**Can Schools Enable Parents to Prevent Summer Learning Loss?
A Text Messaging Field Experiment to Promote Literacy Skills**

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April 2017

Abstract

The vast differences in summer learning activities among children presents a substantial challenge to providing equal educational opportunity in the United States. Most initiatives aimed at reversing summer learning loss focus on school- or center-based programs. This study explores the potential of enabling parents to provide literacy development opportunities at home as a low-cost alternative. We conduct a randomized field trial of a summer text-messaging pilot program for parents focused on promoting literacy skills among first through fourth graders. We find positive effects on reading comprehension among third and fourth graders, with effect sizes of .21 to .29 standard deviations, but no effects for first and second graders. Texts also increased attendance at parent-teacher conferences but not at other school-related activities. Evidence to inform future efforts to reverse summer learning loss is provided by parents' responses to a follow-up survey.

Suggested Citation:
Kraft, M.A., & Monti-Nussbaum, M. (2017). Can schools enable parents to prevent summer learning loss? A text messaging field experiment to promote literacy skills. *The ANNALS of the American Academy of Political and Social Science*, *674*(1), 85-112.

Link to Publisher's Version:
http://journals.sagepub.com/doi/full/10.1177/0002716217732009

We are grateful for the support of Jeremy Chiappetta, Chiv Heng, and the students, teachers and parents of Blackstone Valley Prep. Melissa Lovitz provided outstanding research assistance on this project. All errors and omissions are our own.

Can Schools Enable Parents to Prevent Summer Learning Loss?

Over half a century since the release of the Equality of Educational Opportunity report (the "Coleman Report"), James Coleman's work continues to influence social science and public policy. Among its most important and surprising findings was that "schools account for only a small fraction of differences in pupil achievement," after taking into account students' socioeconomic backgrounds (p. 21). Coleman found that family background factors such as parents' level of educational attainment as well as the amount of reading materials and types of reading practices in the home had far more predictive power than any school characteristics. This seminal finding was received with disappointment by many at the time who hoped to document large gaps in school quality and resources as the primary sources of educational inequality. The report has stood the test of time, though, with re-analyses replicating Coleman's results (e.g., Konstantopoulos and Borman 2011) and a large literature documenting how factors outside of school explain the majority of variation in student achievement (Goldhaber and Brewer 1997; Goldhaber, Brewer, Anderson 1999; Nye, Konstantopoulos, and Hedges 2004; Altonji and Mansfield 2011).

In our view, the Coleman Report and subsequent studies on school effects should not be interpreted to mean that schools do not or cannot matter. Despite the limitations of the public education system, it has long been and remains the primary vehicle for social investment in the United States (Steffes 2012). For example, programs such as Head Start, a free federally funded and nationwide preschool program for poor children, has been shown to close a significant portion of the earnings gap in adulthood between children from poor and middle-income families (Deming 2009). School finance reforms between the early 1970s and 1990s that raised state funding levels for low-income school districts substantially increased students' achievement (Lafortune, Rothstein, and Schanzenbach 2016) and earnings in adulthood (Jackson, Johnson, and Persico 2016). Schools matter, particularly for children from families with limited resources to invest in supplemental educational opportunities.

We interpret Coleman's findings and the larger school-effects literature as highlighting the need and potential for schools to broaden their influence by more directly engaging parents as active partners in students' learning. The positive relationship between parental involvement in their children's education and students' success in school is widely documented (Barnard 2004; Cheung and Pomerantz 2012; Fan and Chen 2001; Houtenville and Conway 2008; Todd and Wolpin 2007). Studies have identified positive learning environments at home; integration of parents into school programs; and strong relationships among school, family, and the community as distinct ways that parent engagement supports student achievement (Hoover-Dempsey et al. 2005; Henderson 1987). However, research has been less successful at identifying how to promote greater parental involvement in students' education both at home and at school (Mapp and Kutner 2013; Anderson and Minke 2007; Hoover-Dempsey et al. 2005). One study found that parents of students attending urban elementary schools reported that direct invitations from teachers to attend school events and encouragement to engage in their students' learning process had the largest influence on their involvement (Anderson and Minke 2007).

Research in recent decades has also helped to identify the roles that schools and home environments play in the time dynamics of educational inequality. We now know minority students and students from disadvantaged backgrounds enter kindergarten well behind their white and more advantaged peers and that these initial achievement gaps at school entry have lasting effects on students' educational attainment (Fryer and Levitt 2004; Quinn 2015).

Research also shows that while these achievement gaps continue to grow as students pass through primary and secondary schooling, this widening is driven primarily by different rates of learning during the summer months when students are exposed to vastly different learning opportunities, and home and neighborhood environments (Atteberry and McEachin 2016; Alexander, Entwisle, and Olson 2001; Cooper et. al. 1996; Downey, von Hippel, and Broh 2004; Downey, von Hippel, and Hughes 2008; Quinn et al. 2016). While estimates of summer learning loss differ between studies and student populations, Atteberry and McEachin (2016) found that, on average, public school students across an unidentified southern state lost between 25 percent and 30 percent of the learning growth that they had gained in the preceding school year in both reading and math. Studies also consistently document large differences in summer learning loss rates across socioeconomic groups amounting to as much as three months of learning (Alexander, Entwisle, and Olson 2007; Burkam et al. 2004; Cooper et. al. 2000; Downey, von Hippel, and Broh 2004).

In this article, we describe and evaluate a school-based pilot text-messaging program intended to engage parents as partners in reducing summer learning loss. The program developed out of a research-practitioner partnership with a public charter school network in Rhode Island with the goal of extending educational supports to families beyond the academic year. We piloted the text-messaging program with two elementary schools in the network that serve a diverse student body where 59 percent of the students are minorities and 63 percent of students are eligible for free or reduced price lunch (FRPL). Figure 1 illustrates the nature and magnitude of summer learning loss among students at these elementary schools. In 2015, student performance on the STAR literacy test decreased by an average of 9.89 scaled score points between June and September, a loss of approximately 8 percent of the preceding year's learning growth.

We estimate the causal effect of the text-messaging program by conducting a field experiment in which half of the 183 families that volunteered to participate in the study were randomly assigned to receive a series of eighteen text messages in July and August of 2015. The messages, developed by school personnel and the research team, encouraged parents to promote summer reading and provided suggestions for specific literacy development techniques and resources. The focus on reading and use of text-messages as the delivery mechanism were informed by several literatures. Efforts to provide more academically enriching summer opportunities to students and reduce summer learning loss have traditionally overlooked the potential role of parents and taken the form of resource intensive school- or center-based programs costing around $1,500 per student. Evidence on the effect of such programs on student achievement is decidedly mixed (Matsudaira 2008; Jacob and Lefgren 2004; Borman and Dowling 2006; Chaplin and Capizzano 2006; Schacter and Jo 2005; Borman, Goetz, and Dowling 2009).

A growing body of research suggests that summer reading programs that provide books and scaffolded reading strategies for students can be a cost-efficient (~$100 per student) and effective way to raise student achievement in reading (Kim 2006, 2007; Kim and White 2008; Allington et al. 2010; Kim and Guryan 2010; White et al. 2014). Fryer (2014) found that paying students to read books during the school year increased reading achievement among second graders. An emerging body of literature also points to the potential of school-based efforts to engage parents more directly in students' learning by communicating with them more frequently (often via text message) and providing them with more detailed information about their students' performance (Bergman 2015; Bergman and Chan 2017; Kraft and Dougherty 2013; Kraft and Rogers 2015). Finally, the frequency and framing of the text messages are motivated by research in behavioral economics that posits that relevant reminders and positive messaging can nudge parents to engage in activities with their children that they intend to do but that happen infrequently due to competing demands, distractions, and other challenges (Thaler and Sunstein 2008; Castleman 2015).

