The Summer Learning of Exceptional Students

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Abstract

The summer activities and summer learning of exceptional students—students who either have an individualized education plan (IEP) or who are English language learners (ELL)—are potentially important yet understudied. We analyze nationally representative survey data to fill this gap. Exceptional students are significantly less likely to participate in organized summer activities and summer daycare, but are more likely to attend summer school and practice math with a parent, than their mainstream counterparts. Exceptional learners make significantly greater reading gains during the summer vacation than their mainstream counterparts. However, this is only true for middle- and high-income exceptional learners. Moreover, the well documented "summer learning loss" of low-income students in reading appears to be entirely driven by lower summer learning rates of low-income exceptional learners. There are no such differences in math achievement.

Keywords: summer learning loss; exceptional students; English language learners; special education

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In 1999, 12% of U.S. kindergarteners spoke a language other than English at home, whom we subsequently refer to as English language learners (ELL), and 7% had a learning disability that resulted in an Individualized Education Plan (IEP).[1] In the 2011 kindergarten cohort, these figures had risen to 16% and 9%, respectively.[2] Students classified as ELLs or who have IEPs are often collectively referred to as exceptional students and face numerous potential inequities and challenges (e.g., Jones et al. 2013). These two groups of students are often educated in mainstream classrooms and programs and both require instructors to modify their usual instructional practices, albeit in sometimes different ways. These similarities likely carry over into organized out-of-school programs as well. Even though these students and their households face unique sets of challenges, in many cases these challenges manifest in common obstacles that students must overcome. For example, exceptional learners might require additional expenditures on tutoring and materials or lack access to suitable summer and extracurricular organized activities.

More than 30% of Hispanic primary school students are ELL (Hemphill and Vanneman 2011) and the Hispanic-White achievement gap at kindergarten entry is largest in homes that do not speak English (Reardon and Galindo 2009).[3] Many ELL students in the U.S., particularly those of Hispanic descent, are either first- or second-generation immigrants, and immigrant-native achievement gaps are well documented in many countries (e.g., Stanat et al. 2012). Poverty potentially magnifies the challenges faced by ELL students as well, as the median Hispanic household income is only about 70 percent as large as median white household income and Hispanic children are more than twice as likely to live in poverty as white children (Reardon and Galindo 2009). Moreover, ELL, low-income, and racial minority students are overrepresented in special education programs (e.g., Artiles et al. 2005).

Households with exceptional children are more likely to face financial burdens related to the children's disabilities (Kuhlthau et al. 2005). These financial burdens can have negative effects on children's health and well-being, which can adversely affect student achievement. Financial burdens may also reduce the available household resources that could be used to improve summer learning for exceptional students in low-income households. Despite increasing attention to the challenges faced by exceptional students from policymakers and educators, and the knowledge that high-quality programs and effective teachers can improve exceptional students' educational achievement (e.g., Cann et al. 2015; Genesee et al. 2005), significant achievement gaps between exceptional and mainstream students remain (e.g., Fry 2007; Lubienski and Lubienski 2006).

Policy makers and educators must understand the determinants of academic success and the factors that contribute to such achievement gaps if the gaps are to be closed. The activities, individuals, and environments to which children are exposed during summer vacation may contribute to the persistence of gaps in achievement between exceptional and mainstream students. Indeed, Heyns (1978) put forth and tested the hypothesis that lower rates of summer learning among socioeconomically disadvantaged students might contribute to the stubborn persistence of achievement gaps between students of different demographic and socioeconomic backgrounds.[4] As a result, a sizable and interdisciplinary body of literature has emerged that documents differences by race and socioeconomic status (SES) in students' summer activities and summer learning gains (e.g., Alexander et al. 2001; Burkam et al. 2004; Chin and Phillips 2004; Cooper et al. 1996; Downey et al. 2004; Gershenson 2013; Quinn 2014). However, this literature focuses almost entirely on racial and SES differences in summer learning, despite the fact that summer learning rates might also vary by ELL and IEP status (Verachtert et al. 2009).

In the case of ELL students, this may result from less exposure to, and conversation with, native English speakers during the summer vacation (Stanat et al., 2012). The current study contributes to this gap in the summer learning literature by examining the summer activities, summer learning rates, and moderators of summer learning rates of exceptional students using nationally representative data on the 1999 U.S. kindergarten cohort from the Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K).

Literature Review and Theoretical Background

Cooper et al. (1996) thoroughly reviewed the early empirical literature on summer learning loss, which includes the influential studies by Heyns (1978) and Entwisle and Alexander (1992) of Atlanta and Baltimore, respectively. A series of more recent studies of summer learning utilize the nationally representative ECLS-K (e.g., Burkam et al. 2004; Downey et al. 2004). A consistent finding in this literature is that low-income students make significantly smaller reading gains during the summer vacation than their more economically advantaged counterparts, while no such difference is found in math gains. However, as Verachtert et al. (2009) note, the existing literature largely ignores the potential differences in summer learning between exceptional and mainstream students.

We are not the first to consider both ELL and IEP students under the singular umbrella of "exceptional" learners. Indeed, there are at least three sources of similarity between ELL and IEP students that suggest they might experience similar patterns of summer learning. First, from a practical and definitional standpoint, it is sometimes difficult to distinguish learning disabilities from the language-acquisition challenges faced by ELL students, so there are likely cases of misdiagnoses in both directions (e.g., Collier, 2001; Cummins, 1989; Hemsely et al., 2014;

Serpa, 2011). Second, and related to the first point, ELL students are overrepresented in special education programs and there is substantial overlap in many districts (REL, 2014; Serpa, 2011). Finally, both groups of students are often exempted from standardized testing and are frequently educated in mainstream classrooms that require instructors to modify their usual instructional practices (e.g., Jones et al., 2013; Liasidou, 2013; Stancavage et al., 2007).

Previous theoretical and empirical research argues that summer learning rates likely vary across students for a variety of reasons such as differences in children's summer time use and exposure to parental involvement (Gershenson 2013) and differential rates of participation in organized summer activities (Chin and Phillips 2004). Borman et al. (2005) discuss four potentially interrelated mechanisms that may cause children in low-SES households to experience smaller achievement gains than their more advantaged counterparts during the summer vacation. First, the "faucet theory" of Entwisle et al. (2001) posits that SES differences in summer learning rates are driven by high-SES households being better able to compensate when the flow of resources from the "school tap" is shut off. Second, differences in summer learning rates may result from different parenting strategies (Entwisle, Alexander, and Olson 1997; Heyns 1978). Third, psychological models suggest that differences in parents' expectations for children's achievement and behavior may lead to differences in summer learning (Entwisle et al. 1997; Hoover-Dempsey and Sandler 1995). Finally, heterogeneity in either access or returns to participation in organized summer activities may contribute to differences in summer learning rates (Cooper et al. 2000).

Many of these potential sources of SES-gaps in summer learning suggest that there may be differences between exceptional and mainstream students' summer learning rates as well, given that ELL and racial minority students are overrepresented in special-education designations and are more likely to live in low-income households (Artiles et al. 2005; Gandara 2010; Lui et al. 2006). For example, Reese et al. (2000) document long-run improvements in English acquisition of students whose parents provide literary activities at home in the native language. However, it is unlikely that all ELL students participate in these types of literary activities at home, especially those living in low-income households (Gershenson, 2013). Therefore, exceptional students might lose ground relative to their mainstream counterparts during the summer vacation. Alternatively, summer may be a time for exceptional students to gain ground on their mainstream counterparts, when they can benefit from well targeted, high-quality programs (Cann et al. 2015; Genesee et al. 2005). The theoretical ambiguity regarding the direction of the "summer learning gap" between exceptional and mainstream students suggests that this is an empirical question, one that we address in this paper.

Previously, only three studies have formally compared the summer learning rates of exceptional and mainstream students. First, using data on kindergarten and first-grade students in Belgium, Verachtert et al. (2009) find that the summer gains made by children who speak a foreign language at home are about 5% of a math test score standard deviation (SD) lower than the summer gains made by native (Dutch) speakers, though this difference is not statistically significant. During first grade, however, the children who speak a foreign language at home make significantly greater gains in math achievement than their native-speaker counterparts. Second, Sandberg-Patton and Reschly (2013) examine the summer learning gains of first through fourth grade students in one Title-1 primary school in rural Georgia. The authors find no statistically significant differences between ELL and non-ELL students' summer reading gains; however, special education students were found to make smaller summer reading gains than their mainstream counterparts. Finally, Shaw (1982) examined the differences in students' summer learning using a sample of 28 schools in Stanislaus County, California and found that special education students experienced summer learning loss in math relative to their mainstream peers. We contribute to these existing studies by examining the summer achievement gains made in both math and reading using rich, nationally representative U.S. survey data that includes information on students' test scores, household characteristics, socioeconomic status, and summer activities. Additionally, we analyze the summer activities of exceptional students in the U.S. and leverage this information to investigate the potential mechanisms through which exceptional students experience differential rates of summer learning.

