombre]* vaya a la escuela. Si no puede llevarlo/a, pídale a un amigo o familiar. Visite `https://bit.ly/2ZsUXg9`. Atte., DGE
Control	No messages	

Notes: All text messages must be limited to 160 characters due to local technological constraints. DGE stands for General Directorate of Education, Mendoza's education ministry. The `bit.ly` link included at the end of the message is a shortened version of the GEM PAD portal URL.

Table A.12: Summary statistics and randomization balance, 2022

	(1) Control	(2) T1	(3) T2	(4) Col. (2)-(1)	(5) Col. (3)-(1)	(6) Col. (3)-(2)
A. Demographics						
Female	48.4	49.1	48.4	0.72	0.06	-0.66
	[50.0]	[50.0]	[50.0]	(0.64)	(0.40)	(0.59)
Argentine	99.2	99.1	99.0	-0.15	-0.19	-0.04
	[8.84]	[9.66]	[9.86]	(0.15)	(0.15)	(0.18)
Has disability	1.83	2.07	2.03	0.24	0.20	-0.03
	[13.4]	[14.2]	[14.1]	(0.16)	(0.18)	(0.20)
N (students)	56,690	56,332	52,658	113,022	109,348	108,990
B. Schooling						
Attends morning shift	57.4	58.4	57.4	1.00	-0.07	-1.06
	[49.4]	[49.3]	[49.5]	(1.53)	(1.56)	(1.49)
Attends afternoon shift	42.0	41.4	42.5	-0.65	0.46	1.11
	[49.4]	[49.3]	[49.4]	(1.54)	(1.57)	(1.50)
Is overage	1.50	1.59	1.69	0.09	0.19	0.09
	[12.2]	[12.5]	[12.9]	(0.18)	(0.20)	(0.23)
N (students)	56,690	56,332	52,658	113,022	109,348	108,990
C. Attendance						
Absence rate pre-intervention	17.6	17.7	17.1	0.06	-0.53	-0.59
	[9.75]	[10.1]	[9.67]	(0.44)	(0.40)	(0.45)
Mon/Fri absence rate pre-intervention	7.05	7.06	6.80	0.00	-0.25	-0.26
	[4.49]	[4.66]	[4.45]	(0.21)	(0.19)	(0.21)
Holiday absence rate pre-intervention	1.28	1.27	1.23	-0.01	-0.05	-0.04
	[1.20]	[1.21]	[1.20]	(0.04)	(0.04)	(0.05)
Chronically absent pre-intervention	78.4	77.2	76.0	-1.22	-2.40*	-1.18
	[41.2]	[42.0]	[42.7]	(1.31)	(1.26)	(1.41)
N (students)	56,485	56,320	52,604	112,805	109,089	108,924
D. Reading fluency						
Words per minute (Apr 2022)	75.8	75.4	75.4	-0.40	-0.39	0.01
	[48.2]	[47.9]	[47.0]	(1.60)	(1.52)	(1.53)
Words per minute (Aug 2022)	91.2	89.8	91.5	-1.49	0.23	1.72
	[51.7]	[51.9]	[51.1]	(1.90)	(1.85)	(1.89)
Performs at critical level (Apr 2022)	30.7	31.1	30.0	0.41	-0.64	-1.06
	[46.1]	[46.3]	[45.8]	(1.66)	(1.59)	(1.65)
Performs at critical level (Aug 2022)	18.1	19.2	17.7	1.15	-0.35	-1.49
	[38.5]	[39.4]	[38.2]	(1.43)	(1.36)	(1.46)
N (students)	43,808	43,977	39,985	87,785	83,793	83,962

Notes: This table reports means for students in the control, T1, and T2 groups in columns 1-3, with standard deviations in brackets. Columns 4-6 report pairwise differences, with school-clustered standard errors in parentheses. Binary outcomes and attendance rates are reported as percentages, and their differences as percentage points. Difference estimates include randomization-strata (department) fixed effects. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.13: Effect of text messages on parent portal logins, 2022

	(1) Mother	(2) Father	(3) Guardian	(4) Any parent
Information (T1)	-1.06	-0.49	0.06	-1.44
	(1.18)	(0.46)	(0.07)	(1.38)
Reminder (T2)	0.60	-0.52	0.19**	0.27
	(1.21)	(0.45)	(0.08)	(1.40)
Control mean	39.1	9.69	0.44	47.2
P-value (T1=T2)	0.20	0.95	0.11	0.24
N (students)	164,777	164,777	164,860	164,777

Notes: This table shows the intent-to-treat (ITT) effect of each intervention on the probability that a parent logged into the *GEM PAD* school portal on or after September 1, 2022 (the first message date). Effects are in percentage points, and control means are percentages. Columns (1)-(3) report effects separately for the mother, father, and guardian; column (4) uses an indicator for any of the three. Impact estimates come from regressions of each outcome on treatment indicators, randomization-strata (i.e., department) fixed effects, and covariates selected by the LASSO procedure. Standard errors are clustered at the school level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.14: Dose-response of messages received on absence rate, 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Information (T1)				Reminder (T2)			
	2022	2023	2024	2025	2022	2023	2024	2025
Messages received	-0.16***	-0.12*	-0.07	-0.02	-0.08**	0.00	0.01	-0.02
	(0.06)	(0.06)	(0.06)	(0.07)	(0.04)	(0.04)	(0.04)	(0.04)
Extrapolated at 7 msgs	-1.15	-0.81	-0.48	-0.17	-0.58	0.03	0.09	-0.13
Control mean	17.0	16.2	16.8	14.4	17.0	16.2	16.8	14.4
AP F-stat (weak IV)	3.22k	3.22k	3.22k	3.22k	20.9k	20.9k	20.9k	20.9k
N (students)	112,298	94,258	77,241	61,458	108,663	91,371	74,959	59,737

Notes: This table shows the causal per-message effect of T1 (information) and T2 (reminder) messages on absence rate (in pp.) for September-November 2022 (after the interventions were randomized) and for 2023-2025 excluding December. Each cell reports the coefficient on messages received ($M_{is} \in \{0, 1, \ldots, 7\}$) from a 2SLS regression that instruments messages received with random assignment to the relevant arm, following Muralidharan et al. (2019); the standard error clustered at the school level is in parentheses. The extrapolated effect at 7 messages is the per-message coefficient multiplied by 7, under the assumptions of constant treatment effects across compliers and a linear dose-response (Angrist and Imbens, 1995; Muralidharan et al., 2019). The Angrist-Pischke F-statistic tests first-stage instrument strength. All specifications include randomization-strata fixed effects and covariates selected by LASSO. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.15: Within-school spillover effects of text messages on no-phone students, 2022-2025

