When Does Inequality Grow?

A Seasonal Analysis of Racial/Ethnic Disparities in Learning in Kindergarten through Eighth Grade

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Kuhfeld, M., Condron, D., & Downey, D. (2019). *When Does Inequality Grow? A Seasonal Analysis of Racial/Ethnic Disparities in Learning in Kindergarten through Eighth Grade.* (The Collaborative for Student Growth at NWEA Working Paper).

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ABSTRACT

What role does schooling play in the development of racial/ethnic inequalities in academic skills? Seasonal learning studies, which allow researchers to compare the growth of achievement gaps when school is in versus out of session, provide important evidence on whether schools reproduce or exacerbate educational inequalities. However, most existing seasonal studies have been restricted to the early grades, limiting our understanding of the relationship between schooling and inequality in the later grades. In this study, we examine seasonal patterns of racial/ethnic achievement gaps in kindergarten through eighth grade using a national sample of over two million students. We find that the Black-White achievement gaps widen during school years and shrink during summers, whereas Asian students generally pull ahead of Whites at a faster rate during summers than during school years. We conclude by discussing the implications of our findings in relation to the broader literature on schools and educational inequalities.

Keywords: *achievement gap; race; elementary schools; longitudinal models*

Racial/ethnic inequalities in academic skills persist as a significant social problem. Asian and White students produce higher test scores than Black, Hispanic, and Native American students (Musu-Gillette et al., 2017), but what role do schools play in shaping these gaps? Children spend the vast majority of their time outside of school, making it difficult to know whether racial gaps in math and reading skills are due to school or non-school influences.[1] The non-school confound represents a formidable methodological challenge for understanding how schools matter.

One approach to this challenge is take advantage of a natural feature of the American school calendar—children typically do not attend school in the summers. This seasonal comparison scholarship focuses on whether gaps grow faster when school is in versus out of session, providing important empirical leverage for understanding how schooling matters. A clear picture does not emerge from this work, however; different gaps expand during different seasons and to varying degrees depending on data sources and measures of skills (von Hippel & Hamrock, 2019). In addition, much of what we know from national data is based on only the first two or three school years and one or two summers during the early elementary years (Downey, von Hippel, & Broh, 2004; Fryer & Levitt, 2004, 2006; Quinn et al., 2016; von Hippel, Workman, & Downey, 2018).

We assess racial/ethnic differences in seasonal learning patterns among over two and a half million students from across the U.S. spanning kindergarten through eighth

[1] Walberg (1984) estimates that the average 18-year old American has spent just 13% of their waking time in school.

grade. Our analyses allow us to draw more definitive conclusions relative to those in past studies because our very large, nationally-weighted sample covers nine school years and six summers.

Seasonal Studies of Racial/Ethnic Achievement Gaps

Sizeable racial/ethnic disparities in academic skills are present when children begin kindergarten, highlighting their non-school origins (von Hippel et al., 2018). The role of schooling is less clear, as schools might widen racial/ethnic gaps, leave them intact, or reduce them (Downey & Condron, 2016). A clear answer has yet to emerge from this research, however, because the early seasonal studies suffered from scaling issues and the more recent work is limited in scope and generalizability (von Hippel & Hamrock, 2019).

Using single-city data on students in Atlanta and Baltimore respectively, Heyns (1978) and Entwisle and Alexander (1994) found that Black-White reading gaps grew faster during summers than school years. This made intuitive sense because Black students disproportionately come from lower socioeconomic status (SES) backgrounds, and evidence had implicated summer as the season when SES gaps expand (Entwisle & Alexander, 1992). However, using the national *Early Childhood Longitudinal Study – Kindergarten Cohort of 1998-99* (*ECLS-K:98*), both Downey and colleagues (2004) and Fryer and Levitt (2004) reached the opposite conclusion. In those data, Black-White gaps widened during kindergarten and first grade and not during the summer in between.

In a critique of the measures of skills used in Entwisle and Alexander's (1992, 1994) *Beginning School Study* (*BSS*) and the *ECLS-K:98*, von Hippel and Hamrock

(2019) demonstrate the impact of two measurement artifacts. First, both the *BSS* and the original release of the *ECLS-K:98* featured test-score scales that were not interval scaled and were not vertically-aligned across grades. Interval-level variables have equal distances between levels; for example, the difference in weight between 9 and 10 pounds is the same difference (one pound) as the difference between 74 and 75. This was not the case with the *BSS* or *ECLS-K:98* test-score scales, however; one-point increments did not represent equal skill gains throughout the scales or across grade levels (they were not vertically aligned). As a result, the studies using *BSS* and *ECLS-K:98* almost certainly overstated the extent to which achievement gaps increase over time and likely distorted estimates of racial/ethnic gaps too. The earlier Thurstone scales used in the *BSS* suggested that variance in skills increases substantially as children age, whereas subsequent scales based on item response theory (IRT) do not typically demonstrate that pattern (von Hippel & Hamrock, 2019).

