Essays on Educational Inequality

Essays on Educational Inequality:

Learning Gaps, Social-Emotional Skills Gaps, and Parent Enrichment Outside of School Time

Kathleen Lynch

Heather Hill
James S. Kim
Jon R. Star
Robert Selman

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ESSAYS ON EDUCATIONAL INEQUALITY

Table of Contents

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Abstract

The achievement gap between high- and low-income children in the United States widened considerably in the last quarter of the twentieth century. Seasonal comparison research suggests that this gap widens primarily during summer vacation: While high- and low-income children learn at similar rates during the school year, high-income children learn more during the summer.

The widening income achievement gap may have been driven in part by increasingly divergent summer experiences of high- and low-income children, as in recent years, high-income parents have increased their investments in their children's cognitive development. However, we have no evidence on how high- and low-income children's summer learning and activities have changed in recent decades. In *Study #1*, I examine how kindergarten children's summer learning and enrichment activity participation changed between 1998 and 2010.

Second, while the growth of *academic achievement* gaps during summer vacation is a widely documented problem, little research has examined how socioeconomic gaps in children's *social-emotional and executive function skills* change over the summer. In *Study #2*, I address these questions.

Thirdly, our understanding of effective policies to ameliorate low-income children's summer learning loss is limited. In *Study #3*, I conduct a randomized experiment of a home-based summer mathematics program aimed at improving low-income children's summer home mathematics engagement and reducing summer learning loss. Taken together, these three studies inform our understanding of how children's out-of-school environment contributes to educational inequality.

Essays on Educational Inequality: Learning Gaps, Social-Emotional Skills Gaps, and Parent Enrichment Outside of School Time

An enduring question in sociology and education is how children's out-of-school environment contributes to educational inequality. In my dissertation, I shed fresh light on this question with three new papers.

The achievement gap between high- and low-income children in the United States widened considerably in the last quarter of the twentieth century (Reardon, 2011). Seasonal comparison research suggests that this gap may widen primarily while children are on summer vacation: While high- and low-income children learn at similar rates during the school year, high-income children appear to learn significantly more during the summer than do low-income children (e.g. Alexander, Entwisle, & Olson, 2007; Downey, von Hippel, & Broh, 2004; Heyns, 1978; von Hippel & Hamrock, 2016). Scholars have argued that affluent children's summer learning advantage likely increases social inequality (Raudenbush & Eschmann, 2015). This advantage may arise because affluent and poor children's home learning environments are more unequal than their school environments, with high-income children enjoying more parent enrichment and extracurricular activities.

The changes in the income achievement gap that Reardon identified may have been driven in part by increasingly divergent summer experiences of high- and low-income children, as in recent years high-income parents have substantially increased their investments in their children's cognitive development. However, to date, we have virtually no evidence on how high- and low-income children's summer learning and activities have changed in recent decades. In *Study #1*, I examine how kindergarten children's summer learning and enrichment activity participation changed across two cohorts of children who began school over a decade apart, in 1998 and 2010. An examination of whether and how the income-based 'summer learning gap' and 'summer activity gap' have changed could provide insight into a key hypothesized mechanism for income-based educational inequality.

Second, while the growth of *academic achievement* gaps during summer vacation is a widely documented problem, we have little to no information on how gaps in children's *social-emotional and executive function skills* change over the summer. Nor do we know how children's summer gains in these skills vary by family socioeconomic status. Yet many of the investments high-SES parents make in their children's summer enrichment experiences, such as camps and summer trips, may be targeted toward improving their children's social-emotional skills. In *Study #2*, I address this gap in the literature by investigating how gaps in high- and low-SES children's executive function and social skills change over summer vacation.

Thirdly, turning to a policy perspective, our understanding of strategies to ameliorate summer learning loss among low-income children is quite limited. Despite policy interest in lower-cost alternatives to summer school, I can identify no prior studies of home-based summer mathematics interventions. In *Study #3*, I conduct a randomized experiment of a home-based summer mathematics program aimed at improving low-income children's summer home mathematics engagement and reducing summer learning loss. This study addresses the gap in our understanding of how low-touch, home-based mathematics interventions may affect low-income children's summer math participation and learning outcomes.

Socioeconomic Gaps in Children's Summer Experiences: 1999 to 2011

Kathleen Lynch

Harvard Graduate School of Education

Author Note

Kathleen Lynch, Harvard Graduate School of Education.

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Correspondence concerning this article should be addressed to Kathleen Lynch, 407 Gutman Library, 6 Appian Way, Cambridge, MA 02138. E-mail: khlynch@post.harvard.edu

ESSAYS ON EDUCATIONAL INEQUALITY

Abstract

A variety of research studies suggest that the socioeconomic status (SES)-based achievement gap may widen primarily while children are on summer vacation. While high- and low-SES children learn at similar rates during the school year, high-SES children appear to learn significantly more during the summer than do low-SES children, perhaps due to differences in the summer enrichment opportunities available to children of high- and low-SES backgrounds.

However, no studies have used recent data to examine children's summer activity participation. Nor have any studies examined how high- and low-SES children's summer activities or learning have changed over time. In this study, I use nationally representative data to examine how socioeconomic gaps in young children's *summer activity participation,* as well as the relationships between SES, summer learning, and summer enrichment, have changed in recent decades. I find that parents across the socioeconomic spectrum increased their reported time investments in home literacy and math activities across cohorts. However, socioeconomic gaps in several out-of-home activities widened across cohorts. I discuss implications for future research.

Socioeconomic Gaps in Children's Summer Experiences: 1999 to 2011

The achievement gap between children from families of high- and low-socioeconomic status (SES) in the United States appears to have widened considerably in the last quarter of the twentieth century (Reardon 2011). Seasonal comparison research suggests that this gap may widen primarily while children are on summer vacation: While high- and low-SES children learn at similar rates during the school year, high-SES children appear to learn significantly more during the summer than do low-SES children (e.g. Alexander, Entwisle, and Olson 2001; 2007; Burkam, Ready, Lee, and LoGerfo 2004; Downey, von Hippel, and Broh 2004; Heyns 1978). In a recent reanalysis of data from three datasets, the Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K), the Beginning School Study (BSS), and the Growth Research Database (GRD), von Hippel and Hamrock (2016) generally confirm the finding that SES gaps grow faster during the summer. Scholars have argued that affluent children's summer learning advantage likely increases social inequality (Downey and Condron 2016; Raudenbush and Eschmann 2015). This advantage may arise because affluent and poor children's home learning environments are more unequal than their school environments, with high-SES children enjoying more parent enrichment and extracurricular activities.

The changes in the SES-achievement gap identified by Reardon may have been driven in part by increasingly divergent summer experiences of high- and low-SES children, as in recent years high-SES parents have substantially increased their investments in their children's cognitive development. However, to date, we have virtually no evidence on how high- and low-SES children's summer enrichment experiences have changed in recent decades. In this study, I examine how kindergarten children's summer activity participation changed across two cohorts of children who began school over a decade apart, in 1998 and 2010. An examination of whether and how the SES-based 'summer activity gap' has changed could provide insight into an important hypothesized mechanism for SES-based educational inequality.

Social Stratification in Children's Summer Experiences: Theoretical Perspectives

While researchers have suggested that the SES-based achievement gap appears to grow during children's summer vacation, the mechanisms for *how* the gap widens outside of school time are not well understood. Seasonal comparison research suggests two key theoretical strands that may bear on this question (Borman, Benson, and Overman 2005), while noting that these strands are overlapping and intertwined.

First, *investment theory* posits that parents invest financial and human capital in their children, and that these investments are correlated with child achievement (Becker 1981; Borman et al. 2005). Relatedly, and specific to summer vacation, Entwisle, Alexander, and Olson (1997) posit that high- and low-SES families respond differently to the turnoff of the school resources 'faucet' during summer vacation: High-SES parents compensate by turning on a 'faucet' of home-based enrichment activities, while low-SES parents are unable to do so. Increasing differential investments of time and money into high-SES children's cognitive development seem one likely cause of the growth of the socioeconomic achievement gap. High-income parents have markedly increased their investments in products and services to boost their children's cognitive development: The 'spending gap' between high- and low- income families on child enrichment items nearly tripled between the early 1970s and the mid-2000s, (Kornrich and Furstenberg 2013), and this was true for young children as well as older children (Kornich 2016). Enrichment activities may expand children's vocabularies and content knowledge, both strong predictors of children's ability to comprehend textbooks (Murnane, Sawhill, and Snow 2012).

Second, *concerted cultivation theory* (Lareau 2002) suggests that parents from different socioeconomic backgrounds have different parenting philosophies and practices: Higher-SES parents tend to value 'cultivating' their children's talents, and encourage extensive child extracurriculars; meanwhile, lower-SES parents are theorized to espouse a philosophy of 'natural growth,' and allow their children more unsupervised free time (Lareau 2002). However, Chin and Phillips (2004) argue that the class-based summer activity gap exists because low-SES parents lack resources to identify and access enriching programs.

As noted above, these two theories are not mutually exclusive but rather overlapping. If low-SES parents lack money, they will be unable to afford to engage in many of the types of activities associated with concerted cultivation. In the same vein, high-SES parents may spend more money and time on activities such as summer camp, while also selecting camps that cultivate their children's talents and interests. Taken together, the two theories imply that the quantity and quality of children's summer enrichment activities are drivers of inequality.

Socioeconomic Gaps in Children's Summer Activities

Prior research has shown that the quantity and quality of children's summer activities depends on family socioeconomic status. I have identified four prior studies that examined SES-based patterns in children's summer activity participation. I describe these studies and the contribution of the current study below.

Heyns (1978) examined children's summer learning and activity participation in Atlanta, and found that summer book reading and library use were positively associated with summer achievement gains. Furthermore, Heyns concluded that even compared with family socioeconomic status and controlling for prior achievement, children's summer book reading was a strong predictor of summer learning (Heyns 1978). Chin and Phillips (2004) conducted a small-scale ethnographic study which documented striking class-based differences in children's summer learning activities. They found that higher-SES parents crafted summer learning opportunities ranging from music lessons to educational trips. By contrast, lower-SES parents often selected summer activities based on price (Chin and Phillips 2004). A limitation of this study is that it was conducted with a small sample of children who attended a single, socioeconomically diverse urban elementary school over a decade ago.

Burkam, Ready, Lee, and LoGerfo (2004) analyzed SES disparities in kindergarten children's summer learning and activities using ECLS-K 1998-99. They found that on a typical summer day, higher-SES children were more likely to have read books with a parent; visited the library; visited a bookstore; gone on a summer trip; participated in dance, music, swimming, or sports lessons; and used a home computer for educational purposes. Low-SES children were more likely to have attended mandatory or suggested summer school, and watched double the number of hours of television as high-SES children. Further, 25% of the SES gap in summer math learning was associated with differential participation in summer activities.

Gershenson (2013) examined the 1989-1990 Activity Pattern Survey of California Children (APSCC), and found that low-income children watched two more hours of television per day than their high-income counterparts, and spent 12 fewer minutes talking with a parent. While this study is the only known time-diary study that has examined children's activities during the summer, it was conducted 25 years ago.

Recent Trends in SES-Based Achievement and Enrichment Gaps

Note that it is not clear whether we should expect SES-based summer enrichment gaps to have widened or narrowed over this time period (late 1990s-early 2010s). On the one hand, income inequality in the United States grew during this period (Reardon and Portilla 2016). Larger income gaps could conceivably lead to larger summer enrichment gaps, if affluent families allocate more resources toward cognitively stimulating summer experiences for their children. On the other hand, achievement gaps at kindergarten entry narrowed slightly over this period (Reardon and Portilla 2016). In addition, the research evidence on whether early childhood enrichment gaps widened or narrowed over this period is mixed. While Bassok et al. (2016) identify narrowing gaps between 1999 and 2011 in kindergarteners' home computer use and in- and out-of-home enrichment activities using ECLS-K, Kalil et al. (2016) use data on preschool-aged children from four national studies conducted from 1988 to 2012, and find increasing income-based gaps in parent behaviors such as reading and teaching numbers and in children's participation in out-of home cultural activities. An important difference between the current study and prior work is the focus on summer vacation. Parents face different child care needs and options during elementary school summers than they did during the kindergarten academic year or when their children were of pre-school age. Given these trends, whether we would hypothesize narrowing or widening summer gaps over this period is thus not entirely clear.

The current study addresses several important gaps in the literature on social stratification in children's summer enrichment. First, existing studies of socioeconomic disparities in children's summer enrichment experiences are outdated. Existing studies include data that are, at their most recent, over a decade old. Second, no comparative studies have examined how the summer enrichment gap has changed over time. Given the hypothesis that the SES-based achievement gap widens during children's summer vacations, there is a need to examine whether and how the SES-based summer enrichment gap has changed in recent decades, and how enrichment activities relate to summer learning. Third, no study to date has examined the relationship between summer enrichment experiences and science learning. Thus, there is a need to understand inequality in children's summer activities, and how these activities relate to cognitive development during the period outside of school, when learning may be more sensitive to family environment and parent investments.

Research Questions

I address these gaps by comparing the summer enrichment experiences of US kindergarteners in 2011 to those of US kindergarteners in 1999. I ask the following descriptive research questions:

(1) Are SES-based *summer enrichment activity participation gaps* larger for children in

the later ECLS-K cohort than they were for children in the earlier cohort?

(2) To what extent does differential participation in summer enrichment activities account for socioeconomic gaps in summer learning in each cohort?

Method

Datasets

I utilize two primary datasets: the Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K) and ECLS-K 2010-11. ECLS-K followed the educational experiences of a nationally representative sample of U.S. children (N=18,211) from kindergarten (1998) through the eighth grade. ECLS-K 2010-11 follows a new cohort of fall 2010 kindergarteners (N=18,200). Both studies used a multistage probability sampling design to first select counties or groups of counties, then schools within the selected counties, and then students within the selected schools (Tourangeau et al. 2001; Tourangeau et al. 2013).

The design, sampling strategy, and measures for ECLS-K and ECLS-K 2010-11 are nearly identical, enabling researchers to conduct cross-cohort comparisons (NCES 2011).

The ECLS-K studies were designed to facilitate analyses of summer learning. Both tested children in literacy and math in kindergarten spring, and re-tested a random 30% sub-sample again in first grade fall. Children were also administered pre- and post-summer general knowledge tests in the 1999 study and science tests in the 2010 study. I can thus estimate summer learning gains. Both studies interviewed parents about their children’s summer activities, such as camp attendance, travel, reading, and television viewing (NCES 2002; NCES 2011).

Participants

The analytic sample includes all children who were subsampled in the fall first grade round, did not attend a year-round school, and for whom race and gender information were nonmissing. The requirement of valid data for race and gender resulted in dropping approximately 50 participants 1999 and 80 in 2011; approximately 130 children in each cohort were excluded because they attended year-round schools. This results in an analytic sample of N = 4,860 children in the 98-99 cohort and N = 4,290 children in the 2010-11 cohort. (All sample sizes are rounded per NCES requirements.)

Measures

I utilize four categories to describe children's summer activity participation: (1) *out-of-home summer institutional enrollments*, or formal institutions where children are enrolled outside the home, including summer school and summer camps; (2) *out-of-home summer cultural activities and trips to novel places,* which may be undertaken for a mix of educational and entertainment purposes; (3) *'active' home time use*, including parent enrichment and children's active home involvement in literacy, mathematics, and educational computer activities; and (4) *'passive' home time use*, including activities primarily done for children's entertainment or distraction, such as television viewing and video and computer games. I describe the measures in each category below.

Out-of-home summer institutional enrollments. The fall first grade parent interview included items which asked whether their child had attended summer camp, attended summer school, or received tutoring. Parents were also asked about the number of camps the child attended and the types of activities the camps included (e.g., music/performing arts, academics, etc.).

Out-of-home summer cultural activities and trips to novel places. The out-of-home summer cultural activities and trips measure is a composite variable, operationalized as the sum of the number of destinations the child visited during the summer, including a play or concert; a zoo or aquarium; an amusement park; a large city (other than the city where the child lived); a museum or historical site; and a beach, lake, river, or state or national park (on a scale of 0-6). While the alpha levels for these scales are relatively low (1999: α=.51; 2011: α=.53), they are similar to those found in prior research on children's activity participation using ECLS-K (Bassok et al. 2016).

'Active' home time use activities. This category included parent enrichment and children's active home involvement in literacy, math, and educational computer activities.

***Literacy activities*.** I utilized a composite measure of home-based literacy activities, operationalized as the average frequency with which the parent reported that he/she read books with the child; did writing activities with the child; and the child looked at or read books on his/her own (with each item on a scale of 1-4, ranging from never to every day; 1999: α=.55; 2011: α=.58). Both datasets also include measures of the number of times the child visited the library and bookstore over the summer, and an indicator of whether or not the child attended any story hours at libraries or bookstores over the summer.

***Mathematics activities*.** In each cohort, parents were asked about the frequency with which they did math activities, such as learning numbers, adding, subtracting, or measuring, with the child (scale 1-4, ranging from never to every day). This variable was recoded to 1 if the parent indicated that they did math activities with the child 3 times per week or more, and 0 otherwise.

Educational computer use. Interview questions asked whether or not the family owned a home computer that the child used, as well as the frequency with which the child used the computer for educational purposes (on a scale of 1-4, ranging from never to every day). This variable was recoded to 1 if the parent indicated that the child used the computer for educational purposes 3 times per week or more, and 0 otherwise.

'Passive' home time use activities. This category included activities primarily done for children's entertainment or distraction, specifically relating to 'screen time' via television, computers, and video games.

TV and computer/video game time. In each cohort, parents were asked about the number of hours and minutes that the child watched TV each day. In 2011, parents reported on how much time the child spent watching TV overall on a typical summer day; in 1999, parents were asked separately about the total amount of time the child spent watching TV at home before breakfast, between breakfast and dinner time, and after dinner time. For each child in 1999, I summed these values to estimate total daily TV time. Parents in each cohort were also asked about the time their child spent playing video or computer games. This item differed in the two surveys: In 1999, parents were asked to rate the frequency with which their child played computer games, on a scale ranging from never (1) to every day (4); in 2011, parents were asked how many hours and minutes per day their child spent playing video games. Due to differences in item wording and scales for the computer/video game measures, standardized scores are used for cross-cohort gap comparisons.