	(1) Absence rate	(2) Weekend absence rate	(3) Holiday absence rate	(4) Chronic absenteeism
A. 2022				
Information (T1)	-0.27	-0.44	-1.01	-2.70*
	(0.36)	(0.40)	(0.77)	(1.40)
Reminder (T2)	-0.31	-0.51	0.22	-1.60
	(0.36)	(0.42)	(0.76)	(1.37)
Control mean	17.6	22.0	22.2	69.7
P-value (T1=T2)	0.92	0.86	0.11	0.42
N (students)	13,388	12,714	12,665	13,389
B. 2023				
Information (T1)	0.05	0.03	0.08	-1.89
	(0.39)	(0.45)	(0.47)	(1.49)
Reminder (T2)	0.01	0.00	-0.52	-0.88
	(0.37)	(0.44)	(0.46)	(1.53)
Control mean	16.7	19.7	18.1	67.5
P-value (T1=T2)	0.92	0.95	0.23	0.55
N (students)	11,151	11,151	11,137	11,180
C. 2024				
Information (T1)	0.07	0.03	-0.08	-2.39
	(0.40)	(0.44)	(0.55)	(1.54)
Reminder (T2)	0.02	-0.08	-0.12	-1.25
	(0.35)	(0.42)	(0.53)	(1.65)
Control mean	17.1	18.5	18.2	71.3
P-value (T1=T2)	0.91	0.83	0.95	0.51
N (students)	8,787	8,787	8,783	8,815
D. 2025				
Information (T1)	0.21	0.19	0.41	0.50
	(0.48)	(0.52)	(0.57)	(1.93)
Reminder (T2)	0.51	0.41	0.57	2.09
	(0.45)	(0.49)	(0.56)	(2.06)
Control mean	15.0	17.2	17.2	61.6
P-value (T1=T2)	0.47	0.65	0.74	0.39
N (students)	6,793	6,793	6,793	6,793

Notes: This table reports intent-to-treat spillovers for students with no parental phone number on file. Panels use September-November 2022 (A) and 2023-2025 excluding December (B-D). Weekend/holiday rates use recorded Mondays/Fridays and holiday-adjacent days as denominators; chronic absenteeism means missing at least 10% of schooldays. Effects are in pp., with department fixed effects, LASSO-selected covariates, and school-clustered standard errors. * 10%; ** 5%; *** 1%.

Table A.16: Heterogeneous ITT effect of text messages on school absences by student characteristics, 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Female				Argentine				Has disability				Is overage			
	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025
A. Student characteristics																
Information (T1)	-0.56**	-0.42*	-0.27	-0.06	0.37	0.27	0.16	0.71	-0.54**	-0.34	-0.16	-0.07	-0.55**	-0.33	-0.17	-0.06
	(0.22)	(0.23)	(0.24)	(0.25)	(0.72)	(0.70)	(0.90)	(0.87)	(0.21)	(0.21)	(0.22)	(0.24)	(0.21)	(0.21)	(0.22)	(0.24)
Reminder (T2)	-0.32	0.06	0.06	0.01	0.50	0.59	-0.54	-0.87	-0.32	0.11	0.18	0.01	-0.32	0.12	0.19	0.02
	(0.21)	(0.24)	(0.23)	(0.25)	(0.75)	(0.75)	(0.80)	(0.76)	(0.20)	(0.23)	(0.22)	(0.23)	(0.20)	(0.23)	(0.22)	(0.23)
Covariate	-0.21**	-0.44***	-0.69***	-0.63***	1.80***	2.45***	2.81***	2.70***	0.02	1.40***	2.06***	0.20	1.51***	5.17***	5.45***	3.28***
	(0.08)	(0.07)	(0.09)	(0.10)	(0.50)	(0.51)	(0.61)	(0.57)	(0.35)	(0.44)	(0.48)	(0.59)	(0.55)	(0.62)	(0.90)	(1.15)
T1 × Covariate	0.01	0.15	0.18	0.00	-0.93	-0.63	-0.34	-0.76	-0.65	-0.19	-1.14	0.69	-0.41	-1.54*	-0.92	0.48
	(0.12)	(0.12)	(0.14)	(0.15)	(0.68)	(0.67)	(0.88)	(0.85)	(0.53)	(0.62)	(0.69)	(0.79)	(0.82)	(0.86)	(1.26)	(1.54)
T2 × Covariate	-0.02	0.08	0.21	0.02	-0.83	-0.50	0.71	0.91	-0.18	-0.27	-1.18*	0.75	-0.37	-1.33	-2.12*	0.19
	(0.11)	(0.12)	(0.13)	(0.15)	(0.70)	(0.74)	(0.80)	(0.74)	(0.50)	(0.60)	(0.68)	(0.79)	(0.81)	(0.88)	(1.11)	(1.49)
N (students)	164,777	138,587	113,730	90,572	158,660	133,722	110,303	88,305	164,777	138,587	113,730	90,572	164,777	138,587	113,730	90,572
	Mother has high school degree				Father has paid job				Attends morning shift							
	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025				
B. Family and school characteristics																
Information (T1)	-0.70***	-0.50**	-0.32	-0.18	-0.94**	-0.15	0.46	-0.08	-0.60*	-0.55**	-0.20	0.03				
	(0.25)	(0.24)	(0.25)	(0.28)	(0.38)	(0.43)	(0.49)	(0.52)	(0.31)	(0.25)	(0.27)	(0.27)				
Reminder (T2)	-0.42*	0.01	0.08	-0.20	-0.50	0.37	-0.01	0.36	-0.32	0.05	0.24	-0.05				
	(0.22)	(0.25)	(0.24)	(0.26)	(0.38)	(0.40)	(0.45)	(0.55)	(0.27)	(0.27)	(0.26)	(0.26)				
Covariate	-0.63***	-1.49***	-1.61***	-1.26***	-0.48**	-0.84***	-0.68***	-0.89**	-0.95***	-1.35***	-1.06***	-0.88***				
	(0.14)	(0.15)	(0.15)	(0.16)	(0.24)	(0.26)	(0.26)	(0.35)	(0.22)	(0.18)	(0.18)	(0.19)				
T1 × Covariate	0.31	0.24	0.14	0.06	0.37	-0.32	-0.88**	-0.16	0.08	0.37	0.04	-0.19				
	(0.22)	(0.22)	(0.23)	(0.25)	(0.35)	(0.39)	(0.43)	(0.48)	(0.31)	(0.24)	(0.26)	(0.26)				
T2 × Covariate	0.20	0.20	0.16	0.32	0.18	-0.35	0.15	-0.35	-0.01	0.09	-0.14	0.14				
	(0.22)	(0.24)	(0.23)	(0.25)	(0.35)	(0.38)	(0.40)	(0.53)	(0.29)	(0.24)	(0.25)	(0.26)				
N (students)	152,431	128,075	105,001	83,233	120,769	101,300	82,194	64,260	164,777	138,587	113,730	90,572				

