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IZA DP No. 14921

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ABSTRACT

Nudging Parents to Increase Preschool Attendance in Uruguay*

This paper presents the results of a nationwide very low-cost behavioral intervention aimed at increasing preschool attendance in Uruguay. Specifically, behaviorally-informed messages were delivered through the government's official mobile app. We document a large reduction in absenteeism, as well as an increase in some measures of cognitive development, though only for children around the median of the attendance rate baseline distribution (between deciles 4 and 6). The intervention was ineffective for children with very high or very low pre-treatment absenteeism levels. Our results, although encouraging, emphasize the limits of these types of interventions, especially for children in families where barriers to reduce absenteeism might be structural rather than behavioral.

JEL Classification: D9, I2

Keywords: preschool attendance, behavioral, cognitive development

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* This investigation was funded by the Inter-American Development Bank. The experiment was registered at AEA RCT registry under IPA IRB Protocol #: 15066.
We thank Gregory Elacqua and Sebastián Gallegos for their insightful comments on the design of the intervention and the staff of Consejo Educación Inicial y Primaria (CEIP) for conducting the campaign. We especially thank Celeste Cruz, Alicia Milán, Oscar Montañés, Andrea Silveira, and Martín Tambucho. Marcia Ruiz, Rayssa Ruiz and Julian Pedrazzi provided excellent research assistance.

I. Introduction

Preschool attendance is crucial for child development and has long-term effects on academic performance, adult human capital, and economic self-sufficiency (Berlinski et al., 2008; Bailey et al., 2020; Conti et al., 2016). A vast literature shows that low-cost behavioral strategies can effectively reduce absenteeism among primary or secondary students (Berlinski et al., 2016; Bergman and Chan, 2021; Bergman, 2021), yet the evidence related to preschool children is not only scarcer, but focuses exclusively on developed countries (Robinson et al., 2018; Rogers and Feller, 2018; Kalil et al., 2019). Moreover, while reducing absenteeism is important in and of itself, direct evidence on the extent to which these types of interventions may improve cognitive development – a crucial predictor of further lifetime academic and labor market performance – is virtually inexistent.

We contribute to filling this gap through the assessment of a nationwide low-cost behavioral experiment designed to increase preschool attendance in Uruguay. This specifically consisted of sending behaviorally-informed messages to parents of preschool children through an official mobile app (*GURÍ*), used by the government to communicate with families. The messages were transmitted for a period of 13 weeks and were automatized (i.e., they were based on students' administrative information already uploaded to the system). They described the short- and long-term benefits of preschool education, provided feedback on their child's absences in the previous three weeks, and helped families plan so as to minimize absenteeism.

We document a significant reduction in absenteeism as well as an increase in the cognitive domain of child development[1], though only for children around the median of the attendance rate baseline distribution. In terms of days attended, we observe a positive effect in deciles 5 and 6 of the baseline attendance rate distribution of 2.02 and 1.34 days, respectively (control mean of 50.64). Similarly, we find an increase in attendance rate on deciles 5 and 6 of 3 and 2 percentage points, respectively (control

[1] Since 2015, Uruguay biannually measures child development in public preschools (ages 3-5). The instrument includes three domains: cognition, motor skills, and socio-emotional skills.

mean of 0.80). Moreover, there is a positive effect on cognition of about 0.16 standard deviations in decile 4 of the pretreatment attendance rate (control mean of 0.48), which is related to the increase in the language component in the same decile , close to 0.26 standard deviations (control mean of 0.38). The intervention was, however, ineffective for children with either very high or very low pre-treatment absenteeism levels (and, as a result, there was no effect on average for the entire sample).

Our results, while encouraging, also highlight the limits of these types of interventions. Children with very high pre-treatment absenteeism rates (absent days surpassing 25%) were immune to the intervention. Given that these children typically come from lower-income families (about half of the individuals falling in the lowest pre-treatment attendance rate decile belong to the bottom 2 quintiles of school socioeconomic status [SES]), the null effect suggests a need for more costly and intensive interventions, likely aimed at reducing barriers more structural in nature. In contrast, the null effect among children with relatively low pre-treatment absenteeism rates (below or equal to 15%) implies that there is an upper bound for these types of policies. The design of our intervention was based on the notion that psychological factors (such as present bias or limited attention) may lead caregivers to act in ways that are against their intentions. This tendency seems to be particularly common in contexts of poverty, where stress factors related to income instability and logistical constraints can weigh on an individual's mental bandwidth (Spears, 2011; Gennetian and Shafir, 2015; Mani et al., 2013). Families with relatively lower pre-treatment absenteeism rates, and likely of higher SES, are presumably less constrained by these types of behavioral constraints and thus less sensitive to behaviorally-informed interventions. Although the intervention affected attendance and cognitive development around the median of the pre-treatment attendance distribution, the specific individuals affected in each type of outcome were not exactly the same. This suggests that the effect on cognitive development was not mediated by attendance, though it may have been directly affected by the treatment.

The Uruguayan context is particularly well-suited for the testing of this type of intervention. Although preschool enrollment has increased, reaching almost universal coverage for four- and five-year-old children, attendance remains at low levels. In 2018, more than a third of children enrolled in public preschool centers had insufficient attendance (i.e., they were absent more than 25% of the school days). Absenteeism is especially high among students enrolled in schools in lower socioeconomic areas.[2] Moreover, the existence of an official mobile app (*GURÍ*, an educational information monitoring system for families, which allows schools and families to communicate) made the intervention easy to implement, inexpensive (virtually free), and scalable.

Our paper contributes to a growing literature that tests the effects of behaviorally-informed (or informational) messages on students' absenteeism. For instance, Bergman and Chan (2021) show that a light-touch intervention consisting of automated student information messages (absences, missed assignments, and grades) sent to parents reduced absenteeism and class failures among middle and high school students. A similar experiment by Bergman (2021) reveals that an SMS intervention to adjust parents' misperceptions about their children's efforts affected student achievement. In a related work by Berlinski et al. (2016), a texting intervention in elementary schools in Chile (containing information about children's test scores, grades, and attendance) was shown to positively affected attendance and test scores.[3] In contrast to these studies, we focus here on preschool children.

A few recent papers have looked specifically at this age group. For instance, Robinson et al. (2018) find that an intervention seeking to change parents' false beliefs about pre-primary education through messages reduced both absenteeism and chronic absenteeism in California. Kalil et al. (2019) reveal that the "Show Up 2 Grow Up" program in Chicago, consisting of sending behaviorally informed text messages to parents for 18 weeks (reminders, feedback on absenteeism, the importance of preschool education,

[2] While students in schools in the highest SES quintile attend, on average, 84% of classes, in the lowest quintile this value drops to 75%.

[3] In a related paper, Cunha et al. (2017) analyze whether the positive impact of communication with parents is due to the personalized provision of information on student absences or because it reinforces the importance of school attendance. They observe that while messages that share information about absences had small effects, those declaring the importance of attendance accounted for the largest part of the effects of attendance feedback messages.

planning prompts) had a positive effect on attendance.[4]

Our paper thus make several contributions to previous work. Relatively few studies have focused on preschool children, and these primarily concern a developed country (US). Moreover, in addition to testing the effects on school attendance, we also consider the impact on child development outcomes (i.e., cognitive, as measured by language, math; executive functions and self projection indicators; motor skills; socioemotional skills; and attitudes toward learning), which represent a crucial set of indicators for predicting long-term development.

