AERA Open
October-December 2018, Vol. 4, No. 4, pp. 1–19
DOI: 10.1177/2332858418819995
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Are We Trending to More or Less Between-Group Achievement Inequality Over the School Year and Summer? Comparing Across ECLS-K Cohorts

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Scholars have argued that schools are "equalizers" because inequalities in test scores by race/ethnicity and socioeconomic status (SES) grow faster over summer vacation than over the school year. In this study, we use nationally representative data from the Early Childhood Longitudinal Study–Kindergarten Classes of 1998–1999 and 2010–2011 to examine the extent to which such patterns have changed over time. Results suggest that more between-group equalizing by race/ethnicity and SES occurred over kindergarten in the recent cohort. However, this was often followed by more inequality widening over summer and more widening or less narrowing over first grade in the latter cohort. The net result was that in recent years, inequality tended to widen more (Black-White) or narrow less (SES and Hispanic-White) over the first 2 years of schooling.

Keywords: *summer learning loss, summer setback, achievement inequality, achievement gap, seasonal learning, ECLS-K*

Since at least the early 20th century, social scientists and educators have worried about the potential negative impact of summer vacation on student learning (Cooper, Nye, Charlton, Lindsay, & Greathouse, 1996). Researchers have been particularly focused on whether summer learning rates differ by students' socioeconomic status (SES) or race/ethnicity in ways that exacerbate between-group inequalities in educational outcomes. Early studies generally found that inequality in literacy by SES grew over the summer (Cooper et al., 1996) and at a faster rate as compared with the school year (Alexander, Entwisle, & Olson, 2001; Heyns, 1978). This evidence was often interpreted as showing that schools were "equalizers" (Alexander et al., 2001; Downey, von Hippel, & Broh, 2004). Summer loss was also generally found in math but equally for students across SES backgrounds (Cooper et al., 1996).

An underexamined question in this line of research is whether and how these patterns might be changing over time. As compared with earlier work, recent studies have drawn more mixed conclusions regarding the seasonal dynamics of achievement inequality (Atteberry & McEachin, 2016; Quinn, Cooc, McIntyre, & Gomez, 2016; von Hippel & Hamrock, 2016). Beneath the cross-study differences in test scaling, modeling, and design, it is difficult to know whether meaningful time trends are occurring. Yet there are reasons to expect that between-group inequality dynamics may have changed over the past several decades. To begin with, inequality in income and parental spending on children's education has been growing (Duncan & Murnane, 2011; Kornrich & Furstenberg, 2013), and the country is becoming increasingly segregated by income and race (Orfield & Frankenberg, 2014; Reardon & Bischoff, 2011). These trends would lead one to expect that achievement inequalities may be widening more over the school year and summer today as compared with the recent past. At the same time, however, there have been efforts to improve early childhood education for children from low-income backgrounds, and the academic rigor of kindergarten (K) has been increasing more for students from low-income backgrounds versus students from wealthier backgrounds (Bassok, Latham, & Rorem, 2016). This would lead to the prediction that, at least over K, inequality trends may be improving.

In this article, we contribute to the literature on seasonal learning by examining the extent to which the equalizing effect of schools on learning disparities by race/ethnicity and SES has been changing over time. The recent availability of data from the Early Childhood Longitudinal Study–Kindergarten Class of 2010–2011 (ECLS-K:2011) provides an opportunity to investigate this question by comparing the seasonal trends across two nationally representative cohorts of students: the ECLS-K:2011 and the Early Childhood Longitudinal Study–Kindergarten Class of 1998–1999 (ECLS-K:1999). In past work, researchers analyzed each

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ECLS-K cohort separately (Downey et al., 2004; Quinn et al., 2016; von Hippel, Workman, & Downey, 2018) but did not formally test for changes in seasonal patterns across cohorts.[1] By comparing two nationally representative studies with quite similar designs, we offer evidence regarding the extent to which true time trends may underlie the contrasting results across decades. When used alongside other evidence, basic descriptive facts such as these will be useful to policy makers aiming to end disparities in educational outcomes by race/ethnicity and SES.

We find that in general, more between-group equalizing occurred over K in 2010–2011 versus 1998–1999. This is in line with research showing that K has become more academically focused of late and that this change has been more pronounced in schools serving students from low-income backgrounds (Bassok et al., 2016). However, this positive trend did not continue past K. Over the post-K summer in 2011, inequalities were stagnant or widened more (vs. 1999), and the equalizing effect of schools did not continue into first grade in 2011–2012. These patterns are what might have been anticipated from research showing increasing segregation and growing gaps in educational spending (Evans, Schwab, & Wager, 2017; Kornrich & Furstenberg, 2013). The net result over the first 2 years of schooling was that achievement inequalities by race/ethnicity and SES widened more or narrowed less in the recent cohort.

Background

Summer Loss and Seasonal Patterns in Inequality

In an early comprehensive review of the literature, Cooper and colleagues (1996) summarized several key findings on summer loss and between-group inequality. They concluded that on average (a) students' achievement scores declined over summer vacation, (b) declines were sharper for math than reading, and (c) the extent of loss was larger at higher grade levels. Importantly, they also concluded that (d) income-based reading inequality grew over the summer, given that middle-class students tended to show improvement in reading skills while lower-income students tended to experience loss. However, they did not find differential summer learning by income status in math or by gender or race in either subject.

The ECLS-K:1999 provided an opportunity to update the picture of seasonal learning dynamics in a nationally representative sample. Downey and colleagues (2004) found that, when controlling for race and other variables, literacy inequality by SES widened more quickly over the summer after K than it did over K or first grade. SES math inequality widened over K, did not change over the summer, and then narrowed over first grade. Schools seemed to narrow Asian-White inequality but exacerbate Black-White inequality. Overall, the authors interpreted their findings as evidence that schools generally served as equalizers.

Recent studies on seasonal learning patterns showed mixed results. Analyzing the ECLS-K:2011, Quinn and colleagues (2016) concluded that the data were consistent with a story in which schools initially narrow inequalities (with the exception of Black-White inequality) but do not maintain this equalizing over time. In some cases, the trend reversed as students aged such that less equalizing occurred over the school year than the summer. The authors did not find consistent evidence of inequality widening over the summer, though one robust summer result was that SES math inequality widened the summer after K. The dynamics of other between-group differences over the summer depended on whether inequality was operationalized in absolute terms (difference in score gains) or relative terms (changes in *z* scores).

Another important source of recent data on seasonal learning patterns is the NWEA Measures of Academic Progress. In line with the ECLS-K:2011 findings, some researchers using national (but not nationally representative) NWEA data found that average-achieving students experience flat learning trajectories over the summer (Rambo-Hernandez & McCoach, 2015). However, another analysis based on NWEA data from over a half million second-through-ninth graders from a southeastern state showed that the average student lost between 25% and 30% of his or her school year learning over the summer (Atteberry & McEachin, 2016). Some NWEA studies showed that inequalities in test scores by race/ethnicity and SES tend to widen over the summer (Atteberry & McEachin, 2016; McCall, Hauser, Cronin, Kingsbury, & Houser, 2006) as well as the school year (Atteberry & McEachin, 2016).

Methodological issues in seasonal analyses. A theme in the recent literature has been the sensitivity of estimates of seasonal inequality patterns to issues of test scaling, modeling, and how inequality is operationalized. Quinn and colleagues (Quinn, 2015; Quinn et al., 2016; Quinn & McIntyre, 2017) emphasized that alternative ways of operationalizing inequality dynamics can lead to different, but not necessarily contradictory, conclusions. Using data from the ECLS-K:1999, Quinn (2015) found that, depending on factors such as modeling strategy and reliability adjustment, one might conclude that Black-White inequality narrows, widens, or remains constant over the summer after K. Patterns can also appear to differ depending on whether one is tracking the size of absolute between-group mean differences over time or changes in relative position (Quinn et al., 2016).

Von Hippel and Hamrock (2016) questioned the conclusions from early seasonal studies on psychometric grounds. For example, the authors argued that in the landmark Beginning School Study (Alexander et al., 2001; Entwisle & Alexander, 1992), the practice of changing the test form in the fall had the effect of exaggerating the extent of summer learning loss. In the ECLS-K:1999, the test scales included

in early data releases were "number right true scores," or estimates of how many test items a student would have answered correctly had he or she taken all of the items in the bank. Such scales do not have claim to equal-interval properties, given that the test items vary in their difficulty. The authors' analyses based on test scales with greater theoretical claim to interval properties did not show the same dramatic inequality widening as students aged. Overall, von Hippel and Hamrock concluded that, net of artifacts, much of the observed between-group inequality is already present at school entry.

Faucet Theory and School versus Out-of-School Learning

Entwisle, Alexander, and Olson's (2000) "faucet theory" offers an explanation for why schools may play a compensatory role when it comes to achievement inequality by income status. According to the theory, the "resource faucet" is on for all students during the school year, enabling students from all backgrounds to make learning gains. Over summer, however, the flow of resources slows for students from disadvantaged backgrounds more so than for students from advantaged backgrounds. Put differently, although high SES students may have access to more or higher-quality resources at school as compared with low SES students, the inequality by SES in home resources is even greater (Downey et al., 2004; Raudenbush & Eschmann, 2015). As such, schools play a compensatory role for low SES students, with inequality in learning widening over the summer but remaining constant (or widening less) over the school year. In early studies, the faucet theory seemed to apply specifically to literacy. The explanation was that students' experiences with vocabulary and print exposure differed by social class over the summer, while students of all backgrounds tended to lose access to math-related instructional experiences when school was out of session (Alexander et al., 2007; Cooper et al., 1996).

Of particular relevance to summer learning, Lareau (2003) argued that middle- and working-class parents engage in different parenting styles that have consequences for their children's development. According to Lareau, middle-class parents engage in "concerted cultivation" to intentionally guide their children's personal and intellectual development. This involves, for example, enrolling their children in organized activities to impart important life skills. Working-class parents, in contrast, allow for children's natural growth; that is, according to Lareau, they tend to believe that the parents' role is to provide for their children rather than actively nurture their talents and intellect.