Notes: This table shows the heterogeneous intent-to-treat (ITT) effect of each intervention on absence rate (percentage points) for September-November 2022 (after the interventions were randomized) and for 2023-2025 excluding December. The two panels report heterogeneity by student characteristics (Panel A) and family and school characteristics (Panel B). Each characteristic is a supercolumn with estimates for 2022-2025 in the columns below it. Impact estimates come from regressions of the absence rate on treatment indicators, a covariate, their interactions, randomization-strata (i.e., department) fixed effects, and covariates determined by the LASSO procedure. Standard errors clustered by school appear in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.17: Heterogeneous ITT effect of text messages on school absences by student attendance, school performance, and achievement, 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Pre-intervention absences				Average grade				Failed subjects			
	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025
A. Student attendance and school performance												
Information (T1)	-0.07	-0.31	0.00	0.23	-0.87	0.51	-0.07	-0.57	-0.54**	-0.43**	-0.24	-0.03
	(0.31)	(0.30)	(0.31)	(0.34)	(0.92)	(0.83)	(0.82)	(0.84)	(0.21)	(0.21)	(0.22)	(0.24)
Reminder (T2)	0.40	0.04	0.39	0.29	-1.31*	0.47	-0.16	-0.50	-0.33	0.04	0.16	0.04
	(0.31)	(0.29)	(0.32)	(0.35)	(0.76)	(0.82)	(0.78)	(0.87)	(0.21)	(0.23)	(0.22)	(0.23)
Covariate	0.50***	0.34***	0.28***	0.22***	-0.61***	-1.08***	-1.18***	-0.97***	1.13***	1.32***	1.58***	1.31***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.07)	(0.06)	(0.05)	(0.07)	(0.15)	(0.13)	(0.13)	(0.16)
T1 × Covariate	-0.02*	0.00	-0.01	-0.01	0.04	-0.11	-0.02	0.06	0.12	0.47**	0.26	-0.21
	(0.01)	(0.01)	(0.01)	(0.01)	(0.10)	(0.09)	(0.09)	(0.09)	(0.25)	(0.20)	(0.20)	(0.22)
T2 × Covariate	-0.03***	0.00	-0.01	-0.01	0.12	-0.05	0.04	0.06	0.03	0.33	0.05	-0.06
	(0.01)	(0.01)	(0.01)	(0.01)	(0.09)	(0.09)	(0.09)	(0.10)	(0.23)	(0.21)	(0.19)	(0.21)
N (students)	164,777	138,587	113,730	90,572	161,763	137,057	112,424	89,542	161,763	137,057	112,424	89,542
	Words/minute				Critical fluency				Low reading comp.			
	2022	2023	2024	2025	2022	2023	2024	2025	2022	2023	2024	2025
B. Student achievement												
Information (T1)	-0.58*	-0.63**	-0.22	0.12	-0.64***	-0.54**	-0.31	-0.24	0.92	0.23	-0.47	0.93
	(0.33)	(0.27)	(0.29)	(0.32)	(0.21)	(0.22)	(0.23)	(0.26)	(0.88)	(0.80)	(0.68)	(0.64)
Reminder (T2)	-0.46*	-0.15	-0.02	0.15	-0.25	0.05	0.15	0.01	0.91	1.74**	0.98	2.17**
	(0.27)	(0.29)	(0.28)	(0.30)	(0.21)	(0.23)	(0.23)	(0.25)	(1.17)	(0.87)	(0.78)	(0.94)
Covariate	-0.01***	-0.02***	-0.03***	-0.02***	0.69***	1.40***	1.61***	1.31***	0.00	0.02**	0.01*	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)	(0.12)	(0.13)	(0.16)	(0.01)	(0.01)	(0.01)	(0.00)
T1 × Covariate	0.00	0.00	0.00	0.00	0.07	0.00	0.21	0.36	0.00	-0.01	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.23)	(0.20)	(0.22)	(0.24)	(0.01)	(0.01)	(0.01)	(0.01)
T2 × Covariate	0.00	0.00	0.00	0.00	-0.20	-0.15	-0.10	0.16	-0.02**	-0.02	0.00	-0.02*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.20)	(0.20)	(0.21)	(0.24)	(0.01)	(0.01)	(0.01)	(0.01)
N (students)	121,520	101,108	79,508	59,673	121,520	101,108	79,508	59,673	1,636	1,618	1,599	1,581

Notes: This table shows the heterogeneous intent-to-treat (ITT) effect of each intervention on absence rate (percentage points) for September-November 2022 and for 2023-2025 excluding December. The average grade and number of subjects failed use math and language only and require both grades to be observed. Impact estimates come from regressions of the absence rate on treatment indicators, a covariate, their interactions, randomization-strata (i.e., department) fixed effects, and covariates determined by the LASSO procedure. Standard errors clustered by school appear in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.18: Causal forest: ITT effect by predicted CATE quintile

	(1) Information (T1)	(2) Reminder (T2)
Quintile 1	0.17	-0.36
	(0.47)	(0.36)
Quintile 2	-1.15***	-0.05
	(0.38)	(0.27)
Quintile 3	-0.59*	-0.81***
	(0.31)	(0.27)
Quintile 4	-0.42	-0.44
	(0.27)	(0.30)
Quintile 5	-1.72***	-0.49
	(0.30)	(0.36)
Overall average treatment effect (ATE)	-0.74**	-0.43*
	(0.29)	(0.26)
Heterogeneity p-value	1.00	0.18
N (students)	78,829	77,555