Given the relative lack of research on exceptional students' summer learning, it is useful to briefly review what is known about exceptional student learning during the school year to see what, if any, knowledge of exceptional student experiences might inform the current study. Achievement gaps between ELL and mainstream students are well documented; for example, ELL students are between 18 and 53 percent more likely to be below basic proficiency levels in mathematics than mainstream students (Fry, 2007, 2008). Various explanations for this achievement gap have been proposed. For example, Fry (2008) suggests that the gap results from ELL students being concentrated in disadvantaged schools, which highlights the importance of controlling for school and classroom characteristics. Artiles et al. (2005), meanwhile, argue that learning is restricted for ELL students who are inappropriately placed in special education programs. Others suggest that the placement of ELL students in English-only classrooms contributes to the achievement gap (Farver, Lonigan, and Eppe 2009; Francis, Lesaux, and August 2006; Jepsen 2010; Gordon and Hoxby 2004; Greene 1997; Pappamihiel 2002; Slavin and Cheung 2005). Compared to English-only classrooms, ELL students tend to be more successful in bilingual programs that are customized to meet their needs (Genesee et al. 2005; Gersten and Baker 2000; Thomas and Collier 2002).

Previous studies also find a significant achievement gap between IEP and mainstream students. (Levinson 2011; McDonnell et al. 2003). Several studies have offered possible explanations for this achievement gap. Mercer (1997) and Bulgren and Carta (1992) suggest that students with learning disabilities are more likely to have memory problems and difficulty staying on task than mainstream students. Evidence is mixed on whether or not students with learning disabilities who receive special education services experience larger gains in math and reading achievement than similar students who did not receive special education services (Ehrhardt et al. 2013; Morgan et al. 2010; Sullivan and Field 2013; Swanson and Hoskyn 1998). Expanding on previous correlational analyses, Sullivan and Field (2013) used a propensity-score matching strategy and found that children with learning disabilities who did not receive special education services experienced moderate positive gains in both math and reading relative to observably similar children who received special education designations. Finally, some students with special needs, though not all, are exposed to enriching summer activities. For example, Clark and Nwokah (2010) showed that organized summer camps provide such students with opportunities to learn through playing in group activities.

Data

Data on summer learning, household characteristics, and summer activities are all taken from the Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K), which was collected by the National Center for Education Statistics (NCES). The ECLS-K sampled more than 20,000 U.S. children from about 1,000 kindergarten programs (i.e., schools) and provides sampling weights that make the date nationally representative of the cohort that entered kindergarten in the 1998-99 academic year. All children were surveyed in the fall and spring of kindergarten and the spring of first grade. However, the analytic sample is restricted to the 30% random subsample of children who were also surveyed in fall of first grade. This facilitates the estimation of learning that occurred between the spring kindergarten assessment and the fall first grade assessment (i.e., during the summer between kindergarten and first grade).

The ECLS-K oversampled certain subsets of the population, so the primary analyses are conducted using NCES-provided sampling weights that adjust for the survey's nonrandom sampling frame and nonresponse based on observables. We further restrict the analytic sample by excluding students who repeated kindergarten, changed schools between school years, or were missing basic demographic or test score data. School changers are excluded to avoid conflating summer learning with shocks to achievement caused by the disruption associated with changing schools. However, the main findings are robust to including students who either repeated kindergarten or changed schools. These restrictions yield a main analytic sample of approximately 1,350 students, 100 of who are exceptional. Approximate sample sizes, rounded to the nearest 50, are reported throughout to comply with NCES rules for restricted-use data.

These data are well suited for the current analysis of exceptional students' summer learning for three reasons. First, the ECLS-K is the only nationally representative survey of U.S. students that contains both fall and spring test scores spanning the summer vacation. Second, the ECLS-K contains information regarding students' summer activities, which facilitates analyses of the behaviors and activities that contribute to summer learning and of underlying differences between exceptional and mainstream students' summer activities. Data on summer activities come from a parent survey administered in the fall of 1st grade. The ECLS-K survey asks parents to report on the summer activities that occurred during the summer between the end of kindergarten and the start of first grade. Third, the age-appropriate reading and mathematics assessments used to calculate summer achievement covered the same content and had the same (low) stakes, so teachers had no incentive to strategically divert resources or instructional time towards a specific test. Both the kindergarten and first grade surveys used the same two-stage cognitive assessment approach when collecting math and reading scores. The same math assessment from kindergarten was re-administrated in first grade. However, the ECLS-K slightly modified the first grade reading assessment by adding more difficult vocabulary words and text. The rationale for this modification was that a higher-than-expected number of students scored near the ceiling in the spring-kindergarten assessment. See NCES (2002) and Fitzpatrick et al. (2011) for further discussion of the ECLS-K assessments. One way we accounted for this is the test scores are standardized by subject and testing period to have mean zero and SD one, using all available test scores. However, in an online appendix we show that all of our main findings are robust to instead using unstandardized IRT scale scores.

Test Timing

Importantly, in both fall and spring semesters, ECLS-K assessments were administered to different students on different days. Fitzpatrick et al. (2011) show that ECLS-K test dates vary randomly between schools, between classrooms within schools, and even between students within the same classroom. The authors exploited this exogenous variation in time between tests to estimate the causal effect of instructional days on academic achievement. In the current context, to avoid conflating summer- and school-year learning, the econometric model must acknowledge that assessments were administered on neither the first nor last days of the academic year. For the summer between kindergarten (K) and first grade (1), there are four relevant dates (d): $d_K^{Spring\ Test}$, d_K^{End}, d_1^{Start}, and $d_1^{Fall\ Test}$. All four of these dates are provided by the ECLS-K. Unfortunately, the ECLS-K does not report the end date of the kindergarten school year. However, the survey does report the first-grade end date, which we use to impute the kindergarten end date. While this solution is imperfect, it is unlikely to compromise the analysis, as within-school changes in end dates from one year to the next are likely small and exogenously determined by factors such as weather (i.e. snow days) and scheduling quirks.

The number of days between these four dates are summarized in table 1. Nearly half of the days between the spring-kindergarten and fall-first grade tests were actually school days. The average summer vacation in the ECLS-K was about 80 days. Of the 70 school days that transpired between the spring kindergarten and fall first grade tests that were not part of the summer vacation, about 55% were at the start of first grade before the fall first-grade test and about 45% were at the end of kindergarten after the spring kindergarten test. Importantly, the average summer vacation and average number of school days before (after) the fall (spring) test were similar for both exceptional and mainstream students.

Descriptive Statistics

Table 2 summarizes the demographic composition and summer activities of the analytic samples of ELL, IEP, exceptional, and mainstream students. Students with either an Individualized Education Plan (IEP) or who did not speak English at home (N = 100) constitute about 7.4% of the full analytic sample (N = 1,350). Of these exceptional students, 59% are only IEP, 40% are only ELL, and only 1% are both IEP and ELL. The analytic sample of exceptional students is approximately 56% non-Hispanic white, 3% non-Hispanic black, and 31% Hispanic.

The remaining 10% is classified as “other race,” which includes Asians, Pacific Islanders, Native Americans, and students of mixed race. The analytic sample of mainstream students contains a significantly higher percent of non-Hispanic white and non-Hispanic black students, while containing a significantly lower percentage of Hispanic and “other race” students. About 38% of exceptional students are female, while males and females are equally represented in the mainstream subsample.

As documented in previous research, these are also significant differences in SES between exceptional and mainstream students. For example, about one fifth of exceptional students reside in households below the poverty line, a poverty rate that is eight percentage points higher than among mainstream students.[5] There are similar, statistically significant gaps in maternal education and the likelihood of having a computer in the home between the two groups. Finally, table 2 documents some significant differences between the summer experiences of exceptional and mainstream students. In particular, relative to mainstream students, exceptional students are 20 percentage points less likely to have participated in an organized summer activity but more than twice as likely to have attended summer school.[6] These findings further motivate our analysis of exceptional students’ summer learning.

Table 3 presents information on the nature of IEPs for our analytical sample, including reasons for their receipt and information on the persistence of IEP status. The majority of IEP students have more than one IEP goal. Table 3 shows that 38% of first-grade IEP students in our analytical sample had multiple IEP goals, 7% had a single IEP goal, and 55% did not have data on IEP goals. The most popular IEP goal in first grade was listening comprehension. By eighth grade, the most popular IEP goal was language arts. A sizable number of students receive an IEP after kindergarten. Of the first-grade students with an IEP in our analytical sample, 48% did not have an IEP in kindergarten. However, by eighth grade, only 21% of the students with an IEP in our analytical sample did not have a prior IEP. These statistics motivate sensitivity checks using alternative definitions of IEP, which are described in the results section. Overall, our main results remain robust when using these alternative definitions of IEP.