Chin and Phillips (2004) investigated how different parenting approaches might relate to students' time use over the summer, and they found that the structure and substance of students' summer experiences differed by social class. However, the authors concluded that these differences stemmed more from parents' differential access to resources, as opposed to differences in their desires to cultivate children's skills and talents. Such resources include the financial resources required for entry into summer programming, the human capital to best assess and support their children's skills, the cultural capital to help students develop their talents, and the social capital to access summer opportunities.

Quantitative researchers examining children's summer activities also found differences by social class on activities relevant to academic development. Gershenson (2013) analyzed time-use diaries and found that the largest difference in students' time use by SES over the summer was in television viewing, with students from low-income families watching 2 hr more per week, on average, as compared with students from wealthier households. Additionally, students from low-income backgrounds spent an average of 12 min less per week in conversation with adults, and their parents spent less time facilitating their children's activities over the summer.

Using data from the ECLS-K:1999, Burkam, Ready, Lee, and LoGerfo (2004) found that over the summer after K, higher SES parents reported taking their children to the library and bookstore more often, as well as taking their kids on more summer trips. Higher SES parents also reported that their children more frequently used the computer for educational purposes, watched less television, and were more likely to participate in sports or other organized activities. High SES students were less likely to attend required summer school, but there were no significant differences by SES in optional summer school attendance or parents' reported frequency of math activities with kids. While there are theoretical reasons to expect that such differences in time use may lead to learning differences over the summer, the ECLS self-report scales for these activities only modestly explained variation by social class in summer learning. Borman and colleagues similarly found, using data collected through a randomized trial of a summer school program in Baltimore, that parental expectations and home-based learning activities did not predict much variation in summer learning. However, the authors did find that parents' promotion of students' summer school attendance seemed to help prevent summer learning loss (Borman, Benson, & Overman, 2005).

The seasonal patterns of inequality during the early years of schooling may be particularly consequential. Raudenbush and Eschmann (2015) proposed a model of school effects in which students benefit more from instruction when they begin at higher skill levels. When children develop skills at a young age, they increase their capacity to benefit from future instruction. Early gains are therefore more valuable than later gains because of this compounding effect. The authors also argued that access to K will disproportionately benefit low SES students because (a) the school/nonschool contrast is greater for low SES students and (b) the skill

difference by SES is smaller among young children, limiting the extent to which high-skill high SES students differentially benefit from instruction.

Why Might Seasonal Inequality Patterns Be Changing Over Time?

Several trends lead to the prediction that the seasonal inequality patterns may have gotten worse over the period covered by the two ECLS-K studies. To begin with, income inequality widened over these years (Reardon & Portilla, 2016). Perhaps fueled in part by this, longitudinal evidence suggests that high-income parents have been increasing spending on their children's cognitive development more so than low-income parents (Duncan & Murnane, 2011; Kornrich & Furstenberg, 2013). This trend may be responsible for the observed widening of income-based test score inequality in cohorts of students born between 1970 and 2001 (Reardon, 2011). Higher incomes may also enable parents to spend more time with their children in ways that promote children's cognitive development. Over this period, the amount of time that college-educated parents spent with their children rose more so than it did for parents without a college degree (Ramey & Ramey, 2010). According to the faucet theory, such investments are most relevant when school is out of session. Consequently, these findings suggest that test score inequality may be growing more over the summer today than in the past.

A major event that took place between ECLS studies was the Great Recession, which occurred over important formative years for the ECLS-K:2011 cohort. Economically, the recession more negatively affected lower-income families, and Black-White and Hispanic-White wealth disparities grew (Kochhar & Fry, 2014). Also important, the recession appears to have affected state and local education budgets (Chakrabarti & Livingston, 2013; Leachman & Mai, 2014), and lower-income schools were harder hit (Evans et al., 2017). Given evidence that family income (Dahl & Lochner, 2012; Duncan, Morris, & Rodrigues, 2011) and school spending (Candelaria & Shores, 2017; Jackson, Johnson, & Persico, 2016) affect children's educational outcomes, we might expect that the recession influenced students' in-school and out-of-school learning. Indeed, some evidence suggests that the recession significantly reduced math and reading achievement, with effects concentrated among students in low-income districts and those serving higher proportions of minoritized students (Shores & Steinberg, 2017).

Research also showed that residential segregation by income grew over the period covered by the ECLS-K studies (Bischoff & Reardon, 2014). This is relevant to studies of seasonal inequality because neighborhood environments are predictive of children's educational outcomes (e.g., Chetty, Hendren, & Katz, 2016). Additionally, analyses based on the ECLS-K:1999 indicated that neighborhood factors predict student learning over summer vacation (Benson & Borman, 2010). Segregation can lead to diverging learning trajectories over the school year as well, given that many school quality indicators differ systematically with the income levels and racial makeup of the student body (Fryer & Levitt, 2004; Jackson, 2009).

While the trends described here all lead to the expectation that between-group inequality may be getting worse over the school year and summer, comparative evidence from the ECLS-K studies shows trends that might lead to more between-group equalizing over the K school year today as compared with the recent past. At the same time as states began attempting to raise academic rigor by adopting the Common Core Standards, K teachers reported spending more time on advanced math content (Engel, Claessens, Watts, & Farkas, 2016). As compared with K teachers in 1998, K teachers in 2010 reported higher academic expectations for incoming students, spent more class time on academic content, and more frequently used standardized tests (Bassok et al., 2016). Importantly, for many of these outcomes, the changes were more dramatic for teachers of low-income students than those of high-income students (Bassok et al., 2016). This leads to the expectation that between-group inequality in test scores may have narrowed more over K during the 2010–2011 school year versus the 1998–1999 school year.

Summary and Research Questions

Much of the early research on seasonal learning patterns suggested that test score inequalities between advantaged and disadvantaged students widened more over the summer than the school year. Recent studies produced mixed results, and researchers have called attention to the ways in which conclusions from these studies can be sensitive to methodological issues. Yet there are reasons to suspect that true seasonal patterns in between-group inequality dynamics may be changing over time, net of any cross-study confounds related to sample composition or methodology. The recent release of the ECLS-K:2011 data provides an opportunity to investigate this question by comparing the inequality trends across two similar nationally representative studies. Basic descriptive facts on whether and how seasonal patterns in between-group achievement inequality may be evolving will inform discussions on how to make schools more equitable.

In this study, we use data from the National Center for Education Statistics' (NCES) nationally representative ECLS-K:1999 and ECLS-K:2011 studies to document how test score inequality trends by SES and race/ethnicity have changed over time. Following past researchers (Alexander et al., 2001; Quinn et al., 2016; von Hippel & Hamrock, 2016), we begin by documenting inequality at school entry and the net changes in inequality over the early years of schooling. We then examine how differences in school year

and summer patterns may contribute to these net changes. Specifically, we ask the following research questions:

Research Question 1: To what extent have trends in math and reading inequality by race/ethnicity and SES changed in total over the first 2 years of schooling across ECLS cohorts?

Research Question 2: How do the changes in achievement inequality over the school year (K/first grade) and over the summer differ across ECLS cohorts?

Methods

Data

We use restricted-use data from the NCES's ECLS-K:1999 and ECLS-K:2011. Each study used a three-stage sampling design in which primary sampling units (counties or contiguous counties) were first sampled, followed by schools within primary sampling units, followed by students within schools. Each study produced a nationally representative sample (when weighted) of students attending K over the 1998–1999 and 2010–2011 school years. In both studies, researchers scheduled achievement tests for the full sample in the fall and spring of K and the spring of first grade. Also in both studies, researchers scheduled assessments in the fall of first grade for a randomly selected subsample of students (approximately 30%). This allows for the estimation of learning over the post-K summer and first-grade school year. We are therefore able to compare inequality changes over K, post-K summer, and first grade across the two cohorts. The ECLS-K:2011 included additional test occasions that allow us to track learning over the summer after first grade and over second grade. For completeness, we also include these rounds in our analyses.

Samples. For all analyses, we include only students who attended schools with a traditional 9-month school calendar. We include observations from any student with at least one test score (for math or reading) in any analyzed wave who are not missing on any of the relevant variables (described later).

In both studies, researchers administered a language screener to students but followed different procedures (see Appendix A for detail). Consequently, some between-group differences are not comparable across surveys.

Outcomes. Our outcomes derive from the math and reading assessments. In each study, assessments were administered one-on-one by trained child assessors. Test dates varied by school, and testing windows in the fall and spring spanned several months.

The ECLS-K tests were based on the National Assessment of Educational Progress frameworks, projected to earlier grades via curriculum frameworks from national and state performance standards. Test content was similar across both studies, with reading assessments measuring print awareness, letter recognition, phonemic awareness, word recognition, vocabulary, and reading comprehension. Math assessments measured number sense, properties, and operations; measurement; geometry and spatial sense; data analysis; statistics and probability; and patterns, algebra, and functions. To avoid floor and ceiling effects, students first answered a set of routing items that determined the appropriate difficulty level for their test questions.

We use scales derived from the theta test metric. In both data sets, theta scores were estimated with a three-parameter item response theory model, which (in theory, if the model assumptions hold) generates a common scale across test waves within each study (Tourangeau et al., 2012).

At present, the NCES has not equated theta scores across the two data sets. Consequently, we cannot make absolute comparisons across cohorts on group means, mean differences, or standard deviations based on the original theta scales. However, we can make relative comparisons by transforming the test scales.

Following past researchers (Quinn et al., 2016), we conduct analyses using test scores transformed in two ways, each of which yields a different operationalization of inequality change. First, we operationalize inequality within each cohort as the between-group (i.e., race or class) difference in the average learning rate over a given period, expressed in fall K test score *SD* units for interpretability (ΔT_{SD_1}; Ho, 2009). For this operationalization, within each data set, we transform student *i*'s theta score at time *t* (i.e., θ_{it}) to $\frac{\theta_{it}}{\sqrt{r_1} \times SD_1}$, where SD_1 is the full-sample *SD* at Wave 1 and r_1 is the theta reliability at Wave 1 (to remove error variance from the standard deviations and render them comparable across data sets). When test scores are transformed in this way, our models (described later) estimate the rate of change in absolute inequality each season (expressed in fall K *SD* units) within each cohort. This transformation allows us to compare the amount of inequality change over a given period in the 2010–2011 cohort to the amount of inequality change over that period in the 1998–1999 cohort, relative to the amount of skill variation at K entry for each cohort. For example, suppose we find that, relative to each cohort's fall K *SD*, inequality narrows more over K in 2010–2011 than in 1998–1999. This would not necessarily imply that the absolute between-group difference in true knowledge reduced more over K in the more recent cohort. Such a conclusion could be reached only if the test scale were the same across cohorts.