Notes: This table shows average treatment effects on September-November 2022 absence rates, measured in percentage points, by quintile of the conditional average treatment effect (CATE) predicted by a causal forest (Athey et al., 2019). Forests use pre-intervention student and family characteristics and attendance, with school-level clustering. Each treatment-control comparison excludes students missing outcomes or covariates. The bottom rows report the overall ATE and a one-sided calibration-test p-value for differential forest predictions. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.19: ITT effect of text messages on reading fluency, 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Words per minute				Critical level (pp.)			
	2022	2023	2024	2025	2022	2023	2024	2025
Information (T1)	-0.29	-0.34	0.47	-0.15	0.23	0.17	0.01	-0.19
	(0.60)	(0.78)	(0.74)	(0.76)	(0.39)	(0.41)	(0.38)	(0.46)
Reminder (T2)	0.05	0.98	0.74	0.14	-0.11	-0.63	-0.54	-0.48
	(0.64)	(0.74)	(0.74)	(0.77)	(0.43)	(0.40)	(0.37)	(0.44)
Control mean	94.2	103	109	112	15.3	9.79	7.23	9.66
P-value (T1=T2)	0.58	0.09	0.72	0.70	0.45	0.04	0.12	0.50
N (students)	127,016	128,527	107,858	86,077	127,016	128,527	107,858	86,077

Notes: This table reports the intent-to-treat (ITT) effect of each intervention on reading fluency from 2022 through 2025. Columns 1-4 report effects on words read per minute, and columns 5-8 report effects on the probability of scoring at the critical level in pp.; column labels indicate assessment years, and control means in columns 5-8 are percentages. Impact estimates come from regressions of each variable on treatment indicators, department fixed effects, and LASSO-selected covariates. We observe 2025 fluency scores for 51.2% of control students, 51.9% of T1 students, and 52.9% of T2 students. Conditional on randomization strata, follow-up is 0.6 pp. higher for T1 (SE 0.5 pp.) and 1.7 pp. higher for T2 (SE 0.5 pp.) than for the control group, so we keep this difference in mind when interpreting the 2025 T2 estimates reported in the table. Standard errors clustered by school are in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.20: Comparison between in- and out-of-sample schools in study 4, 2023

	(1) All schools	(2) Out-of-sample schools	(3) In-sample schools	(4) Col.(3)-(2)
A. Demographics				
Female	48.8	47.9	48.9	0.94*
	[50.0]	[50.0]	[50.0]	(0.53)
Argentine	99.1	98.5	99.2	0.62**
	[9.38]	[12.0]	[9.12]	(0.24)
Has disability	4.99	6.47	4.86	-1.61***
	[21.8]	[24.6]	[21.5]	(0.34)
N (students)	189,749	15,077	174,672	189,749
B. Schooling				
Attends morning shift	58.2	78.5	56.4	-22.1***
	[49.3]	[41.1]	[49.6]	(3.25)
Attends afternoon shift	40.1	0.70	43.5	42.8***
	[49.0]	[8.36]	[49.6]	(0.76)
Is overage	1.58	2.82	1.47	-1.34***
	[12.5]	[16.5]	[12.1]	(0.28)
N (students)	189,749	15,077	174,672	189,749
C. Attendance				
Absence rate	16.1	16.0	16.1	0.10
	[11.3]	[12.4]	[11.2]	(0.65)
Mon/Fri absence rate	6.90	6.82	6.91	0.09
	[4.93]	[5.25]	[4.90]	(0.27)
Holiday absence rate	2.09	2.10	2.09	0.00
	[1.76]	[1.92]	[1.74]	(0.09)
Chronically absent	65.5	62.2	65.8	3.62*
	[47.5]	[48.5]	[47.4]	(1.94)
N (students)	189,865	15,094	174,771	189,865
D. Reading fluency				
Words per minute (wave 1)	75.8	69.5	76.3	6.79***
	[47.2]	[46.3]	[47.2]	(1.32)
Words per minute (wave 3)	102	95.8	102	6.29***
	[49.2]	[49.7]	[49.2]	(1.38)
Performs at critical level (wave 1)	29.1	36.3	28.5	-7.79***
	[45.4]	[48.1]	[45.2]	(1.39)
Performs at critical level (wave 3)	10.5	13.5	10.3	-3.20***
	[30.7]	[34.2]	[30.4]	(0.75)
N (students)	160,083	12,425	147,658	160,083

Notes: This table compares students by their schools' eligibility for the attendance-facilitator program. In-sample schools are the 507 eligible in 2023; the other 219 are out of sample. All characteristics refer to 2023. Columns 1-3 report means and standard deviations in brackets; column 4 reports the in-sample minus out-of-sample difference and school-clustered standard errors in parentheses. Binary variables and absence rates are percentages; differences are percentage points. Attendance excludes December; weekend and holiday absences use total recorded schooldays as the denominator. Chronic absenteeism means missing at least 10% of those days. Background and fluency records are matched to attendance data. Demographics, schooling, and attendance cover 719 schools; fluency covers 718. Reading results use the first and third assessments, excluding words-per-minute scores above 300. N counts available student records per panel; statistics exclude missing values. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.21: DID and difference-in-discontinuities estimates of effects on school grades, 2023-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Math (SDs)			Language (SDs)			Average grade (SDs)			Failed subjects		
	2023	2024	2025	2023	2024	2025	2023	2024	2025	2023	2024	2025
A. Difference-in-differences												
Effect	0.01	0.00	-0.07**	0.01	0.01	-0.04	0.01	0.00	-0.06*	0.00	0.01	0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)
Comparison mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.12	0.14
N (student-years)	316,675	469,283	299,178	316,664	469,321	299,200	316,506	469,067	299,035	316,506	469,067	299,035
B. Difference-in-discontinuities												
Effect	0.00	0.00	0.03	-0.01	0.00	-0.02	0.00	-0.01	0.00	0.01	0.02	0.02
	(0.03)	(0.05)	(0.06)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)	(0.02)	(0.02)	(0.02)
Bandwidth (pp.)	2.27	2.27	2.27	2.45	2.45	2.45	2.33	2.33	2.33	2.24	2.24	2.24
N (student-years)	147,248	145,351	143,379	154,136	152,207	150,093	151,664	149,735	147,724	147,192	145,280	143,332

Notes: This table reports DID and difference-in-discontinuities estimates using repeated cross-sections of students in grades 1-7 in schools eligible for the attendance-facilitator program in 2023. Outcomes use annual grades before recovery exams. Columns 1-3 report math, columns 4-6 language, columns 7-9 the average of these two grades, and columns 10-12 the number of these subjects failed (grades below 7; range 0-2). The average and failure count require both grades. The subject set is held fixed because math and language are available for all grades. Grade outcomes are standardized within grade and year using comparison-group means and standard deviations; failed subjects remain a count. The DID in panel A compares schools first treated in 2023 with eligible comparison schools, excluding 2024 entrants throughout and later-treated comparison schools in the 2025 specification. Regressions use observations from 2022 through the indicated year, with 2022 as the reference, school fixed effects, grade-by-year fixed effects, and year interactions with baseline attendance and critical fluency. Only one comparable pre-program year is used, so no across-year parallel-trends test is reported. The analysis in panel B compares each follow-up with 2022 at the original 85% cutoff in schools' 2022 attendance, retaining those treated later. Local linear regressions allow slopes to differ across sides and periods and include grade-by-year fixed effects. Estimation uses unweighted observations within outcome-specific symmetric bandwidths selected from 2023 data and held fixed across follow-ups. Standardization uses each DID specification's comparison group and, for difference-in-discontinuities, the original comparison group excluding 2024 entrants. Comparison means refer to the indicated follow-up; N counts student-years used in each regression. School-clustered standard errors appear in parentheses. * 10%; ** 5%; *** 1%.