Two recent studies which examined the effects of sending text messages to parents of preschoolers during the academic year helped inform the design of our intervention. York and Loeb (2014) evaluated the effect of READY4K!, a text-messaging campaign implemented among a sample of 440 parents. Parents in the treatment group received three text messages per week that provided facts, tips, and encouragement on how to help preschool children develop their literacy skills. The program increased the frequency of home literacy activities as reported by parents, increased the likelihood that parents asked questions about their children's learning as reported by teachers, and increased student performance on several subdomains of the Phonological Awareness Literacy Screening (PALS) assessment. Hurwitz et al. (2015) evaluated the effect of a six-week intervention where 253 parents of children enrolled in Early Head Start centers were randomly assigned to receive daily tips about parent-child activities that promote learning across a range of domains. The authors found that the intervention increased the total number of learning activities that parents reported engaging in with their children by approximately one fourth of a standard deviation.

Our study provides the first causal evidence of the effect of a school-based text messaging program aimed at supporting parents to promote literacy skills during the summer. This field experiment allows us to explore the potential for literacy-focused text-message interventions to support parents to reduce summer learning loss and enhance parents' engagement in school-based activities. Our study is also the first to examine the effects of any type of text-messaging intervention for parents aimed at increasing student achievement among elementary school students. Prior studies have focused on preschool and kindergarten students (Doss et al. 2016; Hurwitz et al. 2015; York and Loeb 2014) or middle and high school students (Bergman 2015; Bergman and Chan 2017; Kraft and Dougherty 2013; Kraft and Rogers 2015). In our primary analyses, we estimate effects on student achievement captured by two complementary standardized assessments of early literacy and reading skills administered four times across the school year. These multiple vertically equated test administrations allow us to examine the time dynamics and potential for compounding effects of the intervention. We complement these analyses by assessing program effects on multiple measures of parent engagement in school-related activities. We conclude by exploring potential mechanisms using parent responses to surveys and discussing how future programs can address implementation challenges and enhance program design features.

Context and Procedure

Setting

We conducted this research in partnership with Blackstone Valley Prep Mayoral Academy (BVP) located in Cumberland, Rhode Island, during summer 2015. BVP is a network of public charter schools serving students from across four school districts in Rhode Island: Central Falls, Cumberland, Lincoln, and Pawtucket. First opened in 2009, the BVP network has expanded to six schools including three elementary schools, two middle schools, and one high school. Drawing students from across four diverse sending districts allows BVP to serve a more racially and socioeconomically diverse student population than many urban charter schools. Two of the sending districts, Cumberland and Lincoln, are home to more affluent and homogenous populations where less than 30 percent of students are eligible for free or reduced price lunch and between 80 percent and 90 percent are white. In comparison, in the Central Falls and Pawtucket districts 85 percent of students are eligible for FRPL and two thirds are African American or Latino. Consequently, relative to state averages, BVP schools serve an especially diverse student population. BVP schools are also known for their high academic standards and have consistently outperformed the state average as well as their four sending districts on state standardized tests.

Sample

Principals at two of the elementary schools opted to take part in the study. BVP administrators recruited the parents of students rising into first through fourth grades to participate in the program. Out of 522 parent households, 183 opted into the study. This represented an opt-in rate of 35 percent of potential households with a total of 232 students rising into the first through fourth grades. Among the 183 participating families, 137 had one child enrolled in the two participating elementary schools, 43 had two students, and three had three students.

In Table 1, we report the demographic characteristics and previous academic performance of students participating and not participating in the study. Participating students were relatively evenly distributed across first through fourth grades with a racial composition of 32 percent Hispanic, 12 percent African American, 52 percent white, and 3 percent Asian. Nearly 50 percent of the students came from households eligible to receive FRPL and 8 percent were receiving special education services. Students of households that opted into the study, on average, earned higher scores on standardized reading assessments than those of nonparticipant households. Minority, especially Hispanic and African American, students, English language learners, and those eligible for FRPL were less likely to opt-in. These lower take-up rates among minority, non-native English speaking, and lower socioeconomic status families point to the importance of targeted recruitment efforts or opt-out enrollment policies for parent engagement programs.

Text messaging program

Over the course of the spring semester, the research team worked with BVP administrators and lead teachers to design and develop the content of a text-messaging intervention. Parents of the 118 students randomly assigned into the treatment group received a total of 18 text messages from the schools' communication management system, roughly two per week, throughout the months of July and August 2015. Text messages were translated into Spanish for parents who indicated a preference to receive communication in Spanish. All parents, including parents of the 114 students in the control group and those not involved in the study, received ongoing texts and recorded messages from the schools about school-related summer events. .

The text messages were framed as "Pro-tips" about specific literacy and enrichment activities that parents and children could engage in over the summer. The messages emphasized the importance of reading and the role of parents in encouraging reading at home during the summer months. The texts also provided information on resources and ideas for summer learning activities. The content of the messages was organized under three distinct categories:

- **Resources:** messages that provided information about accessible and affordable educational resources parents and students could utilize. These messages about local summer resources were intended to reduce barriers to learning for all families, with a particular emphasis on those with less access to educational activities and familiarity with relevant resources.

  e.g. "Pro-tip: RI public libraries have built suggested kid (and adult) summer reading lists full of great reads. Learn more at www.askri.org"

- **Ideas**: messages that contained suggestions for creative and effective practices and activities for parents to support their children's literacy development. These messages were intended to expand parents' tool-kit of educational activities that could be flexibly and easily integrated into summer schedules.

  e.g. "Pro-tip: Take turns reading OUT LOUD with your scholar. You read a page then your child reads a page, and so on (great at any age)!"

- **Signals:** messages that conveyed information about summer learning loss and reinforced the positive effects of reading and learning outside of classroom time. These messages served to increase the saliency of summer reading and nudge parents whom, for many reasons, might not be consistently helping their children engage in educational activities.

  e.g. "Did you know? Kids who read 4+ books over the summer fare MUCH better on tests in the fall than their peers who read 0–1 books?"

Research Design

Data

Reading achievement. Our primary outcome of interest is student reading achievement captured by two widely used literacy and reading comprehension tests, the Standardized Test for the Assessment of Reading (STAR) and the Strategic Teaching and Evaluation of Progress (STEP). Both assessments are vertically equated, which allows us to document how students' literacy skills changed over time and to pool students' scores across grade levels. The STAR test, developed by Renaissance Learning, is a computer adaptive test that assesses reading comprehension in 10 minutes or less through 25 multiple-choice items that test vocabulary in-context. The test is administered to students starting in 1st grade and is scored on a scale ranging from 0 to 1400.

The STEP test, developed by the University of Chicago Consortium on School Research, is administered by teachers working one-on-one with students to assess a range of reading comprehension skills. Beyond measuring word recognition, reading speed and accuracy, STEP also evaluates comprehension and critical thinking. The assessment is divided into thirteen steps or scale points, which in turn are subdivided into three shorter levels, and is administered to students in Kindergarten through 3rd grade. The STEP assessment is generally scored on a scale ranging from –1 (pre-literacy) to 12 (3rd grade literacy level). Teachers in one of the BVP elementary schools also used the Fountas and Pinnell Benchmark Assessment Systems (BAS) to extend the STEP scoring range up to twenty-seven for students that had reached a 3rd grade literacy level. This reading ability and comprehension assessment, like the STEP, is conducted one-on-one between teachers and students and is graded on a fifteen-point scale. In the other elementary school, scores were capped at twelve on the STEP assessment, which limited our ability to capture growth in reading skills among those students reading above a 3rd grade level. Both the STAR and STEP assessments were administered in September, November, February, and June of the 2015/16 academic year, except in one of the schools where teachers did not administer the STEP assessment in September. Examining how student achievement in reading is affected over the course of the following year allows us to test a common hypothesis in sociology and social psychology that small interventions such as ours can trigger recursive processes that, when sustained, result in a cumulative advantage over time (DiPrete and Eirich 2006; Yeager and Walton 2011).