A notable aspect of our intervention is that, as mentioned, all the messages we sent were automatized and used administrative data already uploaded to the system. Moreover, since we leverage an existent system (*GURÍ*), our intervention did not rely on third-party SMS providers to deliver the messages. This characteristic is not only policy relevant in terms of scale-up feasibility, but also means that the intervention had basically zero cost. While this feature is comparable to Bergman and Chan (2021), most experiments similar to ours differ in this regard.

Our paper continues as follows. Section II describes the experimental design. Section III presents the econometric model, and Section IV the main results. Section V concludes.

II. The experiment

Context

Preschool coverage has dramatically increased in Uruguay in recent years, becoming almost universal for children ages four and five. This trend is a reflection of considerable investments in infrastructure and education personnel aimed at increasing enrollment. Attendance remains, however, an issue. In 2018, the chronic absenteeism rate (class attendance of 90 percent or less) was 81 percent, and insufficient attendance (absent

[4] Doss et al. (2017) also focus on preschool children in the US and show that differentiated information, as opposed to generic messages, improves results.

for 70–139 days of the 187 total instructional school days) was 38 percent (up from 30 percent in 2013). The average number of days absent rose from 34 in 2013 to 41 days in 2018.

The experiment assesed herein was implemented nationwide, in collaboration with the Consejo Educación Inicial y Primaria (CEIP; Early Childhood and Primary Education Council) within the Administración Nacional de Educación Pública (ANEP; National Public Education Administration). CEIP oversees national education policy for preschool and primary education. To improve its administrative capacity, in 2011 CEIP launched *GURÍ*, a unified web-based management system for records and information. It contains data on enrollment, student attendance and grades, and teachers. Familiescan access information on their children through *GURÍ*, and teachers and parents are able to communicate with one another. Appendix Figure A1 shows a screenshot of the *GURÍ* mobile app. Our intervention was purposely designed to be conducted through *GURÍ* and use already existing data such that, if successful, it could easily be scaled up.

Design

The intervention consisted of a text message campaign delivered using the *GURÍ* mobile app. There are several benefits of using a mobile app (as opposed to SMS) to implement communication campaigns. One is the low cost of implementation. Indeed, once the programming of the messages has been done, the expense of expanding and replicating the campaign is almost zero. Moreover, the messages scrapped administrative data already uploaded to the system (classes missed by each student), making the process easily scalable.

A further advantage is that the mobile app is independent of a cellphone number, helping to maintain regular contact with parents. Frequently changing phone number is widespread in Latin America and poses a significant challenge for interventions delivered through text messages (Bloomfield et al., 2019). The app may also prevent parental distrust of the messages, as they are receiving them through an official institutional channel. That said, the effectiveness of mobile apps to deliver information to families can be hindered by low take-up of this technology.

A total of 43 messages were designed to be sent to treatment group parents over the course of the last three months of the school year.[5] Parents in the control group did not receive messages. As some families agreed to participate in the program after it started, we ended up delivering 34 messages per parent on average. Appendix Table A1 presents the number of messages per type of message. We describe their content and underlying rationale in the following sub-section.

Cunha et al. (2017) find that varying message delivery time is more effective than always sending messages at a fixed time. We therefore diversified the day and moment of delivery so as to prevent parents from anticipating the message. We also varied the frequency of the messages each week: one week, we delivered three messages, on Tuesday, Thursday, and Sunday; the following week, we sent four messages, on Monday, Wednesday, Thursday, and Sunday. We limited the number of messages to a maximum of four, as more messages have been found to reduce the effect of the intervention (Cortes et al., 2021). As the literature suggests heterogeneous effects conditional on which messages are sent (Cortes et al., 2021), we also combined weekend and weekdays. Finally, the messages were sent at either 5 pm or 7 pm, and we always sent a message on Thursday because Friday is the day students are most likely to miss class (see Appendix Figure A2).

Message content

Several factors may influence preprimary attendance (Chang and Romero, 2008; Jacob and Lovett, 2017). Some are structural, associated with student characteristics and background (education of parents, household income, community infrastructure, transportation, and school- and community-related factors, among others). Others are tied

[5] The campaign started on September 22nd and ended on December 22nd, 2019.

to cognitive biases that influence parents' decisions. Our intervention focused on the latter, where the design aims to reduce absenteeism by diminishing certain psychological barriers preventing parents from taking their children to preschool.

Specifically, the messages take into account psychological biases identified in several studies as potential barriers for caregivers, especially in low-income contexts. We complemented these findings with the results of 10 focus groups exploring families' perceptions and attitudes, conducted in different regions of Uruguay with a total of 79 parents. They were asked about behavior in different dimensions shown in the literature to be linked to student attendance (the focus group instrument is provided in Appendix Table A2). Information gathered through the focus groups suggested that while some absences are produced by structural factors (such as illness or unexpected events), many (such as thoses related to bad weather, family events, and medical appointments) are preventable. An intervention that targets malleable components of absence could, therefore, increase student attendance. For instance, the focus group findings revealed that false perceptions and beliefs play a role in how parents think about attendance, with parents underestimating the number of days their children missed class. In addition, parents seemed to value preschool education in general, but underestimated its short- and long-term cognitive and life benefits, which may translate into lower investment in their children's attendance.

In light of these considerations, we designed messages to tackle the following cognitive biases or anomalies: mistaken beliefs related to the child's number of absences Bergman and Chan (2021); present bias (related to the cost-benefit of their child avoiding missing preschool); mismatched identity (Gennetian et al. (2016) show that parents might not believe in their own ability to affect their children's lives; and limited attention (parents may be forgetful, especially if cognitive bandwidth is limited, a greater possibility among lower-income families, as Mani et al. (2013) document). Taking these various dimensions into account, we related the messages to four behavioral tools:

(i) ***Feedback.*** We sent a feedback message to parents every three weeks that included the number of times their child was absent.[6] If a child did not miss any days of school, the message ended by congratulating the parent. The idea behind these messages was to correct parents' potentially mistaken beliefs, which could be driven by limited parental attention or by their bias with respect to their child. Several scholars have shown that feedback messages can correct parents' mistaken beliefs about their child's attendance rate and have proven helpful in increasing school attendance Kalil et al. (2019); Robinson et al. (2018); Rogers and Feller (2018); Keren and Wu (2015). For example, one feedback message reads: "*[Parent name], [child name] was absent [number] days in the last three weeks. Help [him/her] develop a habit of responsibility by avoiding missing more days the rest of the year!*".

(ii) ***Planning prompts.*** We sent planning prompts to help parents associate their goals with concrete actions for their fulfillment, or identify potential events that might prevent them from achieving the goal. Parents may mean to bring their children to school every day but fail to do so if they either forget about their intention or procrastinate when they needed to take a specific action. Planning prompts could work in cases of limited attention. They have, moreover, been shown to be effective in reducing student absenteeism (Kalil et al., 2019). An example of this type of message reads: *"[Parent name]: Think about the reasons that may have prevented your child from attending school last year. Create a plan to avoid them this school year!"*.

(iii) ***Positive parental identity.*** We also transmitted positive affirmations of parents' ability to ensure their children attended preschool, meant to increase their receptiveness to the message campaign. As Gennetian et al. (2016) demonstrate, mismatched identity (where parents do not believe they can change their child's attendance through their own efforts) is a common bias parents face when making

[6] We chose this timeframe to increase the probability that the child missed at least one school day in the month. Pre-treatment data showed that 53 percent of students missed at least one day every three weeks.

decisions about their children. Affirming parental identity and their competency can increase their participation in parenting support programs (Gennetian et al., 2016; Rogers et al., 2017). An example of this type of message reads: *"[Parent name], what [child name] learns in preschool will last for a lifetime. Help [her/him] go to preschool. You play an important role in improving [her/his] attendance!"*.