In addition to estimating group differences in learning rates within each cohort, we operationalize inequality as

the rate of change in relative status within each cohort (ΔG_{ES}, where ES = effect size; Ho, 2009). To accomplish this, we transform—within each data set—student i's theta score at time t to $\frac{\theta_{it} - \overline{\theta_t}}{\sqrt{r_t} \times SD_t}$, where r_t is the wave-specific theta reliability (theta reliabilities range from .88 to .97 across subjects, waves, and data sets). In other words, this transformation standardizes scores to a full-sample mean of 0 and a (reliability-adjusted) full-sample SD of 1 at each test wave (sampling weights are used for all standardizations). When scores from this transformation are used, our models estimate the monthly rates at which the relative size of the mean between-group differences change each season within each data set (i.e., relative to the total amount of variation in test scores at each wave).

When test score variances change over time, ΔT_{SD_1} and ΔG_{ES} provide different perspectives on the dynamics of academic inequality. While ΔT_{SD_1} represents the between-group difference in how much students learned over a given period, ΔG_{ES} represents the average between-group difference in group members' changes in relative status (i.e., change in z score) from one test wave to the next. Given that the choice of operationalization has been shown to yield parameter estimates of different magnitudes or significance in the ECLS-K:2011 (Quinn et al., 2016), it is important to keep in mind the differing substantive interpretations of each operationalization.

Analytic Plan

Research Question 1: Total inequality change from K to first grade. For our first research question, we make cross-cohort comparisons in the total inequality changes over the first 2 years of schooling. To answer this question, we fit multilevel longitudinal models and conduct post hoc tests to examine inequality changes. For brevity, we present the Research Question 1 model in more detail in Appendix B.

Research Question 2: Seasonal trends for each ECLS cohort. To answer our second research question regarding changes in the seasonal dynamics of inequality across cohorts, we begin by fitting multilevel models (separately for each subject area and ECLS cohort) of the following form:

$$\begin{aligned} Y_{it} &= \alpha_i + \beta_1 SES_i + \sum_p \eta_p MONTHS_{it}^{(Period\ P)} \\ &+ \sum_k \tau_k (MONTHS_{it}^{(Period\ P)} \times SES_i) + \sum_n \pi_n C_i \\ &+ \sum_l \lambda_l \left(C_i \times MONTHS_{it}^{(Period\ P)} \right) + \epsilon_{it} \\ \epsilon_{it} &\sim N\left(0, \sigma_y^2\right) \perp \alpha_i \sim N\left(\mu_\alpha, \sigma_\alpha^2\right) \end{aligned}, \quad (1)$$

where i indexes student, t indexes time, α_i represents a student-specific random intercept, SES_i is an NCES-created continuous composite variable representing SES (see Appendix C for detail), and $\sum_n \pi_n C_i$ includes the following control variables: (a) a dichotomous variable indicating whether the student was a first-time kindergartener and (b) the child's age in months at the time of the fall K assessment. Importantly, $MONTHS_{it}^{(Period\ P)}$ represents a set of variables giving the number of months of period P (K school year, summer, Grade 1 school year) that student i had experienced at test wave t (models for the ECLS-K:2011 also include the post–Grade 1 summer and the Grade 2 school year). The precision with which these variables are measured differs across cohorts due to differences in how the data were recorded (see Appendix D for detail on these variables). In fitting models of this form, we follow previous researchers who fit similar models to ECLS-K data (e.g., Benson & Borman, 2010; Cheadle, 2008; Downey et al., 2004; McCoach, O'Connell, Reis, & Levitt, 2006; Quinn et al., 2016; Quinn & McIntyre, 2017).[2] This approach accounts for the fact that tests were not administered on the first and last days of school, allowing us to separately estimate rates of inequality change over each school year and summer.

When $Y_{it} = \frac{\theta_{it}}{\sqrt{r_1} \times SD_1}$, the interactions between the period variables and the SES_i variable estimate the extent to which monthly learning rates (expressed in survey-specific fall K SD units) differ by SES over each period ($\Delta T_{SD_1}^{(rate)}$). When $Y_{it} = \frac{\theta_{it} - \overline{\theta_t}}{\sqrt{r_t} \times SD_t}$, these interactions represent the rate at which the standardized mean difference changed during each period ($\Delta G_{ES}^{(rate)}$). After fitting Model 1, we conduct post hoc tests to estimate $\Delta T_{SD_1}^{(rate)}$ and $G_{ES}^{(rate)}$ comparing students from the 10th and 90th percentiles of the SES distribution. Within each cohort, negatively signed estimates for $\Delta T_{SD_1}^{(rate)}$ and $\Delta G_{ES}^{(rate)}$ represent widening inequality over a given period, and positively signed estimates represent narrowing inequality (see Appendix E for sensitivity analyses considering the reliability of the SES composite variable; results are nearly identical to those in the main text). All analyses incorporate recommended sampling weights (see table notes) and adjust standard errors for the dependence of observations within primary sampling units.

To estimate seasonal inequality trends by race/ethnicity, we fit a separate model similar to Model 1 except that we replace SES_i with a vector of mutually exclusive race/ethnicity dummy variables representing Hispanic, non-Hispanic Black, Asian, or "other race" with non-Hispanic Whites as the omitted group (following past researchers [e.g., Fryer & Levitt, 2004], we combine the American Indian/Alaska Native, Alaska Hawaiian/Pacific Islander, and multiracial

categories into the single "other race" category due to their small cell sizes). Additionally, instead of the variables interacting SES_i with the period variables, we include interactions between the period variables and each race/ethnicity dummy.

For SES and race/ethnicity models, we report learning rates over each period for the relevant reference group (i.e., students at the 90th percentile of SES or White students while assuming mean values for controls).

Testing for changes across cohorts. After obtaining the set of described estimates separately for each ECLS cohort, we test whether the differences in the estimates across cohorts are statistically significant. Because the observations in each data set are independent of the observations in the other, we can conduct simple *t* tests. Specifically, we compute the standard error of the cross-cohort difference in the rate of inequality change for a particular comparison over a particular period as follows: $SE\ DIFF = \sqrt{\left(SE^{1999}\right)^2 + \left(SE^{2011}\right)^2}$, where SE^{1999} and SE^{2011} represent the standard errors for the relevant estimated rates of inequality change in the ECLS-K:1999 and ECLS-K:2011, respectively (the degrees of freedom is the sum, across data sets, of the design *df*). See Appendix F for piecewise models that do not adjust for test date and Appendix G for piecewise models that use linear projection to account for test date (results show the same overall patterns as the results in the main text).

Results

We present estimates for math and reading in our tables, but we describe only the math results for narrative simplicity. The reading results fit the same general pattern as seen for math, though the math trends are more pronounced.

Descriptive Statistics

In Tables 1 and 2, we present descriptive statistics for the ECLS-K:1999 and ECLS-K:2011, respectively. We show test score statistics by wave for the full analytic samples and by race/ethnicity (to keep the tables manageable, we exclude the period variables; for full descriptive tables see Appendix H).

As seen across the tables, a higher percentage of kindergarteners were enrolled in full-day K in 2010 (83.3%) versus 1998 (56.4%). These changes differ by race/ethnicity. Supplementary analyses based only on students enrolled in full-day K show the same patterns as those reported in the main text (see Discussion section).

Within each survey, attrition across waves for cross-cohort analytic samples was, at its maximum, approximately 15% (from Wave 1 to Wave 4 in the ECLS-K:2011). See Appendix I for a comparison of the full versus analytic sample, Appendix J for analyses based on multiple imputation, and Appendix K for results based only on students with complete data each wave (all results show same patterns as the main tables).

By tracking the (reliability adjusted) theta *SD* across seasons in Tables 1 and 2, we get a sense of school effects on achievement inequality overall (without regard to race/ethnicity and SES). Although theta scales are not comparable across cohorts, we can compare percentage change in *SD* across seasons. Over K, overall variation in math and reading scores shrank more for the 2010–2011 cohort, decreasing by approximately 16% and 9% (math and reading, respectively) in 2010–2011 as opposed to 4% (both subjects) in 1998–1999. But this positive trend did not continue. Over summer, overall variation increased more in math for the recent cohort (7% vs. 2%) and increased similarly across cohorts for reading (1% in 2011 vs. 3% in 1999). During first grade in 1999–2000, overall math and reading variation shrank (by 11% and 12%, respectively), but overall math variation grew for the recent cohort (by approximately 3%) and decreased only slightly for reading (by 4%). These results suggest that overall, the recent cohort experienced more equalizing over K than the earlier cohort but more inequality widening—or less narrowing—during subsequent seasons.

Research Question 1: Overall Changes in Inequality From K to First Grade

We begin by examining changes across cohorts in the extent to which inequality changed in total from fall of K to spring of Grade 1. In Table 3, we present these results for math (top panel) and reading (bottom panel). Each row represents a different comparison by race/ethnicity or SES. The first three columns of results show the following for the ECLS-K:1999, respectively: estimates of the standardized mean differences in test scores at school entry ("Fall K" column), mean differences in learning from fall K to spring of first grade (expressed in Wave 1 *SD* units, or ΔT_{SD_1}), and the total change in wave-standardized mean differences from K to first grade (ΔG_{ES}). The next three columns show these estimates for the ECLS-K:2011, and the final two columns show estimates of the differences in the inequality changes from K to Grade 1 across cohorts.

As seen in the final two columns of Table 3, we find cross-cohort differences in the extent to which inequality changed from K to first grade. Here, negatively signed cross-cohort differences represent more relative inequality widening, or less narrowing, from K to first grade for the more recent cohort.