Econometric Model and Estimation

Let y^j represent achievement at date j for $j \in \left\{ d_K^{Spring\ Test},\ d_K^{End},\ d_1^{Start},\ d_1^{Fall\ Test} \right\}$. Only the first and last of these are observed, so we rewrite the difference between observed test scores as

$$y_1^{Fall\ Test} - y_K^{Spring\ Test} = \left(y_1^{Fall\ Test} - y_1^{Start} \right) - \left(y_1^{Start} - y_K^{End} \right) - \left(y_K^{End} - y_K^{Spring\ Test} \right), \tag{1}$$

where the middle term on the right hand side (RHS) of equation (1) constitutes summer learning. We then approximate the RHS of (1) using a piecewise-linear function of days between dates

$$y_1^{Fall\ Test} - y_K^{Spring\ Test} = \alpha \left(d_1^{Fall\ Test} - y_1^{Start} \right) - \beta \left(d_1^{Start} - y_K^{End} \right) - \gamma \left(d_K^{End} - d_K^{Spring\ Test} \right) + \varepsilon, \tag{2}$$

where ε is an error term. Student (i), school (s), and year (t) subscripts on the y^j, d^j, and ε in equation (2) are suppressed for notational convenience.[7] The parameter of interest is β, which represents the average daily rate of summer learning, and informs our understanding of the role that summers play in the education production function.

Recall that the primary objective of the current study is to test for differences in summer learning between exceptional and mainstream students. One way to do this is by estimating equation (2) separately for different types of students. Alternatively, equation (2) can be augmented to condition on observed student and school characteristics (X) and interactions between X and $\left(d_1^{Start} - y_K^{End} \right)$:

$$\begin{aligned} y_1^{Fall\ Test} - y_K^{Spring\ Test} = {} & \delta X + \alpha \left(d_1^{Fall\ Test} - y_1^{Start} \right) + \beta \left(d_1^{Start} - y_K^{End} \right) + \lambda X \left(d_1^{Start} - y_K^{End} \right) \\ & + \gamma \left(d_K^{End} - d_K^{Spring\ Test} \right) + \varepsilon, \end{aligned} \tag{3}$$

where X could include lagged achievement $\left(y_K^{Spring\ Test}\right)$.[8] When X does include lagged achievement, the model becomes a familiar lag-score value-added model (e.g., Sass et al. 2014).[9] Summer learning might depend on past achievement for at least two reasons. First, there might be "Matthew Effects" through which high-achieving students continue to learn at higher rates than their lower-achieving peers.[10] Second, convergence in test scores might occur if low-achieving students "catch up" by learning at relatively faster rates. We empirically investigate which, if either, of these scenarios occur in the next section. Finally, to examine whether the determinants of summer learning rates (e.g., household characteristics, summer activities) vary by exceptionality status, we will estimate equation (3) separately mainstream and exceptional students.

Results

Exceptional Students' Summer Activities

Table 4 thoroughly describes the differences between exceptional and mainstream students' participation in eight summer activities. Specifically, four regression specifications are estimated for each summer activity: models that do and do not control for student socioeconomic and demographic characteristics, and models that do and do not disaggregate the exceptional indicator into separate ELL and IEP indicators. The first five summer activities considered in table 4 are binary "participation indicators," so estimates of logit model average partial effects (APE) are reported.[11] As suggested by table 2, there are significant differences by students' exceptionality status in three of these outcomes: participation in organized activities, summer school, and summer day care.

Table 4 shows that these differences are robust to conditioning on student-level control variables, indicating that observed differences between exceptional and mainstream students' summer activities are not entirely driven by higher rates of exceptional designations among racial minority and low-income students. It is also interesting that, for the most part, differential rates of participation in summer activities between exceptional and non-exceptional students are equally driven by ELL and IEP students. Indeed, for no outcome are the ELL and IEP effects significantly different from one another at traditional confidence levels, though the effect of being an exceptional student on participation in organized activities appears to be mostly driven by IEP students rather than by ELL students.[12] That IEP students are less likely to participate in organized summer activities could be partly explained by the fact that IEP students are also about 7 percentage points more likely to be enrolled in summer school, though this only explains about half of IEP's negative effect on the likelihood of participating in an organized summer activity. Another possible explanation is that organized summer activities designed for students with learning disabilities are both less common and more expensive than mainstream summer activities (Williams 2010).

Column 6 of table 4 shows no evidence of significant differences by IEP or ELL status in the number of summer trips to bookstores and libraries, even after controlling for demographic and socioeconomic background. There are significant differences, however, in parental involvement: the positive and significant ordered logit coefficients reported in column 7 of table 4 suggest that the parents of exceptional students practice math with their children more frequently during the summer vacation than do the parents of mainstream students. No such differences are observed in the frequency with which parents read to children. However, the ordered logit coefficients cannot be directly interpreted (Wooldridge 2010), so APE on each categorical indicator (never, sometimes, and frequently) are reported in online appendix table A1. These APE show that after conditioning on observed student characteristics, exceptional students are about seven percentage points more likely to practice math with a parent every day, and about eleven percentage points less likely to never practice math with a parent, during the summer vacation than their mainstream counterparts. These effects are larger among ELL than IEP students, though once again the differences are not statistically significant. In sum, table 4 shows that significant differences in the summer activities of exceptional and mainstream students exist, are roughly similar for both IEP and ELL students, and are robust to conditioning on students' socioeconomic and demographic backgrounds.

Exceptional Students' Summer Learning

Table 5 presents estimates of both gain-score and lag-score variants of equation (3) that allow the effect of summer learning to vary by students' exceptionality status. Columns 1-4 do so for math achievement. The gain-score model estimated in column 1 restricts the difference in summer learning between exceptional and mainstream students to be homogeneous among all exceptional students, regardless of the reason for their classification. The point estimate of the interaction term is positive and fairly large in magnitude, suggesting that exceptional students experienced higher rates of summer learning than their mainstream peers, but is imprecisely estimated. The specification estimated in column (2) allows for ELL and IEP students to experience different summer learning rates, and once again these interaction terms are positive but statistically indistinguishable from zero. Qualitatively similar patterns are observed in the estimates of analogous lag-score models presented in columns (3) and (4). In sum, columns 1-4 of table 5 provide no evidence that exceptional students' summer math learning rates are different from those of their mainstream peers.

Columns 5-8 of table 5 report corresponding estimates for summer reading gains. The gain-score estimates in column (5) show that exceptional students experience larger summer reading gains than their mainstream counterparts, and that this difference is statistically significant at the 5% confidence level. Moreover, this difference is relatively large, as an additional ten days of summer vacation would translate to a gain equal to 15% of a test score SD. Column (6) allows summer learning rates to vary by the type of exceptionality, and these estimates show that the higher rate of exceptional student summer learning documented in column (5) was mostly driven by the summer reading gains of IEP students, though the difference between IEP and ELL students' summer learning rates is not significantly significant at traditional confidence levels, perhaps because of the relatively small number of exceptional students. Nonetheless, the summer learning premium for IEP students reported in column (6) is strongly statistically significant nearly twice as large as the average premium for all exceptional students estimated in column (5). Once again, analogous lag-score estimates reported in columns (7) and (8) paint a similar picture: exceptional students make reading achievement gains relative to their mainstream peers during the summer vacation, and those gains are almost entirely driven by IEP students' summer learning.[13] One possible explanation of this perhaps counterintuitive result is that, as shown in table 4, IEP students enroll in summer school at higher rates than both their ELL and mainstream peers. We further investigate this and other potential explanations in the next section.

Heterogeneity in the Determinants of Exceptional Students' Summer Learning

Table 6 reports estimates of the specification shown in equation (3) for reading achievement separately by students' exceptionality status.[14] The vector *X* in these specifications includes key student characteristics and summer activity indicators, which are allowed to affect exceptional and mainstream students' summer learning rates differently. Both gain-score and lag-score models are reported for reading achievement, as reading is the only subject in which differences between exceptional and mainstream students' summer learning rates were observed in table 5.[15] The first thing to note in table 6 is that for both gain-score and lag-score specifications, the estimated summer learning rate of exceptional students is about 0.02 SD larger than that of mainstream students. This magnitude is consistent with the exceptional student interaction terms reported in columns (5) and (7) of table 5 and confirms that these differences are robust to allowing summer learning rates to simultaneously vary with students' exceptionality status, SES, and participation in summer activities.

Otherwise, a scan of table 6 finds that poverty is the only observable student characteristic by which there are large, consistently statistically significant differences in exceptional students' summer learning rates.[16] This "poverty penalty" in exceptional students' summer learning is more than twice as large as the overall premium experienced by exceptional students during the summer vacation, and suggests that the results discussed above and in table 5 were driven by non-poor exceptional students. Particularly interesting with regards to the general literature on summer learning loss, however, is that there are no statistically significant differences by poverty status in mainstream students' reading summer learning rates. That low-income students experience significantly lower summer reading gains than their more advantaged counterparts is generally considered to be on the most robust, consistent findings in the summer learning loss literature (Burkam et al. 2004; Cooper et al. 1996; Downey et al. 2004).

The results presented in table 6 suggest that the disproportionate summer learning loss experienced by low-income students is almost entirely driven by low-income exceptional students—an important caveat that has not be recognized in the extant literature—and leads to dramatically different policy implications. Moreover, that this result holds in both the gain-score and lag-score models suggests that this is true across the achievement distribution.

