Pre-Analysis Plan (PAP)
Study Title: Reducing Chronic Absenteeism Among Young Learners
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Planned Registration: AEA RCT Registry and OSF
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1. General Information

This study is a randomized controlled trial evaluating a behavioral text-messaging intervention to reduce chronic absenteeism in preschool and kindergarten within Oklahoma City Public Schools (OKCPS). It is led by Ariel Kalil, Michelle Michelini (University of Chicago) and Sebastián Gallegos (Universidad Adolfo Ibáñez), and will be registered on the AEA RCT Registry and OSF. The study will include 2,400 families and begin implementation in October 2025.

2. Background and Motivation

In the wake of the COVID-19 pandemic, chronic absenteeism in U.S. public schools has reached unprecedented levels. Nationally, the chronic absenteeism rate among K–12 students rose to 28.3% in the 2021–2022 school year, more than doubling from pre-pandemic levels. This problem is particularly acute among preschool and kindergarten students, where consistent attendance is especially critical for long-term developmental and educational outcomes. Children who are chronically absent in the early grades are significantly more likely to struggle with reading proficiency, demonstrate poorer behavioral outcomes, and experience cumulative academic setbacks over time.

The challenge is not distributed evenly: low-income and Hispanic families, who are overrepresented in the Oklahoma City Public Schools (OKCPS) district, face particularly high barriers to regular attendance. These may include limited transportation, health issues, unstable housing, and competing work demands. Moreover, parents of young children often do not view early education as essential, perceiving attendance as less critical than in higher grades. This misperception, coupled with post-pandemic anxiety and disengagement from school systems, presents a formidable challenge to improving attendance patterns among the youngest learners.

This study builds on the team's prior work with the "Show Up to Grow Up" (SUGU) intervention, a behavioral messaging program designed to reduce chronic absenteeism in pre-kindergarten programs. The original SUGU RCT found that well-crafted text messages, grounded in behavioral science and tailored to the lived experiences of low-income families, led to a 20% reduction in chronic absenteeism. The current project aims to refine and scale that approach to a broader and more diverse population, incorporating updated behavioral insights and message designs responsive to the post-pandemic context. The intervention's low cost, high scalability, and administrative data infrastructure make it particularly attractive for broader policy relevance and potential replication.

3. Research Questions and Hypotheses

This study asks whether a behavioral text-message intervention can effectively reduce chronic absenteeism among preschool and kindergarten students. The primary hypothesis is that families who receive the intervention will demonstrate higher attendance rates and lower levels of chronic absenteeism relative to the control group. The secondary hypothesis is that treated students will perform better on cognitive assessments. An additional exploratory hypothesis is that treated students will receive fewer behavioral referrals through the first grade. The intervention is grounded in behavioral science and targets parental misperceptions and logistical barriers.

4. Experimental Design

This is a randomized controlled trial conducted with 2,400 families in Oklahoma City Public Schools, including 1,200 preschool and 1,200 kindergarten families distributed across approximately 120 classrooms of 20 students each. All PreK-K families enrolled in the district in fall 2025 are eligible to participate in the study. First, we will consent families to enroll them in the study. Then, we will randomize parent-child pairs 1:1 within schools to either the treatment or control condition, stratified by grade level and gender.[1] Parents of siblings will be randomized with all of the siblings to either treatment and control groups. [2]The intervention group will receive three weekly behavioral messages over an 8-month period. The control group will receive only minimal contact. Outcomes will be tracked for three years, allowing for both short- and long-term impact analysis.

5. Intervention

The intervention consists of three text messages per week sent via SMS or WhatsApp to parents in English or Spanish. Messages are designed using behavioral principles such as salience, planning prompts, social norms, and loss aversion. Content has been updated based on recent findings and includes messages addressing post-pandemic anxiety, beliefs about attendance, and school engagement. A large-scale pilot is already underway, showing promising levels of engagement and message receipt.

6. Outcomes

Primary outcomes are student-level attendance rates (number of days attended divided by the total number of enrollment days[3]) and a binary indicator of chronic absenteeism (attendance below 90%) at the end of each school year (Spring 2026, Spring 2027, Spring 2028). Secondary outcomes are standardized cognitive test scores (Cognitive Toy Box, NWEA MAP) administered in the fall, winter, and spring and collected at the end of the study cohort's PreK-1st grade school years. Exploratory outcomes are school-reported behavioral infractions also collected at the end of each school year. Data will be collected via administrative records and linked to baseline survey data collected from parents.