(iv) ***Gains in the short and long term.*** Finally, we designed messages that emphasized the socioemotional and cognitive skills children gain by attending preschool. These messages also communicated that missing class hampers these gains. The rationale underlying this type of message is that parents may face intertemporal decisions in parental investment that could be problematic for present-biased parents (Bloomfield et al., 2019). These messages were delivered in two variants. The first combined negative and positive framing, while the second disaggregated the benefits of preschool education in the short run (e.g., math skills) and the long run (e.g., future job prospects). Examples of such messages include: *"Hello [parent name]. Have you noticed the change in the development of [child name] since [she/he] has attended preschool? Imagine what it would be like if [she/he] went every day. Don't let the rain be an excuse, take [her/him]!"*; *"Hello [Parent name]. Preschool attendance is associated with greater achievements in educational trajectories. It is important that [child name] attends daily!"*.

All of the messages sent can be found in Appendix, Table A1. We describe, in Table A3, each behavioral bias we sought to counter and how the intervention addressed the latter using one of the four tools presented above.

Participant recruitment and take-up

The experiment addressed the 194 public schools in Uruguay that have only preschool grades. Using CEIP administrative data, we determined that 39,438 parents with children at these schools were registered in the *GURÍ* system. We define eligibility to the program by accessing their GURI session at least once a year. Therefore, the eligible sample of parents was constituted by 19,272 parents, to whom the informed consent was sent, communicating that their school was eligible for participating in a communication campaign to increase attendance and that they could choose whether or not to take part. Among them, 6,799 (17 percent of all parents registered in *GURÍ* and 35 percent of eligible parents) responded, among whom 4,098 (10 percent of all parents registered in *GURÍ* and 21 percent of eligible parents) agreed to participate in the campaign. We randomly assigned 97 preschools to the treatment group and 97 to the control group. We randomized at the school level to anticipate potential spillovers that could contaminate the control group due to the interdependency of observations at the classroom level. Stratified randomization was implemented taking the (i) assignment to treatment to promote *GURÍ* use, (ii) median number of absences, and (iii) jurisdiction. As further discussed below, we used *GURÍ* data to evaluate whether randomization effectively achieved balance.

Treatment Implementation

The intervention took place over a period of 13 weeks, for a total of 63 school days. Table A4 presents descriptive information relative to the messages delivered and read. Parents who enrolled before the intervention began received a total of 43 messages. Those who agreed to participate after the intervention had already started received fewer messages. The mobile app metadata reveals whether parents actually read the messages, showing that, on average, parents read 70 percent of the messages received. Appendix Figure A3 plots the distribution of the messages received by all parents and by those who joined the intervention after the treatment had started.

Data and Balance

We accessed information on attendance using *GURÍ*, which registers student absences. The system also contains basic information on parents, such as the relationship with the child and use of the mobile app. We counted the potential school days, from early March to December (187 days), and subtracted the total days the student was absent to calculate attendance during the intervention. We framed and linked the results of the intervention with child development using a unique and rich database from the Inventario de Desarrollo Infantil (INDI; Child Development Inventory; see also (Vásquez-Echeverría, 2020)). The INDI data covers the sample used in this experiment, with the exception of three-year-old children, for whom there is no INDI information. The INDI was designed to assess school readiness, and covers four domains of child development—cognitive, motor, socioemotional, and attitudes toward learning.[7] Our merged dataset (at the individual level) resulted in a final sample of 2,800 observations. INDI scores were standardized for each level using a nationally representative sample of children attending age 4 and age 5 classrooms, used for the norm-reference and to generate the INDI automatic reports for teachers (Vásquez-Echeverría et al., 2021).

Table A5 and A6 compares the characteristics of and outcomes for parents who have access to *GURÍ* and those who did not. We observe that students whose parents had access to the *GURÍ* mobile app have better overall outcomes than those whose parents did not. They attended school 8.8 days more per year on average and were 4.7 percentage points more likely to go to school. They were also 5.5 percentage points less likely to fall into chronic absenteeism. Students in the sample attended, on average, 145 out of the 187 school days (77 percent). Chronic absenteeism is prevalent, with 79 percent of students having an attendance rate of less than 90 percent.

Table 1 and 2 compares characteristics and outcomes at baseline for students, parents, and schools in our sample. We ran two comparisons. The first looks at the differences between the treatment and control groups for parents who were eligible to

[7] The cognitive domain aims to assess the different skills that are considered basic for the child's transition from early childhood education to primary school. The motor domain refers to the development of the strength and coordination necessary for the execution of common school tasks, such as holding a pencil or moving around a space. The socioemotional dimension refers to the development of knowledge, behaviors, and attitudes necessary for pleasant and effective social interactions. Attitudes toward learning is understood as those motivational, behavioral, and cognitive characteristics that account for the multiple ways in which children engage in the learning process(Kagan et al., 1995).

take part in the messaging campaign. The second differentiates between parents who did and did not enroll in the campaign. There are no statistically significant differences in either subsample between the treatment and control groups.

Table 1: Sample characteristics. Eligible parents

	(1) Control	(2) Treatment	(3) Sample mean	(4) (1) vs. (2), p-value	(5) N
Jurisdiccion	10.98	12.02	11.51	0.28	19272
	(0.72)	(0.65)	(0.48)		
School SES	3.44	3.43	3.44	0.96	18887
	(0.17)	(0.17)	(0.12)		
Grade 3	0.29	0.29	0.29	0.80	19272
	(0.01)	(0.01)	(0.01)		
Grade 4	0.38	0.37	0.38	0.67	19272
	(0.01)	(0.01)	(0.00)		
Grade 5	0.33	0.34	0.34	0.55	19272
	(0.01)	(0.01)	(0.01)		
Father access	0.39	0.39	0.39	0.98	19272
	(0.03)	(0.03)	(0.02)		
Both access	0.37	0.37	0.37	0.99	19272
	(0.03)	(0.03)	(0.02)		
Student sex	0.50	0.49	0.50	0.73	19272
	(0.01)	(0.00)	(0.00)		
Average number of parents registered	249.00	231.15	239.94	0.25	19272
	(12.77)	(8.86)	(7.82)		
Take up ratio (accepts/access)	0.21	0.22	0.21	0.36	19272
	(0.01)	(0.01)	(0.01)		
=1 si accedieron a la app en el ciclo lectivo	1.00	1.00	1.00	19272	
	(0.00)	(0.00)	(0.00)		
access beforexps	0.29	0.28	0.29	0.87	19272
	(0.02)	(0.02)	(0.01)		
answers	0.34	0.36	0.35	0.33	19272
	(0.01)	(0.01)	(0.01)		
answers beforexp	0.20	0.20	0.20	0.57	19272
	(0.01)	(0.01)	(0.01)		
accepts	0.21	0.22	0.21	0.36	19272
	(0.01)	(0.01)	(0.01)		
accepts beforexp	0.12	0.12	0.12	0.48	19272
	(0.01)	(0.01)	(0.00)		
Baseline attendance days	99.87	98.93	99.39	0.36	19272
	(0.73)	(0.72)	(0.51)		
Baseline attendance rate	0.81	0.80	0.80	0.36	19272
	(0.01)	(0.01)	(0.00)		
Baseline chronic absenteeism	0.74	0.75	0.74	0.61	19272
	(0.02)	(0.02)	(0.01)		
Treat exp 1	0.59	0.59	0.59	0.98	19272
	(0.06)	(0.06)	(0.04)		
N	9490	9782	19272		

Notes: Columns 1-3 present estimated averages for all subjects in the sample (treatment and control groups). Column 4 presents estimates of the differences between treatment and control and standard deviations in brackets. Column 5 presents the number of observations for each indicator. Figures in parentheses are standard deviations.