In general for both cohorts, Black-White inequality widened as students aged. However, math inequality widened more from K to first grade among students in the recent cohort (by .126 fall K *SD* more, or .104 more by ΔG_{ES}). In contrast, Hispanic-White and SES math inequalities tend to

TABLE 1
Descriptive Statistics for the ECLS-K:1999 for the Full Analytic Sample and by Race

		All students			Black			Hispanic			White		
	Wave	Mean	*SD*	*n*	Mean	*SD*	*n*	Mean	*SD*	*n*	Mean	*SD*	*n*
Math, θ/SD_1	Fall K	−2.556	1.04	11,070	−2.986	0.892	1,500	−3.097	1.016	1,630	−2.32	0.988	6,870
	Spring K	−1.478	0.996	10,620	−1.954	0.932	1,420	−1.925	0.993	1,590	−1.258	0.934	6,530
	Fall 1st	−0.91	1.018	3,040	−1.327	0.989	370	−1.319	1.03	430	−0.691	0.95	1,880
	Spring 1st	0.158	0.908	10,630	−0.32	0.888	1,400	−0.133	0.891	1,580	0.348	0.856	6,520
Math, wave standardized	Fall K	0.113	1.04	11,070	−0.318	0.892	1,500	−0.429	1.016	1,630	0.349	0.988	6,870
	Spring K	0.092	1.029	10,620	−0.4	0.963	1,420	−0.37	1.026	1,590	0.319	0.965	6,530
	Fall 1st	0.095	1.027	3,040	−0.326	0.997	370	−0.318	1.039	430	0.316	0.959	1,880
	Spring 1st	0.06	1.025	10,630	−0.48	1.004	1,400	−0.269	1.007	1,580	0.274	0.967	6,520
Read, θ/SD_1	Fall K	−2.613	1.02	10,630	−2.905	0.95	1,490				−2.479	0.99	6,880
	Spring K	−1.448	0.975	10,330	−1.789	0.979	1,420				−1.323	0.929	6,540
	Fall 1st	−0.955	1.003	2,980	−1.255	1.026	370				−0.819	0.947	1,880
	Spring 1st	0.263	0.878	10,480	−0.075	0.933	1,400				0.395	0.825	6,520
Read, wave standardized	Fall K	0.077	1.02	10,630	−0.216	0.95	1,490				0.211	0.99	6,880
	Spring K	0.064	0.991	10,330	−0.283	0.996	1,420				0.191	0.945	6,540
	Fall 1st	0.07	0.984	2,980	−0.225	1.006	370				0.204	0.928	1,880
	Spring 1st	0.057	0.97	10,480	−0.316	1.03	1,400				0.203	0.91	6,520
SES		0.03	0.775	11,230	−0.366	0.762	1,500	−0.36	0.677	1,650	0.214	0.722	6,890
First-time K		0.959	0.199	11,230	0.95	0.218	1,500	0.948	0.222	1,650	0.963	0.189	6,890
Age (months) fall K		68.612	4.223	11,230	68.214	4.218	1,500	68.07	4.189	1,650	68.858	4.214	6,890
Full-day K		0.564	0.496	10,910	0.782	0.413	1,450	0.516	0.5	1,570	0.524	0.499	6,730
Summer sch		0.121	0.326	3,360	0.121	0.327	420	0.193	0.395	480	0.098	0.297	2,060

Note. Sample sizes rounded to nearest 10, as required by the National Center for Education Statistics. Theta scales are not equated across ECLS cohorts. Sampling weight C1CW0 applied. Sample sizes by race do not sum to total sample size, because Asian students and "other race" students are included in full models (but inequality estimates are not included in tables for reasons described in full text). Reliability-adjusted full-sample *SD* used in standardization. ECLS-K:1999 = Early Childhood Longitudinal Study–Kindergarten Class of 1998–1999; first-time K = binary indicator (1 = yes, 0 = no); full-day K = binary indicator for whether student was in a full-day (1) or half-day (0) program; K = kindergarten; SES = socioeconomic status—continuous composite of parental income, occupational status, and education level; summer sch = binary indicator for whether student attended summer school during the post-K summer (only available for fall subsample).

narrow for both cohorts from K to first grade. But as with Black-White inequality, things appear to have gotten worse over time. Hispanic-White inequality narrowed less in the recent cohort (by .161 fall K *SD* less, or .154 for ΔG_{ES}), as did SES math inequality (narrowing by .109 fall K *SD* less, or .094 *SD* less by ΔG_{ES}).

We now turn to our second research question to determine when academic outcomes became less equal for the recent cohort. That is, does the explanation for why things look worse overall from K to first grade in the recent cohort lie with what happened during the school year or during the summer?

Research Question 2: Changes in Seasonal Trends Across ECLS Studies

In Tables 4 and 5 (for math and reading, respectively), we present the relevant estimates derived from Model 1 answering our second research question. In the top panel for each table, we show monthly rates of learning in fall K *SD* units for reference group students (the "White students" row for the race/ethnicity models and the "90th percentile SES students" row for the SES models). Under the reference group estimates, we show group differences in monthly rates of learning ($\Delta T_{SD_1}^{(rate)}$). In the bottom panel of each table, we show results for the between-group differences in monthly rates of changes in relative status ($\Delta G_{ES}^{(rate)}$).

To facilitate interpretation, we present these results in Figures 1 to 3. Figure 1 shows, for Hispanic-White and SES math inequality, the differences in learning rates (ΔT_{SD1}, left panel) and changes in relative status (ΔG_{ES}, right panel) by season for both ECLS studies. Figure 2 shows the analogous estimates for Black-White math inequality, and Figure 3 shows the analogous estimates for Black-White and SES reading inequality. In each figure, the *y*-axes represent the

TABLE 2
Descriptive Statistics for the ECLS-K:2011 for the Full Analytic Sample and by Race

		All students			Black			Hispanic			White		
	Wave	Mean	*SD*	*n*	Mean	*SD*	*n*	Mean	*SD*	*n*	Mean	*SD*	*n*
Math, θ/SD_1	Fall K	−0.556	1.03	14,360	−0.868	0.965	1,910	−1.014	1.092	3,400	−0.307	0.918	7,160
	Spring K	0.483	0.862	14,310	0.15	0.877	1,900	0.189	0.879	3,400	0.676	0.792	7,110
	Fall 1st	0.997	0.922	3,990	0.646	0.818	390	0.718	0.816	1,420	1.276	0.928	1,610
	Spring 1st	1.849	0.946	12,210	1.377	0.822	1,510	1.485	0.877	2,950	2.105	0.906	6,110
	Fall 2nd	2.089	0.926	3,640	1.66	0.86	340	1.773	0.877	1,320	2.408	0.856	1,470
	Spring 2nd	2.746	0.901	11,060	2.205	0.886	1,290	2.429	0.876	2,720	2.976	0.819	5,610
Math, wave standardized	Fall K	0.028	1.03	14,360	−0.284	0.965	1,910	−0.43	1.092	3,400	0.277	0.918	7,160
	Spring K	0.014	1.023	14,310	−0.382	1.041	1,900	−0.335	1.043	3,400	0.242	0.94	7,110
	Fall 1st	0.029	1.035	3,990	−0.365	0.917	390	−0.284	0.915	1,420	0.342	1.041	1,610
	Spring 1st	0.02	1.032	12,210	−0.495	0.896	1,510	−0.378	0.957	2,950	0.298	0.988	6,110
	Fall 2nd	0.036	1.018	3,640	−0.435	0.945	340	−0.311	0.964	1,320	0.387	0.94	1,470
	Spring 2nd	0.02	1.018	11,060	−0.591	1	1,290	−0.337	0.99	2,720	0.281	0.926	5,610
Read, θ/SD_1	Fall K	−0.653	1.025	14,420	−0.807	0.947	1,920				−0.475	0.975	7,180
	Spring K	0.546	0.937	14,340	0.344	0.939	1,900				0.715	0.851	7,120
	Fall 1st	1.023	0.95	3,980	0.859	0.917	390				1.215	0.935	1,610
	Spring 1st	1.943	0.913	12,220	1.692	0.869	1,510				2.125	0.863	6,120
	Fall 2nd	2.201	0.812	3,630	1.994	0.756	340				2.425	0.801	1,470
	Spring 2nd	2.674	0.77	11,060	2.419	0.725	1,290				2.834	0.728	5,610
Read, wave standardized	Fall K	0.023	1.025	14,420	−0.13	0.947	1,920				0.202	0.975	7,180
	Spring K	0.016	1.022	14,340	−0.204	1.024	1,900				0.2	0.928	7,120
	Fall 1st	0.028	1.029	3,980	−0.15	0.993	390				0.236	1.013	1,610
	Spring 1st	0.024	1.028	12,220	−0.258	0.979	1,510				0.23	0.973	6,120
	Fall 2nd	0.042	1.028	3,630	−0.22	0.957	340				0.326	1.013	1,470
	Spring 2nd	0.029	1.034	11,060	−0.315	0.974	1,290				0.243	0.978	5,610
SES		−0.052	0.803	13,250	−0.375	0.703	1,700	−0.509	0.717	3,030	0.188	0.736	6,760
First-time K		0.946	0.226	14,500	0.915	0.278	1,930	0.945	0.228	3,440	0.953	0.212	7,190
Age (months) fall K		67.539	4.51	14,500	67.493	4.716	1,930	66.929	4.311	3,440	67.94	4.516	7,190
Full-day K		0.833	0.373	14,110	0.953	0.211	1,880	0.872	0.334	3,340	0.793	0.405	7,030
Summer sch (sum 1)		0.101	0.301	3,970	0.131	0.338	380	0.121	0.327	1,390	0.074	0.262	1,640
Summer sch (sum 2)		0.096	0.295	3,480	0.127	0.334	300	0.11	0.313	1,240	0.068	0.251	1,450

Note. Sample sizes rounded to nearest 10, as required by the National Center for Education Statistics. Theta scales are not equated across ECLS cohorts. Sampling weight W1C0 applied. Sample sizes by race do not sum to total sample size, because Asian students and "other race" students are included in full models (but inequality estimates are not included in tables for reasons described in full text). Reliability-adjusted full-sample *SD* used in standardization. ECLS-K:2011 = Early Childhood Longitudinal Study–Kindergarten Class of 2010–2011; first-time K = binary indicator (1 = yes, 0 = no); full-day K = binary indicator for whether student was in a full-day (1) or half-day (0) program; K = kindergarten; SES = socioeconomic status—continuous composite of parental income, occupational status, and education level; summer sch = binary indicator for whether student attended summer school during the post-K summer (only available for fall subsample).

