Title: A new approach to estimating summer learning rates

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Abstract

The activities and experiences that contribute to summer learning are potentially important inputs to the education production function, yet are relatively understudied by economists. We introduce a method for estimating summer learning rates when tests are not given on the first and last days of the school year and apply this method to using data from the nationally representative Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K).

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BACKGROUND

Improving the quality of publicly provided education, particularly that of socioeconomically disadvantaged students, is a primary goal of state and federal education policy in the U.S., as educational achievement and attainment are thought to improve individual labor-market outcomes and to facilitate intergenerational socioeconomic mobility more generally (e.g., Card & Krueger, 1992; Checchi, 2006; Ellwood & Kane, 2000). To effectively close achievement gaps between students from different socioeconomic and demographic backgrounds, then, it is important that policy makers and educators are aware of the determinants of academic success and the factors that contribute to such achievement gaps.

The activities, individuals, and environments to which children are exposed during summer vacation comprise one potentially important class of inputs in the education production function. Indeed, educational researchers have been interested in the potential detrimental effects of summer vacation on cognitive development for more than a century (Cooper et al., 1996). More recently, the seminal work of Heyns (1978) put forth and tested the hypothesis that higher rates of summer learning loss (SLL) among disadvantaged students might contribute to the stubborn persistence of achievement gaps between students of different demographic and socioeconomic backgrounds. It is therefore important that policy makers and educators understand the causes, consequences, and magnitude of SLL and how SLL varies by students’ demographic and socioeconomic backgrounds.

However, the existing empirical SLL literature yields some contradictory results, perhaps due to variation in the empirical strategies employed in existing studies. Another limitation of the existing literature is that to date, SLL can only be estimated when both fall and spring test scores are available, which effectively limits analyses of SLL to specific school districts and surveys. The current study contributes to these gaps in the SLL literature by presenting a formal approach to estimating summer learning rates, testing for heterogeneity in summer learning rates, and reconciling the sometimes contradictory results in the existing literature that can be applied even when tests are administered only once per year.

RESEARCH QUESTIONS

1) How sensitive are estimated rates of summer learning to different modeling and estimation strategies?
2) How much variation in summer learning rates exists across students, how much of this variation is explained by observable student characteristics?
3) How valid are estimates of summer learning rates based on annual test score data?

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2 Heterogeneous summer learning rates have been referred to as summer learning loss, summer setback, and summer slide in the sociology and education literatures.
SETTING

The analysis is conducted using nationally representative data on the 1998-99 cohort of U.S. kindergarten students. Data on students’ backgrounds, summer activities, and test scores come from the Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K).

RESEARCH DESIGN

The primary goal of this research is to estimate the average daily learning rate during the summer vacation, and to compare this rate to daily school-year learning rates. Importantly, the ECLS-K administered tests in both the spring of kindergarten and the fall of first grade. To avoid conflating summer learning with school-year learning that occurred either before the fall first-grade assessment or after the spring kindergarten assessment, the econometric model must acknowledge that the assessments were administered neither on the first nor last days of the academic year. Accordingly, there are four relevant dates:

A. Spring Kindergarten Assessment Date
B. Kindergarten End Date
C. First Grade Start Date
D. Fall First Grade Assessment Date

Dates A, C, and D are formally reported in the ECLS-K. Unfortunately, the precise date B is unobserved. However, the ECLS-K does report the first grade end date, which we use to impute B, as the analytic sample is restricted to students who attended the same school for both kindergarten and first grade.