Conclusion

This study contributes to the broad literature on summer learning loss by examining the summer activities and summer learning of exceptional student learners who either have an IEP or who speak a language other than English at home (ELL). The extant summer learning literature has yet to consider how exceptional students fare during the summer vacation, despite the presence of achievement gaps between exceptional and mainstream learners and the fact that exceptional learners are significantly more likely to come from low-income, immigrant, and racial/ethnic minority backgrounds. We contribute to this gap in the literature using nationally representative survey data from the 1999 Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K).

Our analysis yields four main results. First, there exist significant differences between how exceptional and mainstream students spend their summer vacations: exceptional students are significantly less likely to participate in organized summer activities and summer daycare programs, but are more likely to attend summer school or practice math with a parent, than their mainstream counterparts. Second, exceptional students experience significantly higher summer learning rates in reading than their mainstream counterparts. Interestingly, this difference is primarily driven by the summer learning of students who have an IEP. Third, reading summer learning rates of exceptional students in low-income households are significantly lower than those of non-poor exceptional students. Finally, we find no evidence of heterogeneity in reading summer learning rates by poverty status among mainstream students. This suggests that the lower rates of summer learning among low-income students documented in the extant summer learning loss literature are primarily attributable to low-income exceptional students, a caveat not yet acknowledged in the broader literature. Importantly, this finding neither contradicts nor invalidates previous research that finds variation by socioeconomic status in students' summer reading gains (e.g., Burkam et al. 2004; Downey et al. 2004). Rather, the current study adds nuance to this general result by uncovering another dimension of heterogeneity in children's summer learning rates and furthers our understanding of the mechanisms through which low-income students fall behind during the summer months.

Our primary contribution, then, is testing for and documenting heterogeneity in summer learning rates along multiple dimensions. In doing so, we document new findings in a well-traversed dataset (e.g., Bitler et al. 2015). Our analysis of heterogeneity along multiple observable dimensions is similar to two recent, prominent studies that further parsed previously studied discrepancies associated with SES and school quality by students' gender. For example, Chetty et al. (2016) show that well-known overall gender gaps in labor market outcomes, which favor males, are reversed for children who grew up in low-income families. Similarly, in the educational context, Autor et al. (2016) show that boys and girls significantly vary in their responsiveness to school quality. These results, like ours, highlight the policy-relevant nuances that can be obfuscated by a singular focus on average differences between groups.

That the lower rates of summer learning among low-income students are almost entirely driven by low-income exceptional learners raises several issues that merit further inquiry and have potential implications for education policy and practice. Regarding the former, the current study is unable to identify why, on average, exceptional learners, particularly those who have an IEP, experience higher rates of summer learning in reading than mainstream students. Nor does the current study identify the unique impediments to low-income exceptional learners' summer learning. The results presented in table 6 find no evidence that any of the summer activities recorded in the ECLS-K are associated with higher rates of summer learning, though this may be due to the relatively crude nature of many of the ECLS-K's summer activity survey instruments. Future research utilizing data with richer descriptions of the types and quality of students' summer activities, as well as the selection mechanisms through which students engage in such activities, would contribute greatly to our understanding of exceptional students' summer learning, and heterogeneity by socioeconomic status in summer learning rates more generally.

Similarly, because the "summer setback" in reading gains among low-income children in the ECLS-K is almost entirely due to the summer learning rates of low-income exceptional learners adds an important caveat to a long-standing, accepted result in the summer learning loss literature, it is important that future research investigates the robustness of this finding in other contexts and datasets. Specifically, probing this result using administrative data from states or large districts would be useful for at least two reasons (Figlio et al. 2015). First, such analyses would provide more statistical power (i.e., larger numbers of exceptional learners) with which to precisely identify differences in learning rates, and further distinguish between IEP and ELL students. Second, data on the entire student population would facilitate research designs that better control for confounding factors. For example, administrative data that includes both fall and spring test scores could be used to compare the summer learning of exceptional and mainstream students who live on the same block or in the same household (i.e., siblings). These differences could then be compared across high- and low-income households and neighborhoods.

Regarding policy and practice, that low-income exceptional learners experience significantly lower summer learning rates in reading than either mainstream students or more-advantaged exceptional students highlights the potential for well designed, well implemented, targeted summer programs. For example, multisite randomized control trials of the K-3 Plus program in New Mexico find significant impacts on ELL and bilingual students' reading gains during the summer vacation in high-poverty schools (Cann et al. 2015). Similarly, an experimental analysis of three-week summer camps offers in a large German city designed to boost immigrant students' German language skills found that a combined treatment of implicit (theatre program) and explicit (German language instruction) supports significantly increased reading achievement (Stanat et al. 2012). These results are consistent with broader evidence that remedial summer programs targeted to low-performing students tend to increase achievement (Cooper et al., 2000). As evidence on the efficacy of summer programs that cater to exceptional learners mounts, these targeted programs have the potential to improve the educational outcomes of exceptional learners who face the compounding challenge of economic disadvantage. The efficacy of summer interventions targeted to IEP students should be similarly evaluated.

Notes

[1] Source: Authors' calculations of the Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K). The National Council of Teachers of English (NCTE) defines ELL students as "active learners of the English language who may benefit from various types of language support programs." The term ELL is usually used in the K-12 context and may or may not indicate a lack of mastery of English. The U.S. Department of Education designates students who do not meet state standards in English Language Arts as Limited English Proficient (LEP). See http://www.ncte.org/library/NCTEFiles/Resources/PolicyResearch/ELLResearchBrief.pdf for additional discussion of ELL and LEP designations. The IEP requires teachers, parents, administrators, and related personnel to work together to put together a plan to improve educational results for a public school student who receives special education services. See the U.S. Department of Education website for more information, http://www2.ed.gov/parents/needs/speced/iepguide/index.html#introduction. The ECLS-K receives reports of IEP status for each student directly from the student's school. The variable in the first-grade data file is named U2RIEP. This is an indicator variable that equals one if the student had an IEP on record at his/her school in kindergarten, and zero otherwise.

[2] Source: Authors' calculations of the ECLS-K: 2011.

[3] In our analytical sample, 24% of Hispanic kindergarten students are ELL.

[4] Heterogeneous summer learning rates have been referred to as summer learning loss, summer setback, and summer slide.

[5] The NCES created the household-level poverty variable by using the imputed household income. For each household, the income was compared to preliminary 1998 Census poverty

thresholds, which vary by household size. Households are classified as poor if the household's income fell below the appropriate threshold.

[6] The organized summer activity indicator was constructed using data from the parent survey in the fall of first grade on whether or not the child participated in dance lessons, music lessons, swimming lessons, team sports, individual sports, or boy scouts over the summer. This variable takes the value one if the child participated in any of these activities, and 0 otherwise.

[7] Hayes and Gershenson (2015) consider higher-order polynomials and conduct RESET specification tests, which confirm that the RHS of equation (2) is approximately linear.

[8] Interacting *X* with the other terms in equation (2) does not appreciably change the estimates of the parameters of interest (the estimated coefficients on vacation length and its interactions).

[9] For example, if $y^{t+1} - y^t = \beta y^t$ and $y^{t+1} = \alpha y^t$, then $\alpha = \beta + 1$. Quinn (2015) notes that in the context of summer learning, gain-score and lag-score specifications are typically not equivalent, as the former estimates "unconditional" summer learning rates, while the latter estimates summer learning rates conditional on achievement in the previous spring.

[10] The "Matthew effect" occurs when early gains in reading skills lead to future gains in reading skills and gains in other subjects (Stanovich 1986).

[11] Average partial effects measure the effect of a one unit change in an element of X on $\Pr(Y = 1|X)$ and are directly comparable to the OLS coefficient estimate (e.g., Wooldridge 2010).

[12] The p-values from t-tests of the equality of the IEP and ELL coefficients are uniformly larger than 0.10.

[13] This result is broadly robust to the operationalized definition of both IEPs and test scores. Regarding the former, online appendix tables A2, A3, and A4 show that this result is robust to coding IEP as a binary indicator equal to one if the child was categorized as having an IEP in any

wave of the ECLS-K, coding IEP as a binary indicator equal to one if the child was categorized as having an IEP in both the kindergarten and first grade waves of the ECLS-K, and to excluding students who did not receive an IEP in kindergarten but did receive one in a subsequent wave of the ECLS-K from the analytic sample, respectively; thus this finding is not unique to IEPs given to kindergarten students. Regarding the latter, online appendix tables A5 and A6 show that this result is robust to instead using unstandardized IRT scale scores and theta scores, respectively. Theta scores are estimates of latent student ability and capture student-specific aptitude in the academic skills measured by the ECLS-K assessments. Using the ECLS-K, Quinn (2015) shows that estimates of racial gaps in summer learning can be sensitive to the standardization, scaling, and assumptions underlying the assessments. We show that our results are robust to using the ECLS-K's theta estimates preferred by Quinn (2015). Finally, online appendix table A7 shows that this finding is robust to using an alternative strategy for adjusting for the fact that tests administered on neither the first nor last days of the school year. Specifically, table A7 uses first and last day of school extrapolated theta scores, which were computed assuming a linear, student-specific learning rate as in Quinn (2015).

[14] Unfortunately, with only 100 exceptional students in the analytic sample, we are unable to estimate these models separately by IEP and ELL status. Interacting the covariates in the baseline model with the exceptional yields qualitatively similar results. We report the estimates of separate models to facilitate a side-by-side presentation.