relevant standardized mean difference in test scores, and the *x*-axes represent time. Triangular points show inequality estimates from the ECLS-K:1999, and circular points show estimates from the ECLS-K:2011. The slopes of the lines connecting the points represent the rates of inequality changes for that season for a given cohort. Solid lines indicate that the group difference in the rates of change for a given period and survey is significantly different from zero ($\alpha = .05$). For a given season, significance asterisks accompany the slopes to indicate when cross-cohort differences in rates of inequality change were statistically significant.[3]

Key Findings

Three patterns emerge from these cross-cohort seasonal comparisons. First, consistent with research showing narrowing SES gaps in academic rigor over K (Bassok et al., 2016), skill inequalities tend to narrow more over K in the

TABLE 3

Math and Reading Inequality and Inequality Changes (K–Grade 1) by Race/Ethnicity and SES: ECLS-K:1999 and ECLS-K:2011

	ECLS-K:1999			ECLS-K:2011			Difference, 2011 – 1999	
	Fall K	ΔT_{SD_1}	ΔG_{ES}	Fall K	ΔT_{SD_1}	ΔG_{ES}	ΔT_{SD_1}	ΔG_{ES}
Math								
Black-White	−0.661***	−0.014	−0.1***	−0.578***	−0.14***	−0.204***	−0.126***	−0.104**
	(0.055)	(0.028)	(0.03)	(0.047)	(0.023)	(0.024)	(0.036)	(0.038)
Hispanic-White	−0.709***	0.25***	0.192***	−0.667***	0.089**	0.038	−0.161***	−0.154***
	(0.041)	(0.028)	(0.028)	(0.039)	(0.033)	(0.035)	(0.043)	(0.045)
10th-90th percentile SES	−1.112***	0.289***	0.184***	−1.185***	0.18***	0.09*	−0.109**	−0.094*
	(0.026)	(0.023)	(0.025)	(0.031)	(0.035)	(0.036)	(0.042)	(0.044)
Reading								
Black-White	−0.454***	−0.04	−0.09**	−0.346***	−0.085**	−0.138***	−0.045	−0.048
	(0.059)	(0.027)	(0.028)	(0.046)	(0.031)	(0.033)	(0.041)	(0.043)
10th-90th percentile SES	−1.089***	0.292***	0.212***	−1.182***	0.227***	0.107***	−0.065~	−0.105**
	(0.03)	(0.026)	(0.027)	(0.03)	(0.027)	(0.029)	(0.037)	(0.04)

Note. Fall kindergarten math and reading inequality by race/ethnicity and SES and inequality changes from fall kindergarten to spring of Grade 1 expressed in fall kindergarten *SD* units (ΔT_{SD_1}) and changes in *z* score (ΔG_{ES}). Estimates shown for ECLS-K:99 and ECLS-K:2011 and for differences across cohorts. Sampling weight C1CW0 applied for ECLS-K:99 and W1C0 for ECLS-K:2010. Standard errors that account for the complex sampling design are in parentheses. ECLS-K:1999 = Early Childhood Longitudinal Study–Kindergarten Class of 1998–1999; ECLS-K:2011 = Early Childhood Longitudinal Study–Kindergarten Class of 2010–2011; K = kindergarten; SES = socioeconomic status—continuous composite of parental income, education, and occupational prestige. Racial/ethnic and SES inequalities estimated in separate models (other race–White, Asian-White, and Hispanic-White inequalities [for reading] are estimated in the same models but not shown). All standardizations adjust for test reliability. Estimates derived from the longitudinal model with random intercepts for students and indicators for test wave, incorporating all available test data, time-varying effects of student age at time of fall kindergarten assessment, and whether student was a first-time kindergartener. See Tables 1 and 2 for sample sizes and Appendix B for models.

~$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

TABLE 4

Math Inequality Changes (Monthly Rates) by Race/Ethnicity and SES Over the School Year and Summer: ECLS-K:1999 and ECLS-K:2011

	ECLS-K:1999			ECLS-K:2011					Difference, 2011-1999		
	K	Summer	Grade 1	K	Summer 1	Grade 1	Summer 2	Grade2	K	Summer	Grade 1
$\Delta T_{SD_1}^{(rate)}$											
White students	0.172***	0.066***	0.153***	0.163***	0.068***	0.123***	0	0.087***	−0.009**	0.002	−0.03***
	(0.002)	(0.008)	(0.003)	(0.002)	(0.012)	(0.004)	(0.009)	(0.003)	(0.003)	(0.014)	(0.005)
Black-White	−0.004	0	0.002	0.009*	−0.028$^{\sim}$	−0.017***	0.014	−0.007$^{\sim}$	0.013*	−0.028	−0.019**
	(0.004)	(0.016)	(0.005)	(0.004)	(0.016)	(0.005)	(0.012)	(0.004)	(0.006)	(0.023)	(0.007)
Hispanic-White	0.016**	−0.022	0.022***	0.036***	−0.062**	−0.004	−0.019	0.013*	0.02**	−0.04$^{\sim}$	−0.026***
	(0.005)	(0.014)	(0.005)	(0.004)	(0.019)	(0.004)	(0.017)	(0.006)	(0.006)	(0.024)	(0.006)
90th percentile SES students	0.164***	0.067***	0.145***	0.144***	0.087***	0.123***	0	0.085***	−0.02***	0.02	−0.022***
	(0.002)	(0.009)	(0.003)	(0.002)	(0.011)	(0.003)	(0.009)	(0.003)	(0.003)	(0.014)	(0.004)
10th-90th percentile SES	0.02***	−0.015	0.023***	0.051***	−0.075***	−0.002	−0.007	0.012**	0.031***	−0.06**	−0.025***
	(0.003)	(0.012)	(0.005)	(0.004)	(0.014)	(0.004)	(0.012)	(0.004)	(0.005)	(0.018)	(0.006)
$\Delta G_{ES}^{(rate)}$											
Black-White	−0.009*	0.015	−0.009$^{\sim}$	−0.006	0.01	−0.023***	0.032*	−0.015**	0.003	−0.005	−0.014$^{\sim}$
	(0.004)	(0.017)	(0.005)	(0.005)	(0.02)	(0.006)	(0.014)	(0.005)	(0.006)	(0.026)	(0.008)
Hispanic-White	0.015**	−0.026$^{\sim}$	0.02**	0.023***	−0.023	−0.008$^{\sim}$	−0.015	0.012$^{\sim}$	0.008	0.003	−0.028***
	(0.006)	(0.015)	(0.006)	(0.004)	(0.019)	(0.005)	(0.02)	(0.006)	(0.007)	(0.024)	(0.008)
10th-90th percentile SES	0.015***	0	0.009*	0.026***	−0.039*	0	−0.012	0.009$^{\sim}$	0.011*	−0.039$^{\sim}$	−0.009
	(0.003)	(0.012)	(0.005)	(0.004)	(0.017)	(0.005)	(0.014)	(0.005)	(0.005)	(0.021)	(0.007)

Note. Monthly math learning rates (White students, high SES students), differences in monthly math learning rates ($\Delta T_{SD_1}^{(rate)}$; top panel), differences in rates of changes in standardized mean differences ($\Delta G_{ES}^{(rate)}$; bottom panel) by race/ethnicity and SES over each school year and summer, and differences in $\Delta T_{SD_1}^{(rate)}$ and $\Delta G_{ES}^{(rate)}$ between ECLS-K:99 and ECLS-K:2011. Sampling weight C1CW0 applied for ECLS-K:99 and W1C0 for ECLS-K:2010. Standard errors that account for the complex sampling design are in parentheses. ECLS-K:1999 = Early Childhood Longitudinal Study–Kindergarten Class of 1998–1999; ECLS-K:2011 = Early Childhood Longitudinal Study–Kindergarten Class of 2010–2011; K = kindergarten; SES = socioeconomic status—continuous composite of parental income, education, and occupational prestige. Racial/ethnic inequalities and SES inequalities estimated in separate models (other race–White and Asian-White inequalities estimated in models but not shown). All standardizations adjust for test reliability. Estimates derived from the longitudinal model with random intercepts for students, incorporating all available test data and adjusting for test date, time-varying effects of student age at time of fall kindergarten assessment, and whether student was a first-time kindergartener. See Tables 1 and 2 for sample sizes.

$^{\sim}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

TABLE 5

Reading Inequality Changes (Monthly Rates) by Race/Ethnicity and SES Over the School Year and Summer: ECLS-K:1999 and ECLS-K:2011

	ECLS-K:1999			ECLS-K:2011					Difference, 2011-1999		
	K	Summer	Grade 1	K	Summer 1	Grade 1	Summer 2	Grade 2	K	Summer	Grade 1
$\Delta T_{SD_1}^{(rate)}$											
White students	0.186***	0.032***	0.177***	0.199***	0.001	0.137***	−0.006	0.067***	0.013***	−0.031$^{\sim}$	−0.04***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.015)	(0.005)	(0.008)	(0.002)	(0.004)	(0.016)	(0.005)
Black-White	−0.003	−0.002	−0.003	−0.007	0.018	−0.01$^{\sim}$	0.023$^{\sim}$	−0.005	−0.004	0.02	−0.007
	(0.003)	(0.016)	(0.005)	(0.005)	(0.018)	(0.006)	(0.014)	(0.004)	(0.006)	(0.024)	(0.008)
90th percentile SES students	0.176***	0.028***	0.17***	0.18***	0.02	0.134***	−0.019*	0.065***	0.004	−0.008	−0.036***
	(0.002)	(0.008)	(0.003)	(0.002)	(0.013)	(0.004)	(0.009)	(0.003)	(0.003)	(0.015)	(0.005)
10th-90th percentile SES	0.026***	−0.003	0.014*	0.037***	−0.019	−0.002	0.039***	0.003	0.011$^{\sim}$	−0.016	−0.016*
	(0.004)	(0.017)	(0.006)	(0.004)	(0.015)	(0.005)	(0.01)	(0.003)	(0.006)	(0.023)	(0.008)
$\Delta G_{ES}^{(rate)}$											
Black-White	−0.005	0.014	−0.012*	−0.013*	0.054**	−0.023***	0.029$^{\sim}$	−0.015**	−0.008	0.04	−0.011
	(0.004)	(0.016)	(0.005)	(0.005)	(0.02)	(0.006)	(0.015)	(0.005)	(0.006)	(0.026)	(0.008)
10th-90th percentile SES	0.024***	0.015	0	0.024***	0.006	−0.012**	0.01	−0.007$^{\sim}$	0	−0.009	−0.012
	(0.004)	(0.016)	(0.006)	(0.005)	(0.017)	(0.005)	(0.012)	(0.004)	(0.006)	(0.023)	(0.008)