Parent engagement. We were also interested in analyzing whether parents who received text messages from BVP about how to support their child's literacy development would be motivated to become more engaged in school activities both during the summer and after the start of the new school year. To examine this question, we worked with BVP to collect several measures of parent engagement by recording whether parents participated in the following chronologically ordered events and activities: a back-to-school ice cream social for teachers, parents, and students; visits where teachers meet with parents at home or another designated location outside of school; and fall semester parent-teacher conferences. At the conclusion of the pilot program we also invited all parents in the study to sign up to receive text messages during the school year about how they could support student learning outside of school time.

Parent survey. We administered surveys to parents after the conclusion of the summer text messaging program to confirm the delivery of the text messages and collect data on potential mechanisms through which the text messages might have affected student outcomes. The survey asked about student reading habits, parent involvement in student learning, and reasons for increased (decreased) reading over summer. The survey included questions about the frequency with which parents and students engaged in the different activities over the summer suggested in the series of text messages (text messages were not mentioned in these questions). Parents responded to each item on a five-point Likert scale ranging from *never (0 times)* to *more than once a week (~30 times).*

The poststudy survey was administered online during early October. Recruitment was done via text, email, school newsletters, and flyers sent home with students. Raffle tickets for a $100 Amazon gift card were offered for participation. These efforts resulted in a 69 percent household response rate among study participants. However, families in the treatment group were 11 percentage points less likely to complete the survey than those from the control group (63 percent treatment vs. 74 percent control). In appendix Table A1, we report the student characteristics of parents who did and did not respond to the survey. Nonrespondents were significantly more likely to be Hispanic, low-income, and to have students who were lower-achieving in reading.

Given the differential survey response rate across treatment status and select student characteristics, we interpret our analyses of potential mechanisms based on parent responses as exploratory rather than causal evidence.

Randomization

We evaluate the causal effect of our pilot text-messaging program to promote literacy skills development by conducting a cluster randomized trial at the household level. Our research design and analyses described below were preregistered with the Institute for Education Sciences What Works Clearinghouse Randomized Control Trial Registry (ID #489). We randomly assigned students and their parents to receive texts or to a control condition in which households only received standard school announcements via text-messages. We chose to assign treatment at the household level to reduce potential spillovers between siblings. If the text messages had an effect on parents' behavior, it would likely change parents' involvement with all their elementary-age children. While this design approach reduces the potential for spillover effects, it does not eliminate the possibility that parents or students in the treatment group could communicate and share information provided in the text messages with parents or students in the control group over the summer or the following school year. We examine the potential threat posed by spillovers in detail below based on self-reported data from the parent survey.

We examine the validity of the randomization process by testing for mean differences across students in the treatment and control groups. As shown in Table 2, there were no statistically significant differences between the two groups across twenty-three observable characteristics, affirming the validity of the randomization process.

Analytic Approach

We begin by estimating the effect of being a student in a household randomly assigned to receive summer learning text messages, *TREAT* (treatment), using a multilevel model as follows.

$$Y_{ij} = \alpha + \beta_1 TREAT_j + \delta X_{ij} + (\nu_j + \varepsilon_{ij}) \qquad (1)$$

Here Y_{ij} represents a given outcome of interest for student *i* from family *j*, X_{ij} is a vector of both household-level controls (sending district and FRPL status) and student-level controls (age, ELL, race, disability, and grade). The coefficient on *TREAT*, β_1, captures our estimate of the intent-to-treat (ITT) effect of summer learning text messages given that we cannot confirm with certainty that all the text messages were received or read by participating parents. A positive and statistically significant estimate of β_1 will suggest that assigning households to receive summer learning text messages improved student achievement in reading. We specify an error structure where individual students are nested within households by fitting models with household random effects, which are orthogonal to *TREAT* by construction.

In a second specification of our model, we include 2014/15 end-of-year STEP test scores to control for baseline literacy levels.

$$Y_{ij} = \alpha + \beta_1 TREAT_j + \lambda STEP_i^{June\,'15} + \delta X_i + (\nu_j + \varepsilon_{ij}) \qquad (2)$$

The addition of STEP scores serves to further test the robustness and increase the precision of our estimates. We are unable to fit corresponding models in our full sample using prior scores on the STAR exam given that baseline STAR scores are not available for incoming 1st graders as the test is not administered in Kindergarten.

Next, we leverage the repeated outcome measures of reading achievement by estimating pooled effects in a student-by-test-period dataset. These stacked models provide a single estimated treatment effect that averages across the four test administrations in 2015/16 and increases the precision of our estimates (McKenzie 2012).

$$Y_{ijt} = \alpha + \beta_1 TREAT_j + \lambda STEP_i^{June\,'15} + \delta X_{ij} + (\nu_j + \varepsilon_i + \eta_{ijt}) \qquad (3)$$

Here we model STAR or STEP test scores for student *i* in family *j* in time *t* where *t* captures the four time periods when students are assessed. Our covariates remain the same as in equation (2), while we expand our multilevel error structure to include both random effects for households (ν_j) and students (ε).

We then test whether the treatment had a differential effect on subgroups of students as specified in the preregistration plan. We do this by refitting equation (2) to include the main effect of a given student characteristic and its interaction effect with the treatment indicator. The subgroups we examine are eligibility for FRPL, race (African American and Hispanic), and grade level (1st and 2nd; 3rd and 4th).

We fit parallel logistic regression models using the same structural components from equation (2) when examining parents' school engagement outcomes. We present parameter estimates from these models as odds ratios as well as marginal effects to facilitate a direct comparison with our achievement results. Finally, we fit corresponding ordered logistic regression models with the same structural components of equation (2) when analyzing responses to survey items, and report the results as proportional odds ratios. For both of these models we account for the multilevel nature of the data by clustering our standard errors at the household level. This approach, which is necessary given the lack of convergence for models with random effects, produces consistent estimates of our parameters but less efficient estimates of our standard errors.

Findings

Take-up

BVP's communication management system allowed us to track the distribution of text messages to parents in the treatment group. These records reveal that 97.29 percent of messages were sent and delivered. To confirm the effective reception of messages, we included questions in the poststudy survey on whether households had received text messages from BVP, if they had received text messages about learning and literacy skills specifically, and if so, how many they had received. As shown in Table 3, households in the treatment group were 32 percentage points more likely to report having received text messages over the summer than households in the control group. On average, households in the treatment group reported receiving an average of almost nine more text messages from BVP over the summer than parents in the control group and more than six more text messages specifically about summer learning and literacy skills. These findings confirm that the delivery of the treatment was largely successful given that recall bias when answering survey questions about past behavior likely contributed to differences in the reported and actual number of texts received.

Effect on literacy skills

We report estimates from our model of the treatment effect on reading achievement scores in Table 4. We include treatment effects for STAR and STEP tests taken in September, November, February, and June of the 2015/16 school year as well as an estimate that pools scores from across these test administrations. Estimates across models, tests, and time periods are uniformly positive, and for STEP, significant at the 0.1 level. Estimates remain largely unchanged when we control for baseline literacy levels with the inclusion of STEP test scores from June of the prior academic year, while the corresponding standard errors become meaningfully smaller due to the reduction in residual variance.

Focusing on models that include STEP baselines scores, we find point estimates ranging from 5.9 to 20.8 scaled score points on the STAR assessments, with a pooled estimate of 13.9 scaled score points (p=.35) although none of these estimates is statistically significant. The magnitude of the pooled estimate, while indistinguishable from zero, is almost one and half times the average rate of summer learning loss in the school. Given that the standard deviation of

STAR test scores among 1st through 4th graders is 215.8, these estimates correspond to effect sizes ranging from .03 to .10 standard deviations (SD) with a pooled estimate of .06 SD.

Treatment effects on student reading fluency as measured by the STEP exam range from .25 to .49 score levels with a pooled estimate of .36 score levels (p=.06). Estimates for the November, June, and pooled effect are all statistically significant at the .10 level. Converting these into effect sizes using the standard deviation of STEP tests among 1st through 4th graders of 2.47, these effects range from .10 to .19 SD with a pooled effect size of .15 SD. Figures 2 and 3 display the time dynamics of the estimated standardized effects for STAR and STEP, respectively. The pattern of results over the course of the 2015/16 school year is suggestive of sustained effects on STAR and incrementally increasing effects on STEP although we do not have the power to distinguish these point estimates across time from each other.