Achievement test scores. I use children's IRT-estimated theta scores on spring and fall math, literacy, science, and general knowledge tests. These scores have been vertically equated using IRT and scaled to allow for cross-wave comparisons (Tourangeau et al. 2013). Literacy assessments measured skills such as word recognition, receptive vocabulary, and reading comprehension. Math assessments measured conceptual and procedural knowledge in domains such as number sense, data analysis, and patterns. A general knowledge test covering science and social studies was administered in 1999, and a science test was administered in 2011.

Socioeconomic status. To operationalize socioeconomic status, I utilize the composite variable for socioeconomic status present in the ECLS-K datasets. In ECLS-K, SES is a continuous variable that indexes parents' income, level of educational attainment, and job prestige.

Time measures. Both ECLS-K datasets include variables indexing the dates on which each child took the spring and fall assessments, as well as the child's school's summer vacation start and end dates.[1] To ensure that estimates of summer learning are not contaminated by school year learning, I replicate the time gap modeling strategy utilized by Burkam et al. (2004), including child-level measures of the spring assessment date to summer vacation start, summer vacation, and summer vacation end to fall assessment date intervals in all analyses of student achievement.

Analyses

I compare summer parent enrichment and activity gaps for the new ECLS-K 2010-11 cohort compared with the earlier 98-99 cohort. I make two kinds of comparisons. First, I describe the differences in *summer activity participation* between high- and low-SES children within each cohort. Specifically, I present descriptive statistics on the average frequency of participation in measured summer activities, for children at the 10th, 50th, and 90th percentiles of family SES within each cohort. Second, I conduct tests to evaluate whether SES-related gaps in summer activity participation are larger for the later ECLS-K cohort than for the earlier cohort.

To estimate SES gaps in summer enrichment activities, I utilize a method similar to Reardon (2011) and Bassok et al. (2016), using composite family SES rather than family income to align with how socioeconomic status has been operationalized in prior seasonal comparison research (e.g., Burkam et al. 2004; Downey et al. 2004). I regress each measure of children's summer enrichment experiences on family socioeconomic status (up to a cubic transformation). I then estimate the rate at which children at the 10th, 50th, and 90th percentiles of family SES participate in each enrichment activity. For each measure, I then compute the 90/10 SES gap, or the average difference in the rate at which children at the 90th percentile of family SES participated in the enrichment experience, compared with children at the 10th percentile. I also compute the 90/50 and 50/10 gaps. I include the appropriate sample weights in all analyses and utilize the Taylor series linearization method to generate correct standard errors. In order to determine whether the SES gaps in children's experiences were significantly different in 2011 than in 1999, following Bassok et al. (2016), Reardon and Portilla (2016), and Kalil et al. (2016), I calculated the standard errors of the differences in gaps between 1999 and 2011, then conducted *t*-tests to evaluate whether the gap had changed significantly from 1999 to 2011.

I also estimate gaps in summer learning in each cohort (Quinn 2015; von Hippel & Hamrock 2016). Several methods have been used in prior research to estimate summer learning gaps. In prior research using the original ECLS-K to examine summer black-white gap trends, Quinn (2015) found that ordinal and interval test score assumptions generally resulted in similar gap estimates using the ECLS-K theta metric. Beyond variability resulting from untestable reliability assumptions, the most consequential differences in gap trends were found to result from different modeling strategies. As Quinn (2015) points out, in the context of descriptive research, different models should be understood as answering different research questions. For the current study, I fit regressor variable models for two reasons. First, they are identical in form to models that have been used in prior research examining summer activity participation in ECLS-K (Burkam, Ready, Lee, and LoGerfo 2004). Second, regressor variable models address a question relevant for both equity and policy, “Do students of different socioeconomic backgrounds who have the same spring score have different fall scores, on average?” (Mullens, Murnane, and Willett 1996). I fit models of the following form:

$$FallScore_i = b_0 + b_1 SpringScore_i + b_1 T_i + b_2 S_i + b_3 D_i + e_i \quad (1)$$

where $FallScore_i$ and $SpringScore_i$ represent student *i*’s fall and spring IRT-estimated q, scores, respectively, both standardized using the spring mean and SD of the full sample; T_i represents a vector of three time gaps, in order to account for variability in spring and fall testing dates and the potential for summer learning estimates to be contaminated with school year learning (Burkam et al. 2004); S_i is an indicator for socioeconomic status; and D_i represents child age in months. To examine the relationships between summer activity participation and summer learning in each cohort, I add measures of children’s participation in enrichment activities to the models above.

To account for missing data, I conducted multiple imputation using Stata's *mi* routines. The imputation models use chained equations and five iterations.

Results

Summer Enrichment Gaps

In Table 1, I present estimates of the average levels of summer activity participation and parent enrichment for children at the 10th, 50th, and 90th percentiles of family socioeconomic status, respectively. In Table 2, I present the estimated 'summer enrichment gaps' between children at the 90th and 10th percentiles of family SES, as well as between children at the 50th and 10th percentiles and the 90th and 50th percentiles. Tables 3 and 4 provide a detailed breakdown of participation rates and SES gaps in the individual summer out-of-home cultural activities and trips, and literacy practices variables included in the composite scales, as well as more details on children's summer camps. I discuss the gaps for each category of summer activities below.

Out-of-Home Summer Institutional Enrollments

Socioeconomic gaps in the proportion of children attending summer camp and in the number of summer camps that children attended increased significantly over this period (see Tables 1 and 2). This was driven by an increase in the proportion of affluent children attending camp, as well as an increase in the number of camps that middle-SES and affluent children attended. The proportion of high-SES children attending summer camp increased from approximately 40% to 53% over this period, while the number of summer camps that high-SES children participated in increased from an average of 1.47 in 1999 to 2.02 in 2011.

Descriptively, in 2011, the camps that low-SES children attended were more likely to include academic activities, computer use, and music or performing arts, while the camps high-SES children attended were more likely to include arts and crafts and sports.

In both cohorts, low-SES children were more likely to attend required or suggested summer school. The 'summer school gap' widened marginally across cohorts, driven by an increase in the proportion of low-SES children enrolled in mandatory or suggested summer school from approximately 5% to 8%. Affluent children were more likely than low-SES children to receive tutoring, and the gap was similar in both cohorts.

Out-of-Home Summer Cultural Activities and Trips to Novel Places.

In both cohorts, high-SES children enjoyed significantly more out-of-home summer cultural activities and trips than did low-SES children. In 2011, of the six categories of destinations surveyed, high-SES children had visited an average of 4.25, while low-SES children had visited 2.71. The summer trip gap widened across cohorts, driven by a decrease in the number of destinations that low-SES children visited in the new cohort compared with the earlier cohort (1999: 3.06; 2011: 2.71).

'Active' home time use activities.

In the areas of home-based math, literacy, and educational computer use activities, parents of all socioeconomic backgrounds reported increases in time expenditures between 1999 and 2011.

Across the socioeconomic spectrum, parents reported that they did math activities with their children more frequently in 2011 than they did in 1999 (see Table 1). For example, the proportion of parents who reported doing math activities with their child at least 3 times per week during the summer was 35%, 33%, and 30% for the 10th, 50th, and

90th percentiles respectively in 1999, compared with 46%, 43%, and 38% in 2011. Low-SES parents reported doing more math activities with their children than high-SES parents, and the gap was similar in both cohorts.

Parents across the socioeconomic distribution reported increased time on home literacy activities, although the increases in composite literacy activities were significant only for middle- and high-SES families. Across the SES distribution, parents reportedly increased the frequency with which they did writing activities with their children during the summer across cohorts. For example, the proportion of parents who reported doing writing activities with the child 3 or more times per week was 53%, 49%, and 42% for families in the 10th, 50th, and 90th percentiles in 1999, and 58%, 54%, and 49% respectively in 2011 (see Table 3). Middle- and high-SES parents also reported that their children read or looked at books on their own marginally more frequently in 2011 than in 1999. Home literacy activity gaps were similar across cohorts.

Across both cohorts, high-SES children visited libraries and bookstores more frequently during summer vacation than their low-SES counterparts. In 2011, low-SES children visited a library or bookstore an average of 5.12 times, while high-SES children visited 7.27 times. However, the library and bookstore visiting gap appears to have narrowed across cohorts, as low-SES children visited a library or bookstore 1.05 more times and high-SES children visited 2.21 fewer times in 2011 than in 1999. High-SES children were more likely to have attended a story hour at a library or bookstore during the summer than low-SES children, with 17% and 18% of low-SES children and 21% and 24% of high-SES children attending in 1999 and 2011, respectively; these gaps were similar across cohorts.

Across the socioeconomic spectrum, children reportedly used the computer for educational purposes more frequently in 2011 than in 1999. In 1999, the proportion of children who used the computer for educational purposes at least 3 times per week during the summer were 24%, 29%, and 37% for children at the 10^{th}, 50^{th}, and 90^{th} percentiles of family SES respectively; in 2011, the respective proportions were 38%, 43%, and 51%. However, as both high- and low-SES children increased their educational computer use, the SES gap did not change significantly.

'Passive' Home Time Use Activities

In both cohorts, low-SES children spent considerably more time watching TV and playing video games during the summer than did high-SES children. In 2011, low-SES children watched TV for an average of 2 hours and 46 minutes per day, while high-SES children watched for an average of 1 hour and 49 minutes per day. In addition, in 2011, low-SES children played video games for an average of 59 minutes per day, while high-SES children played for an average of 38 minutes per day. The gap estimates in Table 2, which utilize unadjusted composite TV time measures from each survey and standardized values for video game playing, suggest that both the summer TV gap and the summer video game gap appear to have widened across cohorts. However, because neither of these items was identical in the two surveys, the conclusion of widening screen time gaps is tentative.

Summer Learning Gaps

In Table 5, I present weighted descriptive statistics by student SES for the analytic sample by testing round for student test scores, number of summer vacation days, number of spring school days, and number of fall school days between tests.

Table 6 presents estimates of family socioeconomic gaps in children's summer learning between kindergarten and first grade in 1999 and 2011, from regressor variable models as described above. The estimates suggest that in both cohorts in both reading and math, high-SES children made greater academic progress over summer vacation than did low-SES children with the same spring test scores. Descriptively, the summer math gap was slightly larger and the reading gap was slightly smaller in 2011 compared with in 1999. Among high- and low-SES children who began the summer with the same math scores, high-SES children had fall math scores that were 0.167 SD higher than low-SES children's in 1999 and 0.213 SD higher in 2011. In reading, among children who began summer with the same test scores, high-SES children had fall scores that were 0.169 SD higher in 1999 and 0.137 higher in 2011. The results also suggest that compared with low-SES children who began summer with the same test scores, high-SES children had higher fall general knowledge scores in 1999 (by 0.222 SD) and higher fall science scores in 2011 (by 0.271 SD).

Relationships between Summer Enrichment Activity Participation and Summer Learning

In Table 7, I present the results of fitting a taxonomy of regression models for the relationships between summer learning and summer enrichment activity participation, in each cohort.

Predictors of Summer Reading Learning

Across both cohorts, children's summer reading learning was positively associated with the frequency of parent-reported home literacy activities (1999: $b = 0.029$, $p < .01$; 2011: $b = .025$, $p < .05$). The correlations between family home literacy practices and summer reading learning are roughly half as large as experimental and quasi-experimental estimates of the impact of summer school reading interventions on standardized reading scores (Lauer et al. 2006).

In 2011, but not in 1999, summer reading learning was also positively associated with the number of trips that the child took to the library (1999: b = 0.005, *ns*; 2011: b = .031, $p < .05$). In both cohorts, home-based literacy activities were stronger predictors of summer reading learning than out-of-home institutional enrollments such as summer camp or out-of-home summer cultural activities and trips, and the relationship between summer reading learning and home literacy activities was roughly half as large as the relationship between summer reading learning and family SES.

Predictors of Summer Math Learning

In 1999, children's summer math learning was positively associated with attending summer camp. A child who attended camp was predicted to score .069 SD higher on fall math tests than a child who did not attend camp after accounting for initial differences in family SES, age, and prior math skills. In other words, the correlation between camp participation and math achievement was comparable to experimental estimates of the impact of out-of-school learning interventions on standardized math scores (Lauer et al. 2006). However, in 2011, the association between camp participation and math achievement was smaller and not statistically significant (b = 0.011; *ns*). On the other hand, in 1999, a child who was tutored was predicted to score 0.121 SD lower on fall math tests than a child who was not tutored, after controlling for SES, age, and prior math achievement. This relationship was positively signed but not significant in 2011 (b = 0.023; *ns*).

For both cohorts, the relationship between summer math learning and TV viewing was negatively signed and marginally significant, such that on average, a one standard deviation increase in TV viewing time was associated with a marginally significant 0.021 SD decrease in fall math scores. Interestingly, in 1999 but not in 2011, computer/video game play was positively associated with fall math scores (1999: b = 0.019; $p < .05$; 2011: b = -0.003; *ns*).

Predictors of Summer Science and General Knowledge Learning

The ECLS-K datasets included pre- and post-summer measures of general knowledge, comprised of science and social studies material, in 1999, and of science in 2011. In 1999,

there was a statistically significant, positive association between number of summer trips taken and children's fall general knowledge scores, after accounting for family SES, child age, and prior achievement, such that a one standard deviation increase in summer trip taking was associated with a 0.026 SD increase in fall general knowledge scores. On the other hand, fall general knowledge scores were negatively associated with summer school attendance. On average, children who attended summer school were predicted to have fall general knowledge scores that were 0.087 SD lower than children who did not attend summer school, controlling for child SES, age, prior achievement, and the other activity variables.

In 2011, fall science scores were negatively associated with having received summer tutoring, such that on average, children who were tutored over the summer had fall science scores that were 0.156 SD lower than their peers who were not tutored, after controlling for the other variables in the model.

Discussion

Below, I discuss the main findings related to each research question, and then discuss the implications in relation to the broader research literature.

First, I examined whether socioeconomic *summer activity participation gaps* were larger for children in the later ECLS-K cohort (2010-11) than they were for children in the earlier cohort (1998-99).

In the area of *out-of-home summer institutional enrollments,* some socioeconomic gaps appear to have widened. The number of summer camps that affluent children attended increased significantly. A growing 'summer camp gap' may be important because summer camps are hypothesized to confer a variety of benefits, notably social benefits such as increased acceptance of diversity (Laird and Feldman 2004). Meanwhile, the summer school gap widened marginally; in 2011, low-SES children were more than twice as likely as high-SES children to be enrolled in mandatory or suggested summer school. While required summer school has the potential to reduce summer learning loss (e.g., Cooper et al. 2000; Kim and Quinn 2014), research on voluntary summer school programs in several large urban districts suggests that the quality of both classroom instruction and the supplemental enrichment activities offered to students is mixed (Augustine et al. 2016).

Meanwhile, the gap in *out-of-home summer cultural activities and trips to novel places* was sizable in both cohorts and also appears to have widened, as low-SES children took fewer trips in 2011 than in 1999. Connecting to other recent research on children's early life experiences, Bassok et al. (2016) used ECLS-K data and found slightly narrowing gaps in spring kindergarten out-of-home activities, such as visits to zoos and museums, whereas Kalil, Ziol-Guest, Ryan, and Markowitz (2016) used data from four nationally representative surveys spanning 1988-2012 and concluded that income-based gaps in children's participation in out-of-home cultural activities widened. Differences in findings may be related to differences in the out-of-home activity measures across studies and survey waves. However, it is also possible that time use gaps may operate differently during the summer from the preschool and academic year periods. During summer vacation, parents may face greater challenges and expenses associated with filling children's time than during the school year. Speculatively, perhaps these extra seasonal expenses may constrain the budgets of low-income families more so than those of high-income families. For low-SES children more so than for high-SES children, TV and video games may fill in some of this time.

In the area of *'passive' home time use activities,* the gap estimates for TV viewing and video game playing are consistent with a scenario in which the SES-based 'screen time gap' has widened. As noted above, I interpret these estimates with caution due to differences in item wording in the two surveys. What is clear is that in both cohorts, low-SES children spent substantially more time over the summer watching TV and playing computer/video games than their high-SES counterparts. Low-SES children's heavy consumption of TV and video games during summer vacation is likely disadvantageous, because TV viewing and video game playing have been linked to aggressive behavior, decreased physical activity, and displaced time for reading and cognitively enriching activities (Gershenson 2014). In 2011, low-SES children watched 57 more minutes of TV and played 21 more minutes of video games each day than did high-SES children. Following Gershenson (2014), assuming that summer is 90 days long, the daily 'screen time gap' of one hour and 18 minutes per day amounts to a 117 hour gap over the summer vacation period. Assuming the average school day is 7 hours long, the extra time that poor children spend on screen time compared with affluent children is equivalent to roughly 17 instructional days.

In the area of *'active' home time use activities*, I find that parents across the income spectrum significantly increased their time investments. Parents at each socioeconomic level reported that they increased the time they spent doing writing activities with their children. Parents across the socioeconomic spectrum also reported that they read books to their children more frequently in 2011 than in 1999, although these increases were significant and somewhat larger for middle- and high-SES families, and nonsignificant for low-SES families.

Parents across the socioeconomic distribution also reported that their children spent more time during the summer using the computer for educational purposes in 2011 than in 1999. These changes may be related to general diffusion of home computer technology; Bassok et al. (2016) have previously noted that the home computer ownership gap narrowed over this period, as lower-cost computer models affordable to lower-SES families went to mass market. However, it is unclear whether increased summer use of a home computer for educational purposes should be expected to result in improved student achievement, or in similar improvements for children of different socioeconomic backgrounds. Some quasi-experimental evidence suggests that the introduction of home computer technology is associated with negative impacts on student math and reading test scores, and may widen inequalities (Vigdor, Ladd, and Martinez 2014). In addition, while the educational games and apps markets have expanded rapidly, there is limited research on most web-based learning applications' effectiveness (Hirsh-Pasek, Zosh, Golinkoff, Gray, Robb, and Kaufman 2015).

The findings related to the first research question suggest the possibility that perhaps parents' monetary investments and time use are operating in different ways during summer vacation. The gap that widened most substantially across cohorts was summer camp enrollment, an out-of-home activity that is often relatively expensive. By contrast, in the same time period, families of all socioeconomic backgrounds increased their average reported summer time investments in home-based enrichment and parenting practices, such as doing writing and math activities and reading books with their children. It may be the case that, as Bassok et al. (2015) suggest, low-SES families have altered their parenting behavior in response to popular messages about early childhood development propagated by universal book-reading campaigns. Low-income parents may have relatively more discretion over their time use while parenting at home than they do over their monetary expenditures for items like camps, resulting in increased investments in summer activities requiring time, but not in those requiring monetary expenditures.