Table A.22: Effects of attendance facilitators on provincial reading fluency, 2023-2025

	(1)	(2)	(3)	(4)	(5)	(6)
	Score (SDs)			Critical level (pp.)		
	2023	2024	2025	2023	2024	2025
A. Difference-in-differences						
Effect	-0.01	0.04	0.05	-0.23	-0.08	0.34
	(0.02)	(0.03)	(0.04)	(0.49)	(0.49)	(0.97)
Comparison mean	0.00	0.00	0.00	6.95	5.86	10.4
N (student-years)	251,959	377,960	242,130	251,959	377,960	242,130
B. Difference-in-discontinuities						
Effect	-0.06	0.01	0.02	1.27	0.96	0.68
	(0.05)	(0.05)	(0.06)	(1.02)	(1.06)	(1.22)
Bandwidth (pp.)	2.16	2.16	2.16	2.08	2.08	2.08
N (student-years)	111,818	111,282	109,654	111,061	110,531	108,905

Notes: This table reports DID and difference-in-discontinuities estimates for students in grades 2-7 in schools eligible for the attendance-facilitator program in 2023. Outcomes use the final provincial fluency assessment each year, excluding records above 300 words per minute. Columns 1-3 report reading-fluency scores in SDs; columns 4-6 report the share at the critical level in percentage points. Scores are standardized within grade and year using each DID specification's comparison group and, for difference-in-discontinuities, the original comparison group excluding 2024 entrants. The DID in panel A compares schools first treated in 2023 with eligible comparison schools, excluding 2024 entrants throughout and later-treated comparison schools in the 2025 specification. Regressions use observations from 2022 through the indicated year, with 2022 as the reference, school fixed effects, grade-by-year fixed effects, and year interactions with baseline attendance and critical fluency. Comparison means refer to the indicated follow-up. Only one pre-program year is available, so across-year parallel-trends tests cannot be conducted. The analysis in panel B compares each follow-up with 2022 at the original 85% cutoff in schools' 2022 attendance, retaining those treated later. Local linear regressions allow slopes to differ across sides and periods and include grade-by-year fixed effects. Estimation uses unweighted observations within outcome-specific symmetric bandwidths selected from 2023 data and held fixed across follow-ups. N counts student-years used in each regression. Students need not be observed in every assessment year. School-clustered standard errors appear in parentheses. * 10%; ** 5%; *** 1%.

Appendix B Focus groups with parents

To understand why nudging interventions had modest effects on attendance, we conducted focus groups with parents covering: a) the family routines that shape students' attendance, including the weekend and holiday patterns documented in study 1; b) the reasons that parents cite for absences, distinguishing those that originate in the household from those that originate at the school; c) parents' use of the province's online parent portal (see section 2.1.1), to track grades and attendance; and d) parents' experiences with the text messages in study 3.

B.1 Sample

The sample for this study included eight of the 520 schools from study 3. One of our objectives was to generate hypotheses about the reasons underlying the results of that study, so we purposefully sampled these schools to span all experimental groups and illustrate the wide array of contexts in the province, including urban, rural, and what is locally known as "marginal" areas (i.e., those with high concentrations of students from low-income families).

B.2 Protocol

We conducted focus groups at the schools where parents sent their children in November 2022, during the final month of study 3. Each session lasted approximately two hours, included 10 to 20 parents, and was led by one of the authors. Local school staff helped convene participants. Parents were told that the conversation would be audio-recorded but that their names would not be collected, so that they could speak freely about both positive and negative experiences.

The protocol covered four thematic blocks that mirror the structure of our results below: a) family habits (transportation, out-of-school time, weekends, and vacations); b) school attendance (the most frequent reasons for absences, responses to force-majeure events, responses to children's requests to skip school, and absences originating at the school); c) the province's online portal; and d) the text messages that the education ministry had sent to parents for study 3. All focus group sessions were transcribed and school-level memos were written to identify recurring themes and illustrative quotes. We translated quotes from Spanish to English with light edits for clarity.

B.3 Results

We organize the findings around the four topics covered in the protocol. Our aim is to generate hypotheses—not to produce frequency counts or tests of significance—so we emphasize themes that recurred across schools and, where relevant, contrasts across them.

B.3.1 How do students spend their time outside of school?

Students' time outside of school revolves around home, extended family, and extracurricular activities, with transportation varying considerably across contexts. Parents reported that when their children are not at school, they most often play at home, watch television, use cell phones, or participate in organized activities such as soccer, dance, English, robotics, karate, or choir. "English class twice a week, hockey twice a week, and choir" was a typical schedule for children whose families could sustain it. In other households—especially in rural and peri-urban schools—children spend afterschool hours at home unsupervised while parents work, sometimes caring for younger siblings, and several parents reported that concerns about neighborhood safety kept their children indoors rather than playing outside with peers.

Weekends and holidays are dominated by family time. Most parents reported staying at home, visiting relatives, or attending religious and sports activities. Few took trips during long weekends, and fewer still during winter or summer breaks, often citing cost, work, or the lack of a vehicle. When parents traveled, some tried to align trips with the school calendar to avoid absences, while others extended long weekends by keeping children home on the adjacent school day: "you relax, and when you remember, the next day is here—they have to go to class and haven't done their homework—and the next day I don't [send them]". These reports are consistent with the pattern around weekends and holidays documented in study 1.