We extend our primary test-score analyses to examine whether the summer learning text messages had a differential effect on students by grade level, socioeconomic status, and race. These analyses are exploratory in nature as they are underpowered to detect small to moderate differences across subgroups. In Table 5, we report estimates from models where we interact the main effect of treatment with indicators for upper grade levels (3rd and 4th grade), FRPL eligibility, Hispanic, and African American.

We find compelling evidence that the positive effects of the text messaging intervention were concentrated among students in the upper elementary grade levels. Estimates for the coefficient associated with the *TREAT**(3rd and 4th graders) variable reported in Table 5 provide the difference in the magnitude of treatment effects between 3rd and 4th graders relative to 1st and 2nd graders, as well as the corresponding significance test of this difference. Focusing on our pooled effect estimates, we find that the treatment effect was 57.2 scale score points (p=.04) larger for upper-grade students relative to lower-grade student on the STAR exam and .65 score levels (p=. 09) larger on the STEP exam. These estimates correspond with effect size *differences* of exactly .26 SD for both reading assessments.

We plot the subgroup effect sizes for 1st and 2nd graders (the standardized coefficient on *TREAT*) and for 3rd and 4th graders (the standardized linear combination of the coefficients on *TREAT* and *TREAT**[3rd and 4th graders]) in Figures 4 and 5, respectively.

As can be seen, point estimates for upper grades (3rd and 4th) for both STAR and STEP illustrate large effects that appear to increase over the course of the semester. Effect sizes for upper grade students ranged from .14 SD to .30 SD on STAR and .24 SD to .38 SD on STEP. Seven out of eight of these estimated effects are significant at the .05 level. For pooled effect estimates, effect sizes for upper grade students were 0.21 SD (p=.036) on the STAR exam and 0.29 SD (p=.008) on the STEP exam. In stark contrast, we find near zero and statistically insignificant effects on lower grade students. One possible explanation for this pattern is that older students, most of whom have mastered basic literacy skills, were more likely to benefit from a general literacy text messaging initiative such as ours. Younger students might need to be exposed to specific pre- and emerging-literacy skill-building activities such as those provided by York and Loeb (2014).

We find little evidence of any differential effects on students based on socioeconomic status given estimates are both positively and negatively signed and never statistically significant. Our estimates do suggest that the text messaging program was differentially more effective for African American students compared to non-Hispanic white students. Estimates for both tests in all four testing periods are positively signed while two for the STEP assessment—

September (*p*=.05) and November (*p*=.04)—are significant at the 0.05 level. These estimates suggest that the text messaging program may advance efforts to reduce educational disparities.

Effect on parent engagement

We next examine the effect of summer learning text messages sent to parents on their engagement in academic events that occurred at the end of the summer and through the fall semester. Although the summer learning text messages did not directly encourage parents to attend or participate in school-related activities, the text messages were intended to help parents become more engaged in the learning process of their children and thus, we theorized, more likely to participate in academic events in general. In Table 6, we report treatment effects, displayed as odd ratios, on attendance at an ice cream summer social event, a home visit with a teacher, and a parent-teacher conference in the fall; and on signing up to receive future messages about learning outside of school time. We find statistically significant effects on one out of the four measures of parent engagement—attending a fall semester parent-teacher conference. We estimate that receiving the summer learning text messages increased the probability that a parent would attend the meeting by a predicted marginal effect of 5.4 percentage points on top of a control group mean of 91 percent. The sign of the predicted marginal effect is negative for the ice cream social, near zero for home visits, and positive for text messages sign-ups. These mixed results suggest that parent engagement in their children's education can take multiple forms (e.g., with students at home, with teachers, with school-wide events) and that effects of interventions intended to promote engagement of one type may translate to additional but not all forms of engagement. Specific direct invitations and reminders might be required for different academic events and forms of engagement (Hoover-Dempsey et al. 2005).

Mechanisms

We explore the potential mechanism through which effects on reaching achievement may operate by analyzing parent responses to a poststudy survey. The survey asked parents about the frequency with which they engaged in specific parent-student learning activities such as reading out loud, explaining new words, and going to a library. In Table 7, we report proportional odd ratios from ordered logistic regression models for responses to individual survey questions. We find no clear pattern of results or statistically significant effects on the frequency of parent's self-reported literacy activities. Estimates are both positive (above one) and negative (below one). Despite the exploratory and limited nature of these data, these estimates do not point toward any specific parent behavior that might have been a primary mechanism for how the summer learning text messages to parents increased students' achievement in reading.

Spillover

Our research design—clustered randomization at the household level—captures any spillover effects among siblings living in the same household. We could not, however, prevent parents in the treatment group from speaking to other parents in the control group about the content of the text messages they received. If parents shared the content of the messages, (e.g., ideas about how to improve reading habits over the summer), with parents in the control group this could attenuate the treatment effect. We examine whether there is evidence of spillover by analyzing parents' responses to a question in the poststudy survey on whether they had shared any of the texts with other BVP parents. We find that 31 percent of parents from the treatment group who responded the question in the survey (n = 63) indicated that they had shared texts with other BVP parents. We also were notified by BVP administrators that on two occasions a

BVP parent posted a comment on the school Facebook page describing the general content of a text message they received. This anecdotal evidence suggests that, if anything, our findings are likely conservative estimates given the potential for the treatment-control contrast to be attenuated by parents in the treatment group influencing the summer reading practices of parents in the control group.

Attrition

Given that test score data are missing for up to 6.5 percent of our sample for some test-score administrations, we test for differential attrition from the study across treatment and control groups for each of our achievement outcomes. Specifically, we explore whether students in the treatment group were more likely than students in the control group to be absent for STAR or STEP assessments during the 2015/16 school year. We accomplish this by predicting the likelihood that a student is missing a score for a given assessment based on their treatment status. We report the estimated coefficients on *TREAT* in Table 8. Differences in missingness rates across the treatment and control group are not statistically significant and never larger than 3.3 percentage points. These tests reveal no evidence to suggest differential attrition poses a threat to our test-score effect estimates.

Lessons for Future Text-Messaging Programs for Parents

Our interpretation of the impact evaluation results described above suggest that summer literacy text-messaging programs for parents have potential but that design details and implementation strategies matter. The process of designing, implementing, and evaluating our pilot text-messaging intervention intended to support parents to engage in literacy enrichment activities with their children during the summer affords several lessons for program redesign and scale-up efforts. Parents' responses to questions about whether they faced any difficult challenges over the summer that limited the amount of reading they could do with their children suggest some parents faced substantial obstacles that were unaddressed by the text-messaging initiative. Across the treatment group, nearly 25 percent of respondents reported facing a unique or difficult challenge that acted as a barrier to engaging in reading activities with their children.

We coded parents' responses to an open-ended follow-up question into five broad categories to describe the general nature of these challenges and present the results in Table 9. The most common challenges reported by parents were vacation conflicts followed by health issues and work demands. For example, one parent wrote that "working all day shifts not coming home till 10 p.m. at night six days a week" presented a significant challenge to engaging in the suggested literacy activities. Another described her challenge as "[My] child's two younger brothers and myself have a lot of serious medical issues. We have a lot of doctor appointments, usually several a week. I am also on the phone a lot due to all these appointments."