Next, I examined the extent to which differential participation in summer activities accounted for socioeconomic gaps in summer learning in the two cohorts.

Consistent with prior research (e.g., von Hippel and Hamrock 2016), the current findings suggest a summer learning advantage for higher-SES children in both cohorts and in all measured subject areas. Descriptively, the gaps appear somewhat larger in math and smaller in reading in the new cohort compared with the earlier cohort. As noted above, however, alternative modeling approaches are possible, and may yield different conclusions about gap changes. An important area for future research is to explore differences in summer learning gaps in greater depth, both to probe their psychometric properties and to glean insights into alternative research questions they may answer.

Regarding relationships between activity participation and summer learning, I find that across both cohorts, summer reading learning was significantly positively associated with participating in home-based summer literacy activities. Summer math learning was positively related to camp attendance and computer game play in 1999, and marginally negatively related to TV viewing in both cohorts. In 1999, children who took more summer trips were predicted to have higher fall general knowledge scores, and children who attended summer school were predicted to have lower fall general knowledge scores, on average. Meanwhile, in 2011, children who were tutored during the summer were predicted to have lower fall science scores.

As noted above, an important caveat to the findings of relationships between summer enrichment activity participation and summer learning is that these analyses are descriptive; findings of significant relationships do not necessarily imply that participating in a given activity causes summer learning gains. For example, it seems unlikely that having been tutored would cause children to experience weaker summer science gains; it may be that parents of children who were experiencing difficulties in kindergarten, and therefore also at risk for difficulties learning over the summer, may have sought out tutoring. In the same vein, children who were better or more enthusiastic readers may have been more likely to both seek out parent-child book exposure, and to experience summer literacy gains. Nonetheless, experimental research indicates that increasing low-income children's book exposure (Allington et al. 2010) and book reading

(Kim 2004) leads to increased summer reading gains, suggesting that parents' efforts to increase their children's summer reading time may contribute to learning gains.

It is also worth noting that participation in many of the activities measured was not significantly associated with summer learning as measured on the ECLS-K assessments of reading, math, and science/general knowledge. Burkam et al. (2004) observed that weak relationships between activity variables and summer learning may be due to both measurement issues and to issues with differential activity participation as an explanation for SES-based differences in summer learning patterns. First, while the ECLS-K captures information about a range of activities hypothesized in the research literature to relate to summer learning, the items primarily ask about the frequency with which parents and children participated in the activity, and do not probe the quality of the interaction or the potential for child learning that the experience afforded. For example, while ECLS-K asked parents how frequently they did math activities with their children, we know nothing abut the mathematical richness of these tasks or the types of mathematical thinking they elicited. Second, the ECLS-K activity measures may capture only 'intentional' influences of social class on summer learning (Bourdieu 1986); parents' role modeling of everyday behaviors, such as book reading or screen time, may have a greater influence on children's summer behaviors and learning than frequencies of activities or trips (Burkam et al. 2004). Future ethnographic studies of children's summer time use, building on Chin and Phillips's (2004) important early study of summer activities among children in a diverse urban elementary school, could shed greater light on these issues.

However, while many of the relationships between the measured summer activities and achievement were not significant, measured summer activities did explain a proportion of the variability in children's summer learning. Controlling for summer activities reduced the association between SES and summer math learning by 29% and 8% in 1999 and 2011 respectively, and between SES and summer reading learning by 10% and 9% respectively. In particular, for the new cohort, the relationships between summer reading and doing home-based literacy activities and visiting the library and bookstore were roughly half as large as the relationships between summer reading and family SES – a measure that captures family income, parent education, and parent occupational prestige. Furthermore, the "active home time use variables" do a better job (and play a stronger role) predicting summer reading than camp, summer school, and tutoring. This is important because, as noted above, summer home literacy activities are malleable. Experimental research indicates that providing low-SES children and parents with summer books and scaffolding to discuss them increases both quantity of summer reading and subsequent literacy achievement, while also being low in cost (e.g., Allington et al. 2010; Kim 2004). Low-SES families indeed increased their reported engagement in these activities across cohorts, pointing further toward the malleability of these activities.

At the same time, some of the areas in which affluent parents have increased their investments during the summer – notably, summer camp – are likely not intended to increase math or reading scores. Rather, affluent parents may conceivably be targeting these investments more toward improving their children's affective and social-emotional outcomes, via extracurricular involvement. To date, we have limited research on the relationships between SES, activity participation and social-emotional learning over summer vacation. Future studies should investigate how SES gaps in children's social-emotional skills change over the summer vacation period, and how parent investments are associated with growth in these areas.

Limitations and Future Directions

The limitations of the current study point to potentially promising directions for future research. As noted above, a limitation of large-scale survey research is that it lacks detailed measures of the quality and nature of children's summer activities and parent-child interactions. Future ethnographic and case study research should examine these issues more closely. A second limitation relates to differences in the survey items administered in 1999 and 2011. While most of the items were identical, wording for some items differed across surveys; for example, because child care items were substantially different across surveys, it was not possible to estimate gap changes in summer child care. This points toward the value of retaining identical items for each construct in future cross-cohort research. In addition, as noted above, summer learning gaps may be operationalized in a variety of ways depending on the research question of interest (Quinn 2015); future studies should probe potential cross-cohort differences in summer learning gaps in greater depth, using a range of modeling approaches that address alternative research questions.

Conclusions

A promising trend is that parents across the socioeconomic distribution reportedly increased their time spent in 'active' home time use activities such as literacy and math activities during the summer. Especially in literacy, these activities may bolster summer learning and thwart summer loss. However, inequality in these activities did not narrow, and socioeconomic gaps in other areas, such as camp, appear to have widened. Summer enrichment gaps on a range of measures continue to favor high-SES children. High-SES children in the contemporary cohort spend more time during the summer participating in summer camps, going on trips, and participating in literacy activities and less time playing video games and watching TV compared with their low-SES counterparts. Given the hypothesis that inequality in young children's summer experiences contributes to longer-term educational attainment gaps (Alexander et al. 2007), the current findings suggest continued cause for concern at the sizable socioeconomic gaps in children’s early summer experiences.

Endnotes

1. Using data from the original ECLS-K, Downey et al. (2004) exploited the fact that different schools were tested at different times to demonstrate that learning rates appeared to be approximately constant for much of the school year.

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Table 1.

Summer Activity Participation for Children between Kindergarten and First Grade in 1999 and 2011

	10th Percentile			50th Percentile			90th Percentile		
	1999	2011	Change	1999	2011	Change	1999	2011	Change
Out-of-home Summer Institutional Enrollments									
Summer Camps									
Attended summer camp (*probability*)	0.088	0.062	-0.026+	0.168	0.177	0.009	0.401	0.529	0.128**
Number of camps attended	1.107	1.166	0.059	1.244	1.518	0.047**	1.466	2.015	0.548***
Summer School and Tutoring									
Attended required or suggested summer school (*probability*)	0.052	0.079	.027+	0.041	0.052	0.011	0.028	0.029	0.001
Received tutoring (*probability*)	0.026	0.039	0.013	0.031	0.044	0.013*	0.042	0.051	0.010
Out-of-home Summer Cultural Activities and Trips to Novel Places									

Number of out-of-home summer cultural activities and trips	3.064	2.710	-0.354***	3.517	3.346	0.008**	4.248	4.247	-0.002
Active Home Time Use Activities									
Literacy Activities									
Home-based literacy activities *(composite)*	2.861	2.905	0.044	2.893	2.953	0.060*	2.945	3.020	0.075*
Visits to the library and bookstore (#)	4.053	5.105	1.052*	6.127	6.008	-0.118	9.479	7.271	-2.208***
Attended story hour at a library or bookstore (*probability*)	0.170	0.179	0.009	0.185	0.202	0.016	0.213	0.237	0.025
Math Activities									
Parent did math activities with child *(frequency)*	0.347	0.456	0.109***	0.329	0.425	0.096***	0.302	0.384	0.082***
Educational Computer Use									
Family owned home computer child used (*probability*)	0.241	0.537	0.296***	0.494	0.744	0.250***	0.857	0.913	0.056**
Child used computer for educational purposes *(frequency)*	0.243	0.382	0.139***	0.289	0.433	0..144***	0.373	0.507	0.133***
Passive Home Time Use Activities									

TV hours daily †	1.246	2.761	†	1.077	2.367	†	0.804	1.816	†

* $p < .05$; ** $p < .01$; *** $p < .001$.
Notes: Missing values imputed using multiple imputation.
† Item differed across surveys.

Table 2.

Socioeconomic Gaps in Children's Summer Learning and Enrichment Activities between Kindergarten and First Grade in 1999 and 2011

	90/10 Gaps			50/10 Gaps			90/50 Gaps		
	1999	2011	Change	1999	2011	Change	1999	2011	Change
Out-of-home Summer Institutional Enrollments									
Summer Camps									
Attended summer camp (*probability*)	0.314	0.467	0.153***	0.008	0.115	0.035***	0.233	0.352	0.118**
Number of camps attended	0.360	0.849	0.489**	0.118	0.352	0.214**	0.222	0.497	0.275**
Summer School and Tutoring									
Attended required or suggested summer school (*probability*)	-0.024	-0.050	-0.026+	-0.011	-0.026	-0.016+	-0.013	-0.023	-0.010
Received tutoring (*probability*)	0.016	0.013	-0.003	0.005	0.005	0.000	0.011	0.008	-0.003
Out-of-home Summer Cultural Activities and Trips to Novel Places									

Number of out-of-home summer cultural activities and trips	1.184	1.537	0.352**	0.453	0.637	0.184***	0.732	0.900	0.169*
Active Home Time Use Activities									
Literacy Activities									
Home-based literacy activities *(composite)*	0.084	0.115	0.031	0.032	0.048	0.016	0.052	0.067	0.015
Visits to the library and bookstore	4.181	1.990	-2.190***	1.598	0.830	-0.768**	2.583	1.161	-1.422***
Attended story hour at a library or bookstore (*probability*)	0.043	0.058	0.016	0.016	0.023	0.007	0.027	0.036	0.008
Math Activities									
Parent did math activities with child *(frequency)*	-0.046	-0.073	-0.027	-0.018	-0.031	-0.013	-0.028	-0.042	-0.014
Educational Computer Use									
Family owned home computer child used (*probability*)	0.615	0.376	-0.239***	0.253	0.207	-0.046*	0.363	0.169	-0.193***

Child used computer for educational purposes *(frequency)*	0.130	0.124	-0.006	0.046	0.051	0.005	0.084	0.073	-0.011
Passive Home Time Use Activities									
TV hours daily	-0.441	-0.945	-0.504**	-0.169	-0.394	-0.225***	-0.273	-0.551	-0.278**
Time spent playing video/computer games weekly (z-score)	-0.132	-0.353	-0.221*	-0.051	-0.147	-0.097**	-0.082	-0.206	-0.124*

* $p < .05$; ** $p < .01$; *** $p < .001$.
Notes: Missing values imputed using multiple imputation.

Table 3.

Summer Enrichment Activities for Children between Kindergarten and First Grade in 1999 and 2011 (Individual Scale items and Summer Camp details)

	10th Percentile			50th Percentile			90th Percentile		
	1999	2011	Change	1999	2011	Change	1999	2011	Change
Summer Camps									
Days/week attended the camp where child spent the most time	4.418	4.328	-0.091	4.452	4.428	-0.024	4.506	4.567	0.062
Hours/day attended the camp where child spent the most time	8.915	7.672	-1.244+	7.839	6.974	-0.866*	6.100	5.998	-0.102
Number of weeks child attended the camp where child spent the most time	4.437	4.816	0.379	4.374	4.296	-0.078	4.272	3.568	-0.704**
Camp included (probability):									
Sports	0.802	0.714	-0.088	0.804	0.735	-0.069+	0.806	0.763	-0.043
Arts and crafts	0.902	0.841	-0.060	0.893	0.868	-0.025	0.877	0.898	0.021
Music/performing arts/drama	0.751	0.623	-0.128*	0.714	0.592	-0.123**	0.649	0.546	-0.103**
Computers	0.284	0.305	0.020	0.241	0.260	0.020	0.180	0.205	0.025
Academic activities †	0.508	0.591	0.083	0.429	0.557	0.128***	0.310	0.508	0.198***

Out-of-home summer cultural activities and trips									
Attended a play or concert *(probability)*	0.161	0.146	-0.015	0.228	0.228	-0.001	0.373	0.387	0.014
Visited a zoo or aquarium *(probability)*	0.532	0.519	-0.013	0.608	0.631	0.023	0.719	0.765	0.046+
Visited an amusement park *(probability)*	0.623	0.523	-0.100***	0.663	0.578	-0.086***	0.724	0.651	-0.073*
Visited a museum or historical site *(probability)*	0.388	0.293	-0.095**	0.559	0.478	-0.082***	0.796	0.734	-0.061*
Visited a beach, lake, river, or state or national park *(probability)*	0.837	0.774	-0.063**	0.898	0.866	-0.032+	0.955	0.940	-0.015
Visited a large city (other than where child lives) *(probability)*	0.481	0.456	-0.025	0.575	0.584	0.009	0.714	0.742	0.029
Literacy Activities									
Parent read books to child *(frequency)*	0.375	0.376	0.001	0.432	0.453	0.020	0.528	0.565	0.037
Parent did writing activities with child *(frequency)*	0.526	0.576	0.050*	0.488	0.540	0.052**	0.422	0.488	0.060*
Child looked at or read books on own *(frequency)*	0.626	0.637	0.011	0.654	0.681	0.027+	0.697	0.738	0.042+

* $p < .05$; ** $p < .01$; *** $p < .001$.
Notes: Missing values imputed using multiple imputation.
† Item differed across surveys.

Table 4.

SES Gaps in Children's Summer Enrichment Activities between Kindergarten and First Grade in 1999 and 2011 (Individual Scale items and Summer Camp details)

	90/10 Gaps			50/10 Gaps			90/50 Gaps		
	1999	2011	Change	1999	2011	Change	1999	2011	Change
Summer Camps									
Days/week attended camp	0.087	0.126	0.039	0.033	0.052	0.019	0.054	0.073	0.019
Hours/day attended camp	-2.815	-2.838	-0.023	-1.076	-1.184	-0.108	-1.739	-1.655	0.084
Number of weeks child attended the camp where child spent the most time	-0.165	-1.023	-0.858+	-0.063	-0.427	-0.363+	-0.102	-0.597	-0.495+
Camp included:									
Sports	0.004	0.049	0.045	0.002	0.021	0.020	0.003	0.028	0.025
Arts and crafts	-0.025	0.056	0.081+	-0.009	0.026	0.035	-0.016	0.030	0.046+
Music/performing arts/drama	-0.102	-0.077	0.025	-0.036	-0.031	0.005	-0.065	-0.045	0.020
Computers	-0.104	-0.100	0.004	-0.044	-0.045	-0.001	-0.060	-0.055	0.005
Academic activities	-0.198	-0.083	0.115+	-0.079	-0.034	0.045+	-0.119	-0.049	0.070+

Out-of-home summer cultural activities and trips									
Attended a play or concert	0.212	0.241	0.029	0.067	0.081	0.014+	0.145	0.159	0.015
Visited a zoo or aquarium	0.187	0.242	0.055	0.076	0.110	0.034	0.111	0.132	0.021
Visited an amusement park	0.101	0.128	0.027	0.041	0.055	0.014	0.061	0.073	0.013
Visited a museum or historical site	0.407	0.442	0.034	0.171	0.185	0.014	0.236	0.257	0.021
Visited a beach, lake, river, or state or national park	0.092	0.166	0.074**	0.045	0.092	0.047**	0.047	0.074	0.027**
Visited a large city (other than where child lives)	0.233	0.278	0.045	0.094	0.124	0.030	0.139	0.154	0.015
Literacy Activities									
Parent read books to child	0.152	0.189	0.037	0.057	0.077	0.020	0.095	0.112	0.017
Parent did writing activities with child	-0.098	-0.088	0.010	-0.037	-0.036	0.002	-0.060	-0.052	0.008
Child looked at or read books on own	0.152	0.189	0.037	0.057	0.077	0.020	0.095	0.112	0.017
Visits to the library and bookstore (#)	4.181	1.990	-2.190***	1.598	0.830	-0.768**	2.583	1.161	-1.422***
Attended story hour at a library or bookstore	0.043	0.058	0.016	0.016	0.023	0.007	0.027	0.036	0.008

* $p < .05$; ** $p < .01$; *** $p < .001$.
Notes: Missing values imputed using multiple imputation.

Table 5.
Weighted Descriptive Statistics by Student SES for Analytic Sample by testing round, Number of Summer Vacation Days, Number of Spring School Days, and Number of Fall School Days between Tests.

		1999						2011					
		10th		50th		90th		10th		50th		90th	
		Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Math													
	Spring	-.873	.023	-.699	.015	-.414	.018	.133	.023	.446	.021	.889	.032
	Fall	-.635	.024	-.457	.015	-.174	.015	.547	.038	.904	.028	1.410	.034
Reading													
	Spring	-.897	.022	-.734	.015	-.459	.023	.130	.038	.455	.026	.915	.033
	Fall	-.701	.026	-.525	.018	-.233	.021	.536	.042	.859	.031	1.317	.035
General Knowledge													
	Spring	-.155	.030	.046	.020	.387	.027	-	-	-	-	-	-
	Fall	.022	.033	.241	.020	.606	.027	-	-	-	-	-	-
Science													
	Spring	-	-	-	-	-	-	-.378	.085	.025	.054	.603	.044
	Fall	-	-	-	-	-	-	-.011	.072	.416	.049	1.02	.049
Time Periods													
	# Days Summer	77.149	.205	77.951	.141	79.209	.234	77.360	1.40	79.542	1.29	78.415	1.15
	# School Days (Spring)	33.374	.206	33.803	.142	34.480	.236	43.661	2.43	40.855	2.05	48.017	2.32
	# School Days (Fall)	43.615	.372	42.444	.255	40.633	.426	56.130	2.81	48.861	3.89	48.254	3.42

Note: Missing values imputed using multiple imputation. Scores standardized using the spring mean and SD of the full sample within subjects and years.

Table 6.
SES Gaps in Children's Summer Learning between Kindergarten and First Grade in 1999 and 2011 (from Regression Models).