*** Significant at 1 percent level ($p < 0.01$), ** significant at 5 percent level ($p < 0.05$), * significant at 10 percent level ($p < 0.1$).

Table 2: Sample characteristics. Parents enrolled in the campaign

	(1) Control	(2) Treatment	(3) Sample mean	(4) (1) vs. (2), p-value	(5) N
Jurisdiccion	11.31	12.17	11.76	0.37	4098
	(0.71)	(0.66)	(0.48)		
School SES	3.36	3.26	3.31	0.69	4026
	(0.17)	(0.19)	(0.13)		
Grade 3	0.29	0.28	0.29	0.70	4098
	(0.02)	(0.01)	(0.01)		
Grade 4	0.38	0.38	0.38	0.83	4098
	(0.01)	(0.01)	(0.01)		
Grade 5	0.33	0.34	0.34	0.52	4098
	(0.01)	(0.01)	(0.01)		
Father access	0.39	0.38	0.39	0.85	4098
	(0.03)	(0.03)	(0.02)		
Both access	0.38	0.37	0.37	0.88	4098
	(0.03)	(0.03)	(0.02)		
Student sex	0.50	0.49	0.49	0.35	4098
	(0.01)	(0.01)	(0.01)		
Average number of parents registered	253.25	236.12	244.33	0.35	4098
	(15.49)	(9.98)	(9.14)		
Take up ratio (accepts/access)	0.23	0.25	0.24	0.12	4098
	(0.01)	(0.01)	(0.01)		
=1 si accedieron a la app en el ciclo lectivo	1.00	1.00	1.00	4098	
	(0.00)	(0.00)	(0.00)		
access beforexps	0.25	0.13	0.19	0.00	4098
	(0.02)	(0.01)	(0.01)		
answers	1.00	1.00	1.00	4098	
	(0.00)	(0.00)	(0.00)		
answers beforexp	0.59	0.53	0.56	0.09	4098
	(0.02)	(0.02)	(0.02)		
accepts	1.00	1.00	1.00	4098	
	(0.00)	(0.00)	(0.00)		
accepts beforexp	0.59	0.53	0.56	0.08	4098
	(0.02)	(0.02)	(0.02)		
Baseline attendance days	99.97	98.82	99.38	0.33	4098
	(0.85)	(0.80)	(0.59)		
Baseline attendance rate	0.81	0.80	0.80	0.33	4098
	(0.01)	(0.01)	(0.00)		
Baseline chronic absenteeism	0.74	0.75	0.75	0.67	4098
	(0.02)	(0.02)	(0.01)		
Treat exp 1	0.58	0.58	0.58	0.99	4098
	(0.06)	(0.06)	(0.04)		
N	1964	2134	4098		

Notes: Columns 1-3 present estimated averages for all subjects in the sample (treatment and control groups). Column 4 presents estimates of the differences between treatment and control and standard deviations in brackets. Column 5 presents the number of observations for each indicator. Figures in parentheses are standard deviations.

*** Significant at 1 percent level ($p < 0.01$), ** significant at 5 percent level ($p < 0.05$), * significant at 10 percent level ($p < 0.1$).

III. Econometric model

We estimate the following equation using OLS:

$$Y_{ij} = \beta_0 + \beta_1 T_j + \beta_2 X_{ij} + \epsilon_{ij} \tag{1}$$

Where Y measures the outcome of interest for student i in school j, T is a dummy variable that takes a value of 1 if the school is part of the treatment variable, X is a vector for control variables, and ϵ_{ij} is the error term. The estimated parameter β_1 captures the causal effect of the treatment on the outcomes of interest. We cluster standard errors at the school level and estimate the effects with several baseline controls at the school or individual levels to increase precision: school jurisdiction, individual access to the mobile app, pre-treatment absences, and a dummy that takes a value of one if the individual participated in a previous experiment. We run our model using two set of outcomes: attendance and cognitive development. Increased attendance is expected to affect child development in that it means greater exposure to learning opportunities. Meanwhile, school absences may translate into missed occasions for problem resolution, motor development, and specific language and math stimulation, important bases of cognitive development.

For the former, we analyze two outcomes: attendance days (absolute) and attendance rate (defined as the number of attended days divided by the total number of school days). For the latter, we analyze the following standardized scores: cognitive (language, math, executive function and self-projection), motor, and attitudes toward learning.

IV. Results

Table 3 shows the average effect of our intervention. For each of our outcomes, we document null effects. These results should be interpreted as an "intention-to-treat" effect. Given that the effect may have been greater among those that read the messages (i.e., more read messages may have translated into more days of preschool attendance), we also present a set of results instrumenting the opening of the messages with the random assignment to treatment. For this analysis, we created a binary variable to identify parents who read 24 or more messages, the average number read in the treatment group. If a parent read 24 or more messages, the variable takes a value of one; if s/he read fewer than 24 messages, the value is zero. As it is the result of randomization, the exogeneity of the instrument is ensured. We document an average null effect (Table A7).

Other papers, such as Kalil et al. (2019), show that average results could mask interesting heterogeneous effects. Baseline attendance rate tends to be correlated with income, thus it is plausible that the campaign had a differential effect in different percentiles of the attendance rate pre-treatment distribution. As Mani et al. (2013) show, the type of cognitive biases that our intervention attempts to tackle tend to be more relevant for poorer individuals. Namely, those who are likely to live in more stressful conditions and thus to have a narrower cognitive bandwidth. If so, we would expect to find a more substantial effect among individuals among the lowest attendance rate percentiles. That said, our focus groups also revealed that in our context, many structural factors trigger absenteeism, such as illness or economic incapacity to deal with unexpected events, which are more likely to be barriers for lower-income parents. Under such constraints, our intervention is likely to be ineffective.

As we do not have access to individual data on income, we use individual pre-treatment attendance rate rates as a proxy. In Figures 1, 2, and 3 we estimate our main model (equation 1) for the ten deciles of this variable for each of our outcomes. To this end, we include nine binary variables for each decile of pre-treatment attendance and the interaction of these deciles times the treatment. In the figures, we plot the total effect of the treatment for each pre-treatment attendance rate decile. That is, the sum of the treatment effect and the interaction of the treatment and each decile.

Table 3: Treatment effect of the campaign (OLS)

Panel A: Attendance

	Attendance days		Attendance rate	
	(1)	(2)	(1)	(2)
Treatment	-0.12	0.47	-0.00	0.01
	(0.75)	(0.36)	(0.01)	(0.01)
Observations	4098	4098	4098	4098
Controls	No	Yes	No	Yes
Mean control	50.64	50.64	0.80	0.80

Panel B: Cognitive domain

	Language		Math		Executive function		Self-projection		Cognition	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Treatment	0.09	0.08	-0.03	-0.02	-0.02	-0.03	-0.00	0.02	0.02	0.03
	(0.08)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.06)	(0.04)	(0.07)	(0.04)
Observations	2807	2740	2806	2713	2827	2788	2,817	2769	2780	2683
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean control	0.38	0.38	0.57	0.57	0.42	0.42	0.36	0.36	0.48	0.48

Panel C: General domain

	Motor		Attitudes toward learning	
	(1)	(2)	(1)	(2)
Treatment	-0.07	-0.01	-0.05	-0.04
	(0.05)	(0.04)	(0.06)	(0.04)
Observations	2813	2731	2838	2801
Controls	No	Yes	No	Yes
Mean control	0.38	0.38	0.39	0.39

Notes: The table presents the estimated treatment effect for students in the sample for different outcomes. Column 1 shows estimates without controls and Column 2 includes the following controls: jurisdiction fixed effects, a dummy indicating if, pre-treatment, the child's number of absences was above the sample median, and the value of the outcome in baseline. Figures in parentheses are robust standard errors clustered at the school level.