[15] More generally, reading is the only subject in which the extant literature on summer learning loss routinely finds evidence of heterogeneity by observable student characteristics in summer learning rates (e.g., Burkam et al. 2004; Downey et al. 2004; Entwisle and Alexander 1992).

Online appendix table A12 reports the same exercise for math, where once again no significant differences are observed.

[16] Online appendix table A8 shows the same qualitative result when the poverty indicator is replaces with an index that purports to measure socioeconomic status (SES). The SES index was created by the ECLS-K and is a weighted average of parents' income, education, and occupation. That the SES interaction term is large and positive, but less precisely estimated than the poverty interaction term, suggests that household income is driving the result. Finally, like the main results in table 5, online appendix tables A9, A10, and A11 show that the qualitative patterns observed in table 6 are robust to using unstandardized scale scores, theta scores, and theta scores extrapolated to the first and last days of the academic year, respectively.

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TABLE 1

Calendar Days Between Important Dates

	Exceptional Students		Mainstream Students	
	Mean	SD	Mean	SD
Spring K test and fall 1st test ($d^D - d^A$)	149.89	21.91	151.69	20.32
End of K and start of 1st ($d^C - d^B$)	81.32	5.41	80.73	5.24
Start of 1st and fall 1st Test ($d^D - d^C$)	37.99	13.78	40.80	14.65
Spring K test and end of K ($d^B - d^A$)	30.58	15.69	30.17	14.32
Days between kindergarten tests	188.06	19.49	186.99	21.18
Days between first-grade tests	210.98	18.83	209.31	20.94
N (Students)	100		1250	
N (Schools)	50		100	

NOTE – Means and standard deviations (SD) are weighted by NCES provided sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, and * p<0.1 indicate the statistical significance of the mean difference between exceptional and mainstream students.

TABLE 2
Student Descriptive Statistics

Student Characteristics	ELL Students	IEP Students	Exceptional Students	Mainstream Students
Does not speak English at home	100%	2.0%	39.9%	0.0%
Individualized Education Plan (IEP)	3.0%	100%	58.9%	0.0%
Both ELL and IEP	3.0%	2.0%	1.2%	0.0%
White	18.9%***	79.5%	55.5%***	76.0%
Black	1.5%	3.8%	2.9%***	11.6%
Hispanic	63.9%***	10.3%	31.2%***	7.5%
Other race/ethnicity	15.7%	6.4%	10.3%*	4.9%
Female	43.8%	34.4%	38.7%**	51.9%
Poverty	18.1%	23.4%	20.3%**	12.2%
Kindergarten Redshirt	8.0%	8.9%	8.6%	6.9%
Mom did not graduate high school	17.5%	12.0%	14.4%**	5.9%
Mom has high school diploma	37.2%	48.7%	43.4%	33.6%
Mom attended some college	25.0%	20.5%	22.6%*	32.0%
Mom has bachelor's degree+	20.3%	18.8%	19.6%*	28.4%
Computer at Home	38.0%*	53.6%	47.8%***	64.1%
Number of Books at Home	56.92	127.90	100.0	114.14
Summer Activities				
Organized Summer Activities	43.7%	32.6%	36.4%***	56.3%
Attended Summer School	17.9%	18.7%	18.6%***	7.6%
# of Trips to Library/Bookstore	7.2	6.3	6.7	6.9
Never Practice Math	10.8%	10.1%	9.3%***	19.5%
Sometimes Practices Math	69.4%	81.2%	77.4%*	70.1%
Practices Math Everyday	19.8%	8.7%	13.4%	10.4%
Never Reads to Child	1.3%	1.0%	1.2%	2.6%
Sometimes Reads to Child	50.2%	54.5%	52.2%	51.9%
Reads to Child Everyday	48.5%	44.5%	46.7%	45.5%
Attended Summer Camp	18.4%	20.4%	19.8%	25.2%
Attended Summer Tutoring	1.3%	3.8%	2.8%	2.3%
Attended Summer Daycare	2.1%	3.8%	3.2%***	10.8%
N Children	50	50	100	1250
N Schools	25	25	50	100

NOTE – Means are weighted by NCES provided sampling weights to account for unequal probabilities of sample selection. *** $p<0.01$, ** $p<0.05$, and * $p<0.1$ indicate the statistical significance of the mean difference between ELL and IEP students, as well as, the statistical significance of the mean difference between exceptional and mainstream students.

TABLE 3
IEP Descriptive Statistics

Number of IEP Goals	K Wave	Grade 1	Grade 3	Grade 5	Grade 8
Multiple Goals	.	38%	34%	50%	73%
Single Goal	.	7%	11%	17%	14%
Missing Data	100%	55%	55%	33%	13%
Type of IEP Goal					
Reading	.	19%	33%	43%	64%
Math	.	12%	21%	28%	52%
Language Arts	.	21%	33%	45%	68%
Science	.	.	.	1%	7%
Articulation	.	4%	17%	16%	3%
Language Pragmatics	.	.	11%	7%	6%
Oral Expression	.	30%	10%	17%	9%
Auditory Process	.	22%	6%	8%	4%
Listening Comprehension	.	34%	6%	12%	7%
Transitional Goals	.	.	.	.	3%
Social Skills	.	8%	5%	10%	22%
Adaptive Behavior	.	0%	3%	3%	16%
Fine Motor Skills	.	6%	11%	6%	1%
Gross Motor Skills	.	6%	7%	3%	5%
Orientation & Mobility	.	5%	1%	3%	0%
Other	.	1%	1%	1%	20%
Timing of IEP Classification					
New IEP	100%	48%	54%	44%	21%
Previously had IEP	0%	52%	46%	56%	79%
N	50	50	100	100	50

NOTE – Means are weighted by NCES provided sampling weights to account for unequal probabilities of sample selection. The ECLS-K provides no information on IEP goals for students in kindergarten.

TABLE 4

Gaps by Exceptionality in Summer Activities

Model:	Binary Logit (APE reported)					Poisson	Ordered Logit	
Activity:	Organized Activities	Summer School	Summer Camp	Tutoring	Day Care	Bookstore/ Library Trips	Practices Math w/ child	Reads to child
Coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exceptional (No Controls)	-0.199***	0.079***	-0.058	0.005	-0.119**	-0.036	0.536**	0.073
	(0.054)	(0.024)	(0.044)	(0.015)	(0.048)	(0.150)	(0.216)	(0.229)
Exceptional (Controls)	-0.119**	0.082***	0.033	0.005	-0.112**	0.060	0.751***	0.276
	(0.047)	(0.025)	(0.044)	(0.017)	(0.054)	(0.111)	(0.222)	(0.224)
ELL (No Controls)	-0.117	0.072**	-0.074	-0.014	-0.155*	0.041	0.737**	0.138
	(0.079)	(0.036)	(0.070)	(0.024)	(0.087)	(0.231)	(0.356)	(0.314)
IEP (No Controls)	-0.236***	0.077**	-0.050	0.012	-0.099*	-0.101	0.306	-0.012
	(0.074)	(0.031)	(0.062)	(0.017)	(0.057)	(0.171)	(0.270)	(0.304)
p value (ELL = IEP)	0.25	0.91	0.82	0.36	0.58	0.61	0.29	0.73
ELL (Controls)	-0.025	0.062	0.068	-0.021	-0.150	0.249	0.809***	0.385
	(0.063)	(0.041)	(0.052)	(0.027)	(0.093)	(0.182)	(0.312)	(0.333)
IEP (Controls)	-0.158**	0.085***	0.012	0.018	-0.092	-0.065	0.602*	0.148
	(0.070)	(0.031)	(0.066)	(0.017)	(0.059)	(0.132)	(0.318)	(0.313)
p value (ELL = IEP)	0.16	0.66	0.53	0.19	0.58	0.17	0.61	0.62

NOTE – N = 1,350. Standard errors are clustered at the school level. The four horizontal bars separate estimates from four distinct specifications. The first two include an aggregate binary indicator of exceptionality, with and without other student-level controls, respectively. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). The next two specifications disaggregate the exceptional indicator into separate ELL and IEP indicators, with and without other student controls, respectively. The vector of controls includes race, poverty status, mother's educational attainment, summer activities, and school characteristics. APE = Average Partial Effect. APE for the ordered logit models described in columns 7 and 8 of this table are provided in table A1 in the online appendix. The dependent variables in the ordered logit models are coded as follows: 1 = Never, 2 = Some days of the week, and 3 = Every day. Regressions are weighted by NCES provided sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 5
Exceptional Students' Summer Learning