Note. Monthly reading learning rates (White students, high SES students), differences in monthly reading learning rates ($\Delta T_{SD_1}^{(rate)}$; top panel), differences in rates of changes in standardized mean differences ($\Delta G_{ES}^{(rate)}$; bottom panel) by race/ethnicity and SES over each school year and summer, and differences in $\Delta T_{SD_1}^{(rate)}$ and $\Delta G_{ES}^{(rate)}$ between ECLS-K:99 and ECLS-K:2011. Sampling weight C1CW0 applied for ECLS-K:99 and W1C0 applied for ECLS-K:2010. Standard errors that account for the complex sampling design are in parentheses. ECLS-K:1999 = Early Childhood Longitudinal Study–Kindergarten Class of 1998–1999; ECLS-K:2011 = Early Childhood Longitudinal Study–Kindergarten Class of 2010–2011; K = kindergarten; SES = socioeconomic status—continuous composite of parental income, education, and occupational prestige. Racial/ethnic inequalities and SES inequalities estimated in separate models (Hispanic-White, other race–White, and Asian-White inequalities are estimated in models but not shown). All standardizations adjust for test reliability. Estimates derived from the longitudinal model with random intercepts for students, incorporating all available test data and adjusting for test date, time-varying effects of student age at time of fall K assessment, and whether student was a first-time kindergartener. See Tables 1 and 2 for sample sizes.
$\sim p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

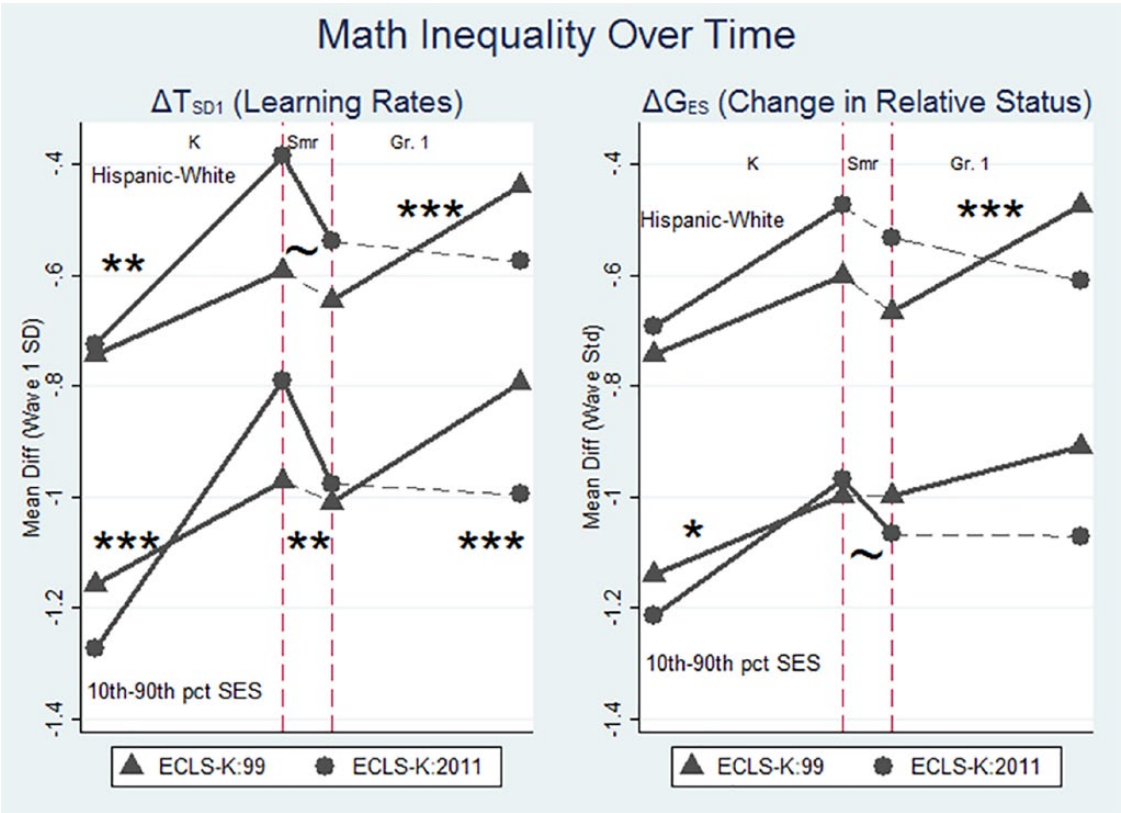

FIGURE 1. *Seasonal changes in Hispanic-White and SES math inequality across ECLS-K cohorts. Solid lines indicate that the rate of inequality change is significantly different from zero at* $\alpha = .05$ *(long dash,* $p < .10$*; short dash, not significant). Asterisks indicate that rates of inequality change for a given between-group comparison and season are significantly different across ECLS-K cohorts:* ~$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$. ECLS-K = Early Childhood Longitudinal Study–Kindergarten Class; SES = socioeconomic status.*

ECLS-K:2011 versus the ECLS-K:1999. However, consistent with broader trends of increasing segregation and economic inequality, we find evidence that summer math learning was more unequal between groups in the recent cohort. Third, by first grade, the trend of increased school year equalizing in the ECLS-K:2011 has faded away, often reversing. That is, achievement becomes more unequal over first grade in the ECLS-K:2011 versus the ECLS-K:1999. This pattern is most striking for math inequality when measuring relative differences in learning rates ($\Delta T_{SD_1}^{(rate)}$). We now turn to a more detailed presentation of each key finding.

More equalizing over K in recent years. Math inequality between students from the 90th and 10th percentiles of SES narrowed over K for both cohorts. This can be seen by the positive slopes over K in the left panel of Figure 1. However, this inequality narrowed more over 2010–2011 versus 1998–1999 (with narrowing of .051 vs. .02 *SD* per month; see Table 4).

In the recent cohort, we also see an increase in the rate of math inequality narrowing over K for Hispanic-White and Black-White relative learning rates ($\Delta T_{SD_1}^{(rate)}$). This can be seen by the steeper positive K slopes for the ECLS-K:2011 in the left panels of Figures 1 (Hispanic-White) and 2 (Black-White). In 2010–2011, Hispanic students learned .036 fall K *SD* more per month than White students (fourth column, $\Delta T_{SD_1}^{(rate)}$ panel of Table 4). Consequently, we see .02 *SD* more equalizing per month over K in 2010–2011 versus 1998–1999 (ninth column). Also in 2010–2011, Black students learned .009 fall K *SD* more per month than White students (fourth column of $\Delta T_{SD_1}^{(rate)}$ panel of Table 4). This amounted to .013 *SD* more inequality narrowing per month as compared with 1998–1999 (third from last column of Table 4, $\Delta T_{SD_1}^{(rate)}$ panel).

When inequality is operationalized as changes in relative status ($\Delta G_{ES}^{(rate)}$), trends are similar to those for $\Delta T_{SD_1}^{(rate)}$ but less pronounced. Additionally, not all cross-cohort differences that were statistically significant by $\Delta T_{SD_1}^{(rate)}$ were significant by $\Delta G_{ES}^{(rate)}$. This can be seen by comparing the K periods in the right-hand panels ($\Delta G_{ES}^{(rate)}$) and left-hand panels ($\Delta T_{SD_1}^{(rate)}$) of Figures 1 and 2.

This picture of more school year equalizing over K is followed by a less optimistic picture of summer dynamics.