Transportation is a recurring source of friction. Families reported using a mix of walking, biking, motorcycles, cars, public buses, school vans, and rides from relatives or neighbors, often switching modes depending on weather, work schedules, or vehicle availability. Public transport is a particular pain point: buses are infrequent, unreliable, or skip stops during peak school times ("if you don't catch a bus by 7:15 am. . . the bus won't stop for you"), and the cost of fares is non-trivial for low-income families, with one parent describing how she rotates which of her children attends school each week depending on what she can afford in bus fare. Unpaved streets turn impassable in the rain, and road-safety concerns keep some parents from letting children bike or walk alone, especially along rural routes without paved shoulders. These frictions help explain some absences in rural and marginal areas.

B.3.2 Why do students miss school?

Illness is the most frequently cited reason for absences. They described repeated bouts of colds, flu, gastroenteritis, and chronic conditions that spread among siblings and pull children out of school for days or weeks. This seasonal clustering of illness might explain the monthly climb in absences leading into the winter break documented in study 1. Parents struggle to justify these absences because emergency-room staff refuse to issue medical certificates, and family doctors cap them at 48 hours, which is shorter than many recoveries. "If you go to the

Emergency Room, they don't give [the certificate]... mine had the flu for two weeks, but they did give me a certificate". Parents perceive this as a source of unfairly accumulated absences.

Weather and road conditions shape a second, seasonal set of absences, especially at schools with unpaved access roads. Some parents described streets that become "lagoons" when it rains, and others described equivalent stretches of mud that made walking or biking impossible. The *zonda* wind (a hot, dry foehn wind that descends from the Andes) and extreme summer heat and winter cold were also cited as reasons to skip school, because schools were perceived as structurally unprepared ("no school is prepared for thirty kids in a classroom with a fan"). That parents cite rain, wind, and temperature as determinants of whether they send their children to school supports the relevance of the rainfall instrument in study 2.

A substantial share of the absences parents reported were not initiated by the family at all, but by the school system, including teacher strikes and absences, school disinfections and closures for force-majeure events (water or septic outages). These were communicated to parents via WhatsApp—often only that morning—and not all parents received these messages, due to intermittent coverage or lack of prepaid data ("I took the time to calculate that out of the 20 absences attributed to my child, only two [were our fault]"). Parents across nearly all schools expressed frustration that the online portal does not account for teachers' absences, and several described feeling "reprimanded" for absences over which they had no control.

Student-initiated requests to skip school were relatively infrequent, but parents attributed them to bullying, conflicts with teachers, academic struggle, and end-of-year fatigue. Parents seemed unwilling to grant these requests but made exceptions at the margins. Several parents questioned the fairness of requiring students who had already passed all subjects to attend school in the final weeks, suggesting the time would be better spent supporting students who were behind. Others felt their children's progress had been held back by classmates' absences and favored keeping even high-performing students in school through the end of the year.

B.3.3 Do parents use the online platform to track attendance?

Parents reported low and uneven engagement with the online portal, for reasons that are largely infrastructural. The parents who did log in—typically a minority at each focus group—used the platform mainly to track grades and absences, checking it roughly once a week to once a month. Several parents described connectivity as the binding constraint: living outside cellular coverage, sharing a single phone, or relying on prepaid data credit that they preferred not to spend on the portal. Others reported being unable to reset passwords, change email addresses, or complete the login process, with one parent describing a two-year effort to update her email before she could access her child's record. At some schools, administrators printed report cards on request as a workaround for families without reliable digital access.

Regular users raised complaints about the information in the portal. Grades are uploaded late, with varying levels of detail across teachers; the absence module offers only a binary justified/unjustified flag, with no way to record what caused an absence; and some parents reported discrepancies between grades on the portal and those on official printed certificates used for secondary-school enrollment. These concerns led parents to view the portal as an incomplete substitute for the paper report card it had replaced, and several requested that the province continue issuing printed records as a hedge against system outages or errors.

When asked what additional information they would want, parents converged on three requests: assignment dates to help children prepare, more granular reporting of reasons for absences, and more timely grade uploads. Some suggested that the platform flag students who might benefit from pedagogical or psychological support, citing cases in which they had only identified their child's needs after a prolonged period of academic or emotional struggle.

B.3.4 How did parents experience the text messages?

Parents' reactions to the text messages were mixed, and the pattern helps make sense of the modest effects estimated in study 3. Some found the messages useful as reminders—especially those who work long hours or whose older children travel to school on their own—and reported that the messages "put you on alert". Others were confused by the messages, worried that their child had escaped from school, or found the texts accusatory when the absences being flagged were due to illness with a valid certificate, a teacher's absence, a strike, or a disinfection ("it seems unfair that I'm being reprimanded... for something for which I'm not responsible"). This mismatch between the content of the messages and the reality parents faced appears to have eroded the credibility of the messages for a non-trivial share of recipients.

Several features of how the messages were delivered came up as areas for improvement. First, parents reported that absences were often tallied with a lag, so messages arrived days—sometimes weeks—after the absence, limiting their usefulness as prompts. Second, messages were sent via SMS, but several said they would have preferred WhatsApp instead, and some did not receive the SMS messages at all due to phone-number changes or coverage issues. Third, parents asked for messages that included the specific dates of absences rather than cumulative counts, so they could cross-check the information against their own records.

Parents who did not receive messages were interested in them, especially for older children, and several suggested same-day notifications. Parents also proposed messages about upcoming tests, teacher absences, class cancellations, and support referrals. Taken together, these observations suggest that the impact of text-messaging interventions in this setting may be constrained less by the principle of informing parents than by the quality and timeliness of the underlying attendance data, the channel through which messages are delivered, and the extent to which the ministry's data matches what parents already know.

Appendix C Prior research

Table C.1 offers an overview of prior randomized evaluations of interventions in which parents are notified of their children's school outcomes (including, but not limited to, absenteeism), presented in chronological order of publication.

C.1 Search strategy

We did not conduct a systematic review of all studies involving notifications of parents in developed and developing countries. Instead, we first identified evaluations of interventions that notified parents of their children's absences. Then, we tracked studies cited in those evaluations, which typically involved notifications for parents of other school outcomes (e.g., missed assignments or grades). Finally, we included evaluations referred to us by colleagues.

C.2 Inclusion criteria

We included studies conducted from 2000 to 2024 in primary or secondary schools in developed or developing countries. We included evaluations of interventions that involved notifications to parents, regardless of the medium through which these notifications were delivered (e.g., letters, text messages, e-mails) and of the outcomes covered (e.g., absences, missed assignments, or grades). We did not include, however, descriptive or correlational studies of student absenteeism or of parental involvement. We only included studies that employed randomized experiments. We included both journal articles and working papers.