Text-messaging interventions should be designed with careful attention paid to the content, frequency, and duration of the initiative, especially as they pertain to helping specific groups of families and their children. Our program delivered messages that promoted literacy activities to students that ranged from slightly under six to just over ten years old. The effects that we found are largely concentrated among elementary school students in higher grades, suggesting our focus on reading activities may have been less appropriate for parents with younger children still developing preliteracy skills. A recent study by Doss et al. (2016) found evidence supporting this hypothesis. The authors found larger effects for an early literacy text-messaging program that was differentiated and personalization based on the child's developmental level compared to one that delivered more general literacy suggestions to parents of preschool students. Furthermore, several parents' open-ended survey responses expressed the desire for messages to be more relevant to their students' coursework in the prior and upcoming school years. Together, insights from these studies point to the importance of targeting grade-specific skills with text messaging literacy interventions. They also point to the potential to further individualize text-messaging interventions based on students' performance on interim reading assessments such as the STEP and STAR exams. The possibility of automating the targeting of more specific messages based on age, achievement, or other characteristics would allow similar interventions to increase their efficacy while remaining scalable and cost-effective.

Future text-messaging interventions might attempt to increase participation and impacts by refining several program implementation practices. Opt-in policies may cause programs to miss families whose children experience the largest summer learning loss even when opting in only requires replying to a text message. Changing the default setting to be opt-out can dramatically increase participation rates for parent informational interventions delivered via text message (Bergman & Rogers, 2017). Our study also illustrates the critical importance of updating cellphone records proactively throughout the summer and academic year. We found that approximately one out of every four phone numbers provided by parents did not work six months later.

Responses on the parent survey also reveal the importance of identifying which parent in a household should receive the texts. In our study, texts were sent to the primary phone number listed in parents' contact information records. Parents reported that in some instances this was not the parent who was home most often or who was most likely to engage with his or her child in literacy development activities. Text-messaging programs might instead aim to send messages to all adult members of a household as well as to older siblings in certain cases. This would both increase the likelihood that messages reach the adult most likely to interact with students. It might also generate momentum for a focus on literacy development at home by prompting adults to discuss the tips and activity suggestions that they receive. Finally, the enthusiasm of several parents who posted the literacy development techniques they practiced with their children on the schools' social media sites points to the potential of using social networks to amplify the impact of text messaging interventions.

Conclusion

The Coleman Report first documented how students' experiences outside of school are the dominant influence on their success inside the classroom. This seminal finding and a large body of subsequent evidence affirming it (Goldhaber and Brewer 1997; Goldhaber, Brewer, and Anderson 1999; Nye, Konstantopoulos, and Hedges 2004; Altonji and Mansfield 2011), could be interpreted to mean that efforts to address inequitable educational outcomes need not directly involve schools at all. We posit, though, that schools can magnify their potential impacts by engaging parents and partnering with them to further support students' learning. This text-messaging study illustrates one of many potential ways in which schools can leverage their relationships with parents to help create better learning opportunities for students beyond the school walls and academic calendar.

The sustained and even increasing positive effects on the literacy skills of upper elementary students throughout the school year suggest the text message intervention effects were the result of a process of cumulative advantage, cumulative exposure, or both (DiPrete and Eirich 2006). Scholars have posited that reading ability develops through a virtuous cycle where, for example, having a larger vocabulary improves reading comprehension, which in turn improves textual inferences and expands vocabulary (Stanovich 1986). It could be that improvements in students' literacy skills over the summer allowed them to access and benefit more from literacy instruction during the school year. It is also possible that the intervention had a lasting effect on the frequency and quality of literacy activities that parents engaged in with their children at home beyond the summer intervention. This cumulative benefit of the increase in the quality of learning opportunities outside of school could also explain the larger effects that we observed over time.

Text-messaging interventions such as the one that we studied are particularly attractive given evidence that they can be taken to scale with limited financial investments and have been shown to be effective across a range of contexts (Castleman 2015). Our intervention leveraged texts as a way to deliver encouragement, reminders, and suggestions for literacy activities. The feedback that we received from parents about this intervention suggests that future development and scaling-up efforts of text-messaging campaigns during the summer would benefit from efforts to address challenges that limited parents' ability to provide enriching literacy activities for their children. For example, schools could experiment with combining a text messaging campaign with a program to provide summer reading materials or transportation to libraries, museums, and other learning activities. The results of this intervention coupled with feedback from parents suggest that similar interventions could be improved by individualizing the content of the messages based on students' specific learning abilities and needs.

Many of the inequitable educational outcomes documented in the Coleman Report remain more than 50 years later. Addressing these persistent inequities will require schools and educators to move beyond the traditional domain of the classroom. This study provides an example of how schools have the potential to extend their influence on students' educational opportunities by partnering with and enabling parents.

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Figures

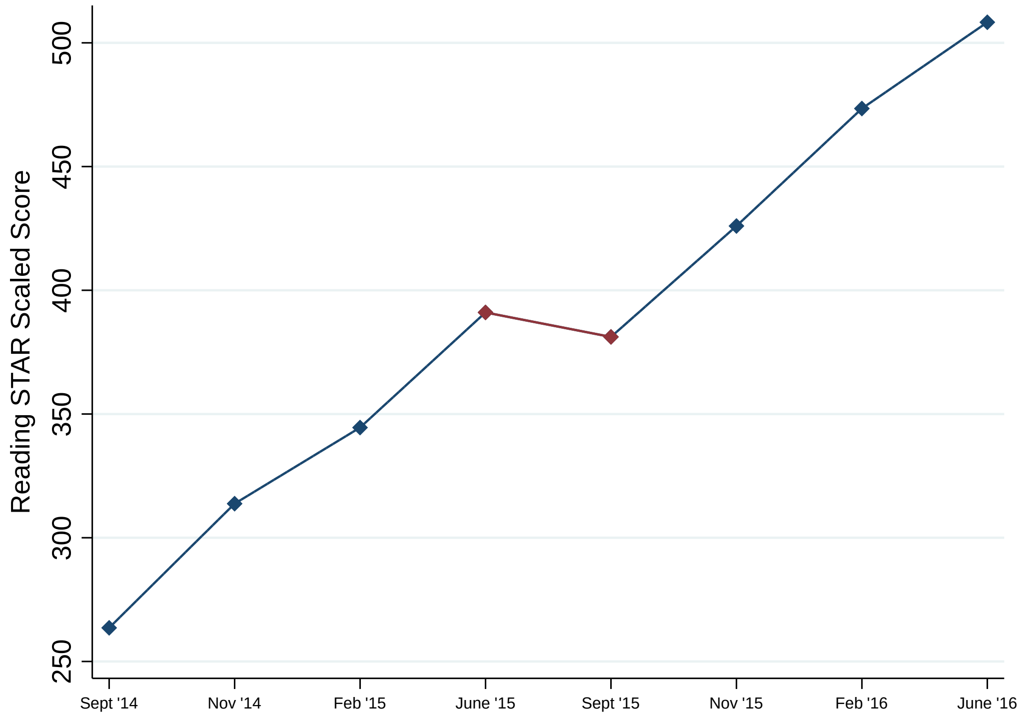

Figure 1. Summer Learning Loss on the STAR Reading Assessment

NOTE: Average STAR scaled scores for students in the 2nd through 4th grade from beginning of the 2014/15 academic year to end of the 2015/16 academic year. Students that were assigned to the treatment group are not included in the figure, as their 2015/16 scores were potentially influenced by the treatment. Students included in the figure are those with complete test data across all testing periods (n = 366).