	90/10 Gaps			50/10 Gaps			90/50 Gaps		
	1999	2011	Change	1999	2011	Change	1999	2011	Change
Math	0.167	0.213	0.046	0.064	0.089	0.025	0.103	0.125	0.021
Reading	0.169	0.137	-0.032	0.064	0.057	-0.007	0.104	0.080	-0.025
Science	-	0.271	-	-	0.113	-		0.158	
General knowledge	0.222	-	-	0.085	-	-	0.137		

Table 7.

Results of Fitting A Taxonomy of Regression Models for the Relationship between Summer Learning and Summer Enrichment Activity Participation

	Reading				Math				General Knowledge		Science	
	1999		2011		1999		2011		1999		2011	
Prior Same-Subject Spring Score	0.880***	0.876***	0.890***	0.885***	0.840***	0.828***	0.933***	0.934***	0.840***	0.830***	0.800***	0.788***
Child SES	0.069***	0.062***	0.058***	0.053***	0.068***	0.048***	0.080***	0.074***	0.094***	0.083***	0.101***	0.088***
Child Age	0.015	0.017+	-0.006	-0.007	0.024*	0.025*	0.015	0.015	0.018	0.021+	0.061**	0.061***
Time Gap 1	0.054***	0.054***	0.077***	0.079***	0.056***	0.053***	0.094***	0.093***	0.038*	0.035+	0.038**	0.038**
Time Gap 2	0.026	0.026**	0.022	0.021	0.011	0.009	0.017	0.016	0.017	0.015	0.036*	0.036*
Time Gap 3	0.107***	0.107***	0.177***	0.178***	0.121***	0.118***	0.218***	0.218***	0.028+	0.024	0.053**	0.053**
Literacy Activities		0.029**		0.025*		-0.001		-0.025+		0.016		0.011
Visits to the library		0.005		0.031*		0.018+		0.014		0.013		0.003
Math Activities		-0.008		-0.009		0.002		0.003		-0.006		-0.013
TV hours watched (z-scored)		-0.011		-0.004		-0.021+		-0.021+		0.003		-0.013

Video games hours played (z-scored)		-0.004		0.016+		0.019*		-0.003		0.002		-0.006
Child attended camp		0.018		0.007		0.069*		0.011		0.028		0.024
Summer School		0.052		-0.067		-0.075		0.080+		-0.087*		-0.105+
Child was tutored		0.003		0.039		-0.121*		0.023		-0.058		-0.156*
Summer Trips		0.003		0.001		0.021+		0.004		0.026*		0.022
Observations	4860	4860	4290	4290	4860	4860	4290	4290	4860	4860	4290	4290
Adjusted R^2	.812	.815	.786	.788	.752	.756	.756	.756	.758	.758	.647	.649

* *p* < .05; ** *p* < .01; *** *p* < .001.
Notes: Missing values imputed using multiple imputation.

Inequality and the Summer Social-Emotional Learning Gap

Family Income, Summer Vacation, and Children's Social-Emotional Skills

Children's social and emotional learning skills, including executive function and social skills, are important for both school success and later life outcomes (Evans & Rosenbaum, 2008; Gresham, Elliott, Vance, & Cook, 2011; Parker & Asher, 1987). *Executive function (EF) skills* are interdependent processes that control and regulate cognition, behavior, and emotion, and affect children's learning abilities (Tourangeau et al., 2013). *Social skills* include behaviors affecting a child's development of social competence and adaptive functioning (Gresham & Elliott, 2007).

Prior research has documented that low-SES children have weaker executive function competencies (Evans & Rosenbaum, 2008) and social skills (Duncan & Magnusson, 2011) than do high-SES children. Socioeconomic gaps in children's social and behavioral competencies such as self-regulation skills appear to contribute to the SES-based achievement gap (Evans & Rosenbaum, 2008).

Over the summer vacation period, high-SES parents make greater investments than low-SES parents in summer experiences that may potentially be targeted at boosting social skills, such as camp attendance and enriching summer trips (Lynch, 2016). These summer investments may contribute to SES-based 'social-emotional skills gaps.' However, to date, we have little to no knowledge of how gaps in children's social-emotional skills change over summer vacation. Nor do we know how children's summer experiences may relate to changes in children's social-emotional skills over the summer.

I address these gaps in the literature by investigating how high- and low-SES children's executive function and social skills change over summer vacation, in the context of a nationally representative sample of children ($N = 4290$) in kindergarten and first grade. An examination of whether and how children's social-emotional skills decline during the summer, and whether summer social skills losses vary by family SES, could provide insight into how out-of-school time contributes to inequality in children's social-emotional skills.

Note that it is unclear whether we would expect socioeconomic gaps in children's social-emotional and executive function skills to widen or narrow over summer vacation. On the one hand, during summer vacation, low-SES children may spend more time in family contexts at risk for economic pressures and resulting family stress, which could result in disproportionate social-emotional losses for low-SES children during summer vacation. On the other hand, if low-SES children's school environments are more harmful to their social-emotional skills than their home environments, for example, due to the in-school influence of aggressive classmates (Jones & Molano, 2016), we might expect low-SES children to exhibit relative improvements in social-emotional skills during the summer.

Socioeconomic Gaps in Children's Social-Emotional Skills

Low-SES children possess significantly lower levels of social-emotional skills compared with their higher-SES counterparts. SES is highly predictive of children's executive function (Hackman & Farah, 2009). At kindergarten entry, children in the bottom SES quintile are rated nearly two-thirds of a standard deviation below children in the top quintile in teacher-reported attention skills, and one-fourth of a standard deviation worse in antisocial behavior (Duncan & Magnusson, 2011). The SES gap in antisocial behavior nearly doubles over the course of elementary school (Duncan & Magnusson, 2011).

These gaps matter, because children's social-emotional skills are predictive of their later educational attainment and life outcomes. Children's learning-related social skills, including following directions, staying on task, and organizing work materials, predict later academic achievement (e.g., McClelland, Morrison, & Holmes, 2000; Yen, Konold, & McDermott, 2004). Children's executive function skills predict mathematics and reading achievement in preschool through high school (e.g., Blair & Razza, 2007; Bull & Scerif, 2001). In addition, children with persistent behavior problems are far less likely to graduate high school or attend college, and children with antisocial behavior problems are more likely to commit crimes as adults (Duncan & Magnusson, 2011).

Need for the Current Study

The current study will address important gaps in the literature on social stratification in children's learning and development. Little to no existing research has examined whether socioeconomic gaps in children's social-emotional skills and executive function widen during summer vacation. The current study uses data from a nationally representative sample to address these questions. Given that key achievement gaps appear to widen during children's summer vacations, and there is growing evidence that social-emotional skills are also critical for children's outcomes, there is a need to examine whether and how SES-based inequalities in children's social-emotional and executive function development also widen outside of school time.

Research Questions

In this study, I examine whether children from different family socioeconomic backgrounds who share the same levels of social-emotional and executive function skills in spring of kindergarten have different average levels of these skills after they return from summer vacation in the fall. I also examine the extent to which differential participation in summer activities is related to children's social-emotional skills in the fall of first grade.

Method

Data

I use data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-11 (ECLS-K 2010-11). ECLS-K 2010-11 is a longitudinal study that follows the educational experiences of a nationally representative cohort of fall 2010 kindergarteners (N=18,200).

ECLS-K 2010-11 was designed to facilitate analyses of how executive function and social skills change over summer vacation. Children's EF and social skills were measured in kindergarten spring, and measured again for a random 30% sub-sample of children in first grade fall. I can thus estimate summer gains in social-emotional and EF skills.

Participants

The analytic sample includes all children who were subsampled in the fall first grade round, did not attend a year-round school, and for whom race and gender information were nonmissing (N = 4,290).

Measures

I describe the measures used in the current study below. See Table 1 for a summary.

Executive function. In ECLS-K 2010-11, executive function constructs were measured both prior to and following summer vacations in both kindergarten and first grade, for a randomly chosen subsample of children. Two key EF constructs were measured pre- and post-summer: *working memory* and *cognitive flexibility*.

Working Memory. Working memory is the ability to remember information while simultaneously engaging in other cognitively demanding activities (Gathercole, Alloway, Willis, & Adams, 2006). Working memory was measured with the *Numbers Reversed* subtest of the Woodcock-Johnson III Test of Cognitive Abilities (Woodcock, McGrew, & Mather, 2001). In this task, children are presented verbally with increasingly long strings of numbers, and asked to repeat them back in reverse (Tourangeau et al., 2013).

Per NCES recommendations, I use the *W* scores, which are derived from a special transformation of the Rasch ability scale which provides a common, equal-interval scale that represents both child ability and task difficulty.

Cognitive flexibility. Cognitive flexibility refers to the ability to shift perspectives or refocus attention flexibly (Diamond, 2006). Cognitive flexibility was measured with the *Dimensional Change Card Sort (DCCS)* (Zelazo 2006). In this task, children are asked to sort picture cards according to a changing set of rules. For example, children might be asked to sort the cards first by color, then by shape, then by a more complex set of rules (Tourangeau et al., 2013).

Kindergarten and first grade scores are on a scale ranging from 0-18. Per NCES recommendations (Tourangeau et al., 2015), I use standardized scores for comparisons.

Social skills and Approaches to Learning. Children's *social skills* and *approaches to learning (ATL)* were measured pre- and post summer via teacher reports. Because these measures were completed by different teachers in the spring and fall, they are subject to measurement error due to different raters; while this adds noise to estimates, it is unlikely to bias estimates of socioeconomic score gaps.

Social Skills. Social skills were measured with the Social Skills Rating System (NCS Pearson 1990) scales, including (1) *self-control* (4 items); (2*) interpersonal skills* (5 items); (3) *externalizing behavior problems* (6 items); and (4) *internalizing behavior problems* (4 items).

Approaches to Learning. Teachers also rated children's *approaches to learning*. In this measure, teachers were asked to report how often children exhibited a set of learning behaviors, including (1) keeping belongings organized; (2) showing eagerness to learn new things; (3) working independently, (4) easily adapting to changes in routine; (5) persisting in completing tasks; (6) paying attention well; and (7) following classroom rules.

Summer activity participation. As described in Study 1, I use the following measures of children's summer activities, derived from the fall first grade parent survey.

Literacy activities. I used a composite measure of home-based literacy activities, operationalized as the average frequency with which the parent reported that he/she read books with the child; did writing activities with the child; and the child looked at or read books or his/her own (on a scale of 1-4, ranging from never to every day [$a = 0.58$]).

TV and video game time. Parents reported on how much time the child spent watching TV on a typical summer day, in hours and minutes. Parents were also asked how many hours and minutes per day their child spent playing video games.

Out-of-home summer institutional enrollments. I use parent-reported measures of whether the child attended summer school or summer camp.

Out-of-home summer cultural activities and trips to novel places. The out-of-home summer cultural activities and trips measure is a composite variable, operationalized as the sum of the number of destinations the child visited during the summer, including a play or concert; a zoo or aquarium; an amusement park; a large city (other than the city where the child lived); a museum or historical site; and a beach, lake, river, or state or national park (on a scale of 0-6) ($a = 0.53$).

Socioeconomic status. To operationalize family socioeconomic status, I use the composite measure of family SES in the ECLS-K dataset, which indexes parents' education, income, and occupational prestige.

Analyses

To examine whether socioeconomic inequality in children's executive function and social-emotional skills widens (or narrows) during summer vacation, I use the analytic approach described in Quinn (2014) to estimate summer social-emotional learning and executive function gaps using the regressor variable modeling strategy, discussed below. All models compare children in the top decile of family SES ('high-SES') to children in the bottom decile ('low-SES'). All models employ the appropriate weights and account for the complex ECLS-K sampling design. I employ multiple imputation using chained equations and five iterations to account for missing data.

Analytic Models. In the summer learning context, gap estimates in the regressor variable model are derived from regressing fall scores on spring scores and family SES (Quinn, 2015; see e.g., Burkam et al., 2003). In a descriptive context, the regressor variable models address the question, "Do children from different family socioeconomic backgrounds who share the same spring score have different fall scores, on average?"

To account for censoring in the dependent variables, for each measure of social-emotional skill, I fit separate tobit regression models examining student *i*'s fall IRT-estimated q score, standardized using the spring mean and SD of the full sample, as a function of his/her spring IRT-estimated q score, an indicator for child *i*'s socioeconomic status; and child *i*'s age in months. Projected scores were calculated using each student's individual estimated kindergarten and first grade rates of learning, taking into account the dates on which each child was tested at each wave (Quinn, 2015); analyses using the unadjusted spring and fall scores yield similar results.

To examine the relationships between summer activity participation and summer SEL growth in each cohort, I add measures of children's participation in enrichment activities to the models above.

Results

Table 2 presents weighted mean fall and spring scores for high- and low-SES children for each measure, standardized by the spring mean and standard deviation of the full sample. Descriptively, on every measure of both executive function and social-emotional skills, high-SES children outperformed low-SES children (note that externalizing and internalizing behavior problems are reverse-scaled, such that higher scores indicate more behavior problems).

The social skills and approaches to learning scores were created using identical measures in fall and spring, allowing for comparisons of scale mean scores across time points. Descriptively, for all variables except internalizing behavior problems, teachers rated both high- and low-SES children lower in the fall than in the spring (see columns 1 and 4).

Regression Models.

In Table 3, I present estimated socioeconomic gaps and marginal effects of family SES on summer social-emotional and executive function learning, in the regressor variable regression framework. Among children from high- and low-SES backgrounds who share the same spring score, high-SES children have better fall scores on every measure (see column 3). The gaps favoring high-SES children range from roughly 0.1-0.3 SD and are statistically significant for all variables except externalizing behavior problems.

Predictors of Summer Social-Emotional Skills and Executive Function Growth

In Table 4, I present the results of fitting a taxonomy of tobit regression models for the relationships between social-emotional skills and summer enrichment activity participation. The most noteworthy finding is that on every outcome except internalizing behavior problems, the amount of time that children spent playing video games over the summer was significantly and negatively associated with their fall social-emotional skills, controlling for their spring skill levels, SES, age, and the other activity variables in the models. For example, an average child who did not play video games on a typical summer day would be expected to score at the 53rd percentile on social skills, whereas an average child who played video games for five hours per day would be expected to score at the 43rd percentile. Similarly, an average child who did not play video games on a typical summer day would be expected to score at the 49th percentile on externalizing behavior problems, whereas an average child who played video games for five hours per day would be expected to score at the 61st percentile on this measure. Most other summer activity variables were not significantly associated with fall social-emotional and executive function scores; one exception is number of summer trips that the child took, which was associated with marginally greater fall interpersonal skills and marginally lower levels of internalizing behavior problems, controlling for the other variables in the models.

Table 5 presents the results of fitting a taxonomy of tobit regression models for the relationships between executive function skills and summer enrichment activity participation. In these models, one significant relationship between summer activities and executive function measures emerges -- a significant and positive relationship between participation in summer camp and children's fall working memory scores, controlling for spring scores and the other variables in the model.

Discussion

The current study examined whether children’s summer gains or losses in executive function and social skills differed by family socioeconomic status, as well as whether children's participation in summer activities was associated with their summer social-emotional learning and executive function development.

Descriptively, teachers rated both high- and low-SES children worse in the fall than in the spring on measures of self-control, externalizing behavior problems, approaches to learning, and interpersonal skills. These differences may reflect the effect of summer vacation; perhaps absent the demands and structure of the classroom, children lose ground in areas such as rule-following and organization. Reduced opportunities to socialize with peers in the school context could also lead to weakened skills in social interactions. However, it is also possible that spring-to-fall declines in measured social skills and approaches to learning could be driven by a rater effect; different teachers rated children in the spring and the fall, and it is possible that teachers at a higher grade level (here, first grade teachers) applied a higher standard to children's skills in these areas than did kindergarten teachers, biasing fall scores downward. On the other hand, we might have expected teachers to provide systematically lower ratings in the spring as compared to the fall, consistent with a 'teacher burnout' effect near the end of the school year (Abidin & Robinson, 2002; Jones & Molano, 2016). The potential sign of any bias in teacher rater effects is thus not entirely clear. For internalizing behavior problems, teachers rated children somewhat better in the fall than in the spring; this may reflect the greater difficulty that teachers have in detecting internalizing behavior problems relative to more visible behavior problems, given that first grade teachers would have had less time to observe such behaviors when surveyed in the fall.

The regressor variable model results suggest that on average, among children from high- and low-SES backgrounds who shared the same spring score, high-SES children had better fall scores. These differences are statistically significant for all variables except externalizing behavior problems (whose sign is still in the expected direction). These findings are consistent with a scenario in which low-SES children experience greater social-emotional skills and executive function losses over summer vacation, compared with their high-SES counterparts. An interesting alternative hypothesis is that perhaps the divergent fall scores of high- and low-SES children reflect a differential SES-based 'first grade adjustment gap.' First grade is typically associated with new academic demands and tighter classroom structures as compared with kindergarten (Bassok et al., 2016), and it is possible that high-SES children may adjust more easily to these new environments. Future research analyzing seasonal trajectories in SES gaps in children's learning across multiple grade levels and time points should examine this possibility.

The finding of consistent, negative associations between children's summer video game playing and their fall social-emotional skills is suggestive of the detrimental social effects of this activity. As noted in Study 1, in 2011, low-SES children played 21 more minutes of video games each day during the summer than did high-SES children, amounting to roughly 32 additional hours of extra time that poor children spend playing video games compared with affluent children over the course of the summer. Because video games with violent content increase children's aggressive behavior and decrease prosocial behavior (Anderson & Bushman, 2001), low-SES children's greater exposure to them over summer vacation may exacerbate existing SES social-emotional disparities. Meanwhile, the finding of a positive relationship between summer camp attendance and children's fall working memory scores is more of a puzzle, but perhaps the academic or enrichment content that children frequently encounter at camp promoted their development of recall and memory skills.