C.3 Reporting effects

We report the direction of statistically significant effects on all outcomes measured in each study in the units used by the authors. Specifically, we report the difference between experimental groups adjusted for baseline performance if available. Otherwise, we report the difference between experimental groups without any covariates other than randomization blocks if applicable. If neither is available, we report the difference between experimental groups adjusted for baseline performance and any other covariates that the authors included. Finally, we report effects on both the average participant and on sub-groups of participants.

Table C.1: Impact evaluations of interventions to reduce student absenteeism

(1) Study	(2) Setting	(3) Sample size	(4) Randomization level	(5) Outcomes at baseline	(6) Experimental groups	(7) Results
Bursztyn and Coffman (2012)	Four randomly chosen districts of Brasilia, Distrito Federal (Brazil)	210 families enrolled in a conditional cash transfer (CCT) program (children ages 13-15) across 11 schools; children with older CCT-eligible children were excluded	Family level	Not applicable	• C: Families received BRL 120 (USD 60) per month, conditional on the child attending 85% of classes each month. • T: Parents were presented with choices between their current CCT and an unconditional cash transfer (UCT) of increasing amounts; they were told 5% of parents would receive the chosen transfer; children were offered the same choices. − T1 (baseline): the CCT is the same as the one parents already received. − T2 (text message): before choices between CCT and UCT, parents are offered a free text message when their child misses a schoolday. − T3 (don't tell): parents are told their child would not be informed if the cash transfer changed from CCT to UCT.	• T1 (baseline): − 82% of parents are willing to pay to keep the conditionality on the transfers. − Parents willing to forgo over 6% of their pre-CCT household monthly income. − 54% of children are willing to pay to keep the conditionality on transfers. • T2 (text message): − 34% of parents are willing to pay to keep the conditionality on transfers. • T3 (don't tell): − 30% of parents are willing to pay to keep the conditionality on transfers.
Kraft and Dougherty (2013)	One charter school in Boston, Massachusetts (United States)	140 rising grades 6 and 9 students attending MATCH Charter Public School's four-week summer academy	Two-step randomization: • Randomly assigned students to class-taking groups. • Randomly assigned class-taking groups to control or treatment groups (stratified by subject teacher).	• Homework completion rate: 85.2% • Participation per class period: 6.25 • Teacher redirects students' attention per class period: 0.24	• T: For five consecutive days: − One phone call home per day from fiction or non-fiction English teacher, evaluating each student's academic progress and classroom behavior, describing upcoming homework assignments and tests, and suggesting something the student should continue to do well or try to improve on. − One text/written message from their math teacher identifying something the student had done well or pointing out something he/she could do better. • Same as T after the study.	• T: − 4.10 pp. (40%) increase in odds of turning in completed homework. − 25% decrease in instances of teachers redirecting students' attention. − 15% increase in student participation.

Avvisati et al. (2014)	Créteil school district, Paris (France)	4,300 students in grade 6 in 183 classes across 34 middle schools; two-thirds of schools were from disadvantaged areas	Class level	• Absence: 4.20 half-days • 11% disciplinary sanctions • 29% earned top marks for conduct (all outcomes from control group at endline)	• T: Three meetings with parents, led by school principals, to advise them on how to help their children succeed in school. – Sessions conveyed four messages: all parents can help their child, regardless of background; students need to do homework to do well in school; parents should scrutinize schoolwork; children should feel their parents understand the demands of teachers and principals. • C: No participation in meetings.	• T: – 1.10 half-day reduction in truancy. – 4.60 pp. reduction in disciplinary sanctions. – 6.50 pp. more likely to earn top marks for their conduct. – 0.12 SD increase in French achievement using teacher marks.
Kraft and Rogers (2015)	One large urban school district, Northeast (United States)	435 high-school students enrolled in a credit-recovery program from over 30 high schools	Parent level	• Attendance rate: 89% • Number of courses failed: 1.38	• T: Four weeks of e-mail, text, or phone calls (based on preferences) written by teachers but delivered by research assistants to parents of students: – T1 (positive information): messages cite something positive that the student has done, behaviorally or academically. – T2 (improvement information): messages cite something the student needs to work on that week. • C: No communication.	• T1 (positive information): – No effect on probability of passing, failing, dropping out, or being dismissed from the course (with or without baseline covariate adjustment). – 1.90 pp. decrease in absence. – No effect on teachers' perceptions of students, students' perceptions of their communication with parents, or students' self-assessments. • T2 (improvement information): – 8.80 pp. increase in passing rates (9.10 pp. with covariate adjustment). – 8.10 pp. decrease in dropout rates (7.60 pp. with covariate adjustment). – No effect on failure or dismissal rates (with or without covariate adjustment). – No effect on teacher or student perceptions. – Improvements in students' self-assessments.

Robinson et al. (2018)	California, United States	10,504 students in kindergarten to grade 5 across 10 school districts	Household level	• Average annual absences: 8.24 days	• T1(Mailing Only): Personalized mailing to parents with information on number of their child's total accumulated absences in school year with message about the utility value of attendance • T2 (Mailing 1 Supporter): Personalized mailing to parents with information on number of their child's total accumulated absences in school year with message about utility value of attendance and an additional insert that urged parents to rely on social network for getting their children to and from school • C: Normal school communication	After 1 year and 6 rounds of treatment: • T1: − 0.50 reduction in days absent • T2: − 0.56 reduction in days absent − 25% reduction in chronic absenteeism
Rogers and Feller (2018)	Philadel-phia, United States	28,080 students in kindergarten to grade 12 across 203 schools	Household level	• Average annual absences: 16.3 days	• T1 (Reminder): Personalized mailing to parents with information on importance of attending school and their ability to influence their child's attendance • T2 (Total absences): Personalized mailing to parents with information on the number of their child's total accumulated absences in school year • T3 (Relative absences): Personalized mailing to parents with information on their child's accumulated absences in the school year compared to absences of a typical student in the classroom • C: Normal school communication	After 1 school year and up to 5 rounds of treatment: • T1: − 0.60 reduction in days absent − 3 pp. reduction in chronic absences • T2: − 1.10 reduction in absences − 3.60 pp. reduction in chronic absences • T3: − 1.10 reduction in absences − 4.10 pp. reduction in chronic absences