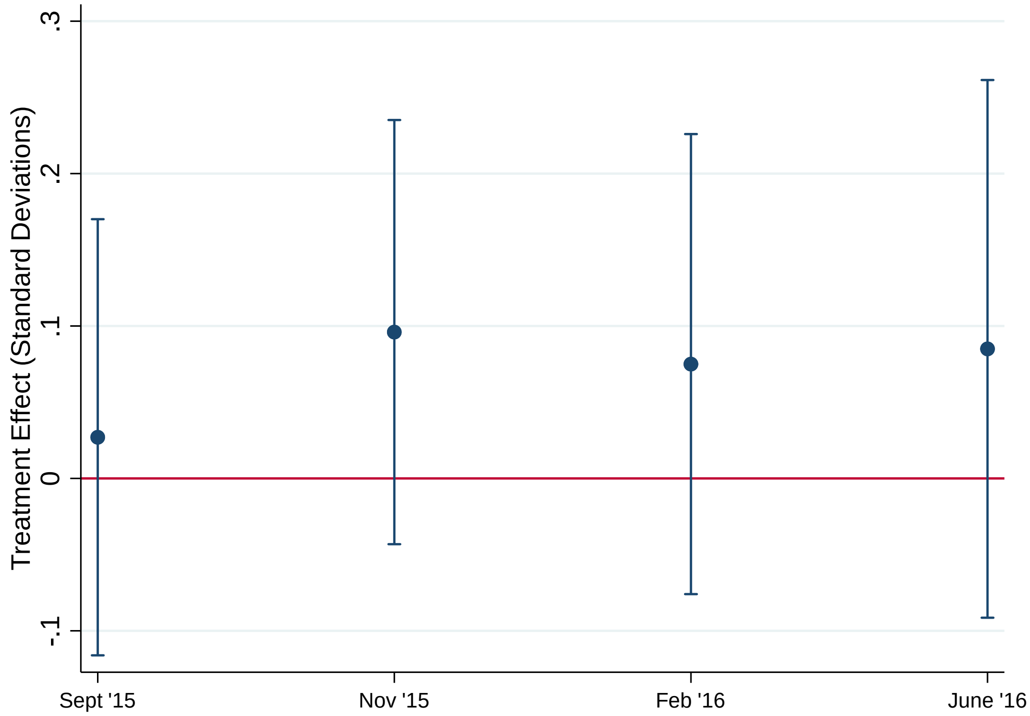

Figure 2. Effect Sizes on the STAR Reading Assessment across the School Year

NOTE: STAR scaled scores are standardized relative to the average of all 1st to 4th graders in the study schools. Model for treatment effects is estimated with household random effects and includes student demographics, grade level, school, sending district, and June 2014/15 STEP scores as covariates.

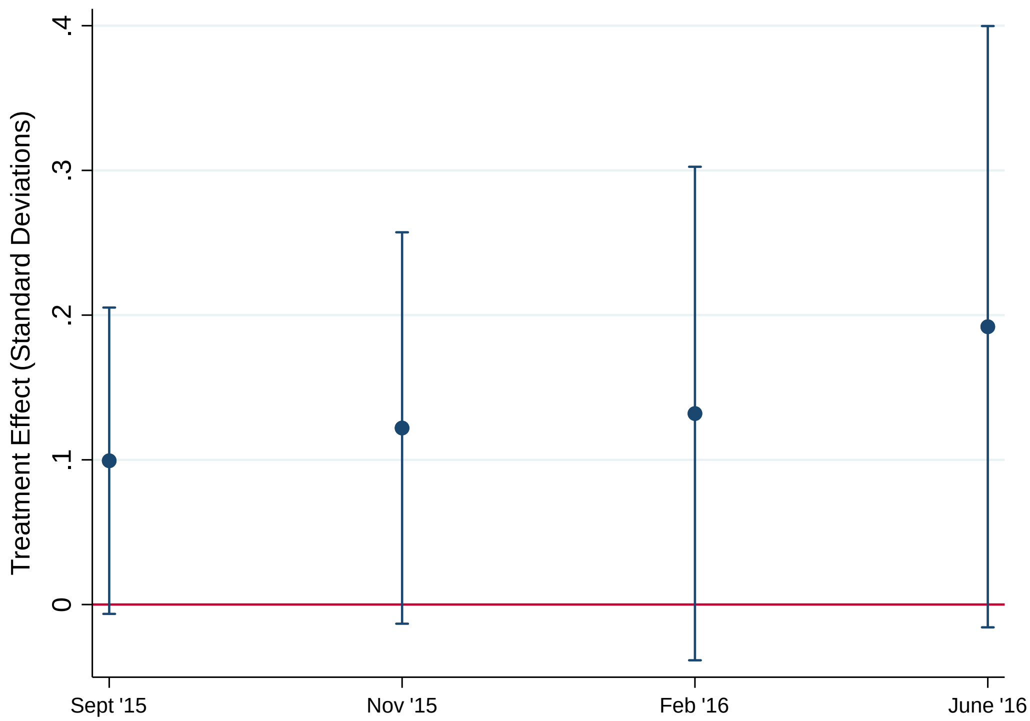

Figure 3. Effect Sizes on the STEP Reading Assessment across the School Year

NOTE: STEP scaled scores are standardized relative to the average of all 1st to 4th graders in the study schools. Model for treatment effects is estimated with household random effects and includes student demographics, grade level, school, sending district, and June 2014/15 STEP scores as covariates.

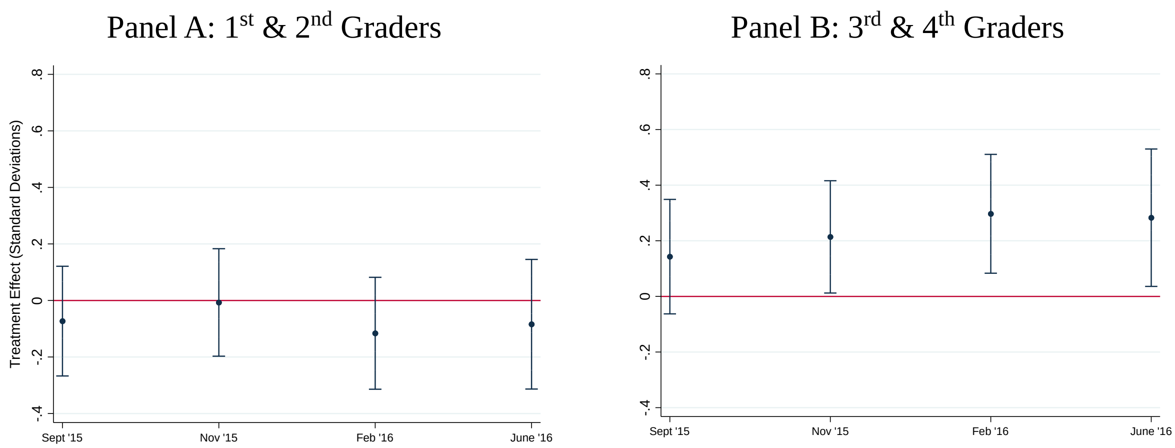

Figure 4. Effect Sizes by Grade Level on the STAR Reading Assessment across the School Year

Notes: Estimates from equation (2) where *TREAT* is replaced by two mutually exclusive treatment indicators, *TREAT**(1st & 2nd Graders) and *TREAT**(3rd & 4th Graders). See Figure 2 for further model details.

Panel A: 1^{st} & 2^{nd} Graders　　　Panel B: 3^{rd} & 4^{th} Graders

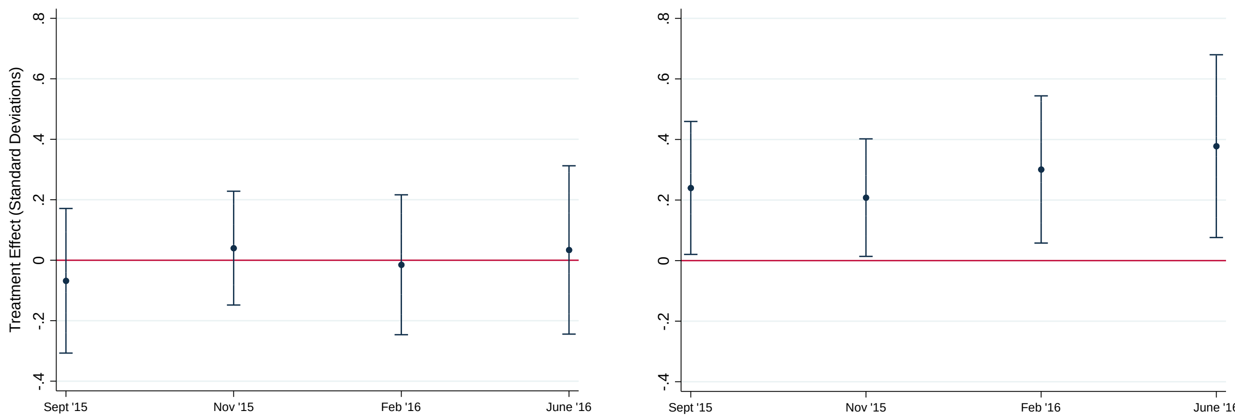

Figure 5. Effect Sizes by Grade Level on the STEP Reading Assessment across the School Year

Notes: Estimates from equation (2) where *TREAT* is replaced by two mutually exclusive treatment indicators, *TREAT**(1^{st} & 2^{nd} Graders) and *TREAT**(3^{rd} & 4^{th} Graders). See Figure 3 for further model details.