Let \( y_j \) represent achievement at date \( j \) for \( j = A, B, C, \) and \( D \). Only \( y_D \) and \( y_A \) are observed, though the difference between observed test scores can conceptually be decomposed as follows:

\[
y_D - y_A = (y_D - y_C) + (y_C - y_B) + (y_B - y_A).
\]  

(1)

The middle term on the RHS of equation (1) constitutes learning that occurs during the summer vacation, which is the object of interest in the current study. We exploit two facts in order to estimate summer learning rates. First, the date \( d \) is observed for each \( j \). Second, cognitive development in early childhood is a cumulative process that occurs systematically over time (McCoach et al., 2006; Muthen et al., 2003). Accordingly, the RHS of (1) can be approximated by the sum of three general functions of time:

\[
y_D - y_A = f(d_D - d_C) + g(d_C - d_B) + h(d_B - d_A) + \epsilon,
\]  

(2)

where \( \epsilon \) is an error term that acknowledges that the functions on the RHS of equation (2) are approximations of the true learning that occurred between dates \( j \) and \( j+1 \) for each \( j \). Student \( (i) \) and school \( (s) \) subscripts on the \( y_j, d_j \), and \( \epsilon \) in equation (2) are temporarily suppressed.
Equation (2) can be estimated by OLS after assuming tractable functional forms of \( f, g, \) and \( h, \) which could be nonlinear (McCoach et al., 2006).\(^3\) However, we begin our analysis by assuming that \( f, g, \) and \( h \) are linear in \((d^{d+1} - d^d)\), as Fitzpatrick et al. (2011) find school-year learning rates in the ECLS-K to be approximately linear. We do allow for different slopes in each of the three time periods, otherwise the RHS of equation (2) would simplify to \( f(d^D - d^A) + \epsilon. \)

The derivative of \( g \) with respect to \((d^C - d^B)\), which is a scalar when \( g \) is linear, is the daily rate of summer learning. Whether this parameter can be given a causal interpretation depends primarily on whether or not the \( \epsilon \) in equation (2) is correlated with summer vacation length (i.e., \( d^C - d^B \)), as Fitzpatrick et al. (2011) have shown that ECLS-K assessment dates \( d^D \) and \( d^A \) are essentially random. For example, it could be that parents sort into school districts based on academic calendars or that summer vacation length is determined by school resources. While we cannot directly test for this type of endogeneity, we can test for systematic differences in summer vacation length by observable household and school characteristics in two ways. The results of these tests generally provide no evidence of systematic differences in summer vacation lengths based on observables. Nonetheless, regardless of whether these estimates are given a causal interpretation, a contribution of the current study is to provide an accurate description of the distribution average summer learning rates.

Regarding research question 2, it is straightforward to model heterogeneity in summer learning rates by generalizing the model presented in equation (2) to allow for a student-specific function \( g \). This can be done using both interaction terms and random coefficient models.

Finally, to address research question 3, the approach characterized by equation (2) can be modified for use when only annual test scores, say from each spring, are available. In this case, dates A, B, and C remain the same, but date D becomes the date of the spring first-grade assessment. Model 2 is then estimated in the same fashion, using the new date D and the spring of first-grade test score. Because the ECLS-K contains both fall and spring first-grade test scores, the validity of summer learning rates estimated using the spring-spring approach can be inferred by comparing such estimates to the “preferred” estimates generated by the fall-spring approach.

**DATA**

Data on summer learning, household characteristics, and summer activities are taken from the Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K), which was collected by the National Center for Education Statistics (NCES). The full sample of more than 20,000 children from about 1,000 kindergarten programs (i.e., schools) was designed to be nationally representative of the cohort that entered kindergarten in the 1998-99 academic year. Certain subgroups of the population were oversampled, so the primary analyses are conducted using NCES-provided sampling weights that adjust for the survey’s nonrandom sampling frame.

All children in the initial sample were surveyed in the fall and spring of kindergarten and the spring of first grade. However, the analytic sample is restricted to the 30 percent random subsample of children who were also surveyed in fall of first grade. This facilitates the

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\(^3\) Alternatively, equation (2) could be estimated non-parametrically (e.g., Eren & Henderson, 2008), though such an analysis is beyond the scope of the current study.
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). We further restrict the analytic sample by excluding students who experienced a mid-year classroom change, repeated kindergarten, changed schools between kindergarten and first grade, or were missing basic demographic or test score data. School changers are excluded to avoid conflating SLL with shocks to achievement caused by the disruption associated with changing schools, though it is worth noting that including school changers in the analytic sample and conditioning on a binary “school change” indicator yields qualitatively similar results.