Conclusions and Future Directions

The current findings raise a number of questions, which point toward potentially productive areas for future research. First, the descriptive finding that children’s social-emotional skills were weaker after summer vacation, as well as the finding from the regressor variable models that high- and low-SES children with the same spring SEL and EF scores had different average fall scores, raise theoretical questions about how social-emotional learning and executive function skills may develop differently in school versus outside of school time. Prior research on how math and reading gaps widen over the summer has focused largely on the *concerted cultivation* (Lareau, 2002) and *investment* (e.g., Becker, 1981) models, which share a number of similarities. Under the *investment model*, parents are theorized to invest time, money, and human capital resources into their children's development with the hopes that these 'investments' will pay dividends in their children's future. Under the *concerted cultivation model*, parents of different socioeconomic backgrounds are theorized to espouse different parenting styles and practices (Becker, 1981). High-SES parents are theorized to focus their attention on 'cultivating' their children's unique talents and skills through highly structured activity participation featuring extensive adult supervision, whereas low-SES parents are theorized to believe that children should be given substantial unstructured free time (Lareau, 2002). Prior research has suggested that these SES-based parenting differences may explain differential summer math and reading loss for high- and low-SES children. For example, summer reading gaps may widen because high-SES parents invest more time in reading books with their children (Burkam et al., 2004).

With regard to understanding socioeconomic gaps in summer social-emotional learning and executive function loss, these theoretical models may also be pertinent. For example, high-SES parents may view summer camps as an 'investment' in their children's social skills development, providing children with structured opportunities to socialize with peers under adult supervision. High-SES parents may also view summer programs and activities as providing opportunities to cultivate specific interests and talents, which could confer social-emotional and affective benefits. Low-SES children have fewer of these opportunities during summer vacation, which could contribute to summer gaps. Future qualitative and case study research would be beneficial to build our understanding of how high- and low-SES parents promote their children's social-emotional development during summer vacation.

In addition, one factor not emphasized in these models is the influence of children's peer groups. Peers clearly influence children's social skill development; for example, children in classrooms with more aggressive peers exhibit larger increases in aggressive behavior (Yudron, Jones, & Raver, 2014). In the context of academic learning, prior research has argued that socioeconomic gaps grow during the summer because high- and low-SES children's home learning environments are more unequal than their school learning environments (Downey, von Hippel, & Broh, 2004; Raudenbush & Eschmann, 2015). Analogously, if high- and low-SES children's peer groups' social skills are more unequal during the summer than during the school year, this may contribute to summer social-emotional learning gaps. Future research exploring how socioeconomic gaps in children's peers' social skills change between the summer and the school year could shed light on this issue.

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Table 1.
Study Measures.

Construct	Measure	Sub-constructs	Description
Social-Emotional Skills and Behaviors	Social Skills Rating System	Self Control Interpersonal Skills Internalizing Behavior Problems Externalizing Behavior Problems	Teacher-reported measure of students' degree of self-control and interpersonal skills, as well as presentation of two categories of behavior problems: (1) internalizing behavior problems, such as sadness and anxiety; and (2) externalizing behavior problems, such as aggressive acts and poor temper control.
	Study-designed scale	Approaches to Learning	Teacher-reported measure of the extent to which the child keeps belongings organized; shows eagerness to learn new things; works independently, easily adapts to changes in routine; persists in completing tasks; pays attention well; follows classroom rules.
Executive Function Skills and Approaches to Learning	Dimensional Change Card Sort (DCCS)	Cognitive Flexibility	Children are asked to sort picture cards according to a changing set of rules. For example, children might be asked to sort the cards first by color, then by shape, then by a more complex set of rules.
	Numbers Reversed subtest, Woodcock-Johnson III (Woodcock, McGrew, & Mather, 2001)	Working Memory	Children are presented verbally with increasingly long strings of numbers, and asked to repeat them back in reverse.

Table 2.
Weighted Descriptive Statistics by Percentile of Student SES for Analytic Sample.

		Family SES Percentile					
		10th			90th		
		Scale Mean	Stdized Mean	Stdized SD	Scale Mean	Stdized Mean	Stdized SD
Social-Emotional Skills							
Self control	Spring	3.224	-0.057	1.055	3.313	0.074	1.199
	Fall	3.190	-0.106	1.101	3.273	0.016	1.047
Interpersonal skills	Spring	3.174	0.140	1.057	3.355	-0.112	1.105
	Fall	3.111	-0.099	1.104	3.183	-0.200	1.026
Internalizing behavior problems	Spring	1.541	0.121	1.221	1.380	-0.139	1.127
	Fall	1.489	0.038	1.317	1.358	-0.174	0.874
Externalizing behavior problems	Spring	1.599	-0.029	1.005	1.507	-0.164	1.087
	Fall	1.622	0.004	1.013	1.600	-0.027	1.002
Approaches to learning	Spring	3.158	-0.039	1.106	3.339	0.205	1.078
	Fall	2.935	-0.337	1.097	3.150	-0.049	1.088
Executive Function Skills							
Cognitive flexibility	Spring		-0.207	1.224		0.332	0.893
	Fall		-0.176	1.120		0.233	0.874
Working memory	Spring		-0.411	1.150		0.342	0.933
	Fall		-0.342	1.133		0.404	0.919

Note: N=4,290. Scores are projected scores, standardized using the spring mean and SD of the full sample. Internalizing and externalizing behavior problems are reverse-scaled, such that higher scores indicate more behavior problems.

Table 3.
Estimated SES gaps and marginal effects of family socioeconomic status on summer social-emotional and executive function learning.

	Family SES Percentile		
	10th	90th	Gap
Social-Emotional Skills			
Self control	-0.127	0.021	0.148*
Interpersonal skills	-0.245	-0.538	0.191*
Internalizing behavior problems	-0.016	-0.050	0.207**
Externalizing behavior problems	0.080	0.016	-0.064
Approaches to learning	-0.257	-0.050	0.207**
Executive Function Skills			
Cognitive flexibility	-0.075	0.220	0.295***
Working memory	-0.053	0.219	0.272***

Note: N=4,290. Scores used are projected scores, standardized using the spring mean and SD of the full sample.

Table 4.

Results of Fitting Tobit Regression Models for the Relationship between Summer Social-Emotional Skills and Summer Activity Participation

	Self Control		Interpersonal Skills		Approaches to Learning		Internalizing Behavior Problems		Externalizing Behavior Problems	
Spring Skill Score	0.499***	0.493***	0.433***	0.427***	0.663***	0.655***	0.314***	0.314***	0.730***	0.730***
SES	0.092***	0.078*	0.099***	0.084**	0.098***	0.085**	-0.064*	-0.040	-0.039	-0.022
Age	0.019	0.020	0.024	0.026	0.056*	0.058*	-0.014	-0.013	-0.013	-0.014
Literacy Activities		0.011		0.005		0.025		-0.019		-0.004
TV Hours		-0.026		0.003		-0.008		0.027		-0.010
Video Game Hours		-0.053*		-0.059*		-0.065*		-0.027		0.082**
Summer Camp		-0.019		-0.025		-0.017		-0.009		-0.026
Summer School		-0.032		-0.021		-0.037		-0.029		0.019
Summer Trips		0.025		0.052+		0.028		-0.049+		0.009

* $p < .05$; ** $p < .01$; *** $p < .001$.
Note: N=4,290. Coefficients are standardized tobit regression coefficients.

Table 5.

Results of Fitting Tobit Regression Models for the Relationship between Summer Executive Function Skills and Summer Enrichment Activity Participation

	Cognitive Flexibility		Working Memory	
Spring Skill Score	0.366***	0.361***	0.695***	0.688***
SES	0.149***	0.130***	0.129***	0.098**
Age	0.075**	0.072**	0.065*	0.061*
Literacy Activities		-0.014		0.026
TV Hours		-0.011		-0.008
Video Game Hours		-0.019		-0.009
Summer Camp		0.013		0.066**
Summer School		-0.037		-0.035
Summer Trips		0.025		0,005

Note: N=4,290. Coefficients are standardized tobit regression coefficients.

Appendix A
Variables List

Executive Function
Working Memory: *Working memory* is the ability to remember information while simultaneously engaging in other cognitively demanding activities (Gathercole, Alloway, Willis, & Adams, 2006). Working memory was measured with the *Numbers Reversed* subtest of the Woodcock-Johnson III Test of Cognitive Abilities (Woodcock, McGrew, & Mather, 2001). In this task, children are presented verbally with increasingly long strings of numbers, and asked to repeat them back in reverse (Tourangeau et al., 2013).

Per NCES recommendations, I use the *W* scores, which are derived from a special transformation of the Rasch ability scale which provides a common, equal-interval scale that represents both child ability and task difficulty. X*NRWABL (where * indexes round); flag for children who took the assessment in Spanish in kindergarten or first grade: X*FLSCRN. (All children took the test in English in second grade.)

Cognitive flexibility: *Cognitive flexibility* refers to the ability to shift perspectives or refocus attention flexibly (Diamond, 2006). Cognitive flexibility was measured with the *Dimensional Change Card Sort (DCCS)* (Zelazo 2006). In this task, children are asked to sort picture cards according to a changing set of rules. For example, children might be asked to sort the cards first by color, then by shape, then by a more complex set of rules (Tourangeau et al., 2013).

Kindergarten and first grade scores are on a scale ranging from 0-18; second grade scores are on a scale from 0-10. Per NCES recommendations (Tourangeau et al., 2015), I use standardized scores for comparisons. Kindergarten and first grade: X*DCCSTOT; Second grade: X5DCCSSCR, X6DCCSSCR.

Social Skills
Social skills were measured with the Social Skills Rating System (NCS Pearson 1990) scales, including (1) *self-control*; (2*) interpersonal skills*; (3) *externalizing behavior problems*; and (4) *internalizing behavior problems*. Teachers also rated children's *approaches to learning*, such as keeping belongings organized; showing eagerness to learn new things; working independently; adapting easily to changes in routine; persisting in completing tasks; paying attention well; and following classroom rules.

Children have scores on four scales: self-control (4 items); interpersonal skills (5 items); externalizing behavior problems (6 items); and internalizing behavior problems (4 items). X*TCHCON, X*TCHPER, X*TCHEXT, X*TCHINT.

Approaches to Learning
Scale score for a set of items which asked teachers to report how often children exhibited a set of learning behaviors, including (1) keeping belongings organized; (2) showing eagerness to learn new things; (3) working independently, (4) easily adapting to changes in routine; (5) persisting in completing tasks; (6) paying attention well; and (7) following

classroom rules. X*TCHAPP, except for children who were held back in kindergarten, whose scores are indexed with X4KTCHAPP.

Academic Background
Achievement Scores: Children's spring kindergarten θ scores in mathematics, literacy, and science are included as controls in some models. I use scores on the θ scale, in which students' latent ability θ_{it} was estimated using a three-parameter IRT model (Reardon, 2008).

Kindergarten Repeater: X1FIRKDG.

Time Gaps
Variables indexing time gaps between child assessments, and exposure to each school year and summer vacation period, are included in all models. Derived from X*ASMTMM , X*ASMTDD, X*ASMTYY, X*SCHEMM, X*SCHEDD; X*SCHBMM, X*SCHBDD.

Summer Activities
Summer Trips: Sum of the number of summer destinations the child visited, including museums, historical sites, zoos/aquariums, amusement parks, beaches/lakes/rivers, state/national parks, plays/concerts, and a large city. P3ARTMUS, P3ZOOS, P3AMUSPK, P3BEACHS, P3PLYCRT, P3LRGCTY.

Television Viewing: Average number of hours per week that the child watched television. P3TVHR, P3TVMIN.

Video Games: Variable indicating the number of hours per day that the child played video games. P3VIDHR, P3VIDMIN.

Summer School: Variables indicating whether the child attended required, suggested, or optional/parent-elected summer school, and summer school duration. P3SUMSCH, P3SMREQ, X3SUMSH.

Home Computer and Educational Computer Use: Variables indicating whether or not the child's family had a home computer that the child used, and how often the child used the computer for educational purposes during the summer. P2HOMECM, P3COMEDU.

Summer Literacy Activities: A composite variable estimated with PCA of children's summer literacy activities, including how often the child did writing activities, read books with a parent, read books on his/her own, visited libraries or bookstores, and attended story hours. P3DOWRIT, P3RDBKTC, P3RDALON, P3VISLIB, P3STHLIB.

Summer Mathematics Activities: Variable indicating how often a parent or other family member did math activities with the child. P3DOMATH.

Camps: Variables indicating whether or not the child attended any summer camps, number of camps attended, hours spent at the camp where the child spent the most time, and which activities this camp included (e.g. computers, academic activities, sports). P3DONCMP, P3NUMCMP, P3NUMDCMP, P3NUMHCMP, P3NUMWCMP, P3CMPSPT, P3CMPART, P3CMPACA, P3CMPPCT.

Tutoring: Variables indicating whether or not the child received tutoring over the summer, duration of tutoring, and in which subjects the child was tutored. P3TUTOR, P3NUMDTUT, P3NUMHTUT, P3NUMWTUT, P3TUTREA, P3TUTMTH, P3TUTSCI, P3TUTLAN, P3TUTOTH, PSTUTFRGL, P3TUTOTH.

Weights
Weights: Student-level weights: W3CF3P3T0, W6CF6PF60; Stratum: W3CF3P3TSTR, W6CF6PF6STR; PSU identifiers: W3CF3P3TPSU, W6CF6PF6PSU.

Student Demographics
SES: Composite measure of parents' education, income, and occupational prestige. X4SESL_I.

Other Demographics: Gender: X_CHSEX_R; Race: Series of dummy variables recoded from X_RACETHP_R; Home Language: X4LANGST; Age: Child's age in months at the time of the fall first grade assessment, X3AGE; Single-parent household status: Derived from P2CURMAR.

Effects of a Summer Mathematics Intervention for Low-Income Children: A Randomized Experiment[1]

Low-income children score more than a standard deviation below high-income children on mathematics achievement tests (Duncan & Magnuson, 2011; Reardon, 2011). Because children's mathematical knowledge is cumulative (Hiebert & Wearne, 1996), weak foundations of early mathematical knowledge built up in the elementary and middle school grades may block low-income children's opportunities for future success in advanced mathematics coursework, a critical gatekeeper to STEM career pathways (NCTM, 2000).

Summer learning loss among low-income children is a widely documented problem. Research examining seasonal patterns in children's learning often indicates that achievement gaps in reading and mathematics between high- and low-income children grow primarily while children are on summer vacation. In an early landmark study, Heyns (1978) found that among middle school children in Atlanta, socioeconomic status (SES)-based achievement gaps grew more quickly while children were on summer vacation than during the school year. In a longitudinal study examining the achievement of a panel of Baltimore children from the first through the ninth grade, Alexander, Entwisle, and Olson (2007) found that low-SES children's summer learning losses in reading and mathematics accumulated over the elementary and middle school years. They concluded that low-SES children's cumulative summer deficits contributed substantially to SES-based differences in high school course 'tracking', high school completion, and four-year college attendance

[1] This paper is co-authored with James S. Kim, Harvard University.

(Alexander, Entwisle, & Olson, 2007). More recently, the finding that the SES achievement gap widens during summer vacation has been replicated in nationally representative data from the Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K) (Downey, von Hippel, & Broh, 2004). Further, also using ECLS-K data, Burkam et al. (2004) found that approximately 25% of the SES-based summer math gap could be explained by differential participation in summer activities, most notably whether the child used a computer for educational activities during the summer.

Policy Responses to Low-Income Children's Summer Learning Loss

Summer learning loss among low-income children poses both equity and achievement challenges for educators and policymakers. For example, many urban school districts have developed programs aimed at ameliorating summer learning losses among low-income children, with most efforts focused on literacy and mathematics (examples include Chicago, New York, and Boston; see, for example, Jacob & Lefgren, 2004; Mariano & Martorell, 2013; Matsudaira, 2008). In an update of Cooper, Charlton, Valentine, Muhlenbruck and Borman's (2000) review of the summer school literature, a recent meta-analysis of the K-8 summer mathematics program literature from the past decade (Quinn, Lynch, & Kim, 2014) indicates that low-income students who attend school-based summer mathematics programs outscore their counterparts who do not attend such programs by an average of .11 SD on subsequent mathematics assessments. While this meta-analysis includes school-based summer mathematics programs, including summer school and camps, it includes no studies of home-based summer math programs, as none were found in the literature. Yet as noted below, there are both theoretical and practical reasons to hypothesize that the effects of school-based and home-based summer interventions could differ (Kim & Quinn, 2013). Most notably, school-based programs generally offer the support of classroom teachers who lead and scaffold instruction; in addition, many school-based programs provide additional resources such as enrichment activities (McCombs et al., 2011). By contrast, home-based summer interventions, such as home-based summer book reading programs, generally do not involve support from classroom teachers, and instead rely on parents and family members or the students themselves to motivate and support summer learning activities (e.g., Allington et al., 2010).

Noting that summer school programs are expensive, requiring school teachers, staff, and facilities (McCombs et al., 2011), education researchers and policymakers have recently called for the investigation of home-based and online summer academic interventions as low-cost alternatives to summer school (Allington et al., 2010; Walters & Sorensen, 2013). *Computer-based* summer interventions hold out potential promise, both for their impacts on achievement and for their cost-effectiveness. Online and computer-based programs have the potential to provide students with customized instruction and rapid feedback (Balacheff & Kaput, 1996). Recent meta-analyses of both elementary (Slavin & Lake, 2008) and secondary (Slavin, Lake, & Groff, 2009) mathematics interventions provided during the regular school year find that computer-assisted instruction programs are effective on average at improving student math achievement, although effect sizes were relatively modest (+0.19 SD for elementary students; +0.08 SD for secondary students). In addition, computer-based summer interventions may have the potential to reduce costs for hiring summer school teachers and keeping schools open.

Home-based summer interventions may also provide cost-effective policy alternatives. In the domain of literacy, researchers have found that, on average, home-based literacy interventions appear to be equally as effective and more cost-effective than summer school at improving reading outcomes (Kim & Quinn, 2013). In addition, a growing body of evidence suggests that children's engagement with mathematics at home may be beneficial for children's mathematics attitudes and achievement. The importance of the home environment for children's mathematical development is evident in the fact that the income-based mathematics achievement gap is already present at school entry (Lee & Burkam, 2002; Starkey, Klein, & Wakeley, 2004). Researchers have found that home math inputs, including the amount of math-related talk parents engage in with their children, predict preschool children's later math achievement, even after controlling for family SES (Gunderson & Levine, 2011; Levine, Ratliff, Huttenlocher, & Cannon, 2012; Levine, Suriyakham, Rowe, Huttenlocher, & Gunderson, 2010). In an experimental study conducted with a sample of mostly middle- to upper-middle class families during the academic year, parent-child home reading of topical math passages on a tablet increased children's math achievement across the school year (Berkowitz et al., 2015). In a review of the causal evidence on parent involvement in homework, Patall, Cooper, and Robinson (2008) found that parent homework involvement improved children's homework completion rates, and decreased the rate of homework problems such as negative affect about homework or receiving a homework-related school punishment – both of which could potentially benefit children's achievement in the longer term. Hoover-Dempsey, Battiato, Walker, Reed, DeJong, and Jones (2001) suggest that through activities such as modeling, reinforcement, and instruction, parent involvement in children's homework may influence proximal outcomes such as positive attitudes toward learning, positive perceptions of self-competence, and a belief in the importance of effort for success, which in turn may shape children's achievement outcomes.