Tables

Table 1. Student Characteristics among Study Participants and Nonparticipants

	All students	Students in study	Students not in study	Difference	*P-value*
STEP June 14/15	8.19	8.13	8.23	–0.10	0.714
STAR reading June 14/15	398.18	438.30	376.67	61.63	0.001
STAR math June 14/15	563.17	572.85	557.99	14.86	0.175
Age	7.87	7.74	7.94	–0.2	0.042
Female	50.5	50	50.7	–0.7	0.854
Asian	3.5	3.4	3.5	–0.1	0.931
Black	12	11.6	12.2	–0.6	0.572
Hispanic	44	32.3	50.9	–18.6	0.000
White, not Hispanic	39.9	52.2	32.7	19.5	0.001
Native American	0.6	0.4	0.8	–0.4	0.888
Free or reduced price lunch	68.8	53.4	77.2	–23.8	0.000
English as a second language	9.4	3.4	12.7	–9.3	0.000
Special education	9.9	6.9	11.5	–4.6	0.078
Rising 1st grade	24.5	28.1	22.6	5.5	0.137
Rising 2nd grade	25.1	25.1	25.1	0.0	0.976
Rising 3rd grade	24.8	23.8	25.3	–1.5	0.639
Rising 4th grade	25.4	22.5	26.9	–4.4	0.245
Elementary school 1	50.1	53	48.6	4.4	0.414
Elementary school 2	49.6	47	50.9	–3.9	0.414
CF Sending district	26.1	15.1	32.2	–17.1	0.001
CU Sending district	26.9	32.3	23.9	8.4	0.101
LN Sending district	15	22.4	11	11.4	0.000
PA Sending district	31.3	29.3	32.4	–3.1	0.195
N (Students)	670	232	438		

NOTE: Sample sizes for baseline test scores are not constant across variables (STEP: 232 students in study and 390 students not in study; STAR: 163 students in study and 305 students not in study). Rising 1st graders do not have STAR baseline scores as the test is not assessed in kindergarten. Age is as of 07/01/2015. P-values of the difference estimated from models where a given characteristic is regressed on an indicator for opting into the study and household random effects. CF= Central Falls, CU= Cumberland, LN= Lincoln, and PA= Pawtucket.

Table 2. Baseline Characteristics, by Treatment Status

	Students in treatment group	Students in control group	Difference	*P-value*
STEP June 14/15	7.96	8.30	–0.34	0.428
STAR reading June 14/15	446.92	430.19	16.73	0.539
STAR math June 14/15	567.63	577.76	–10.13	0.558
Age	7.69	7.79	–0.10	0.530
Female	51.7	48.2	3.5	0.601
Asian	2.5	4.4	–1.9	0.443
Black	12.7	10.5	2.2	0.449
Hispanic	28.0	36.8	–8.8	0.150
White, not Hispanic	55.9	48.2	7.7	0.548
Native American	0.8	0.0	0.8	0.326
Free or reduced price lunch	55.9	50.9	5.0	0.379
English as a second language	2.5	4.4	–1.9	0.440
Enrolled in special education	7.6	6.1	1.5	0.656
Rising 1st grade	31.4	24.8	6.6	0.267
Rising 2nd grade	23.7	26.5	–2.8	0.623
Rising 3rd grade	23.7	23.9	–0.2	0.973
Rising 4th grade	21.2	23.9	–2.7	0.624
Elementary school 1	50.0	56.1	–6.1	0.182
Elementary school 2	50.0	43.9	6.1	0.182
CF sending district	14.4	15.8	–1.4	0.567
CU sending district	33.9	30.7	3.2	0.604
LN sending district	23.7	21.1	2.6	0.627
PA sending district	27.1	31.6	–4.5	0.912
N (Students)	118	114		
N (Parents)	91	92		

NOTE: Sample sizes for baseline test scores are not constant across variables (STEP: 118 students in treatment group and 112 students in control group; STAR: 79 students in treatment group, and 84 students in control group). Rising 1st graders do not have STAR baseline scores as the test is not assessed in kindergarten. Age is as of 07/01/2015. P-values calculated by regressing the indicator for treatment on each variable with household random effects. CF= Central Falls, CU= Cumberland, LN= Lincoln, and PA= Pawtucket.

Table 3. Confirmation of Treatment Delivery

	Did Parent receive texts	Number of texts received	Number of summer learning texts received
Treat	0.311***	8.131***	6.067***
	(0.078)	(1.364)	(1.352)
Constant	0.515***	3.249***	2.666***
	(0.053)	(0.927)	(0.944)
N (Students)	161	159	136

NOTE: OLS regressions are unconditional but include a random effect for households. Standard errors shown in parenthesis.
* p<0.1. ** p<0.05. *** p<0.01.

Table 4. Effects of Summer Learning Texting Intervention on Reading Achievement

	Sept 15/16		Nov 15/16		Feb 15/16		June 15/16		Stacked periods	
					Panel A: STAR					
Treat	6.26	5.89	20.44	20.75	15.02	16.08	18.05	18.37	12.39	13.92
	(20.40)	(15.82)	(20.96)	(15.42)	(21.00)	(16.54)	(23.86)	(19.39)	(20.19)	(15.17)
STEP June 14/15		y		y		y		y		y
N (students)	224	224	225	225	223	223	224	224	896	896
Effect size	0.03	0.03	0.09	0.10	0.07	0.07	0.08	0.09	0.06	0.06
					Panel B: STEP					
Treat	0.543	0.246	0.333	0.301*	0.282	0.326	0.488	0.476*	0.330	0.361*
	(0.447)	(0.210)	(0.284)	(0.171)	(0.294)	(0.214)	(0.323)	(0.263)	(0.279)	(0.193)
STEP June 14/15		y		y		y		y		y
N (students)	112	112	223	223	227	227	217	217	779	779
Effect size	0.22	0.10	0.13	0.12	0.11	0.13	0.20	0.19	0.13	0.15

NOTE: Columns show treatment estimates from OLS models that include as covariates student demographics, grade level, school, and sending district. The second column for each outcome includes scores on the STEP exam from June of 14/15 as a control for baseline achievement. All models include household random effects. In last column of Panel B for grade interactions, we fit the model via restricted maximum likelihood (REML) as the sample is not large enough to converge. Sample for Sept 15/16 is reduced because only one school tested in that period. Effect size shows the treatment estimate in standard deviations relative to the average of all 1st to 4th graders in the study schools. Standard errors are shown in parenthesis.
* p<0.1. ** p<0.05. *** p<0.01.