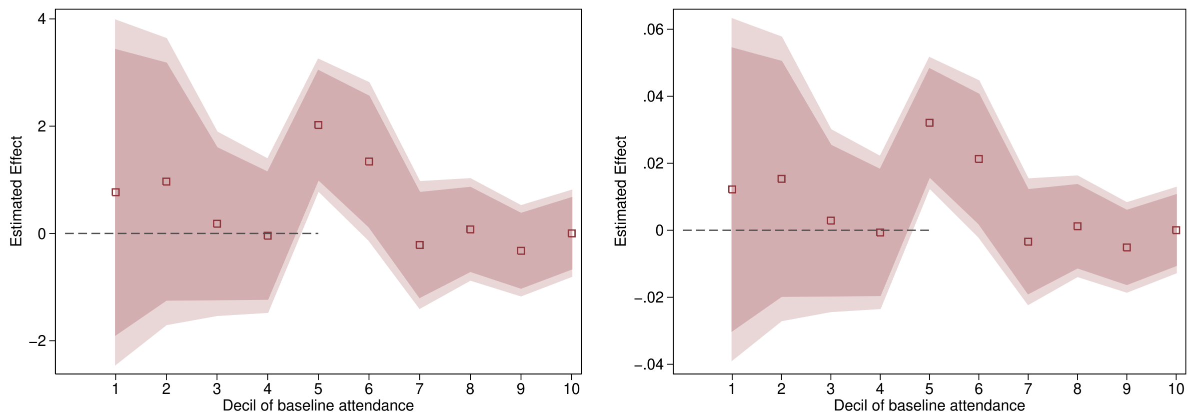
*** Significant at 1 percent level (p ¡ 0.01), ** significant at 5 percent level ($p < 0.05$), * significant at 10 percent level (p ¡ 0.1).

Interestingly, we find a significant effect for the two sets of outcomes (attendance and cognitive development) close to the median of the pre-treatment individual attendance rate. With regard to attended days, our effect close to deciles 5 and 6 of the pre-treatment attendance rate is approximately 1.8 days. There were 63 potential days and the number of attended days in the comparable deciles of the control group was 50.4 in the period. This represents an increase of 3.5% in the number of attended days. When expressed in terms of attendance rates, the effects are approximately 2 percentage points in deciles 5 and 6 of the pre-treatment attendance rate. The attendance rate in the control group was 0.8.

In terms of cognitive outcomes, we are able to identify significant effects at 5% or 10% for some deciles of the attendance rate pre-treatment distribution in the cognition domain and, in particular, in language. In the case of cognition, we identify a significant effect (at 10%) of 0.2 standard deviations only in decile 4 of pre-treatment baseline attendance. The effects seem to be driven by language, where we identify an effect of 0.23 standard deviations (significant at 5%), again for decile 4. For decile 7, there is also a significant effect of 0.21 standard deviations. That only cognition and, specifically, language, were the child development outcomes affected by our intervention might be explained by the fact that these are the domains typically most affected by socioeconomic gradients (Paxson and Schady, 2007).

Figure 1: Treatment effect by attendance rate pre-treatment decile

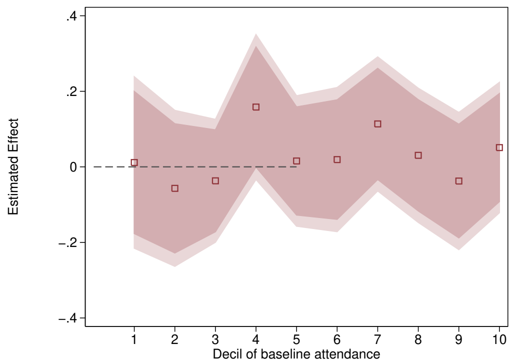
(a) Attendace days (b) Attendance rate



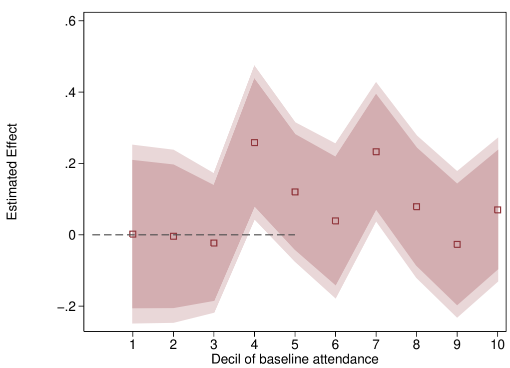
Notes: Each figure presents the sum of the effect of a treatment dummy and the interaction of that dummy with the corresponding attendance rate decile. The darker area reflects the 90% confidence interval and the lighter area the 95% confidence interval.