7. Data Collection and Consent

Data will come from OKCPS administrative sources and baseline surveys administered to parents in Fall 2025. These surveys capture demographic information, attendance-related beliefs, and household characteristics. We plan to use an opt-out consent model pending school district approval. All data will be stored and analyzed in compliance with IRB and FERPA guidelines.

8. Statistical Analysis Plan

The main analysis will estimate intent-to-treat (ITT) effects using OLS regression. We will control for randomization strata and pre-specified covariates to improve precision. l. We will estimate the following specification

(1) $Y = \beta_0 + \beta_1 R + \beta_2 X + u$

[1] The original Pre-Analysis Plan proposed randomization at the classroom level, stratified by grade level, and child gender. However, after examining the sample available for randomization, we found that many classroom-level strata contained fewer than two observations. To ensure valid assignment, we revise the stratification to occur at the school, grade, and gender level. This adjustment reduces the number of strata and ensures that nearly all strata include at least two children.

[2] This is a conservative approach, because siblings are not fully treated (but we will consider them as if they were). As in our previous work, we will document the prevalence of siblings, measured with a dummy for whether the parent had more than one child enrolled in the same preschool. In our previous work, the average was 10%, balanced by treatment status, and there were no differential effects by sibling status.

[3] We define intervention days as all days during the program period. These are classified as either non-attendance days (weekends/holidays) or attendance days (when school was open). Due to student turnover in preK and K, it is important to separate enrolled but absent children from those who are no longer enrolled. A potential school day counts as a day enrolled for a particular child if she appears on the daily class attendance records. Among enrolled days, we classify attendance as present or absent. Each child's attendance rate is then calculated as the number of days present divided by the number of days enrolled.

where Y is child attendance or chronic absenteeism when assessing our main research question; Y will be test-scores or children's behaviors when assessing our secondary research question. R is an indicator for random assignment to the treatment group, and u is an idiosyncratic error term. Our parameter of interest is β_1, which is an intention-to-treat (ITT) effect or, equivalently, the average difference in the outcome for parents randomized to the treated group compared to those randomized to the control group. We will estimate equation (1) pooling children in preK and Kindergarten; we will supplement specification (1) including the interaction between treatment status and a dummy for grade attended to allow for heterogenous treatment effects. Following Bruhn and McKenzie (2009), we will control for our randomization method in all our specifications, so the vector X includes stratum dummies. We will also include covariates coming from the OKCPS administrative sources and our surveys, including parent and student gender and age; student grade level and prior preschool experience, household socio-economic characteristics, language spoken at home (Spanish or English), whether the student has PreK or K siblings in the school, parental baseline beliefs about school attendance, and school commute times. We will also test whether there is missing data on these variables by treatment status. In our previous work we found that the joint response rate of 92%, with nonresponse uncorrelated with treatment status. We will estimate equation (1) on our full sample including dummies for missing values. All in all, the inclusion of these covariates should not change the magnitude of our coefficient of interest given the randomization of our treatment, and rather serves to increase precision of our estimates. We will report Eicker-Huber-White standard errors for all our estimates because we will randomize our intervention at the individual level. Had we randomized a cluster of individuals (like preschool center or classroom level) to treatment instead, then we would need to cluster at that unit level. That is not the case in the present design (Abadie et al., 2023).
Given that we measure attendance rate as a factor of enrolled potential school days (see footnote 2) we do not expect to have a significant number of outliers in our data, where outliers are children with very low (or very high) attendance rates relative to the average. If we end up having some outliers, we do not expect them to differ systematically by treatment assignment, given randomization. Therefore, we do not plan to trim outliers in our main analysis.

9. Subgroup Analyses

We will estimate treatment heterogeneity across key subgroups: parental language preference (English vs. Spanish), kindergarteners without prior preschool experience, families with low baseline beliefs about the importance of school attendance, and long school commute times. These subgroups are pre-specified based on theory and prior findings from the SUGU pilot.

10. Power Calculations

Using effect sizes from previous studies, we calculated that the study is powered at >80% to detect meaningful effects. The minimum detectable effect (MDE) for chronic absenteeism is 5.5 percentage points, for attendance rate is 2 percentage points, and for test scores is approximately 0.11 standard deviations. These estimates assume conservative baseline variance and no stratification gains.

11. Timeline

Baseline activities and randomization will take place in July–September 2025. Intervention delivery will run from October 2025 to May 2026. Two years of follow-up data will be collected during the 2026–2027 and 2027–2028 school years. Final analysis and dissemination will occur by December 2028.

12. References

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