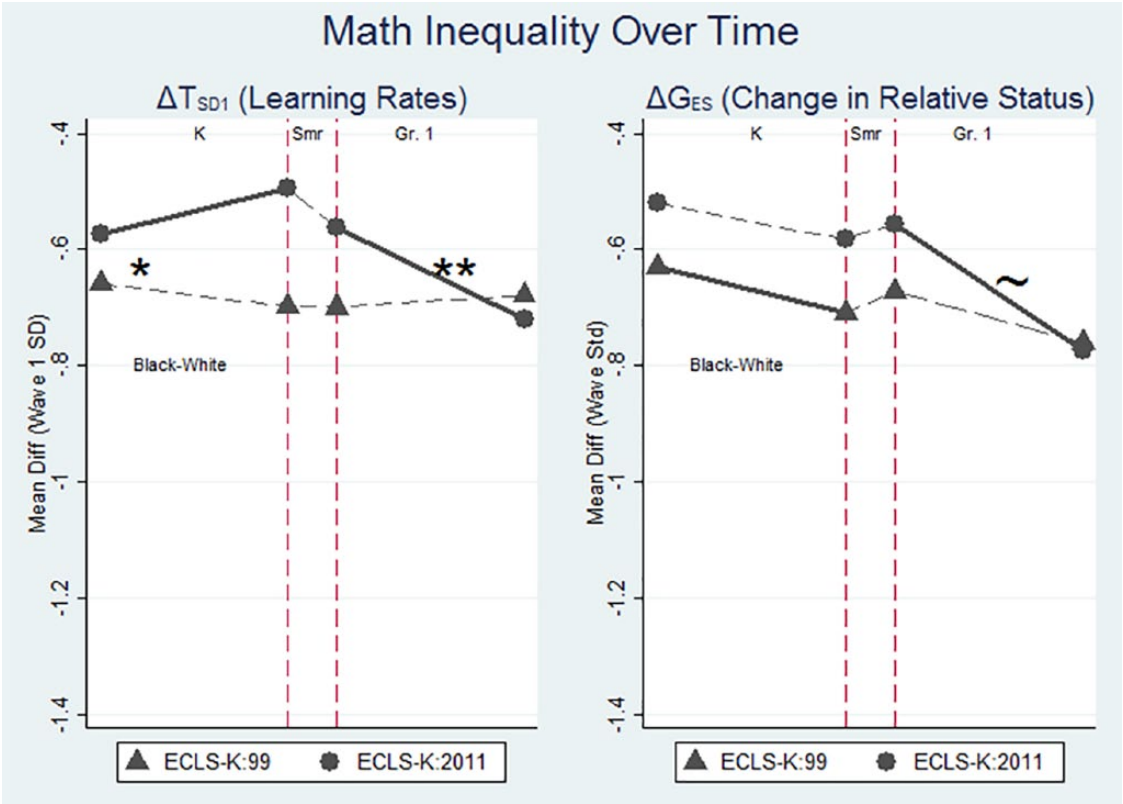

FIGURE 2. *Seasonal changes in Black-White math inequality across ECLS-K cohorts. Solid lines indicate that the rate of inequality change is significantly different from zero at* $\alpha = .05$ *(long dash,* $p < .10$*; short dash, not significant). Asterisks indicate that rates of inequality change for a given season are significantly different across ECLS-K cohorts: ~*$p < .10$*.*
*$p < .05$. **$p < .01$. ***$p < .001$. ECLS-K = Early Childhood Longitudinal Study–Kindergarten Class.*

More inequality widening over summer in recent years. In the left-hand panel of Figure 1, we see that over the summer of 1999, students from the 10th and 90th percentiles of SES learned math at statistically equivalent rates. In the summer of 2011, however, the steep negative slope indicates that low SES students learned less math than high SES students (.075 *SD* per month less). This led to a significant difference across cohorts of .06 *SD* more inequality widening per month in the recent cohort (second column from last, Table 4). Most of this cross-cohort difference seems to be due to low SES students gaining less over the summer (relative to the fall K *SD*) in 2011 versus 1999 (low SES students in 1999: .067 – .015= .052 *SD* per month; low SES students in 2011: .087 – .075 = .012 *SD* per month). When operationalized as change in relative status, math inequality by SES widened by a marginally significant .039 *SD* more per month in the recent cohort (second column from last, $\Delta G_{ES}^{(rate)}$ panel).

Over the summer of 2011, Hispanic students learned significantly less math than White students (see the significant negative summer slope in the left-hand panel of Figure 1). This came after Hispanic and White students showed statistically equivalent math learning rates over the summer of 1999. However, the cross-cohort difference in summer inequality change did not reach statistical significance. Black-White math inequality did not change significantly over the summer in either cohort (see Figure 2).

More inequality over first grade in recent years. The positive trends that we saw over K reversed during first grade, when inequality in math learning (ΔT_{SD_1}) widened more or narrowed less in the recent cohort in every case. As indicated by the flat slopes over Grade 1 in the left panel of Figure 1, absolute Hispanic-White and SES math inequality did not change significantly over the 2011–2012 school year. This contrasts the significant narrowing of these inequalities over first grade in the ECLS-K:1999. For SES and Hispanic-White inequality, this resulted in approximately .025 *SD* less narrowing per month over Grade 1 in the later cohort (last column, $\Delta T_{SD_1}^{(rate)}$ panel of Table 4). Operationalized as change in relative status, math inequality by SES narrowed over first grade in the ECLS-K:1999 but was constant in the ECLS-K:2011. However, this cross-cohort difference was not statistically significant (right panel, Figure 1). For

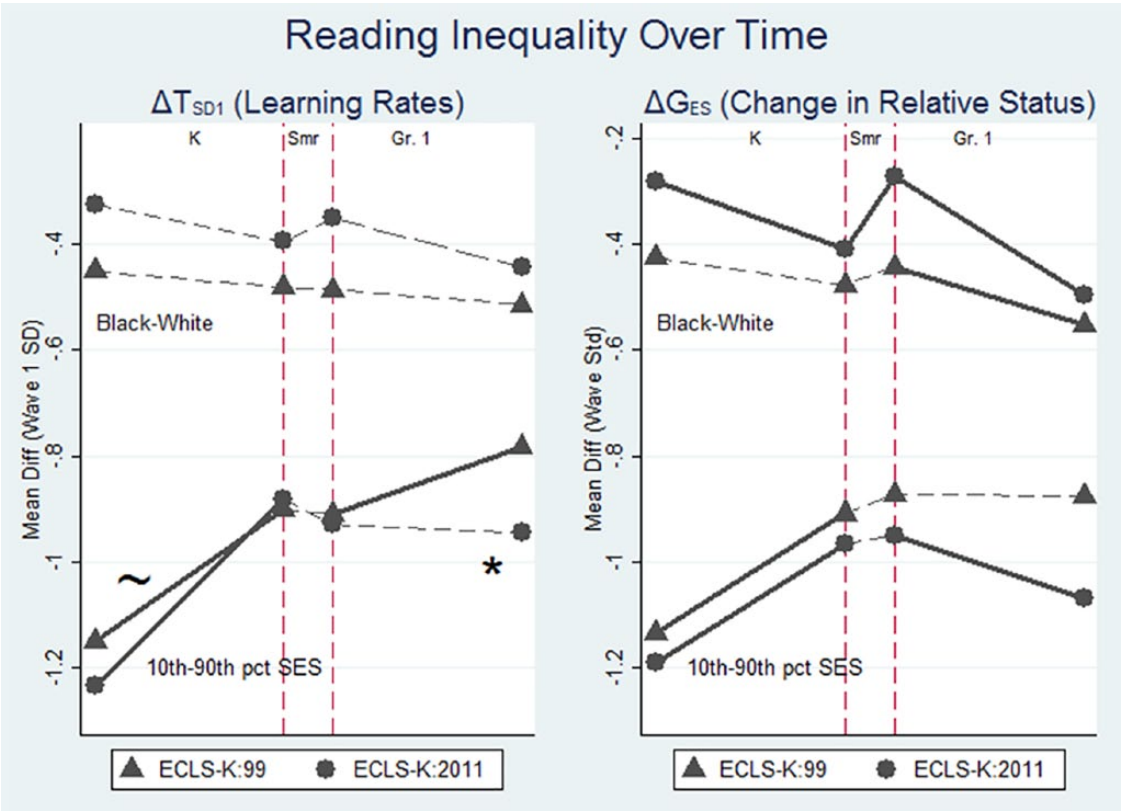

FIGURE 3. *Seasonal changes in Black-White and SES reading inequality across ECLS-K cohorts. Solid lines indicate that the rate of inequality change is significantly different from zero at* $\alpha = .05$ *(long dash,* $p < .10$*; short dash, not significant). Asterisks indicate that rates of inequality change for a given between-group comparison and season are significantly different across ECLS-K cohorts:* ~$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$. ECLS-K = Early Childhood Longitudinal Study–Kindergarten Class; SES = socioeconomic status.*

Hispanic-White changes in relative status, we found .028 *SD* less narrowing per month over Grade 1 in the recent cohort (last column, $\Delta G_{ES}^{(rate)}$ panel).

In the ECLS-K:2011, Black students learned .017 *SD* less per month over first grade as compared with White students (sixth column, $\Delta T_{SD_1}^{(rate)}$ panel of Table 4). This represented significantly more inequality widening as compared with the ECLS-K:1999, in which Black and White students showed equal rates of math learning over Grade 1. Similarly for changes in relative status, Black-White inequality grew more over first grade in the recent cohort by a marginally significant amount (see the negative slopes for Grade 1 in the right-hand panel of Figure 2).

Summer 2 and Grade 2 (ECLS-K:2011). In Tables 4 and 5, we also include the ECLS-K:2011 results for the post–Grade 1 summer and Grade 2 school year. Here, we see a slowing of between-group inequality changes. In most cases, inequalities are stagnant over the summer after Grade 1 (with the exception of significant Black-White math inequality widening by ΔG_{ES} and significant SES reading narrowing by ΔT_{SD_1}). Some between-group equalizing occurs over Grade 2, but the magnitudes are always smaller than the equalizing that we saw over K (Black-White inequality is again an exception, with significant widening by ΔG_{ES} for math and reading). Unfortunately, it is not possible to know how these trends compare with those for the earlier cohort.

Discussion

Using data from the ECLS-K:1999 and ECLS-K:2011, we examined changes across cohorts in the seasonal dynamics of academic achievement inequality by SES and race/ethnicity. Schools seem to accomplish more equalizing over K today than in the past, but there is evidence of more inequality widening over the summer after K. This is followed by an even less optimistic picture over Grade 1, when between-group inequality became greater in the ECLS-K:2011 than the ECLS-K:1999. The net result was that in the recent cohort, inequality often widened more (Black-White) or narrowed less (Hispanic-White and SES) from the beginning of K to the end of first grade.

While the majority of inequality is already present at K entry in many cases (Reardon, 2011; von Hippel & Hamrock, 2016), the magnitudes of some of these cross-cohort differences are meaningful. Math inequality between students at

the 10th and 90th SES percentiles narrowed by .031 fall K *SD* more per month over K in the recent cohort. This amounts to approximately .29 *SD* more narrowing total over that school year (assuming the average 9.5-month school year), which represents 25% of the standardized mean difference measured in the fall of K in 2010. Over first grade in the 1998–1999 cohort, Hispanic-White math inequality narrowed by .026 *SD* more per month (ΔG_{ES}) as compared with the 2010–2011 cohort. Aggregated over the school year, this comes to approximately .25 *SD* less narrowing over that grade for the recent cohort. This represents 37% of the standardized mean difference in fall of K in 2010.