	Math				Reading			
	Gain-Score		Lag-Score		Gain-Score		Lag-Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(d^D - d^C)$	0.007***	0.007***	0.008***	0.008***	0.004***	0.004***	0.005***	0.005***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$(d^C - d^B)$ summer vacation	0.001	0.001	-0.001	-0.001	0.007***	0.007***	0.005**	0.005*
	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$(d^B - d^A)$	0.003***	0.003***	0.001	0.001	0.002**	0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exceptional	-1.169		-0.679		-1.158*		-0.946	
	(1.185)		(0.985)		(0.598)		(0.575)	
ELL		-2.354		-1.905		-0.585		-0.539
		(1.735)		(1.469)		(0.908)		(0.938)
IEP		-0.589		-0.054		-2.147***		-1.877***
		(1.633)		(1.368)		(0.772)		(0.693)
Exceptional×$(d^C - d^B)$	0.016		0.008		0.015**		0.012*	
	(0.015)		(0.012)		(0.007)		(0.007)	
ELL×$(d^C - d^B)$		0.031		0.024		0.009		0.008
		(0.022)		(0.018)		(0.011)		(0.012)
IEP×$(d^C - d^B)$		0.008		-0.000		0.027***		0.023***
		(0.019)		(0.016)		(0.009)		(0.008)
Adjusted R^2	0.0418	0.0414	0.700	0.700	0.0420	0.0424	0.808	0.808
Tests of Equality (*p* values)								
(*ELL*) = (*IEP*)		0.40		0.32		0.22		0.29
ELL×$(d^C - d^B)$ = IEP×$(d^C - d^B)$		0.36		0.27		0.25		0.34

NOTES – N = 1,350. Standard errors are clustered at the school level. All models include student-level controls: race, poverty status, mother's educational attainment, summer activities, and school characteristics. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6

Heterogeneity in Average Summer Reading Learning Rates in the ECLS-K

	Gain Score Model		Lag Score Model	
	Exceptional	Mainstream	Exceptional	Mainstream
	(1)	(2)	(3)	(4)
$(d^D - d^C)$	0.006*	0.004***	0.007**	0.004***
	(0.003)	(0.001)	(0.003)	(0.001)
$(d^C - d^B)$ (Summer; S)	0.045***	0.018**	0.023*	0.014**
	(0.017)	(0.007)	(0.012)	(0.007)
$(d^B - d^A)$	0.005*	0.002**	0.003	0.001
	(0.003)	(0.001)	(0.002)	(0.001)
Lag-score×S	.	.	-0.013*	-0.003
			(0.007)	(0.002)
Poverty ×S	-0.032	-0.003	-0.047**	-0.005
	(0.022)	(0.007)	(0.021)	(0.006)
Org. Summer Activity×S	-0.020	-0.006	-0.002	-0.003
	(0.022)	(0.006)	(0.020)	(0.005)
Summer school×S	-0.026	-0.011	-0.012	-0.008
	(0.021)	(0.007)	(0.011)	(0.006)
Summer library/bookstore trips×S	-0.001	-0.001*	-0.000	-0.001
	(0.001)	(0.000)	(0.001)	(0.000)
Parent reads every day×S	-0.017	-0.002	-0.017	-0.002
	(0.018)	(0.005)	(0.015)	(0.005)
Attends summer camp×S	0.017	0.002	0.005	0.004
	(0.025)	(0.005)	(0.021)	(0.005)
Attends summer tutor×S	-0.041**	0.021	-0.041	0.013
	(0.017)	(0.013)	(0.035)	(0.014)
Attends summer day care×S	0.067***	0.000	0.025	0.001
	(0.023)	(0.007)	(0.017)	(0.007)
Adjusted R^2	0.18	0.03	0.81	0.80
Joint sig. of interactions (*F*)	7.91***	1.02	7.14***	1.18
N	100	1,250	100	1,250

NOTE – Standard errors are clustered at the school level. All models include all un-interacted student-level controls and "summer length." The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

The Summer Learning of Exceptional Students

TABLE A1

Ordered Logit Average Partial Effects (APE)

Frequency:	Never	Sometimes	Everyday
	(1)	(2)	(3)
A. Practices Math with Parent			
Exceptional, No Controls	-0.081**	0.030**	0.051**
	(0.032)	(0.013)	(0.021)
Exceptional, Controls	-0.110***	0.040***	0.070***
	(0.032)	(0.013)	(0.021)
ELL, No Controls	-0.112**	0.041*	0.070**
	(0.053)	(0.021)	(0.034)
IEP, No Controls	-0.046	0.017	0.029
	(0.040)	(0.015)	(0.026)
ELL, Controls	-0.119***	0.043**	0.076**
	(0.045)	(0.018)	(0.030)
IEP, Controls	-0.088*	0.032*	0.056*
	(0.046)	(0.017)	(0.030)
B. Reads with Parent			
Exceptional, No Controls	-0.002	-0.016	0.018
	(0.005)	(0.051)	(0.057)
Exceptional, Controls	-0.006	-0.058	0.065
	(0.005)	(0.047)	(0.053)
ELL, No Controls	-0.003	-0.031	0.034
	(0.008)	(0.071)	(0.078)
IEP, No Controls	0.000	0.003	-0.003
	(0.007)	(0.068)	(0.075)
ELL, Controls	-0.009	-0.081	0.090
	(0.008)	(0.070)	(0.078)
IEP, Controls	-0.003	-0.031	0.035
	(0.007)	(0.066)	(0.073)

NOTE – N = 1,350. Standard errors are clustered at the school level. The APE in panels A and B of this table correspond to the ordered logit models presented and discussed in columns 7 and 8 of table 4, respectively. The four horizontal bars in each panel separate estimates from four distinct specifications. The first two include an aggregate binary indicator of exceptionality, with and without other student-level controls, respectively. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). The next two specifications disaggregate the exceptional indicator into separate ELL and IEP indicators, with and without other student controls, respectively. The vector of controls includes race, poverty status, mother's educational attainment, summer activities, and school characteristics.

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

TABLE A2

Exceptional Students' Summer Learning (IEP defined as ever IEP from K-8)

	Math				Reading			
	Gain-Score		Lag-Score		Gain-Score		Lag-Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(d^D - d^C)$	0.007***	0.007***	0.008***	0.008***	0.004***	0.004***	0.005***	0.005***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$(d^C - d^B)$ summer vacation	0.001	0.001	-0.001	-0.001	0.006**	0.006**	0.005*	0.005*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$(d^B - d^A)$	0.003***	0.003***	0.001	0.001	0.002**	0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exceptional	-0.576		-0.363		-0.871***		-0.716**	
	(0.485)		(0.423)		(0.288)		(0.284)	
ELL		-2.321		-1.808		-0.630		-0.554
		(1.632)		(1.358)		(0.884)		(0.912)
IEP		-0.337		-0.182		-0.985***		-0.840**
		(0.731)		(0.718)		(0.343)		(0.352)
Exceptional×$(d^C - d^B)$	0.007		0.003		0.011***		0.008**	
	(0.006)		(0.005)		(0.004)		(0.004)	
ELL×$(d^C - d^B)$		0.030		0.023		0.009		0.008
		(0.020)		(0.017)		(0.011)		(0.011)
IEP×$(d^C - d^B)$		0.004		-0.000		0.012***		0.010**
		(0.009)		(0.009)		(0.004)		(0.004)
Adjusted R^2	0.04	0.04	0.70	0.70	0.04	0.04	0.81	0.81
Tests of Equality (*p* values)								
(*ELL*) = (*IEP*)		0.35		0.40		0.73		0.79
ELL×$(d^C - d^B)$ = IEP×$(d^C - d^B)$		0.31		0.34		0.81		0.90

NOTE – N = 1,350. Standard errors are clustered at the school level. All models include student-level controls. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or ever had an Individualized Education Program (IEP) from kindergarten to eighth grade. All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A3

Exceptional Students' Summer Learning (IEP defined as having IEP in K and 1st grade)

	Math				Reading			
	Gain-Score		Lag-Score		Gain-Score		Lag-Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(d^D - d^C)$	0.007***	0.007***	0.008***	0.008***	0.004***	0.004***	0.005***	0.005***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$(d^C - d^B)$ summer vacation	0.001	0.001	-0.001	-0.001	0.007***	0.007**	0.006**	0.005**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
$(d^B - d^A)$	0.003***	0.003**	0.001	0.001	0.002**	0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exceptional	-1.731		-1.007		-1.217*		-0.886	
	(1.213)		(1.082)		(0.693)		(0.672)	
ELL		-2.286		-1.859		-0.543		-0.503
		(1.690)		(1.446)		(0.909)		(0.939)
IEP		-3.377**		-1.811		-3.435***		-2.748***
		(1.582)		(1.473)		(0.860)		(0.833)
Exceptional×$(d^C - d^B)$	0.021		0.011		0.016*		0.011	
	(0.015)		(0.013)		(0.008)		(0.008)	
ELL×$(d^C - d^B)$		0.030		0.023		0.008		0.007
		(0.021)		(0.018)		(0.011)		(0.012)
IEP×$(d^C - d^B)$		0.039**		0.019		0.041***		0.032***
		(0.019)		(0.017)		(0.010)		(0.010)
Adjusted R^2	0.066	0.072	0.709	0.710	0.066	0.071	0.813	0.814
Tests of Equality (*p* values)								
(*ELL*) = (*IEP*)		0.63		0.98		0.03**		0.09*
ELL×$(d^C - d^B)$ = IEP×$(d^C - d^B)$		0.74		0.86		0.04**		0.12