However, evidence to support the larger idea that offering students free online math instruction to do at home, without teachers, is likely to be effective is lacking. For example, some proponents have suggested that programs such as Khan Academy, which has over 10 million users each month and support from funders such as Google and the Gates Foundation, could transform schooling by at least partially replacing classroom instruction with web-based instructional video clips and online practice (e.g., Wagner, 2011). However, to date there has been no rigorous evaluation of Khan Academy except as a supplement to classroom teachers' instruction (which we discus below) (Snipes, Huang, Jaquet, & Finkelstein, 2015).

Despite policy interest and the success of home-based summer interventions for low-income children in reading, we can identify no prior studies of home-based summer mathematics interventions. In the current study, we conducted a randomized experiment of a home-based summer mathematics program aimed at improving children's summer home mathematics engagement and reducing summer learning loss. The current research is needed to address the gap in our understanding of how low-touch, home-based mathematics interventions may affect low-income children's summer math participation and learning outcomes.

Summer Mathematics Intervention

Tenmarks is an online mathematics program in which participating students complete 'worksheets' of math questions adjusted to their skill level. The Tenmarks program is of policy interest for several reasons. First, over one million students in all 50 US states and over 126 countries have used Tenmarks, either through their schools or through personal subscriptions (Tenmarks, 2012). The program is also reportedly used by teachers in over 85% of U.S. school districts (Tenmarks, 2015). However, despite widespread use and time expenditures, to date there has been no evaluation of the program's effectiveness. Second, the Tenmarks program is low-cost (and at time of writing is available free on Amazon.com), and is relatively typical of free math practice programs available on the Internet. Thus the Tenmarks program represents a low-cost summer math intervention which is in mass use, but whose effects have not been examined.

Research Questions

In this study we examine whether being randomly assigned to an offer of a free summer-long subscription to an online mathematics program (Tenmarks), or to an offer of the Tenmarks program plus a free laptop computer, caused students to experience higher levels of summer home and family mathematics engagement, and/or higher subsequent mathematics achievement and attitudes, compared to their peers in the control group. Given the voluntary nature of this summer intervention, we further explore what factors predicted program participation, and whether the benefits of offering the summer mathematics intervention varied depending on students' background characteristics, family resources, and/or mathematics attitudes or intrinsic motivation for doing mathematics.

Method

Research Design

In order to estimate the causal impact of the intervention on students' subsequent family and home math engagement and math achievement and attitudes, we randomly assigned students to either (1) the math program only condition; (2) the math program plus a free laptop computer condition; or (3) the control group. We randomly assigned students at the individual level to improve the power of the study design and to assess the efficacy of the program when delivered to individual students (Burkam, Ready, Lee, & LoGerfo, 2004).

Site

The study was conducted in a large, urban school district in the Northeast region of the US. More than eighty percent of the students in the district are non-white, and more than three quarters of the students are eligible for free or reduced price school lunches.

Sample

We purposefully sampled schools that were located in the highest poverty neighborhoods where students were most at-risk of summer learning loss. Four schools serving high populations of minority youth and high proportions of students eligible for free or reduced price school lunch participated in the study. Participating schools included one elementary school (School 1), one middle school (School 2), one middle/high school (School 3), and one high school (School 4). To be included in the study sample, principals and teachers had to sign a memorandum of understanding agreeing to implement the study procedures for obtaining active parental consent, to administer assessments, and to random assignment of students to conditions. A total of 263 students consented to participate.

Table 1 provides descriptive statistics on the study sample in each school, as well as a comparison of demographic characteristics of the study sample with students in the overall school, district, and state. Compared with the district overall, sample students were similar in proportion minority (87% in the sample; 87% in the district overall) and somewhat less likely to be free/reduced lunch eligible (59% in the sample; 70% in the district overall). Sample control group students in grades 4 and 8 performed similarly to district students in grades 4 and 8 on a set of math items from the National Assessment for Educational Progress (NAEP) (described below) (51% in the sample vs. 48% in the district overall). In a broader context, sample control students answered fewer of the NAEP items correctly than children in the state overall (state overall = 58%) and a similar number to the national average (U.S. overall = 51%).
No statistically significant differences between experimental and control groups were found on any of the measured baseline covariates. Table 2 provides descriptive statistics for covariates in the overall sample and by experimental group.

Program Description

Key components of the Tenmarks program were curriculum materials that adjusted content to children's individual skill levels as they worked, embedded text and video 'hints' that students could click on for assistance, and digital games that children could unlock as rewards for completing worksheets. The program developers intended for students to complete three worksheets each week for ten weeks. See Appendix 1 for examples of the Tenmarks materials. See Figure 1 for a hypothesized logic model for the

Tenmarks program. It was hypothesized that participating in an online summer mathematics practice program would increase low-income students' summer home math engagement, and that Tenmarks worksheet completion would improve students' knowledge of mathematics and distal outcomes of mathematics test scores. In addition, given the voluntary nature of the intervention, which occurred over summer vacation, we hypothesized that children's background characteristics, home resources, and affective characteristics may moderate the program's effectiveness, such that children with greater access to home resources and higher levels of academic effort, mathematics confidence, and intrinsic motivation for doing mathematics would participate at higher levels and thus obtain greater benefits.

The control condition was 'business as usual.' Control students were free to participate in whatever other summer activities were available to them. Approximately 43% of control students reported participating in other summer programs, and 16% reported attending summer school. These summer activities are discussed further below.

Measures

We use data from five sources for most analyses presented in this report: (1) parent registration forms; (2) student pre-surveys; (3) district administrative records; (4) student post-surveys, which included a national assessment-based mathematics test; and (5) program usage data for the Tenmarks website. First (1), all parents completed a registration form before their children began the program; this included demographic information such as the child's grade and whether the family had home Internet access at baseline. Second (2), in the last week of school prior to summer vacation, and prior to random assignment, teachers administered the pre-survey. The pre-survey included items measuring students' academic effort, intrinsic motivation for doing mathematics, math confidence, and parent supervision; the response rate was 97%. Third, (3) district administrative records were used to collect students' demographic data, as well as scores on district curriculum-based mathematics assessments administered before and after summer vacation. (More detail on these assessments is provided below.) Spring and fall math scores were present in the district data for 82% and 84% of students, respectively. Fourth, (4) after summer vacation and the Tenmarks program had concluded, approximately six weeks into the school year, teachers administered the student post-survey. The post-survey included a 30-item national assessment-based math test composed of NAEP items (described below), and measures including students' family home math engagement, intrinsic motivation for doing math, and summer activity participation. The response rate for the post-survey was 74%. Lastly, (5) we collected program usage data provided by the Tenmarks website developers indicating how many times each child logged in to the program and how many online math worksheets each child completed.

An attrition analysis indicated that students who had and did not have district assessment scores generally did not differ demographically, by experimental group, or on a range of pretreatment measures; the exception was that students who were eligible for free lunch were more likely to have usable scores ($p<.05$). Students who submitted the post-survey also generally did not differ from nonrespondents on a range of pretreatment measures. However, post-survey nonrespondents were more likely to be in the control condition than in the program plus laptop condition ($p<.05$). In addition, they were less likely to be from School 3 than from Schools 1 or 2. We conducted analyses using both

imputed scores estimated using multiple imputation, and ordinary least squares regression with listwise deletion. For the multiple imputation analysis, we utilized Stata's *mi impute chained* routine, which employs an iterative imputation technique which imputes multiple variables using chained equations, a series of univariate imputation methods with fully conditional specification of prediction equations
(StataCorp, 2013a), using ten multiply imputed datasets. We present results using the complete case analysis; the results from the imputed data are in Appendix 2.

Outcome variables. We describe each of the outcome variables that we use in our analyses below.

Intrinsic Motivation for doing mathematics. Both before and after the intervention, we measured children's intrinsic motivation for mathematics using the Intrinsic Motivation Inventory (IMI) Interest/Enjoyment subscale, which has been used in prior educational evaluations and validated for use as the child self-report measure of intrinsic motivation for an activity (Plant & Ryan, 1985; Ryan, 1982). The scale is comprised of seven items, and operationalized as the degree to which students enjoyed doing math, thought that math was fun to do, thought that math was boring (reverse-coded), felt that math did not hold their attention (reverse-coded), would describe math as very interesting, felt that math was quite enjoyable, and agreed that while they were doing math, they were thinking about how much they enjoyed it (Cronbach's $\alpha = .92$ at both pre- and post-survey) (Plant & Ryan, 1985; Ryan, 1982). The IMI score is a composite variable estimated with principal components analysis composed of the child's responses to the scale items. Higher values of this variable indicate greater intrinsic motivation for doing math.

***Summer home and family mathematics engagement*.** The post-summer survey included four items that asked children about their summer mathematics home activities and family involvement, adapted from the Literacy Habits Survey (Paris et al., 2004), which has been used in prior evaluations of summer programs to measure summer home literacy involvement (Kim, 2007; Kim & White, 2008; Paris et al., 2004). The items were adapted to reflect a focus on mathematics (Cronbach's $\alpha = .72$). Children selected one of four responses: less than once a month; once or twice a month; once or twice a week; and almost every day. The following items comprised this scale:

1. During summer vacation, how often did you talk about math with someone in your home?
2. During summer vacation, how often did your parents (or someone in your family) help you do math at home?
3. During summer vacation, how often did your parents encourage or tell you to do math?
4. During summer vacation, how often did you do math at home?

Students' scores on this index are comprised of a composite variable estimated with principal components analysis, composed from the four survey items. In addition, the survey included a single, binary item which asked students whether their mother or father did any math with them this summer; students selected yes or no.

Mathematics enjoyment. The post-summer survey included three items related to students' level of mathematics enjoyment, drawn from the NAEP Mathematics Student Questionnaire (NCES, 2011) (Cronbach's $\alpha = .88$). Students selected from four responses: strongly agree, agree, disagree, and strongly disagree. The items measured the extent to which students agreed that math was fun and they did not want to give it up; they liked math, and math was one of their favorite subjects. Students' scores on this index are comprised of a composite variable estimated with principal components analysis, composed from the four survey items.

Achievement measures. Two achievement assessments were administered. Both math tests are designed to assess student mastery of either national or local district curriculum standards. The first was a district curriculum-based math assessment administered to all students in the school district in September and June. This is a computer-adaptive test, vertically aligned using IRT to allow for comparisons across time points. We collected students' demographic information and scores from the June and September administrations of this exam, in order to capture differences in students' scores that emerged over the summer vacation. Students completed the June test within a few weeks of the end of the school year (before random assignment), and completed the September test in the second week of the subsequent fall semester.

Because the district's curriculum-based math assessments are secure instruments, we were unable to inspect the items for alignment with the Tenmarks intervention. As a result, we administered a second, national assessment-based mathematics test to participants as a fall post-test. This assessment was comprised of 30 randomly selected publicly released items from the National Assessment of Educational Progress (NAEP), representing a range of content areas and difficulty levels.[2] Students in grades four, five,

[2] For each test form, we randomly selected items to reflect the same breakdown of domains as the 2011 NAEP targets (e.g., for the 4th grade form, 40% number properties items, 20% measurement items, etc.). Within these domains, we randomly selected 20% 'hard' items, 60% 'medium' items, and 20% 'easy' items.

and six received a test form containing items from the fourth grade NAEP, and students in grades seven, eight, and nine received a test form containing items from the eighth grade NAEP; in this way, all students saw assessment items within two grade levels of their own. Using publicly released NAEP items allows us to measure students' achievement against NAEP benchmarks of "what students should know and be able to do in a given grade" in the United States (Gorman, 2010).

Covariates. In addition to the baseline levels of the variables described above, we collected information on the following covariates.

Parent supervision. The pre-survey included three parent supervision items adapted from the National Education Longitudinal Study of 1998 (NELS:88), which asked students to rate (on a scale including "Never," "Rarely," "Sometimes," and "Often") how often their parents or guardians checked on whether they had done their homework, were home when they returned from school, and limited the amount of time they could spend watching TV (Institute of Education Sciences, 2011). Students' scores on this index are comprised of a composite variable estimated with principal components analysis, composed from the survey items. Although Cronbach's α for this scale was low (.41), the NELS items have been used in prior survey research and research on parent involvement (Sui-Chu & Willms, 1996).

Mathematics confidence. The pre-summer survey included four items related to students' level of mathematics confidence, adapted from the High School Longitudinal Study of 2009 (HSLS:09) (Institute of Education Sciences, 2011) (Cronbach's α = .85).

Students selected from four responses: strongly agree, agree, disagree, and strongly disagree, indicating the degree to which they felt confident that they could do an excellent job on tests in their math class; felt certain that they could understand the hardest material in their math book; felt certain that they could master the skills being taught in their math class; and felt confident that they could do an excellent job on assignments their math class. Students' scores on this index are comprised of a composite variable estimated with principal components analysis, composed from the four survey items.

Academic effort. Students' scores are comprised of a composite variable estimated with principal components analysis of the extent of students' academic effort, composed from seven pre-survey items such as, "I work very hard at school" (which students rated on a scale including "Never," "Some of the time," "Half of the time," "Most of the time, and "All of the time") The items are adapted from Fryer (2011) (Cronbach's $\alpha = .54$).

***Demographic information*.** This included students' race, gender, free lunch eligibility, and home Internet access at baseline.

Procedures

Within two weeks of the end of the school year (but before random assignment was conducted), students completed the spring district curriculum-based math assessment as part of their regular instructional regimen. In the last week of school in June, just prior to summer vacation but also prior to random assignment, teachers administered the pre-summer survey to students in their classrooms.

After random assignment, Tenmarks staff members visited each school in order to give each student who was randomly assigned an offer of the Tenmarks online math program login credentials for the Tenmarks website, entitling each student to a free Tenmarks subscription. The staff members also provided a brief demonstration of the website's features. At the same time, students who were randomly assigned a free laptop computer received instructions on how to pick up the computer. In order to receive a computer, students were required to participate in an afterschool or evening computer training, accompanied by a parent or guardian. Although all children in the program plus laptop condition were assigned to receive a laptop, our analyses are intent-to-treat estimates since we did not (nor could we) ensure compliance.

Each week throughout the summer, a Tenmarks staff member randomly selected one student from each school who had completed Tenmarks worksheets to receive a small gift card. Students also received weekly text messages encouraging them to log in to Tenmarks. Since approximately one third of students reportedly lacked home Internet access at baseline, text messages also provided locations of public libraries, community centers, and open school buildings with Internet-equipped computers for student use. No control group students logged into the program, according to information provided by Tenmarks.

The following fall, during the second week of school, students completed the fall district curriculum-based math assessment. Approximately six weeks into the fall term, teachers administered the national assessment-based math test and post-survey.

Results

The results section is organized as follows. First, we provide a descriptive picture of summer mathematics learning loss, intrinsic motivation loss, and activity participation over the summer vacation period for the sample. Next, we present intent-to-treat estimates of the intervention's impacts on summer mathematics engagement and student outcomes. Lastly, we describe the effects of intervention dosage on program outcomes, and explore what factors predicted program participation.

Summer achievement and summer motivation loss

First, we examined descriptively whether sample children experienced losses in mathematics achievement or intrinsic motivation for doing mathematics over the summer.

Following Cooper et al. (1996), we estimated the effects of summer vacation on achievement by calculating for each sample in the control group the standardized mean difference (Cohen's *d*) (Cohen, 1988). This metric allows us to express the difference in students' achievement scores in the fall relative to their scores in the spring, irrespective of the specific test metric. Children in the control group on average experienced summer losses on the district assessment (d = -0.48 SD). This estimate is somewhat larger than the average summer loss effect size for math computation reported in Cooper et al. (1996) (d = -.32), and larger and oppositely signed than Cooper et al.'s finding that summer vacation had a positive effect on math application (d = +0.17). Since the district assessment scores were not broken out by problem type or mathematics subdomain, we cannot tell whether summer losses were greater for computation than application problems.

Using the same procedures as above, we estimated the relationship between summer vacation and children's intrinsic motivation for doing mathematics, calculating the standardized mean difference between control group students' scores at pre- and post-summer on the Intrinsic Motivation Inventory scale. On average, children experienced decreases in their intrinsic motivation for doing mathematics over the testing period. (d = -.32 SD).

Summer activity participation

We begin with a brief summary of children's reported summer activities. Over half (53%) of children reported that they did not attend a summer camp or summer program during summer vacation. Free/reduced price lunch-eligible children were somewhat less likely to report attending a summer program (44%) compared with higher-income children (51%). Six percent of the children who did report attending a summer program said that it was Tenmarks. Approximately 16% of children reported that they attended summer school, and 10% reported that they attended a summer school that had a math component. Summer camp and summer school attendance did not differ significantly by experimental group.

Estimated impacts on summer mathematics engagement and student outcomes

In Table 3, we present a taxonomy of fitted regression models in which we estimate the intent-to-treat impact of offering students a chance to participate in the online summer mathematics program or offering the same opportunity plus a free laptop computer, on the proximal and distal outcomes and the two mediators shown in the intervention logic model (Figure 1). In order to estimate the causal impact of the experimental condition, for each outcome, we fit a regression model with the outcome as the dependent variable and the two treatment conditions as predictors. Models control for relevant variables measured at baseline: the family/home math engagement model (M.1.1) includes a control for baseline level of parent supervision; the math assessment models include controls for prior spring math score and, for the national assessment-based math test, student grade level (M.2.1 and M.3.1); the intrinsic motivation model (M.4.1) includes a control for baseline level of intrinsic motivation; and the math enjoyment model (M.5.1) includes controls for baseline levels of intrinsic motivation and academic effort. We also fit all models with school fixed effects, to account for the nesting of students within schools at baseline; the results are similar to those below. The results from the main effects models are similar in the OLS and multiple imputation analyses; in the interaction models, the statistical significance of some estimates varies across models, which we note below. See Appendix 2 for the imputation results.