Figure 2: Treatment effect by pre-treatment attendance rate decile

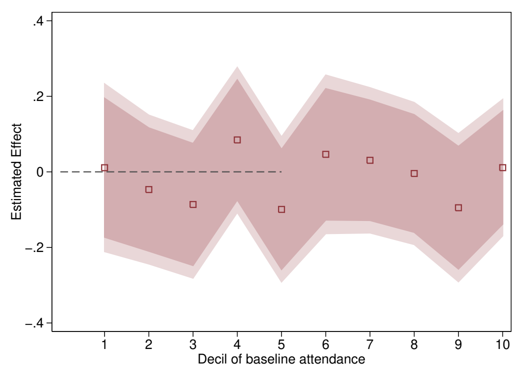
(a) Cognition



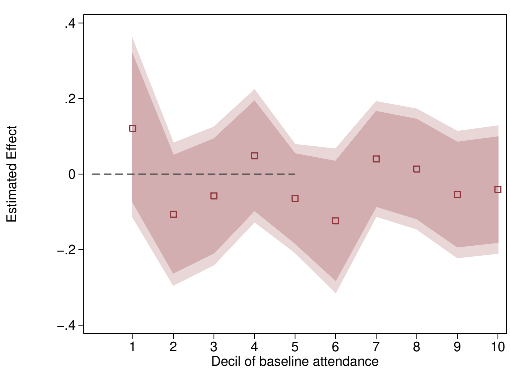
(b) Language



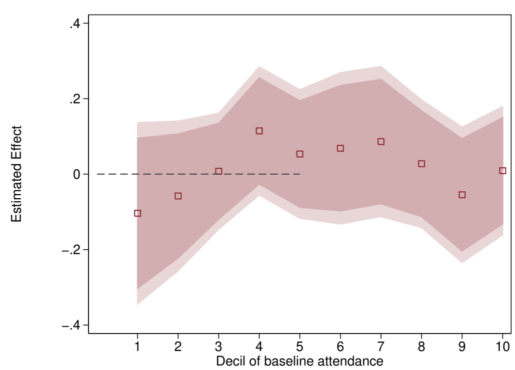
(c) Math



(d) Executive function



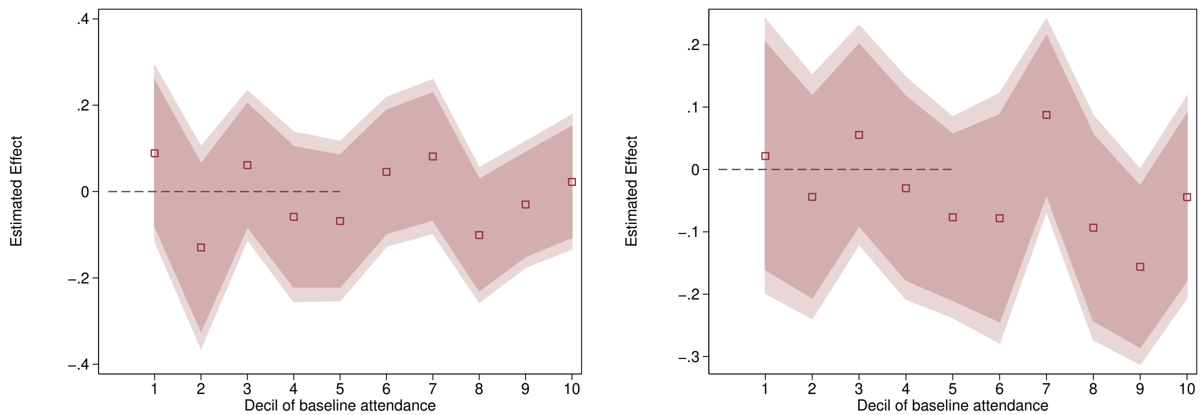
(e) Self-projection



Notes: Each figure presents the sum of the effect of a treatment dummy and the interaction of that dummy with the corresponding attendance rate decile. The darker area reflects the 90% confidence interval and the lighter area the 95% confidence interval.

Figure 3: Treatment effect by pre-treatment attendance rate decile

(a) Motor (b) Attitudes tower learning



Notes: Each figure presents the sum of the effect of a treatment dummy and the interaction of that dummy with the corresponding attendance rate decile. The darker area reflects the 90% confidence interval and the lighter area the 95% confidence interval.

Our intervention was likely not powerful enough to change the behavior of the families with the most stringent and structural barriers. Improving situations characterized by very low levels of pre-treatment attendance rates may require more intensive and costly intervention. At the other end of the spectrum, psychological barriers were plausibly not important for individuals at relatively high pre-treatment attendance rates. This might be due to a simple mechanical factor: increasing an already high rate is more complicated. In addition, if the pre-treatment attendance rate is a reasonably good proxy for income, these families were of relatively higher SES, and thus perhaps-less sensitive to our intervention (Mani et al., 2013).

Interestingly, although the intervention affected attendance and cognitive development around the median of the pre-treatment attendance distribution, the specific individuals affected in each type of outcome were not exactly the same. This may be due to our intervention affecting cognitive development not through higher attendance but by directly influencing caregivers' parental practices.

While the average effects of our intervention are null, the magnitude of the effects close to the median of the pre-treatment attendance distribution (where our treatment reaches its maximum effect) is sizeable and comparable to those found in similar studies conducted in developed countries. For instance, Kalil et al. (2019) identify an effect of 0.04 and 0.023 in the quantiles 25 and 50 on attendance rate (where their treatment reaches a maximum effect). We identify an effect of 0.029 and 0.025 on the deciles 5 and 6 of the pre-treatment attendance distribution. Although our effect is slightly smaller, our intervention was also shorter: 13 versus 18 weeks in their case. Similarly, the largest treatment effect identified by Robinson et al. (2018) (decile 10 of pre-treatment absenteeism) is one day, which in their context translates to a drop in missed days of approximately 14.5%. Where our treatment reaches its maximum effect (deciles 5 and 6 of pre-treatment attendance), we identify an effect of approximately 1.8 days, which, in our context, represents a drop of approximately 14.4% in missed days.

V. Discussion

Governments can make a concerted effort to expand access to preschool services. However, early education is typically not compulsory, meaning that it is ultimately up to families to decide whether they will enroll and bring their children on a regular basis (Mateo-Diaz and Rodriguez-Chamussy, 2016). While structural issues—such as lack of transportation or the need to align work and preschool schedules—account for some of preschool absences, cognitive biases also affect parents' decisions relative to their children's attendance. Fortunately, very low-cost interventions have proven effective in modifying cognitive biases.

To address such cognitive barriers in the context of Uruguay, we designed an intervention based on information gathered in focus groups with parents of preschool children. The findings are consistent with those of previous studies.

Our contribution is novel in that it is the first to use behavioral science to address low preschool attendance in a developing country. Moreover, previous work employed workshops or sent text messages, while our intervention took advantage of an already existent government mobile application as the channel of communication between preschool centers and families.

The results suggest that cognitive biases seem to affect people in the middle of the attendance distribution to a greater extent. Indeed, nudges were successful in influencing the behavior of parents whose children were positioned close to its median, but not those in either the low or high segments. While families at the lower end of the distribution may also have cognitive biases, they face greater structural barriers (e.g., lack of transportation). Meanwhile, children with the highest rates of attendance likely come from families who are already aware of the importance of early education. . This finding is relevant to the tailoring of future interventions and efforts to improve the targeting of public resources.

Furthermore, we see that behavioral nudges can have implications for inequality. Indeed, the nudges were particularly effective in tackling misconceptions about the importance of preschool in five departments in northeast Uruguay, an area characterized by a lower socioeconomic profile than the rest of the country. The fact that our intervention successfully increased attendance in these areas, and that this in turn is connected with better development outcomes for this group, suggests that such interventions might help to narrow socioeconomic and geographic gradients.

Future research could vary the intensity of and exposure to treatment, the time of the year it is administered, the channels used to diffuse the nudges, the context, the cognitive barriers tackled, and the behavioral tools employed. Intervention design is especially important given that the intensity of the treatment (i.e., the number of messages a parent reads) increased the effects in remote regions.

Technology can be a key ally in contexts where the issue is not necessarily the service itself but the mindset behind daily decisions to access the latter. Given the low cost and scalability of these types of interventions, implementation is quite straightforward, and could be particularly effective at preventing massive drop outs of children and youth who were in the middle of their studies during the COVID-19 pandemic. Working in tandem with beneficiaries and their families can help ensure they continue their learning journeys.

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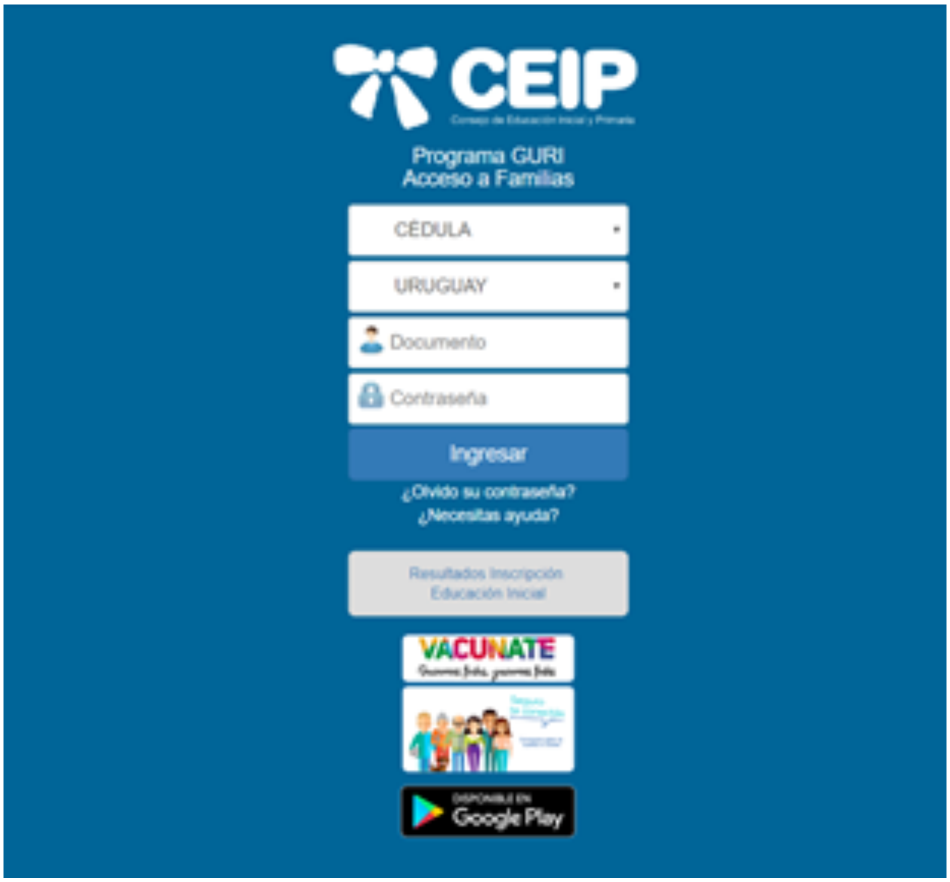
VI. Appendix