NOTE – N = 1,350. Standard errors are clustered at the school level. All models include student-level controls. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP) in both kindergarten and first grade. All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A4

Exceptional Students' Summer Learning (Excluded students who receive IEP designation after Kindergarten)

	Math				Reading			
	Gain-Score		Lag-Score		Gain-Score		Lag-Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(d^D - d^C)$	0.008***	0.008***	0.008***	0.008***	0.004***	0.004***	0.005***	0.005***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$(d^C - d^B)$ summer vacation	0.001	0.001	-0.001	-0.001	0.006**	0.006**	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$(d^B - d^A)$	0.003***	0.003***	0.002	0.001	0.002**	0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exceptional	-1.068		-0.532		-1.376**		-1.085*	
	(1.098)		(0.889)		(0.571)		(0.556)	
ELL		-2.285		-1.779		-0.708		-0.585
		(1.627)		(1.370)		(0.899)		(0.928)
IEP		-0.478		0.047		-2.374***		-2.060***
		(1.615)		(1.343)		(0.744)		(0.682)
Exceptional×$(d^C - d^B)$	0.014		0.006		0.018**		0.013**	
	(0.013)		(0.011)		(0.007)		(0.007)	
ELL×$(d^C - d^B)$		0.030		0.022		0.010		0.008
		(0.020)		(0.017)		(0.011)		(0.012)
IEP×$(d^C - d^B)$		0.007		-0.002		0.030***		0.025***
		(0.019)		(0.016)		(0.009)		(0.008)
Adjusted R^2	0.05	0.05	0.69	0.69	0.04	0.04	0.80	0.80
Tests of Equality (*p* values)								
(*ELL*) = (*IEP*)		0.39		0.33		0.19		0.25
ELL×$(d^C - d^B)$ = IEP×$(d^C - d^B)$		0.35		0.27		0.22		0.30

NOTE – N = 1,250. Standard errors are clustered at the school level. All models include student-level controls: race, poverty status, mother's educational attainment, summer activities, and school characteristics. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP) in both kindergarten and first grade. The sample excludes students who did not receive an IEP in kindergarten but did receive one in a subsequent wave of the ECLS-K. All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE A5

Exceptional Students' Summer Learning Using Unstandardized IRT Scale Scores

	Math				Reading			
	Gain-Score		Lag-Score		Gain-Score		Lag-Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(d^D - d^C)$	0.072***	0.072***	0.079***	0.078***	0.067***	0.066***	0.063***	0.063***
	(0.016)	(0.015)	(0.013)	(0.013)	(0.015)	(0.014)	(0.014)	(0.014)
$(d^C - d^B)$ summer vacation	0.005	0.004	-0.009	-0.010	0.060*	0.059	0.070**	0.069*
	(0.045)	(0.045)	(0.043)	(0.043)	(0.036)	(0.036)	(0.035)	(0.035)
$(d^B - d^A)$	0.026**	0.025**	0.013	0.012	0.007	0.006	0.014	0.013
	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
Exceptional	-9.882		-6.491		-11.018		-12.274	
	(10.700)		(9.422)		(7.636)		(7.461)	
ELL		-21.332		-18.219		-6.714		-6.986
		(15.728)		(14.055)		(12.917)		(12.169)
IEP		-4.222		-0.513		-22.761***		-24.343***
		(14.779)		(13.083)		(8.601)		(8.984)
Exceptional×$(d^C - d^B)$	0.128		0.076		0.135		0.154*	
	(0.131)		(0.115)		(0.092)		(0.090)	
ELL×$(d^C - d^B)$		0.276		0.230		0.095		0.101
		(0.196)		(0.173)		(0.161)		(0.152)
IEP×$(d^C - d^B)$		0.056		-0.001		0.268**		0.292***
		(0.175)		(0.154)		(0.103)		(0.107)
Adjusted R^2	0.05	0.05	0.70	0.70	0.05	0.05	0.81	0.81
Tests of Equality (*p* values)								
(*ELL*) = (*IEP*)		0.37		0.32		0.34		0.29
ELL×$(d^C - d^B)$ = IEP×$(d^C - d^B)$		0.33		0.27		0.40		0.34

NOTE – N = 1,350. Standard errors are clustered at the school level. All models include student-level controls: race, poverty status, mother's educational attainment, summer activities, and school characteristics. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A6

Exceptional Students' Summer Learning (Using Theta Scores)

	Math				Reading			
	Gain-Score		Lag-Score		Gain-Score		Lag-Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(d^D - d^C)$	0.003***	0.003***	0.004***	0.004***	0.002***	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$(d^C - d^B)$ summer vacation	0.001	0.001	-0.000	-0.000	0.003***	0.003***	0.003**	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$(d^B - d^A)$	0.002***	0.002***	0.001*	0.001*	0.001***	0.001***	0.001*	0.001*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Exceptional	-0.754		-0.524		-0.722**		-0.610*	
	(0.547)		(0.464)		(0.325)		(0.311)	
ELL		-1.362		-1.155*		-0.550		-0.562
		(0.822)		(0.696)		(0.533)		(0.533)
IEP		-0.438		-0.197		-1.216***		-1.028**
		(0.726)		(0.639)		(0.430)		(0.398)
Exceptional×$(d^C - d^B)$	0.010		0.006		0.009**		0.008**	
	(0.007)		(0.006)		(0.004)		(0.004)	
ELL×$(d^C - d^B)$		0.018*		0.015*		0.008		0.008
		(0.010)		(0.009)		(0.007)		(0.007)
IEP×$(d^C - d^B)$		0.006		0.002		0.015***		0.012**
		(0.009)		(0.008)		(0.005)		(0.005)
Adjusted R^2	0.05	0.05	0.72	0.72	0.06	0.06	0.80	0.80
Tests of Equality (*p* values)								
(*ELL*) = (*IEP*)		0.33		0.26		0.37		0.53
ELL×$(d^C - d^B)$ = IEP×$(d^C - d^B)$		0.29		0.22		0.43		0.62

NOTE – N = 1,350. Standard errors are clustered at the school level. All models include student-level controls: race, poverty status, mother's educational attainment, summer activities, and school characteristics. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A7

Exceptional Students' Summer Learning [Theta Score – Extrapolation Model]

	Math				Reading			
	Gain-Score		Lag-Score		Gain-Score		Lag-Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(d^D - d^C)$	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.
$(d^C - d^B)$ summer vacation	0.001	0.001	-0.000	-0.001	0.003*	0.003*	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
$(d^B - d^A)$	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.
Exceptional	-0.911		-0.620		-0.775**		-0.643*	
	(0.686)		(0.570)		(0.361)		(0.337)	
ELL		-1.539		-1.297		-0.483		-0.504
		(1.054)		(0.885)		(0.591)		(0.574)
IEP		-0.626		-0.307		-1.278***		-1.055***
		(0.871)		(0.751)		(0.433)		(0.388)
Exceptional×$(d^C - d^B)$	0.012		0.007		0.010**		0.008*	
	(0.008)		(0.007)		(0.004)		(0.004)	
ELL×$(d^C - d^B)$		0.020		0.016		0.007		0.007
		(0.013)		(0.011)		(0.008)		(0.007)
IEP×$(d^C - d^B)$		0.008		0.003		0.016***		0.013***
		(0.010)		(0.009)		(0.005)		(0.005)
Adjusted R^2	0.04	0.04	0.65	0.65	0.05	0.06	0.76	0.76
Tests of Equality (*p* values)								
(*ELL*) = (*IEP*)		0.45		0.35		0.27		0.43
ELL×$(d^C - d^B)$ = IEP×$(d^C - d^B)$		0.41		0.30		0.31		0.50

NOTE – N = 1,350. Standard errors are clustered at the school level. All models include student-level controls: race, poverty status, mother's educational attainment, summer activities, and school characteristics. The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A8

Heterogeneity in Average Summer Reading Learning Rates in the ECLS-K

	Gain Score Model		Lag Score Model	
	Exceptional (1)	Mainstream (2)	Exceptional (3)	Mainstream (4)
$(d^D - d^C)$	0.005	0.004***	0.006**	0.004***
	(0.003)	(0.001)	(0.003)	(0.001)
$(d^C - d^B)$ (Summer; S)	0.044**	0.017**	0.024**	0.013**
	(0.017)	(0.007)	(0.011)	(0.006)
$(d^B - d^A)$	0.004	0.002**	0.002	0.001
	0.005	0.004***	0.006**	0.004***
Lag-score×S	.	.	-0.016**	-0.003
			(0.006)	(0.002)
SES Index ×S	0.005	0.003	0.024	0.002
	(0.017)	(0.005)	(0.015)	(0.005)
Org. Summer Activity×S	-0.015	-0.006	0.006	-0.003
	(0.020)	(0.006)	(0.016)	(0.005)
Summer school×S	-0.028	-0.010	-0.008	-0.008
	(0.024)	(0.007)	(0.014)	(0.007)
Summer library/bookstore trips×S	-0.001	-0.001*	-0.001	-0.001
	(0.001)	(0.000)	(0.001)	(0.000)
Parent reads every day×S	-0.016	-0.003	-0.016	-0.003
	(0.018)	(0.005)	(0.015)	(0.005)
Attends summer camp×S	0.016	0.002	-0.016	0.004
	(0.023)	(0.005)	(0.016)	(0.005)
Attends summer tutor×S	-0.035**	0.023*	-0.036	0.015
	(0.017)	(0.012)	(0.030)	(0.013)
Attends summer day care×S	0.072***	0.000	0.038*	0.000
	(0.025)	(0.008)	(0.020)	(0.007)
Adjusted R^2	0.14	0.03	0.80	0.80
Joint sig. of interactions (*F*)	7.78***	1.15	9.80***	1.16
N	100	1,250	100	1,250