Impacts on summer home and family mathematics engagement

Compared with their counterparts in the control group, children who were offered the intervention scored higher on the measure of summer home and family mathematics engagement. We find that being randomly assigned to an offer of the most intensive treatment, the program plus laptop condition, caused children to report levels of family/home math engagement .19 SD higher than their peers in the control group, and this difference was statistically significant ($B = .39$, $p = 0.04$; $\beta = .19$) (Model M.1.1). For example, the proportion of students who reported doing math at home ‘almost every day’ during summer vacation was 14% in the control group, 18% in the program only treatment group, and 30% in the program plus laptop treatment group. This result appeared to be driven by children in the program plus laptop condition reporting that they did math more frequently at home ($B = .47$, $p < .01$; $\beta = .21$) and that their parents encouraged or told them to do math more frequently ($B = .61$, $p = 0.02$; $\beta = .26$); the differences between groups in frequency of talking about math at home and parents helping with math were not significant. The point estimate for the program only condition was also positive, but was not statistically significant (B = .19, p = 0.32; β=.09). In addition, results for the single item asking whether the child's father or mother did any math with them this summer were not significant.

We examined the possibility that the impact of the intervention varied by participant characteristics by considering interactions between baseline characteristics and experimental group. For the family and home math engagement outcome, we found that there was a statistically significant interaction between the program plus laptop computer condition and home internet access (B = .91; p = .02), suggesting that the effects of receiving an offer of the program plus laptop on family/home math engagement depended on whether the child had access to the Internet at home (see Table 4, Model M.1.2, and Figure 2). To further explore this issue, we fit separate models examining the impact of the intervention offer on family/home math engagement for children who did and did not have Internet access. Among children who had access to the Internet at baseline, the effect of the program plus laptop condition was significant and positive (B = .75; p < .01), while the effect for children who lacked internet access at baseline was oppositely signed and not significant (B = -.18; p = .56). However, this interaction was not significant in the imputation model. Interactions with students' grade level, prior math achievement, gender, free lunch eligibility, and baseline levels of academic effort, math intrinsic motivation, parent supervision, and math confidence were not significant. Results from additional moderator analyses are available from the authors on request.

Impacts on achievement and affective outcomes

Treatments' impacts on the distal achievement outcomes were statistically insignificant. For the national assessment-based math test, the effects of the program only condition (B = .03; p = .86; β =.01), and the program plus laptop condition (B = -.09; p = 0.55; β = -.04), were not significant (Model M.2.1).

Examining interactions between participant characteristics and experimental group, we found that first, there was a statistically significant interaction between the program only treatment and student grade level (elementary versus middle/high) (β = -1.29; $p < .01$), suggesting that the impact of the program only on students' national assessment-based math scores depended on students' grade level (see Model M.2.2 and Figure 3). To further understand this difference, we fit separate models for older (grades 6-9) and younger (grades 3-5) children. We found that for older children (N=135), the program only condition had a positive effect on national assessment-based math scores (B = .33; p = .04; β = .16). Among older children, the .16 impact is large enough to offset approximately a third of the loss in summer math skills overall (which was reported earlier in the results). On the other hand, for younger children, the effect of the program only was negative (B = -.96; p = .01; β = -.44). For the program plus laptop condition, the effects were not significant for either group (older: B = .01; p = .95, β = .00; younger: B = -.31; p = .32, β = -.15). Lastly, for the program only condition, there was a significant interaction with baseline level of parent supervision, such that the relationship between the program only condition and national assessment-based math scores depended on baseline level of parent supervision (see Model M.2.4 and Figure 4; the significance of relationship is marginal in the imputation model). Students in this condition who reported lower levels of parent supervision at baseline had higher adjusted fall national assessment-based math scores.

The effects of treatment on the district curriculum-based fall mathematics assessment were also statistically insignificant (program plus laptop, $B = .04$, $p = 0.78$, $\beta = .02$; program only, $B = -.07$, $p = 0.59$, $\beta = -.03$) (Model M.3.1). No significant interactions of measured covariates with treatment assignment were found. We also fit models with student intrinsic motivation for doing math and math enjoyment as outcomes, but results of these analyses were not statistically significant (see Models M.4.1 and M.5.1), nor were significant interactions between covariates and treatment assignment found.

Intervention dosage

The number of math “worksheets” that participants completed over the summer provides an indication of participants’ take-up of the intervention. Each worksheet included ten math problems, with embedded hints and videos students could click for support. Approximately 60% of participants who were offered a subscription to Tenmarks completed at least one worksheet over the summer, and the average number of worksheets completed was 15.39 (SD = 24.07). Among students who completed any worksheets, the average number completed was 26.10 (SD = 23.88). Since the program developers intended for students to complete three worksheets per week for ten weeks, the average student completed slightly over half of the dosage the developers recommended, and approximately 40% of students received no dosage. Students’ actual usage of the materials was thus substantially less frequent than what the developers intended. The number of worksheets children in the treatment groups completed was correlated with their reported home and family mathematics engagement (program plus laptop: $r = .27$, $p = 0.03$; program only: $r = .22$; $p = .08$).

In order to explore whether take-up of the intervention caused children to experience improved outcomes, we conducted an instrumental variables analysis using the number of worksheets completed as the take-up measure. The instrumental variables approach provides an estimate of the treatment effect on the treated; when participants are assigned randomly to conditions, treatment assignment may be used as an instrument for participation in the intervention (Angrist et al., 1996). We utilized Stata's *ivregress* routine, with the *2sls* option (StataCorp, 2013b), with random assignment to treatment serving as an instrument for participation. The second-stage, or outcome, equations included a mediator variable measuring the number of worksheets completed, reflecting students' actual participation in the intervention.

The IV results did not indicate that increased participation in the intervention caused increased mathematics achievement scores (district curriculum-based measure: $B = -.02$; $p = .91$; national assessment-based measure: $B = -.04$; $p = .79$), although in line with the findings above, it did cause increased home and family mathematics engagement ($B = .34$, $p < .05$).

What predicted participation?

Given the voluntary nature of the intervention, which occurred over the summer vacation period, it is also of interest to understand what factors predict student take-up and participation. We fit a series of models using zero-inflated poisson regression to explore which factors predicted the number of times students logged into Tenmarks, among those in the treatment groups. The logit model component of the poisson regression used student-reported home internet access at baseline to predict the latent binary outcome of whether the student was a certain zero.

We found that girls logged in fewer times than boys (*B* = -.45; *p* = .02), and that low-income children (i.e., eligible for free or reduced price school lunch) logged in marginally fewer times than middle-income children (*B* = -.39; *p* = .06). On the other hand, children with higher baseline scores on the parent supervision index logged in significantly more frequently (*B*= .21; *p* = .03), and children with Internet access logged in marginally more often (*B* = .37; *p* = .10). Number of logins was not significantly predicted by children's grade level, prior math achievement, or any of the affective/motivational constructs measured at baseline (academic effort, intrinsic motivation for doing mathematics, or mathematics confidence).

Limitations

The limitations of the current study suggest several potentially productive areas for future research. First, we note that an important limitation of the current study is its relatively small sample size. The effects of summer programs on academic achievement generally are expected to be small; in recent studies, school-based summer math programs had an average effect size of +0.08 SD. Furthermore, these programs tended to be significantly more intensive than the current intervention, involving substantial classroom instructional time and teacher interaction. The current study's relatively small sample size clearly limited its power to detect small effects, as well as the precision of the estimates obtained. In the future, replication studies with larger sample sizes are needed in order to estimate the effects of the intervention with greater precision.

Second, as noted above, all participating students volunteered for the study; although they were demographically relatively similar to others in their schools and district, still they may have been unusually motivated to participate in the program. Future studies could include larger samples, and examine contexts in which the program is mandatory.

Third, as is generally the case with surveys and self-report measures, the child self-report measures of home and family math engagement used in this study are probably susceptible to self-report and social desirability bias. Summer time-diary studies that include measures of children's summer math activities are rare (for an exception, see Gershenson, 2013) and would be helpful for confirming the current results. In prior research with a nationally representative sample, parent self-reports of children's summer activities, such as the use of computers for educational activities, were a significant predictor of children's summer learning loss (Burkam, Ready, Lee, & LoGerfo, 2004). In addition, time diary studies would be useful for capturing a more fine-grained range of summer mathematics activities. While the current research utilized a measure adapted from the Literacy Habits Survey (Paris et al., 2004), which has been used in summer home-based literacy intervention research, it is possible that a time diary could have captured a richer range of informal family mathematical involvement, such as that involved in measuring and estimating in household chores.

Discussion and Conclusions

In summary, this study utilized random assignment to examine the impacts of a summer online mathematics program on children's summer home and family mathematics engagement and mathematics achievement.

We found that the more intensive treatment condition, an offer both of the Tenmarks program and a free laptop computer, caused children to report significantly higher levels of summer home and family mathematics engagement compared with children in the randomly chosen control group. The intervention thus appears to have succeeded at improving students' summer home involvement in mathematics. This is despite the fact that the intervention was relatively "low touch"; the more intensive variant was comprised of an offer of a free online summer program plus a laptop valued at a few hundred dollars. The results suggest that low-income children's reported home math engagement can be increased with the provision of a relatively low-touch intervention.

This increased engagement, however, did not translate into main effects of improved distal achievement outcomes. While the lack of significant findings may be related to power limitations due to sample size, several limitations of the current intervention may also have limited its impacts on achievement. As we discuss below, these limitations imply one of two options. On the one hand, perhaps modifications to the program may be possible that would increase the program's impact. On the other hand, while the program may be relatively easy to implement, the lack of positive effects on student achievement may call into question the program's underlying theory of action.

The first possibility is that modifications to the program may be possible that would increase the program's impact. First, the math activities included in the Tenmarks software may not have been interesting enough to attract students' attention and elicit engagement during summer vacation, which children often associate with leisure activities. The low worksheet completion rate suggests this possibility. From a student engagement perspective, some policymakers have argued that academic summer programs may benefit from recognizing American summer culture, differentiating themselves from typical school year programming with activities that emphasize student engagement, inquiry, and curiosity (McCombs et al., 2011).

Family resource constraints may also have prevented the predominantly low-income families in the sample from reaping the full potential benefits of a digital intervention during summer vacation. The intervention required Internet access, which 36% of students lacked at baseline. As school districts explore online alternatives for summer learning, summer credit recovery, and supplemental educational services for low-income populations (Heinrich & Nisar, 2013; Walters & Sorensen, 2013), ensuring that children from low-income families have access to technological supports outside of school time is an important concern. However, in the current study, even students who did have Internet access did not garner significant achievement benefits, suggesting that ensuring that all students have digital access will not be enough to make the treatment effective.

Furthermore, parent interactions around mathematics during the summer vacation period may have needed more structure in order to be effective. While the child-report measures suggest that the amount of home mathematics engagement increased as a result of the program plus laptop treatment, parents and guardians may not have known how to translate their intentions to encourage their children into effective strategies for supporting their children's mathematics learning. Parents' mathematics skills may be remembered from their own schooling, and mismatched with contemporary mathematics curriculum content (Peressini, 1998; Remillard & Jackson, 2006). During summer vacation, when the daily flow of structured mathematics instruction and support from teachers is turned off, parents may find it particularly challenging to support home mathematics practice effectively. Some evidence suggests that home-based summer reading programs are more effective when they provide specific instructions for parent interactions. For example, the National Reading Panel (2000) found little evidence for the effectiveness of home-based summer reading programs in which students were merely provided books and asked to read silently alone, with little or no feedback from parents. By contrast, in studies where children were provided with instructions on how to read aloud to their parents and discuss books with family members (e.g. Kim, 2006), low-SES students enjoyed sizeable reading gains, perhaps due to the comprehension scaffolding and feedback they received from interacting with parents.

If this is the case, one fruitful avenue for future research may be to explore strategies for helping parents make home mathematics engagement over the summer more effective, perhaps with improved curriculum materials. One possible model might provide parents with structured materials and instruction in providing their children with one-on-one tutoring during summer vacation, perhaps in coordination with a digital intervention. Substantial research supports the efficacy of mathematics tutoring interventions (e.g. Cohen, Kulik, & Kulik, 1982; Fryer, 2011; Ritter, Barnett, Denny, & Albin, 2009). While most research on math skills tutoring has been conducted in schools, with either peers or other adults as tutors, a meta-analysis of the literature on parent tutoring in math (Erion, 2006) found that parent tutoring has an overall positive impact on students' math achievement. For example, Thurston and Dasta (1990) found that parent tutoring improved students' knowledge of math facts, and this translated to improved school performance. However, research is lacking on how best to structure parental tutoring during summer vacation, when children are not exposed to the routine supports of daily mathematics instruction. Future research could help school districts seeking to reduce achievement gaps via summer remediation to support children's experiences in these programs more effectively.

However, as noted above, a second possibility is that the online intervention was simply ineffective at teaching children mathematics, due to flaws in the intervention's underlying theory of action. In this viewpoint, perhaps the intervention offer was successful at encouraging children to engage in more mathematics than they otherwise would have, but the intervention was inadequate to translate this effort into improved mathematics skills in the way envisioned in the program logic model. Prior research on computer-assisted instruction suggests that even under relatively ideal conditions, in which students often spent several sessions each week during the academic year completing math exercises in a computer lab fully equipped with the needed technology and staffed by a teacher or paraprofessional, effect sizes on student achievement were relatively modest, at +0.19 in elementary school (Slavin & Lake, 2008) and +0.08 in secondary school (Slavin, Lake, & Groff, 2009). By contrast, in the current intervention, students experienced difficulties with access to technology; they likely also experienced distractions, as many other summer leisure pursuits called for their attention. Under these conditions, students may have had minimal motivation to expend time and effort on completing math worksheets. Perhaps most importantly, students in the current intervention lacked support from a teacher. Worksheets and videos alone, unconnected to school instruction, may simply have been inadequate to teach children mathematics under these conditions. It may be the case that online interventions such as Tenmarks could be more beneficial with substantial changes to the program's logic model, recasting the online materials as a supplement to a more traditional summer program with teacher scaffolding. In a recent random assignment study of the Elevate Math summer program, in which seventh-grade students spent three hours each day receiving math instruction from a certified teacher, plus one hour each day using Khan Academy, treatment group students experienced significant improvements in algebra readiness (+0.7 SD) relative to the control group (Snipes et al., 2015). Although it is unclear whether the usage of Khan Academy was instrumental to these gains, this study nonetheless suggests the potential for using online materials as a supplement to classroom-based summer school math instruction.

A related possibility is that the materials were effective for some students and not others. The supplemental interaction analysis suggested that the program only condition had a positive effect on older students' national assessment-based math scores, but a negative effect on younger students' scores. Although this result may simply be stochastic, it suggests the possibility of greater intervention effects for older students. Some research indicates that children left to learn mathematics with limited teacher involvement may develop mathematical misconceptions (Erlwanger, 1973). This problem may have been compounded for younger children in the current intervention, who in addition to lacking access to a teacher over the summer months, may have struggled with the reading load required in the Tenmarks program's instructions and word problems. Research conducted with literacy apps has suggested that in some cases, young children's learning may even be harmed by the digital format, perhaps because of distracting interactive elements which interrupt their ability to pay attention to the content (Parish-Morris, Mahajan, Hirsh-Pasek, Golinkoff, & Collins, 2013). Younger children may experience greater success when they receive more scaffolded help from parents. For example, in a study conducted with higher-income children and their parents during the academic year, Berkowitz et al. (2015) found that first-graders who responded to numerical story problems delivered via app with a parent experienced math learning gains.

On the other hand, older students may have been more accustomed to the online learning format and better able to read and interpret the content, aiding learning gains. This pattern of different effects for older and younger children found for the national assessment-based outcome in the program only condition, however, was not statistically significant for the program plus laptop condition, and was not detected on the district mathematics assessment. It is possible that the district assessments, which were used as general benchmark tests, may not have been well aligned to the Tenmarks program content; however, we could not investigate this issue due to the secure nature of the district tests. The hypothesis that home-based mathematics programs that require independent student use may be more effective for older students, who need less scaffolding to do this work on their own, merits follow-up. In addition, strategies to better support younger students' summer mathematics learning, such as increased parent scaffolding, merit attention.

Returning to the program's logic model, we also note the absence of some of the moderator effects that we hypothesized. Children's program participation was not significantly predicted by any of the child-level affective/motivational constructs measured at baseline. On the other hand, several family and home resource measures did predict children's participation. Higher-income children logged in to the program marginally more often than did children eligible for a subsidized lunch, and children with home Internet access and higher levels of parent supervision also logged in more frequently. These differences suggest the relative importance of home and family resources in shaping children's summer activities and mathematics engagement.

Future Directions

This study raises several questions for future research. First, our finding that a relatively low-touch intervention increased low-income children's summer mathematics participation suggests that the summer vacation period may represent an underutilized opportunity to increase low-income students' engagement with math. While participation was lower than what the program developers intended, many children did participate over the course of the summer, and as a result they did more math than they otherwise would have. However, this increased participation did not translate into improved overall distal achievement outcomes. As this is the first study we know of that has examined a home-based summer math intervention, these findings are preliminary. As suggested above, future design research, in line with that which has been conducted in literacy (e.g., Kim, 2006, 2007; Allington et al., 2010), is needed in order to develop curricula and intervention supports that would help low-income children to translate their increased time spent on summer mathematics into improved mathematics achievement.

In addition, our preliminary finding that children had lower intrinsic motivation for doing mathematics after the summer vacation period suggests that it may be productive to explore how children's attitudes and orientations toward mathematics and STEM develop or decline during summer vacation, an extended period away from the 'resources faucet' of schools. Because intrinsic motivation is an important predictor of children's STEM attainment (Gottfried, Marcoulides, Gottfried, & Oliver, 2013), it is important to understand whether and how summer vacation periods may contribute to STEM motivation losses later in children's academic careers. The findings from the current study thus point towards avenues for future research, in order to improve our understanding of effective strategies to reduce low-income children's summer learning loss in math.

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Table 1.