Table 5. Tests for Differential Effects of Summer Learning Texting Interverntion on Reading Achivement

	Sept 15/16			Nov 15/16			Feb 15/16			June 15/16			Stacked periods		
	Panel A: STAR														
Treat	–15.25	12.17	10.82	–1.20	27.907	21.74	–24.35	6.69	8.50	–15.16	21.96	18.23	–12.70	17.33	16.60
	(21.53)	(24.13)	(21.374)	(21.044)	(23.392)	(20.81)	(21.95)	(25.06)	(22.060)	(25.57)	(29.27)	(25.87)	(19.95)	(22.89)	(20.42)
Treat x 3rd & 4th	45.01			46.73			87.47***			72.41**			57.23**		
	(31.34)			(30.72)			(32.001)			(36.70)			(28.42)		
Treat x FRPL		–11.81			–13.55			17.59			–6.76			–6.44	
		(34.07)			(33.14)			(35.27)			(41.24)			(32.35)	
Treat x Hispanic			–26.02			–15.17			13.10			–21.47			–18.35
			(35.76)			(34.73)			(36.98)			(43.30)			(34.02)
Treat x Afri. Amer.			29.86			33.22			29.70			63.70			28.44
			(50.59)			(49.45)			(53.89)			(62.90)			(48.57)
N (students)	224	224	224	225	225	225	223	223	223	224	224	224	896	896	896
	Panel B: STEP														
Treat	–0.168	0.212	0.107	0.098	0.247	0.080	–0.037	0.074	0.094	0.089	0.185	0.220	0.052	0.214	0.120
	(0.301)	(0.319)	(0.276)	(0.239)	(0.258)	(0.229)	(0.292)	(0.325)	(0.284)	(0.352)	(0.393)	(0.346)	(0.265)	(0.279)	(0.245)
Treat x 3rd & 4th	0.763*			0.417			0.773*			0.843			0.651*		
	(0.405)			(0.343)			(0.425)			(0.518)			(0.384)		
Treat x FRPL		0.064			0.104			0.475			0.554			0.280	
		(0.453)			(0.366)			(0.459)			(0.559)			(0.396)	
Treat x Hispanic			0.035			0.271			0.574			0.614			0.516
			(0.485)			(0.379)			(0.477)			(0.583)			(0.411)
Treat x Afri. Amer.			1.330*			1.083**			0.440			0.518			0.662
			(0.685)			(0.538)			(0.689)			(0.842)			(0.590)
N (students)	112	112	112	223	223	223	227	227	227	217	217	217	779	779	779

NOTE: Columns show treatment estimates and interaction effects for subgroups of interest from OLS regressions that include as covariates student demographics, grade level, school, sending district, and June STEP 14/15 scores. All models include household random effects. In last column of Panel B for grade interactions we fit the model via restricted maximum likelihood (REML) as the sample is not large enough to converge. Sample for Sept 15/16 is reduced because only one school tested in that period. Standard errors are shown in parenthesis.
* $p<0.1$. ** $p<0.05$. *** $p<0.01$.

Table 6. Effects of Summer Learning Texting Intervention on Parent Engagement

	Attend ice cream social	Host home visit or meet teacher outside school	Attend parent-teacher conference	Sign up for additional text messages
Treat	0.697	1.011	5.640**	1.427
	[1.151]	[0.031]	[2.154]	[0.733]
N (students)	231	231	231	231
Marginal effect	–0.082	0.002	0.054	0.037
	(0.071)	(0.066)	(0.027)	(0.049)

NOTE: Odd ratios and marginal effects reported in table. Logistic regressions include as covariates student characteristics, indicators for grade level, school, and sending district, as well as June 14/15 STEP scores. FRPL not included in the vector of student covariates for Parent Conference Attendance as it predicts the outcome perfectly. ESL was not included in the vector of student covariates for “sign up for additional text messages” as it predicts failure perfectly. Standard errors clustered at the household level. T statistics are shown in brackets and standard errors shown in parentheses.

* p<0.1. ** p<0.05. *** p<0.01.

Table 7. Exploratory Effects of Summer Learning Texting Intervention on Parent-Student Literacy Activities

	Treatment	T-Stat	N (students)
Told a story to child	1.629	[1.339]	158
Read a book out loud to child	1.228	[0.560]	158
Gave a book to child to read	0.534	[1.625]	159
Asked child about books he/she read	0.685	[0.964]	158
Encouraged child to read on his/her own	1.224	[0.409]	161
Encouraged child to write on his/her own	0.619	[1.306]	160
Wrote with child	0.778	[0.640]	158
Explained new words to child	0.874	[0.365]	158
Took child to library	0.491*	[1.936]	160
Checked out books from library with child	0.581	[1.492]	160
Took child to a museum	1.575	[1.204]	159
Helped child with BVP homework packet	0.929	[0.178]	161

NOTE: Survey questions are about how often parents and children participated in a given activity. Parents answered questions about each student in a household using a 5 point Likert scale, ranging from never to more than once a week. Odd ratios shown in table. Ordered logistic regression include as covariates student demographics, grade level, school, sending district, and STEP June 14/15 scores. Standard errors clustered at the household level. T statistics in brackets.
* $p<0.1$. ** $p<0.05$. *** $p<0.01$.

Table 8. Differential Attrition Tests

	Treatment
STAR Sept 15/16	–0.001
	(0.024)
STAR Nov 15/16	–0.013
	(0.024)
STAR Feb 15/16	–0.024
	(0.027)
STAR June 15/16	–0.001
	(0.024)
STEP Sept 15/16	0.033
	(0.029)
STEP Nov 15/16	–0.027
	(0.026)
STEP Feb 15/16	–0.001
	(0.020)
STEP June 15/16	–0.012
	(0.033)
N (students)	232

NOTE: Attrition coefficients attained by regressing a binary indicator for missing data on an indicator for treatment status. Models include household random effects. Standard errors in parenthesis.
* p<0.1. ** p<0.05. *** p<0.01.

Table 9. Coded Responses to the Types of Challenges that Limited Parents' Abilities to Read with their Children During the Summer

	Treatment	Control	In analysis
Health issues	3	2	5
Work demands	2	4	6
Summer plans	8	3	11
Family challenges	3	4	7
Student resistance	0	1	1
Undisclosed	0	2	2
N (Parents w/unique challenge)	14	13	27
N (Parents survey responders)	60	70	130

NOTE: Table shows response counts for a survey question asking whether parents faced any unique challenges that impeded their ability to read with their children over the summer months. Challenge types were determined by analyzing parents' short answer responses. Each response was coded for each of the types of challenges parents mentioned. Counts are at the household level.

Appendix

Table A1. Baseline Characteristics of Students in Analysis, by Survey Respondents

	All students in study	Responded survey	Did Not respond survey	Difference	*P-value*
Received treatment	0.51	0.47	0.59	–0.12	0.091
STEP June 14/15	8.13	8.29	7.76	0.52	0.257
STAR reading June 14/15	438.30	465.32	380.62	84.71	0.009
STAR math June 14/15	572.85	585.47	545.92	39.55	0.025
Age	7.74	7.76	7.69	0.07	0.703
Female	50.0	48.4	53.5	–5.1	0.476
Asian	3.4	3.1	4.2	–1.1	0.667
Black	11.6	11.2	12.7	–1.5	0.971
Hispanic	32.3	26.7	45.1	–18.4	0.005
White, not Hispanic	52.2	58.4	38.0	20.4	0.145
Native American	0.4	0.6	0.0	0.6	0.505
Free or reduced price lunch	53.4	42.9	77.5	–34.6	0.008
English as a second language	3.4	3.1	4.2	–1.1	0.664
Special education	6.9	4.3	12.7	–8.4	0.02
Rising 1st grade	28.1	30.4	22.9	7.5	0.238
Rising 2nd grade	25.1	22.4	31.4	–9.0	0.142
Rising 3rd grade	23.8	21.1	30.0	–8.9	0.143
Rising 4th grade	22.5	25.5	15.7	9.8	0.101
Elementary school 1	53.0	53.4	52.1	1.3	0.938
Elementary school 2	47.0	46.6	47.9	–1.3	0.938
CF sending district	15.1	13.0	19.7	–6.7	0.057
CU sending district	32.3	36.0	23.9	12.1	0.069
LN sending district	22.4	23.0	21.1	1.9	0.755
PA sending district	29.3	26.7	35.2	–8.5	0.626
N (students)	232	161	71		

NOTE: Characteristics of students in households that responded and did not respond to the parent survey. P-values calculated by regressing the indicator for treatment on each variable, model uses household random effects.