Figure A1: *GURÍ* app screenshot



Note: Example of *GURÍ* app used in the experiment.

Table A1: Number of messages sent, by type of message

Type of message	*Number of messages*
Welcome message	1
Feedback (false beliefs)	5
Importance of preschool and short-term effects of absence (present bias)	13
Importance of preschool and long-term effects of absence (present bias)	8
Positive parental identity (mismatched identity)	5
Planning prompts (limited attention)	10
Goodbye message	1
Total	43

Figure A2: Distribution of absences by day of week, March 4–May 17, 2019

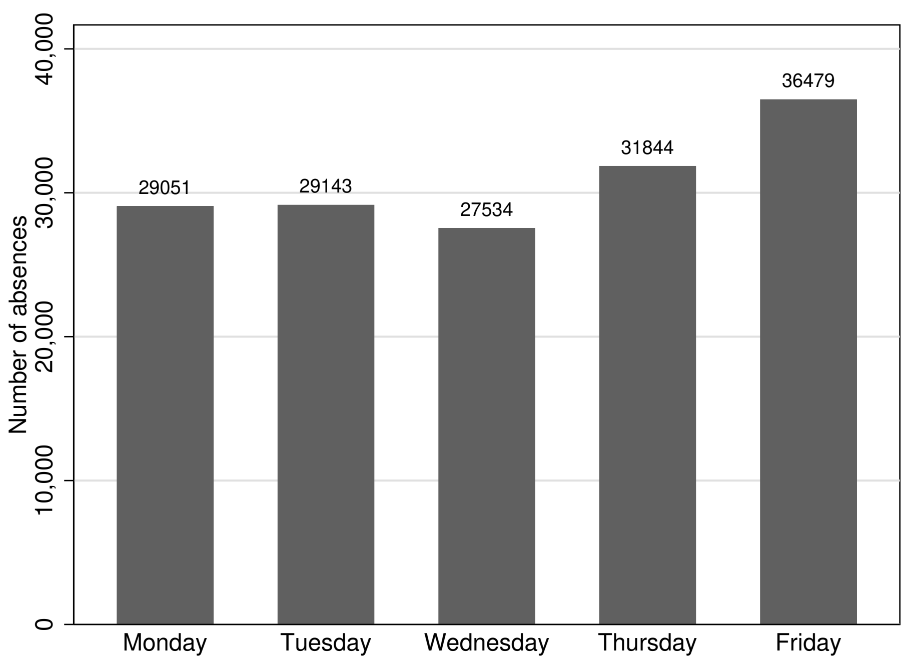


Table A2: Topics covered in focus groups

1. Knowledge of early childhood education and its importance
a. What do children learn in preschool?
b. Is it different from primary school?
c. What is the most important thing a child age 3–5 should learn?
d. How important is preschool to your child's (early) education?
e. Who do you think is better able to teach your child what he or she should learn at this age?
f. How important is it for you that your child shares with other children his or her age in preschool? Why?
2. Perception of absences
a. Does your child frequently miss school?
b. If we ask you today, on average per month, how many days your child missed preschool, would you be sure of the answer? Hint: Make sure to capture the reasons (why parents say no or yes).
c. How many times a month does your child arrive late or leave early?
d. What are the most frequent reasons for your child missing preschool? What are the most frequent reasons why your child is late or leaves early?
3. Consequences of regularly missing preschool for child's development
a. What do you think are the consequences for your child's development, if any, of regularly missing preschool?
b. Would you say that regular preschool attendance is less, as, or more important than primary school attendance?
c. What do you think are the long-term consequences (school and adult), if any, of regularly missing preschool?
d. What are the long-term consequences if someone is late for preschool? Hint: We refer to the impact on learning, disposition, socioemotional development, integration into the classroom, etc.
4. Ability of parents to influence the fate of their children (locus of control)
a. Do you believe that the decisions you make as a parent affect the future possibilities of your child, or are these possibilities already fixed by their context?
b. Can you change your child's intelligence?
c. Can you change your child's personality?
5. Effect of social norms on early childhood education
a. In your social circle, how important is education?
b. In your social circle, how important is preschool education?
6. Quality of the educational center
a. What criteria did you use to choose the center in which your child is enrolled?
b. Would you be interested in having the power to evaluate the center and provide information in order to improve the center's quality?
c. Would you be willing to collaborate in such an initiative?

Table A3: Behavioral biases addressed by the intervention

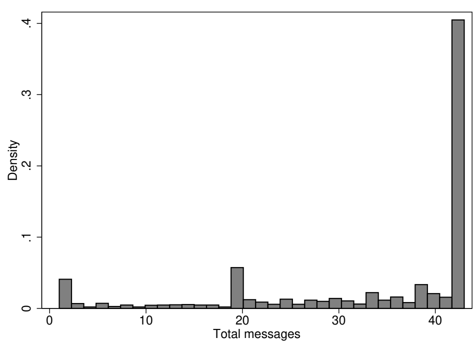
Behavioral bias	*Description*	*Type of message*	*Example*
False beliefs	Parents underestimate how often their children are absent.	Feedback	[Parent name]: [Child's name] missed [number] days of preschool in the last three weeks. Daily attendance is important, don't let [him/her] be missed!
Present bias	Most people tend to invest less than optimally in a specific activity when the reward for engaging in the activity is received only in the future. Parents can fail to internalize the future benefits derived from their investments and consequently make short-sighted investment decisions in their children.	Gains in the short term	[Parent name]: Did you love it when [child's name] showed you how [she/he] could tie their shoes by [him/herself? [She/he] learns that and more every day in preschool. Do not stop taking [him/her] there!
		Gains in the long term	[Parent name]: Did you know that if [child's name] attends preschool every day, it generates lasting habits that will reflect in later grades? Don't let [him/her] be missed!
Mismatched identity	Parents do not believe that they can change their child's attendance through their own efforts.	Positive parental identity	[Parent name]: What you do for [child's name] today—for example, taking [her/him] to preschool so [she/he] does not miss—will be reflected in [her/his] future. You have a key role in your child's education!
	Parents are not receptive to intervention goals.		
Limited attention	Parents forget to make decisions they intended to make and fail to take actions they planned to take. Day-to-day tasks may distract parents from more distant goals and cause them to pay limited attention to beneficial parenting practices.	Planning prompts	[Parent name]: Organize your time so that [child's name] can go to preschool every day. There are new lessons this week. Take [her/him]!