Dizon-Ross (2019)	Two districts: Machinga and Balaka (Malawi)	2,634 households with at least two children enrolled in grades 2 to 6 in 39 primary schools	Household level (stratified on the between-sibling test-score gap and the estimated literacy rate in the household's village).	• Test scores (out of 100): Math: 45.4, English: 44.5, Chichewa: 51.5, Overall: 47.1.	• T: Surveyors visited households and walked parents through two report cards (one per child), in randomized order, showing each child's performance on all school-administered tests in the most recent term, expressed as a percent-correct score, the Malawian grading scale, and the within-class percentile ranking in math, English, and Chichewa, and the average of the three. • C: No report-card intervention.	• Parents hold inaccurate beliefs about the academic skills of their children: − The average gap across all subjects is 20 pp. or 1.20 SDs. − Beliefs about the between-sibling gap diverge from the true gap by 1.10 SDs, with 31% of parents wrong about which child is higher-scoring. • Parents allocate investments according to their (incorrect) beliefs: − Parents are more willing to pay for textbooks in the subjects for which they believe their children to be doing better. − Parents allocate more scholarship tickets to the sibling they think does better. − Parents with lower levels of education are less accurate in their beliefs. • T: − If the child's score increases by 1 pp., the chance that his/her parents update by 1 pp. increases by 25%. − Information causes investments to become 3-6 times more steeply aligned with performance across the investments (slopes increased 200-500%). − High-performing children are more likely to be enrolled in school a year later (dropout falls to nearly 0%, from a control mean of 2%). − Low-performing children are less likely to be enrolled a year later (dropout doubles from 2% to 4%). − No effects on attendance or expenditure. − Information has a larger effect among less educated parents (they update their beliefs more than more educated parents and this aligns their preferred difficulty level for textbooks more than more educated parents).

Bergman (2021)	Los Angeles, United States	306 students in grades 6 to 11 in one K-12 school	Student level	• Full-day attendance rate: 95% • GPA: 2.10/4.00	• T: − Mailing, SMS or phone calls -according to parents' preference- for every assignment their child missed, detailing assignment name and class whenever possible − Mailing, SMS or phone calls -according to parents' preference- every five to eight weeks on their child's course grades − Mailing, SMS or phone calls -according to parents' preference- notifications about upcoming final exams • C: Normal school communication	After 6 months and a median of 10 rounds of treatment: • T: − 28% reduction in classes missed − 25% increase in assignment completion − 0.21 sd. increase in Math test score − 0.19 sd. increase in GPA
Musaddiq et al. (2024)	Four public school districts in the metro-Atlanta area	22,883 students in grades K to 12	• Student level (stratified by district and high school versus 8th grade). Targeting students who after the first 3-4 months of classes were predicted to be chronically absent (i.e., missing 15 school days in the year).	• Attendance prior to treatment assignment	• - T: monthly text message to parents (starting in November) notifying them about the number of school days their child had missed this year and which percentile they were in compared to their peers. The text message for parents of high school students included "Students with fewer absences are more likely to graduate." • C: Business-as-usual. All districts sent a letter home when a child had missed 3 school days unexcused. A follow-up letter is sent at 5, 8, and 10 absences. One district had an expectation that teachers call parents when a child was absent.	• • T: − 2-3% reduction in end-of-year absences (0.40-0.67 fewer days) across all four districts. − 2-6% reduction in probability of chronic absenteeism across all four districts. − 3-4% reduction in absences (0.67-1 fewer days) in the two districts that implemented with fidelity. − 4-7% reduction in probability of chronic absenteeism in the two high-fidelity districts. − Effects concentrated in grades K-8; no significant effect in high school.

Berlinski et al. (2025)	Two disadvantaged municipalities of Santiago (Chile)	1,447 students in grades 4 to 8 across 8 elementary schools; siblings were excluded	Two-step randomization: • Randomly assigned classes to a high (75%) or low (25%) share of the treatment. • Randomly assigned students to control or treatment groups according to high/low class shares.	• Attendance rate: 88% • Grade promotion rate: 95% • Final grade average: 5.50	• T: Three types of text messages sent to parents, starting on different dates. – Weekly attendance messages indicated the number of days that the child had been absent from school. – Monthly behavioral messages indicated the number of positive and negative behaviors the child exhibited in class. – Weekly grades messages indicated the grades that the child obtained in math. – After 2.50 months, treatment classes were randomized to a DVD that explained to parents how to interpret the text messages. • C: No additional communication.	• T: – No effect on end-of-year math grades, but 0.09 SD effect on standardized math grade and 2.70 pp. increase in propensity to score above 4 (out of 7). – No effect on monthly attendance or cumulative days attended, but 4.70 pp. increase in propensity to have cumulative attendance above 85%. – No effect on share of positive/negative notes, but 20.3 pp. decrease in propensity of receiving extremely negative notes for at-risk students (no main effect). – No effect on share of passing rates or school transfers.
Lichand et al. (2026)	São Paulo (Brazil)	19,253 students in grade 9 across 287 schools	Two-stage randomization: • Schools are assigned to 5 sub-samples: – T1, T2, C1; – C2; – T1, T2, T3, C1; – T2, C1; or – T4, C1. • Students are randomized within-class to each group.	• C2 (endline): – Math attendance: 87% – Math GPA: 0 (std.) – Promotion to HS: 94% – Math test score: 0 (std.)	• T: Three types of weekly text messages sent to parents, for 18 weeks (all information presented as categories): – T1 (individual information): information on number of math lessons students missed or arrived late to, or assignments completed. – T2 (salience): emphasis on importance of paying attention to attendance, punctuality, or assignments. – T3 (relative information): same as T1, with comparison to the median peer. – T4 (engagement): suggestions for parents with non-curricular activities to do with their children. (This group was not comparable to others at baseline; effect is estimated using diff-in-diff). • C: Two types of control groups: – C1: no additional communication, in schools where peers receive messages. – C2 (pure control): no additional communication across the entire school.	• T1+T3 (information): – 2.10 pp. increase in math attendance (five additional classes). – 0.07 increase in math GPA. – 2.60 pp. increase in math promotion. – 0.11 SD increase in math test score. – T1 and T3 yield similar effects for attendance, GPA, and math test scores, but not promotion (T1 does better). • T2 (salience): – 2.10 pp. increase in math attendance. – 0.09 increase in math GPA. – 3 pp. increase in math promotion. – 0.10 SD increase in math test score. • Effects of T1-T3 on non-treated students with treated peers are very similar, suggesting spillovers. • T4 (engagement): – 1.50 pp. increase in math attendance. – 0.12 increase in math GPA. – Effect scales with frequency: 3 messages/week raises attendance by 2.50 pp. and GPA by up to 0.15 SD.