Descriptive Statistics of Selected Baseline Characteristics of Participants, by School

School	School Description		N (% of total sample)	Grades	% Internet access at baseline	% Subsidized Meals	% Minority	% Female	% NAEP Math Correct
School 1	Public, grades K-8	Sample	65 (.33)	3-8	.63	.74	.98	.56	.50*
		School Overall				.91	.99	.50	--
School 2	Public, grades 6-8	Sample	99 (.38)	6-8	.36	.56	.96	.59	.39*
		School Overall				.70	.97	.50	--
School 3	Public exam school, grades 7-12	Sample	87 (.33)	7-8	.97	.41	.74	.72	.59*
		School Overall				.53	.72	.57	--
School 4	Public, grades 9-12	Sample	12 (.05)	9	.33	.6	.83	.45	.25*

	School Overall	.76	.99	.49	--
Sample Overall		.59	.87	.62	.51**
District Overall		.70	.87	.48	.48
State Overall		.35	.33	.49	.58
U.S. Overall					.51

* Scores for control group.
** Scores for fourth and eighth graders in the control group only, to allow for comparisons with same-grade test-takers.

Table 2.

Descriptive Statistics for Covariates and Assessments, For Full Sample and by Experimental Group

Variable	Scale/ (Range in current sample)	Full Sample	Control Group	Tenmarks Only Group	Tenmarks Plus Laptop Group
Spring Math Benchmark Score	% correct (.03-1.00)	.62	.64	.63	.60
Internet	% Yes	.63	.62	.62	.64
Gender	% Female	.62	.69	.61	.57
Grade	(3-9)	6.40	6.41	6.37	6.42
Race	%				
	White	.11	.13	.07	.15
	Black	.38	.34	.37	.42
	Asian	.10	.09	.10	.09
	Hispanic	.31	.31	.37	.25
	Other	.02	.01	.01	.02
	Not reported	.09	.13	.08	.07
Free Lunch	% Eligible	.59	.60	.60	.56
Parent Supervision	Mean = 0, SD = 1 (-3.55, 1.24)	0	.02	.08	-.09
Academic Effort	Mean = 0, SD = 1	0	-.03	.14	-.11

	(-3.98, 1.42)				
Mathematics Intrinsic Motivation	Mean = 0, SD = 1 (-2.39, 1.28)	0	-.05	-.03	.08
Mathematics Confidence	Mean = 0, SD = 1 (-3.71, 1.33)	0	-.05	.10	-.04
Spring math benchmark score present		.82	.77	.80	.89
Fall math benchmark score present		.84	.81	.83	.87
Fall national assessment-based math score present		.74	.66	.75	.81

Table 3.

Results of Fitting a Taxonomy of Regression Models for Family/home math engagement, NAEP Math Test, District Mathematics Benchmark Assessment, Mathematics Intrinsic Motivation, and Mathematics Enjoyment as a Function of Treatment Assignment and Student Background Characteristics

	Model M.1.1 Family Home Math Engagement	Model M.2.1 National assessment-based Math Assessment	Model M.3.1 District curriculum-based Math Assessment	Model M.4.1 Mathematics Intrinsic Motivation	Model M.5.1 Mathematics Enjoyment
Intercept	-.22 (.14)	.13 (.11)	.01 (.09)	-.01 (.11)	.08 (.11)
Tenmarks Only	.19 (.19)	.03 (.15)	-.07 (.13)	.03 .15	.01 (.15)
Tenmarks + Laptop	.39* (.18)	-.09 (.14)	.04 (.12)	.06 .15	-.08 (.15)
Baseline Parent Supervision	.20** (.07)				
Spring Math Score		.70*** (.00)	.73*** (.05)		
Test Form		-.65*** (.15)			
Baseline Mathematics Intrinsic Motivation				.67*** (.06)	.67*** (.07)
Baseline Academic Effort					-.18* (.07)
Adj. R^2	.05	.40	.50	.45	.40
N	170	176	196	152	158

* p < .05; ** p < .01; *** p < .001
Note: Standard errors in parentheses.

Table 4.

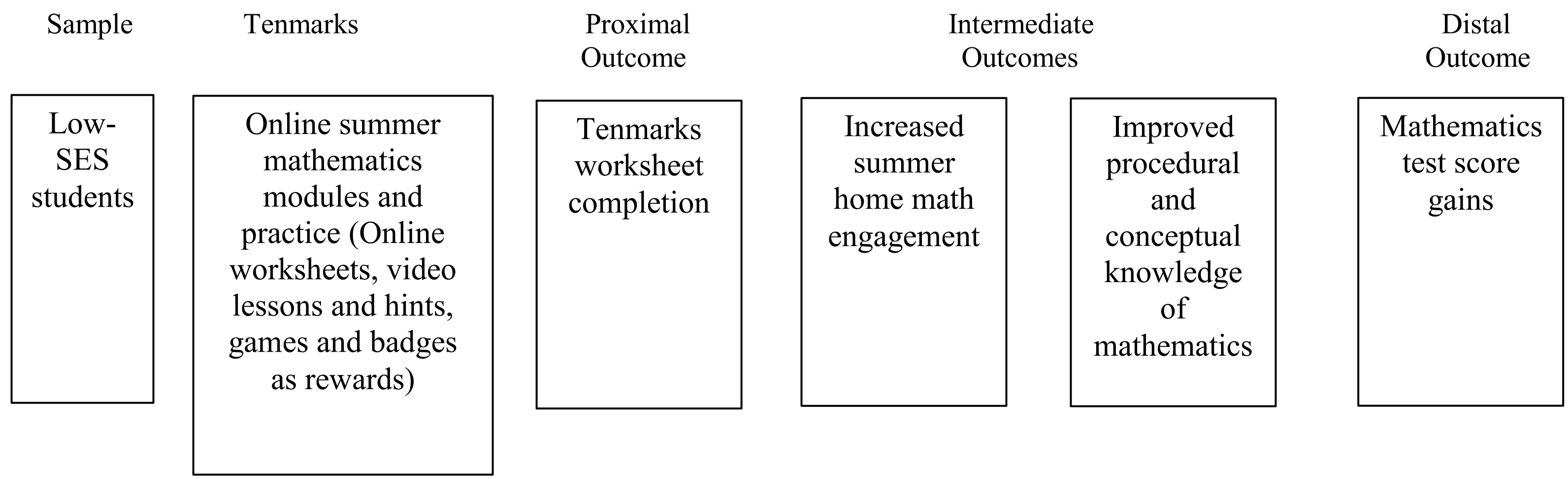
Results of Fitting Selected Interaction Models for Family/Home Math Engagement and NAEP Math Test Outcomes

	Model M.1.1 Family Home Math Engagement	Model M.1.2 Family Home Math Engagement (Internet X Treatment)	Model M.1.3 Family Home Math Engagement (Race X Treatment)	Model M.2.1 National assessment-based Math Assessment	Model M.2.2 National assessment-based Math Assessment (Grade level X Treatment)	Model M.2.3 National assessment-based Math Assessment (Parent Supervision X Treatment)
Intercept	-.22 (.14)	.05 (.22)	-.52 (.16)	.13 (.11)	-.01 (.12)	-.03 (.12)
Tenmarks Only	.19 (.19)	.20 (.30)	.44† (.23)	.03 (.15)	.33* (.16)	.31 (.16)+
Tenmarks + Laptop	.39* (.18)	-.16 (.30)	.85*** (.23)	-.09 (.14)	.01 (.16)	.01 (.16)
Spring Math Score				.70*** (.00)	.70*** (.00)	.70*** (.06)
Elementary age				-.65*** (.15)	-.14 (.24)	-.13 (.23)
Elementary age X					-1.29*** (.33)	-1.10** (.34)

Tenmarks Only					
Elementary Age X Tenmarks plus Laptop				-.31 (.32)	-.21 (.33)
Internet	-.46 (.28)				
Internet X Tenmarks Only	.04 (.38)				
Internet X Tenmarks Plus Laptop	.91* (.38)				
Black		.98** (.29)			
Black X Tenmarks Only		-.86* (.38)			
Black X Tenmarks plus Laptop		-1.31** (.38)			

Baseline Parent Supervision	.20** (.07)	.20** (.07)	.20** (.07)			.04 (.10)
Baseline Parent Supervision X Tenmarks Only						-.34* (.14)
Baseline Parent Supervision X Tenmarks Plus Laptop						-.10 (.14)
Adj. R^2	.05	.08	.10	.40	.45	.47
N	170	170	170	176	176	169

† p <.1; * p < .05; ** p < .01; *** p < .001
Note: Standard errors in parentheses.



Potential Moderators of Participation and Effects

- Family and home resources (Internet access, income level, parent supervision)
- Child affective characteristics (academic effort, mathematics confidence, intrinsic motivation for doing mathematics)
- Prior mathematics achievement
- Demographic characteristics (grade level, race, gender)

Figure 1. Hypothesized Tenmarks intervention logic model.

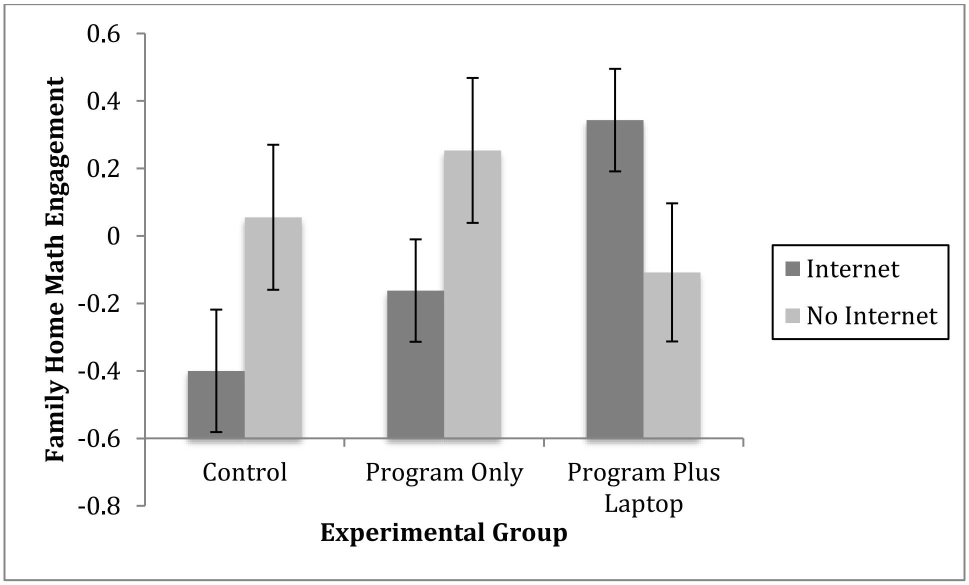


Figure 2. Estimated family/home mathematics engagement as a function of treatment assignment and baseline home Internet access.

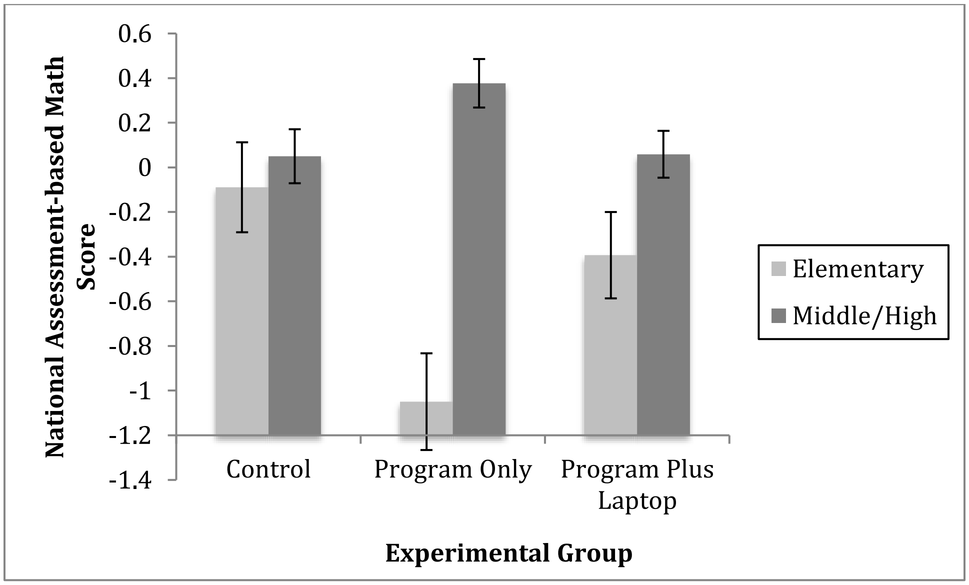


Figure 3. Estimated fall national assessment-based math scores as a function of treatment assignment and grade level.

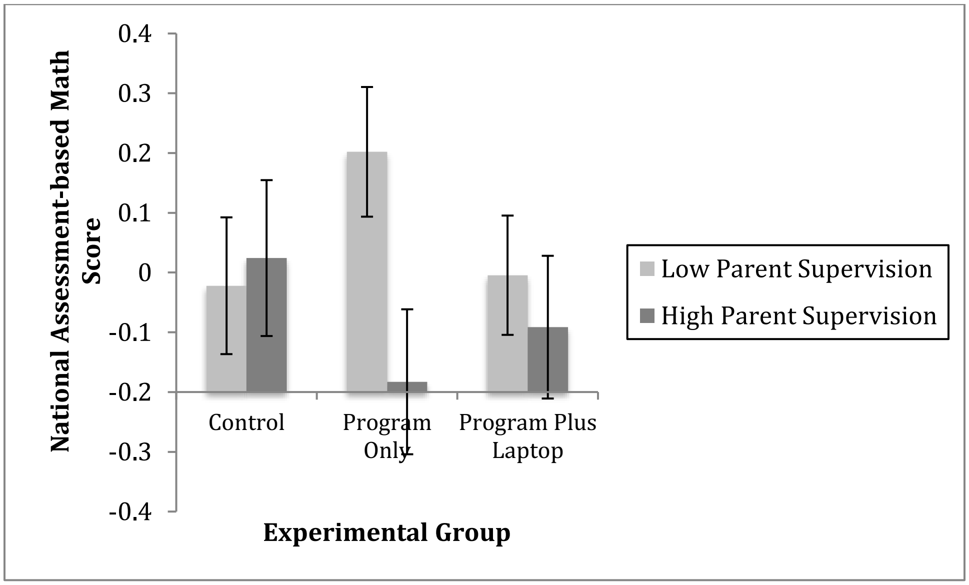


Figure 4. Estimated fall national assessment-based math scores as a function of treatment assignment and baseline level of parent supervision (low = 25th percentile; high = 75th percentile).

Conclusion

The role of out-of-school time in shaping educational inequality is an important concern for both social science theory and for educational policy and practice. The first two studies presented above shed light on how seasonal inequality in children's learning, enrichment experiences, and social-emotional skills is developing and widening, illuminating key hypothesized mechanisms for how the socioeconomic achievement gap widens. The third study utilized a rigorous experimental design to contribute to our understanding of policies to ameliorate summer learning gaps. Below, I summarize the main study results, and discuss implications of the current research.

First, a variety of research studies suggest that the socioeconomic status (SES)-based achievement gap may widen primarily while children are on summer vacation. While high- and low-SES children learn at similar rates during the school year, high-SES children appear to learn significantly more during the summer than do low-SES children, perhaps due to differences in the summer enrichment opportunities available to children of high- and low-SES backgrounds. However, no studies have used recent data to examine children's summer activity participation. Nor have any studies examined how high- and low-SES children's summer activities or learning have changed over time. In Study 1, I used nationally representative data to examine how SES gaps in children's summer enrichment experiences, as well as the relationships between SES, summer learning, and summer enrichment, have changed in recent decades. I found that parents across the socioeconomic spectrum increased their reported time investments in home literacy and math activities across cohorts. However, the SES gap in summer camp attendance widened considerably across cohorts. SES gaps in many other summer enrichment activities remained sizable in both cohorts.

Second, while the widening of SES-based academic achievement gaps during summer vacation has been the subject of a number of prior studies, no prior studies have examined how SES-based gaps in children's *social-emotional and executive function skills* change over the summer. In *Study #2*, I used nationally representative data to address this gap in the literature. I found that while children of different socioeconomic backgrounds made similar average declines in SEL and EF over the summer, among low-SES and high-SES children who began summer vacation with the same levels of SEL and EF skills, low-SES children had weaker skills at the end of the summer. I also found that on average, children who spent more time playing video games during the summer had significantly weaker social-emotional skills in the fall, controlling for their prior spring social-emotional skills and other background characteristics.

Turning toward the development of policy interventions to ameliorate summer learning inequality, Study #3 presents the results of a randomized experiment of a home-based summer mathematics program aimed at improving low-income children's summer home mathematics engagement and reducing summer learning loss. The study was conducted in a large, high-poverty urban public school district. Children in the third to ninth grade (N=263) were randomly assigned to an offer of an online summer mathematics program, the same program plus a free laptop computer, or the control group. Being randomly assigned to the program plus laptop condition caused children to experience significantly higher reported levels of summer home mathematics engagement relative to their peers in the control group. Treatment and control children performed similarly on distal measures of academic achievement.

Taken together, these three studies provide new insights into how children's out-of-school environment contributes to educational inequality, and point toward new directions for future research. Gaps in how high- and low-SES children spend their time during summer vacation are persistent and large. High-SES children are much more likely than low-SES children to attend summer camp, and spend more time during the summer doing activities such as reading and taking educationally enriching trips. These activities may contribute to stronger summer growth in academic learning, and potentially to lower declines in summer social-emotional and executive function learning for high-SES children. Future research is needed to examine the potential contributions of children's summer activity participation to summer social-emotional and executive function gaps. In addition, future qualitative research conducted during children's summer vacations could aid in understanding the potential contributions of parenting philosophies and peer groups to summer social-emotional learning gaps.

An experimental intervention which aimed to support low-SES children's summer mathematical development and reduce learning loss was effective at improving children's summer home and family math engagement, but did not lead to improvements in subsequent test scores. This study suggests the malleability of children's summer experiences – here, offering low-SES children a relatively low-touch intervention did increase the amount of time they spent over the summer doing math. However, in light of the findings from Study 1 demonstrating high-SES children's formidable advantages in summer enrichment experiences, such low-touch programs seem unlikely to be sufficient to close summer learning gaps. By contrast, programs such as summer school, while much more resource-intensive, are known to be effective at improving low-SES children's summer math achievement (Quinn, Lynch, & Kim, 2014).

The argument that schools are compensatory for children's academic skills (Downey & Condron, 2016) suggests that out-of-school environments exacerbate inequality. Downey and Condron (2016) suggest that social scientists should highlight to the public and policymakers the fact that socioeconomic gaps widen primarily outside of school time. The aim is to spur policymakers to look beyond schools to improve the broader social conditions that drive inequality in children's outcomes. The current findings highlighting persistent inequality in children's summer experiences point toward the importance of looking beyond the confines of schools to understand and ameliorate socioeconomic inequality.