Table A4: Summary statistics for messages sent and read

Item	*Mean*	*Standard deviation*	*Median*	*Minimum*	*Maximum*
Number of messages sent	34	13	42	1	43
Number of messages read	24	15	24	0	43
Percent of messages read	70	40	80	0	100
Observations	2,165				

Figure A3: Distribution of number of text messages sent

(a) All parents



(b) Parents who joined the intervention after treatment started

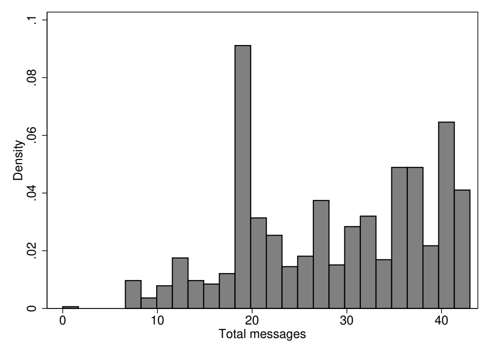


Table A5: Sample characteristics. Comparison between non eligible and eligible parents

	(1) No access	(2) Access	(3) Sample mean	(4) (1) vs. (2), p-value	(5) Observations
School SES	3.33	3.44	3.38	0.19	38435
	(0.12)	(0.12)	(0.11)		
Grade 3	0.30	0.29	0.30	0.12	39438
	(0.01)	(0.01)	(0.01)		
Grade 4	0.37	0.38	0.38	0.84	39438
	(0.01)	(0.00)	(0.00)		
Grade 5	0.32	0.34	0.33	0.10	39438
	(0.01)	(0.01)	(0.01)		
Father access	0.34	0.39	0.36	0.01	37364
	(0.02)	(0.02)	(0.02)		
Both access	0.30	0.37	0.34	0.00	37364
	(0.02)	(0.02)	(0.02)		
Student sex	0.49	0.50	0.49	0.48	37364
	(0.00)	(0.00)	(0.00)		
Average number of parents registered	240.29	239.94	240.12	0.94	39438
	(7.55)	(7.82)	(7.27)		
Attendance days	140.67	149.50	144.99	0.00	39438
	(1.11)	(0.81)	(0.92)		
Attendance rate	0.75	0.80	0.78	0.00	39438
	(0.01)	(0.00)	(0.00)		
Chronic absenteeism	0.81	0.76	0.79	0.00	39438
	(0.01)	(0.01)	(0.01)		
Baseline attendance days	94.11	99.39	96.69	0.00	39438
	(0.67)	(0.51)	(0.56)		
Baseline attendance rate	0.76	0.80	0.78	0.00	39438
	(0.01)	(0.00)	(0.00)		
Baseline chronic absenteeism	0.80	0.74	0.77	0.00	39438
	(0.01)	(0.01)	(0.01)		
N	20166	19272	39438		

Notes: Columns 1–3 present estimated averages for all subjects in the sample and respective variables. Column 4 presents estimates of the differences between treatment and controls. Column 5 presents the number of observations for each indicator. Figures in parentheses are standard deviations.

*** Significant at 1 percent level ($p < 0.01$), ** significant at 5 percent level ($p < 0.05$), * significant at 10 percent level ($p < 0.1$).

Table A6: Sample characteristics. Comparison between participants and nonparticipants

	(1) Do not accept	(2) Accept	(3) Sample mean	(4) (1) vs. (2), p-value	(5) Observations
School SES	3.47	3.31	3.44	0.00	18887
	(0.12)	(0.13)	(0.12)		
Grade 3	0.29	0.29	0.29	0.74	19272
	(0.01)	(0.01)	(0.01)		
Grade 4	0.38	0.38	0.38	0.79	19272
	(0.01)	(0.01)	(0.00)		
Grade 5	0.34	0.34	0.34	0.95	19272
	(0.01)	(0.01)	(0.01)		
Father access	0.39	0.39	0.39	0.89	19272
	(0.02)	(0.02)	(0.02)		
Both access	0.37	0.37	0.37	0.86	19272
	(0.02)	(0.02)	(0.02)		
Student sex	0.50	0.49	0.50	0.89	19272
	(0.00)	(0.01)	(0.00)		
Average number of parents registered	238.75	244.33	239.94	0.09	19272
	(7.57)	(9.14)	(7.82)		
Attendance days	149.38	149.96	149.50	0.32	19272
	(0.82)	(0.94)	(0.81)		
Attendance rate	0.80	0.80	0.80	0.32	19272
	(0.00)	(0.01)	(0.00)		
Chronic absenteeism	0.76	0.76	0.76	0.54	19272
	(0.01)	(0.01)	(0.01)		
Baseline attendance days	99.40	99.38	99.39	0.95	19272
	(0.51)	(0.59)	(0.51)		
Baseline attendance rate	0.80	0.80	0.80	0.95	19272
	(0.00)	(0.00)	(0.00)		
Baseline chronic absenteeism	0.74	0.75	0.74	0.40	19272
	(0.01)	(0.01)	(0.01)		
N	15174	4098	19272		

Notes: Columns 1–3 present estimated averages for all subjects in the sample and respective variables. Column 4 presents estimates of the differences between treatment and controls. Column 5 presents the number of observations for each indicator. Figures in parentheses are standard deviations.

*** Significant at 1 percent level ($p < 0.01$), ** significant at 5 percent level ($p < 0.05$), * significant at 10 percent level ($p < 0.1$).

Table A7: Treatment Effect of the Campaign (IV)

Panel A: Attendance

	Attendance days		Attendance rate	
	(1)	(2)	(1)	(2)
Read 24 or more messages	-0.20	0.80	-0.00	0.01
	(1.30)	(0.63)	(0.02)	(0.01)
Observations	4098	4098	4098	4098
Controls	No	Yes	No	Yes
Mean control	50.64	50.64	0.80	0.80
F-test	1150.36	1205.26	1150.36	1205.26

Panel B: Cognitive domain

	Language		Math		Executive function		Self-projection		Cognition	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Read 24 or more messages	0.15	0.13	-0.06	-0.04	-0.05	-0.08	-0.01	0.03	0.05	0.06
	(0.10)	(0.08)	(0.07)	(0.05)	(0.08)	(0.07)	(0.08)	(0.05)	(0.08)	(0.05)
Observations	2807	2740	2806	2713	2827	2788	2,817	2769	2780	2683
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean control	0.38	0.38	0.57	0.57	0.42	0.42	0.36	0.36	0.48	0.48
F-test	855.42	854.33	855.30	844.38	855.29	848.89	854.74	854.21	854.28	855.45

Panel C: General domain

	Motor		Attitudes toward learning	
	(1)	(2)	(1)	(2)
Read 24 or more messages	-0.13	-0.08	-0.08	-0.07
	(0.15)	(0.09)	(0.07)	(0.06)
Observations	2813	2731	2838	2801
Controls	No	Yes	No	Yes
Mean control	0.38	0.38	0.39	0.39
F-test	854.38	853.47	856.77	856.11

Notes: Table presents the estimated treatment effect for students in the sample for different outcomes. Column 1 shows estimates without controls and Column 2 includes the following controls: jurisdiction fixed effects, a dummy indicating if pre-treatment the child's number of absences was above the sample median and the value of the outcome in baseline. Figures in parentheses are robust standard errors clustered at the school level.

*** Significant at 1 percent level ($p < 0.01$), ** significant at 5 percent level ($p < 0.05$), * significant at 10 percent level ($p < 0.1$).

Figure A4: Timeline of intervention