Interpreting Results

As noted earlier, test scales have not been equated across ECLS studies. This has implications when interpreting our results. For example, the decreased relative rate of math growth over K for high SES students in the ECLS-K:2011 versus the ECLS-K:1999 does not necessarily represent an absolute decrease in the amount that students learned each month. We cannot tell whether high SES kindergarteners in 2010–2011 learned less, more, or an equal amount over each month as compared with high SES kindergarteners over 1998–1999. Rather, what these results suggest is that, relative to the amount of skill variation at K entry, high SES kindergarteners developed math skills at a slower rate in the more recent cohort. A similar point applies to differences in inequality changes. For example, the larger K learning rate advantage for low versus high SES students in the ECLS-K:2011 represents a larger advantage relative to the fall K *SD*. If a common scale were available across studies, we might discover that the differences in learning rates over K by SES stayed the same or even got worse across cohorts in terms of absolute learning. Keeping in mind that our comparisons should not be interpreted in absolute terms, we proceed with a discussion of the results.

The finding that more equalizing generally occurs over K now as compared with the past coheres with earlier work showing that the increasing academic rigor of K has been more dramatic for low-income students than for high-income students (Bassok et al., 2016). This trend could be linked to the major curricular change that occurred over this period—namely, the widespread adoption of the Common Core Standards. Even if implementation of the new standards did not differ by social class—indeed, even if implementation was better for higher-income students—the increase in curricular rigor could nevertheless have been more dramatic for low-income students than for high-income students. This may help explain the increased between-group inequality narrowing over K.

Although comparisons across ECLS studies show narrowing Hispanic-White gaps in full-day K participation, differential enrollment across time does not explain any of the inequality changes shown here: Our main results replicate when restricting both ECLS samples to students enrolled in full-day K (see Appendix L).

Our finding that math inequality by SES grew more over the summer in 2011 versus 1999 is consistent with research showing the longer-term trend that high-income parents have been increasing spending on their children's cognitive development more so than have low-income parents (Duncan & Murnane, 2011; Kornrich & Furstenberg, 2013). However, it is not clear why math inequality but not reading inequality widened by SES over the summer. One possibility is that lower-income students have increased their participation in summer reading programs but not math programs. Unfortunately, we are limited in the extent that we can examine this in the data: While the ECLS-K:2011 distinguishes between attending summer school for math versus reading, the ECLS-K:1999 does not.

The pattern of widening inequalities over Grade 1 in the recent cohort is broadly consistent with trends of increasing segregation by income and increasing educational spending gaps. Perhaps the disproportionate increase in academic rigor over K for low-income students did not continue into the first grade, or perhaps the skills typically taught in K (letter sounds, counting) are more responsive to increases in academic rigor than are the skills that students learn in first grade.

The changes across cohorts in inequality dynamics are more pronounced for math than reading. The school year changes are consistent with the notion that math is more sensitive to school effects than reading. According to this argument, a greater share of the skills relevant to reading achievement (e.g., vocabulary acquisition, language exposure, print exposure) are acquired outside of school, making school-based math instruction more impactful than reading instruction (e.g., Burkam et al., 2004; Cooper et al., 1996; Murnane, 1975). As such, we might expect the differential changes in schooling experiences by SES over this period (Bassok et al., 2016; Shores & Steinberg, 2017) to have had a greater impact on math inequality than reading. Yet we also find that math inequality by SES grew over the post-K summer in 2011. While this finding is consistent with previous analyses of the ECLS-K:2011 (Quinn et al., 2016; von Hippel et al., 2018), it differs from the ECLS-K:1999 and other early studies showing that reading inequality but not math inequality by SES widened over the summer (Cooper et al., 1996). Research is needed into the ways in which math-relevant summer learning experiences may have become more stratified by class in recent years.

An unexpected result over first grade was that—relative to the variation in fall K for their respective cohorts—students from all examined groups learned less in the ECLS-K:2011 than the ECLS-K:1999 (but the decrease was sharper for students from disadvantaged, rather than advantaged, backgrounds). As discussed earlier, one potential explanation might be that the ECLS-K:2011 data are picking up the effects of the Great Recession, which would have affected students' school and nonschool environments. Research suggests that the recession significantly reduced math and reading achievement and that effects were

concentrated among students in low-income districts and districts serving higher proportions of minoritized students (Shores & Steinberg, 2017). This is consistent with our observed overall decreases in relative learning rates and greater average decreases for students from minoritized and less economically advantaged backgrounds. Again, the greater between-group equalizing over K in the recent cohort may be a sign that the disproportionate increase in rigor over K for lower-income students (Bassok et al., 2016) counteracted recession effects that school year.

Limitations and Future Research

As discussed here, a strength of the ECLS data is that they cover the early childhood years when equalization efforts may have maximum payoff (Raudenbush & Eschmann, 2015). Nevertheless, a limitation to this study is that we cannot know the extent to which these patterns generalize to later grades. Although it appears that inequalities remain more constant each season as students get older, we are able to examine only a limited number of grades, and the trend may change in middle or high school. Additionally, while the similarity of the two ECLS studies makes them ideal for investigating trends over time with minimal cross-study confounds, we are limited in that we have only two cohorts and cannot know the extent to which the trends found here are representative of trends over a broader period.

The finding of more inequality narrowing over K in the ECLS-K:2011 than the ECLS-K:1999 is an encouraging result that should be better understood. Was the differential increase in academic rigor by SES (Bassok et al., 2016) driven by cultural changes or by the national move toward common standards? Are there lessons from the K period that might be applied in later grades? Regarding the summer period, do differential changes in time use by SES help explain why inequality widened more in math but not reading? Analyzing trends on the ECLS-K survey items that inquire about parents' activities with their children might be a useful exercise for future research. Investigating these issues, while beyond the scope of the present article, could lead to improved policies and practices for ending inequality in educational outcomes.

Another area for future research is documenting the extent to which the seasonal dynamics of achievement inequality differ by geography and grade level. The ECLS-K studies are useful because they provide a summary of what is happening on average across the country, but there is likely variation across locales. For example, the seasonal patterns in NWEA data from a southeastern state (Atteberry & McEachin, 2016) differ from the national patterns found in the ECLS-K:2011. However, differences other than geography may explain these contrasting findings, including the grade levels of students in each sample. Additionally, given the heterogeneity that exists within the Hispanic population (and Asian population, for whom estimates are not shown here), it will be important to disaggregate trends for these groups to develop an understanding of the unique needs of the various ethnic groups that compose these broader groups (Teranishi, 2007).

Future research can investigate the opportunity gaps that lead to inequality in academic outcomes. Given that test score inequalities result from historical and systemic inequities (Milner, 2012), it is important to develop greater understanding about how differential access to resources has led to the current dynamics in which some achievement inequalities are widening faster during post-K summer and first grade as compared with the past. We reiterate Gutierrez's (2008) call for more research on effective teaching and learning environments for minoritized populations, with richer descriptions of what these environments look like.

Conclusion

Researchers analyzing seasonal learning patterns in the ECLS-K:1999 concluded that schools serve as equalizers. However, the school and nonschool contexts in which students find themselves today differ from those experienced by students at the turn of the century. We find that, in general, more between-group equalizing occurred over K in 2010–2011 versus 1998–1999. This coheres with research showing that K has become more academically focused of late and that this change has been more pronounced in schools serving students from low-income backgrounds (Bassok et al., 2016). However, this positive trend did not continue past K. Over the post-K summer in 2011, inequalities were stagnant or widened more (vs. 1999), and the equalizing effect of schools did not continue into first grade in 2011–2012. Consequently, the net result over the first 2 years of schooling was that achievement inequalities by race/ethnicity and SES widened more or narrowed less in the recent cohort. This overall trend is what might have been anticipated based on increasing segregation and less equitable educational spending in school and nonschool environments (Evans et al., 2017; Kornrich & Furstenberg, 2013). While these patterns did not hold universally, the instances in which they did not hold were instances of no significant change in trends rather than examples of significant changes in the opposite direction. These findings raise the question of whether there are any lessons to be learned from the K period that could be applied to help reverse the trend of increased inequality widening over first grade.

Acknowledgments

This research was supported by a grant from the American Educational Research Association, which receives funds for its AERA Grants Program from the National Science Foundation under Grant DRL-0941014. Opinions reflect those of the authors and do not necessarily reflect those of the granting agencies. This document has been approved for dissemination to nonlicensed personnel by the Institute of Education Sciences. We are grateful to North Cooc for providing feedback on this article.

Notes

1. Von Hippel et al. (2018) examined seasonal patterns across ECLS-K studies with goals different from ours here and with different models. Von Hippel et al. were interested in the ways in which test scaling may have distorted the findings in the work by Downey et al. (2004), and they sought to determine whether Downey and colleagues' conclusions replicate with new data based on the improved theta scores. As such, von Hippel et al. did not formally test for changes across cohorts. In contrast, we are interested in the substantive question of change over time; therefore, we formally test for changes. We also interpret the results with a different goal and in the context of a different literature. Another important difference is that von Hippel et al. (like Downey et al.) included race/ethnicity and SES together in the same models. Unlike these authors, we are interested in changes in the unadjusted trends. Our logic is that the unadjusted inequalities are what we ultimately want to eradicate, so it is these inequalities whose progress we should track over time. Finally, von Hippel and colleagues' models used theta scores standardized by the fall K mean and *SD*. We take the additional step of including models that use wave-standardized scores. As discussed in this article, doing so provides an alternative operationalization of inequality.

2. Our models do not exactly replicate those of past researchers, who often included more covariates in their models and estimated racial/ethnic and SES trends from the same model. Additionally, other researchers treated within-student residual variance as a known quantity to allow for identification of an overparameterized random effects model (Benson & Borman, 2010; Cheadle, 2008; Downey et al., 2004; von Hippel et al., 2018).

3. For graphic purposes, the inequality changes are projected to the beginning and end of each season in the figures (assuming a 9.5-month school year and 2.5-month summer); therefore, beginning- and end-of-school-year standardized mean differences in the figures do not match the observed inequalities at the time of measurement shown in Table 3.A Sidak adjustment can be made for a family-wise alpha of .05; with this adjustment, the critical values for a two-tailed test of a cross-cohort difference in a given season is ±2.99 for math (3 between-group comparisons × 3 seasons × 2 operationalizations of inequality = 18 comparisons) and ±2.86 for reading (2 between-group comparisons × 3 seasons × 2 operationalizations of inequality = 12 comparisons).

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