PRELIMINARY FINDINGS

Table 1 reports unconditional OLS estimates of average daily learning rates during three time periods: kindergarten, first grade, and between spring of kindergarten and fall of first grade \((d^D - d^A)\). Columns 1 – 4 report estimates for math achievement. Columns 1 and 2 report daily school-year learning rates for kindergarten and first grade, respectively, that are similar to the parameters estimated by Fitzpatrick et al. (2011). Interestingly, column 3 shows that the effect of one day on achievement gains between dates A and D is nearly identical in magnitude to the effect of one day in first grade, despite the fact that almost half of the days between dates A and D are during the summer vacation. This challenges the general finding of average summer losses in math achievement. Column 4 probes further by estimating the baseline specification presented in equation (10) and finds the learning rate during summer vacation \((C - B)\) to be statistically indistinguishable from zero while both the end of kindergarten \((B - A)\) and the start of first grade \((D - C)\) learning rates are positive and significant. However, the SL rate is imprecisely estimated and not significantly different from the school-year learning rates. Columns 5 – 8 of table 4 report estimates of the same four specifications for reading. Once again, the daily learning rate between dates A and D is similar in magnitude to the school-year learning rates reported in columns 1 and 2. Interestingly, the estimates of the baseline specification reported in column 8 suggest that the rate of SL is positive significantly greater than learning rates during both the end of kindergarten and the start of first grade. These results are robust to conditioning on a rich set of control variables. Analyses of heterogeneity and using only spring test scores are currently in progress and will be completed by early 2015.
REFERENCES


Table 1: Gain-Score Estimates of Average Daily Learning Rates

<table>
<thead>
<tr>
<th></th>
<th>Math Achievement</th>
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<th>Reading Achievement</th>
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<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
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<tr>
<td>Days between K tests</td>
<td>0.004***</td>
<td></td>
<td>0.006***</td>
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<td></td>
<td>(0.001)</td>
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<td>(0.001)</td>
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<tr>
<td>Days between first-grade tests</td>
<td>0.005***</td>
<td></td>
<td>0.003**</td>
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<td></td>
<td>(0.001)</td>
<td></td>
<td>(0.001)</td>
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<tr>
<td>Days between spring K and fall</td>
<td></td>
<td>0.005***</td>
<td>0.004***</td>
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<tr>
<td>first-grade tests ( (d^D - d^A) )</td>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
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<tr>
<td>Start of first grade – fall first-</td>
<td>0.007***</td>
<td></td>
<td>0.004***</td>
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<tr>
<td>grade test ( (d^D - d^C) )</td>
<td>(0.002)</td>
<td></td>
<td>(0.001)</td>
<td></td>
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<tr>
<td><strong>Summer Vacation</strong> ( (d^C - d^B) )</td>
<td><strong>0.004</strong></td>
<td></td>
<td><strong>0.009</strong>*</td>
<td></td>
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<tr>
<td></td>
<td>(0.005)</td>
<td></td>
<td>(0.003)</td>
<td></td>
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<tr>
<td>End of K – spring K test ( (d^B - d^A) )</td>
<td>0.002*</td>
<td></td>
<td>0.002***</td>
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<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td>(0.001)</td>
<td></td>
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<tr>
<td>Adjusted R^2</td>
<td>0.01</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
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<tr>
<td>Tests of Equality</td>
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<tr>
<td>( (d^C - d^B) = (d^D - d^A) ) (p-value)</td>
<td>0.33</td>
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<tr>
<td>( (d^C - d^B) = (d^B - d^A) ) (p-value)</td>
<td>0.97</td>
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</tbody>
</table>

Notes: N = 1,350 (rounded to nearest 50). Standard errors are robust to clustering at the school level. These specifications contain no controls. The dependent variable is the unadjusted difference between standardized test scores. *** p<0.01, ** p<0.05, * p<0.1.