NOTE – Standard errors are clustered at the school level. All models include all un-interacted student-level controls and "summer length." The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE A9

Heterogeneity in Average Summer Reading Learning Rates (Unstandardized Scale Scores)

	Gain Score Model		Lag Score Model	
	Exceptional	Mainstream	Exceptional	Mainstream
	(1)	(2)	(3)	(4)
$(d^D - d^C)$	0.086**	0.058***	0.088**	0.055***
	(0.034)	(0.014)	(0.034)	(0.014)
$(d^C - d^B)$ (Summer; S)	0.439***	0.137*	0.827***	0.316***
	(0.142)	(0.082)	(0.242)	(0.104)
$(d^B - d^A)$	0.048*	0.009	0.043	0.015
	(0.028)	(0.014)	(0.031)	(0.014)
Lag-score×S	.	.	-0.016*	-0.004
			(0.009)	(0.003)
Poverty ×S	-0.524*	-0.053	-0.610**	-0.063
	(0.264)	(0.077)	(0.272)	(0.079)
Org. Summer Activity×S	-0.141	-0.031	-0.030	-0.044
	(0.256)	(0.065)	(0.260)	(0.067)
Summer school×S	-0.106	-0.054	-0.159	-0.106
	(0.157)	(0.082)	(0.146)	(0.082)
Summer library/bookstore trips×S	-0.007	-0.006	-0.006	-0.007
	(0.009)	(0.005)	(0.009)	(0.005)
Parent reads every day×S	-0.281	-0.036	-0.219	-0.027
	(0.195)	(0.069)	(0.194)	(0.064)
Attends summer camp×S	0.099	0.045	0.067	0.053
	(0.290)	(0.063)	(0.269)	(0.061)
Attends summer tutor×S	-0.417	0.138	-0.528	0.173
	(0.327)	(0.191)	(0.453)	(0.175)
Attends summer day care×S	0.501**	0.034	0.327	0.009
	(0.226)	(0.096)	(0.227)	(0.095)
Adjusted R^2	0.17	0.04	0.81	0.80
Joint sig. of interactions (*F*)	4.64***	0.53	7.14***	1.18
N	100	1,250	100	1,250

NOTE – N = 1,350. Standard errors are clustered at the school level. Standard errors are clustered at the school level. All models include all un-interacted student-level controls and “summer length.” The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A10

Heterogeneity in Average Summer Reading Learning Rates in the ECLS-K (Theta)

	Gain Score Model		Lag Score Model	
	Exceptional	Mainstream	Exceptional	Mainstream
	(1)	(2)	(3)	(4)
$(d^D - d^C)$	0.003*	0.002***	0.004**	0.002***
	(0.002)	(0.001)	(0.001)	(0.001)
$(d^C - d^B)$ (Summer; S)	0.030***	0.008**	0.011	0.003
	(0.008)	(0.004)	(0.010)	(0.004)
$(d^B - d^A)$	0.003**	0.001**	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Lag-score×S	.	.	-0.012	-0.005
			(0.008)	(0.003)
Poverty ×S	-0.022	-0.003	-0.029**	-0.004
	(0.016)	(0.004)	(0.012)	(0.003)
Org. Summer Activity×S	-0.009	-0.003	-0.001	-0.002
	(0.012)	(0.003)	(0.012)	(0.002)
Summer school×S	-0.017*	-0.005	-0.012*	-0.004
	(0.010)	(0.004)	(0.006)	(0.003)
Summer library/bookstore trips×S	-0.001	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Parent reads every day×S	-0.013	-0.001	-0.012	-0.001
	(0.010)	(0.002)	(0.009)	(0.003)
Attends summer camp×S	0.006	0.001	0.000	0.001
	(0.014)	(0.002)	(0.013)	(0.002)
Attends summer tutor×S	-0.040***	0.016**	-0.045**	0.012
	(0.010)	(0.008)	(0.021)	(0.008)
Attends summer day care×S	0.041***	-0.001	0.019*	-0.001
	(0.012)	(0.003)	(0.011)	(0.003)
Adjusted R^2	0.22	0.04	0.80	0.80
Joint sig. of interactions (*F*)	11.47***	1.12	5.70***	1.39
N	100	1,250	100	1,250

NOTE – Standard errors are clustered at the school level. All models include all un-interacted student-level controls and "summer length." The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A11

Heterogeneity in Average Summer Reading Learning Rates in the ECLS-K (Theta extrapolation)

	Gain Score Model		Lag Score Model	
	Exceptional (1)	Mainstream (2)	Exceptional (3)	Mainstream (4)
$(d^D - d^C)$	.	.	.	.
	.	.	.	.
$(d^C - d^B)$ (Summer; S)	0.032***	0.007*	0.010	0.002
	(0.010)	(0.004)	(0.012)	(0.004)
$(d^B - d^A)$	.	.	.	.
	.	.	.	.
Lag-score×S	.	.	-0.015	-0.006*
			(0.010)	(0.003)
Poverty ×S	-0.015	-0.002	-0.024	-0.004
	(0.018)	(0.005)	(0.015)	(0.004)
Org. Summer Activity×S	-0.011	-0.003	-0.000	-0.002
	(0.014)	(0.003)	(0.014)	(0.002)
Summer school×S	-0.017	-0.005	-0.012	-0.005
	(0.011)	(0.005)	(0.008)	(0.005)
Summer library/bookstore trips×S	-0.001	-0.000	-0.001	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Parent reads every day×S	-0.015	-0.001	-0.012	-0.001
	(0.012)	(0.003)	(0.011)	(0.003)
Attends summer camp×S	0.011	0.001	0.004	0.002
	(0.014)	(0.003)	(0.013)	(0.003)
Attends summer tutor×S	-0.051***	0.017**	-0.056**	0.013
	(0.013)	(0.008)	(0.024)	(0.009)
Attends summer day care×S	0.043***	0.001	0.014	0.001
	(0.015)	(0.004)	(0.014)	(0.004)
Adjusted R^2	0.09	0.02	0.74	0.75
Joint sig. of interactions (*F*)	8.67***	0.96	4.89***	1.34
N	100	1,250	100	1,250

NOTE – Standard errors are clustered at the school level. All models include all un-interacted student-level controls and "summer length." The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE A12

Heterogeneity in Average Summer Math Learning Rates in the ECLS-K

	Gain Score Model		Lag Score Model	
	Exceptional (1)	Mainstream (2)	Exceptional (3)	Mainstream (4)
$(d^D - d^C)$	0.014***	0.007***	0.011***	0.007***
	(0.005)	(0.002)	(0.004)	(0.001)
$(d^C - d^B)$ (Summer; S)	0.022	-0.001	0.007	-0.008
	(0.018)	(0.006)	(0.021)	(0.005)
$(d^B - d^A)$	0.003	0.003**	-0.001	0.002
	(0.004)	(0.001)	(0.004)	(0.001)
Lag-score×S	.	.	0.004	0.008*
			(0.018)	(0.004)
Poverty ×S	-0.063	-0.006	-0.083	-0.008
	(0.050)	(0.008)	(0.055)	(0.009)
Org. Summer Activity×S	-0.026	0.003	-0.014	0.003
	(0.023)	(0.006)	(0.022)	(0.005)
Summer school×S	0.011	0.004	0.028	0.014
	(0.034)	(0.009)	(0.030)	(0.008)
Summer library/bookstore trips×S	0.001	-0.000	0.001	-0.000
	(0.001)	(0.000)	(0.001)	(0.001)
Parent helps with math every day×S	-0.012	0.004	0.001	0.008
	(0.046)	(0.009)	(0.041)	(0.008)
Attends summer camp×S	-0.047**	0.002	-0.047**	0.000
	(0.022)	(0.007)	(0.020)	(0.006)
Attends summer tutor×S	-0.005	0.023	0.005	0.021
	(0.032)	(0.024)	(0.060)	(0.024)
Attends summer day care×S	0.034	0.010	0.001	0.012
	(0.034)	(0.008)	(0.030)	(0.009)
Adjusted R^2	0.10	0.03	0.59	0.69
Joint sig. of interactions (*F*)	1.89*	0.79	2.02*	1.14
N	100	1,250	100	1,250

NOTE – Standard errors are clustered at the school level. All models include all un-interacted student-level controls and “summer length.” The exceptionality indicator equals one if the student either spoke a language other than English at home (ELL) or had an Individualized Education Program (IEP). All regressions are weighted by NCES sampling weights to account for unequal probabilities of sample selection. *** p<0.01, ** p<0.05, * p<0.1.