Second, in many of the earlier studies, students took different tests in the fall than they had taken the previous spring. As a result, it is difficult to draw conclusions about summer patterns because spring to fall changes in scores "were confounded with changes in test form" (von Hippel & Hamrock, 2019, p. 47). Students often did less well on fall tests not so much because of "summer setback" but because they confronted a different test than the one they took in the spring. Adaptive testing has emerged as a preferred method for developing interval scales. On a computer, children take tests that adapt to their prior and current performance in drawing questions tailored to their skill levels from a pool of items ranging in difficulty. Students do not take distinctly different tests each school year; instead, the test administered in the fall overlaps in both content and questions with the test given the prior spring, facilitating the development of a vertically-aligned scale with equal intervals.

Unfortunately, much of the early seasonal literature on racial/ethnic learning gaps used measures of skills that were not interval scales and did not use adaptive testing. This limits confidence in their conclusions. Therefore, we next highlight evidence from a small handful of recent studies that used vertically aligned, interval measures of skills derived from multi-stage or computer adaptive testing. These studies relied on data from the more recent *ECLS-K:2011* and from *NWEA*, our own data source. The *ECLS-K:2011* assessment used a two-stage adaptive test (where students were routed into easier or harder test forms based on their initial performance), while *NWEA*'s assessments adapted at item-level and allowed for the measurement of both on-grade and off-grade state standards.

Recent Insights from Seasonal Studies

Studies using both the *ECLS-K:2011* (Quinn et al., 2016; von Hippel et al., 2018) and data from the *NWEA* (von Hippel & Hamrock, 2019) have found that Black-White gaps grow during school years and either hold steady or shrink during summers. This is an especially troubling pattern because most seasonal studies have found that schools are neutral or even compensatory across other dimensions of inequality, such as SES (Downey et al., 2004; von Hippel et al., 2018). As Quinn and colleagues (2016) put it, "Black-White gaps stand out because their dynamics are more consistent with schools exacerbating rather than alleviating inequality" (p. 451). By eighth grade, Black-White gaps are notably larger than they were at the beginning of kindergarten (von Hippel & Hamrock, 2019), and the best evidence we have suggests that gap growth occurs primarily during school years and not summers.

Patterns for the Hispanic-White gap are less clear. In the *ECLS-K:2011*, the Hispanic-White math gap grew faster during summers while the reading gap grew faster during school years (von Hippel et al., 2018). In the *NWEA* data, Hispanic-White math and reading gaps grew during school years and shrank during summers, widening the gaps by about one fifth between kindergarten and eighth grade (von Hippel & Hamrock, 2019). On balance, then, Hispanic-White gaps trace primarily to school years but at the same time appear to grow less over time compared to Black-White gaps.

Skill disparities between Asian and White students are distinct because in this case the minority group outperforms the dominant group on average (Musu-Gillette et al., 2017). The best seasonal evidence on Asian students comes from Yoon and Merry (2018), who used *NWEA* data on more than 130,000 Asian and White students from kindergarten through seventh grade. Comparing summer and school-year rates of gap growth, they found that "the Asian advantage would be larger if learning rates were to progress during the school year as they did in the summer" (p. 692). In other words, Asian students increase their skill advantages during summers at faster rates than they do during school years. The exception was that Asians' math advantage grew faster during school years than during summers from fourth grade onward. Overall, schools appear to slow the growth of the Asian advantage in reading and math early on while leaving the math advantage intact during the later years.

Extending Past Studies

The key drawback to the *ECLS-K:2011* is that it only allows for seasonal analyses of the first three school years and two summers. As a result, analyses based on those data do not tell us whether and how the seasonal dynamics identified thus far apply to later years (Gamoran, 2016). In addition, the seasonal dynamics in *ECLS-K:2011* are murky; findings often differ depending on the academic subject and grade level. For instance, "…all math gaps except the Black-White gap narrow over K, while only SES and Asian-White reading gaps narrow. Additionally, gap widening is more common over Grade 1 for reading than math and gap narrowing more common over Grade 2 for math than reading" (Quinn et al., 2016, p. 449). We advance the literature by studying children in kindergarten through eighth grade, giving us nine school years to compare to six summers over the course of the elementary and middle-school years and increasing our ability to draw broader conclusions about the role of schools in shaping racial/ethnic skill gaps.

Studies using *NWEA* data also have limitations. Yoon and Merry (2018) and von Hippel and Hamrock (2019) analyzed large samples (roughly 135,000 and 177,000 respectively), but the former was limited to Asian and White students and neither incorporated weighting in order to make their samples nationally representative. As we elaborate below, we use a weighting procedure to make our sample of over two and a half million students consistent with national parameters. Our study features the most comprehensive seasonal analysis of racial/ethnic learning disparities to date.

Method

The data for this study come from the Growth Research Database (GRD) at *NWEA*. We use the test scores from 2,652,382 unique students in 20,944 schools who tested at least once between kindergarten and eighth grade during the 2015-16, 2016-17, and 2017-18 school years. Our sample is limited to students in U.S. public schools with traditional nine-month calendars.

We follow three different cohorts of students over three school years; in other words, we estimate each model using three independent groups of students: (a) students who entered kindergarten in the fall of 2015-16, students who started third grade in the fall of 2015-16, and students who started sixth grade in the fall of 2015-16. We use this design rather than a panel design for three reasons: (a) we maintain grade coverage while avoiding attrition problems that occur in long-term panel studies, (b) we avoid concerns inherent in wide vertical scales about the constancy of the developmental construct across nine years (e.g., rudimentary math skills measured in kindergarten compared to algebraic and geometric knowledge measured in 8th grade), and (c) we lack the historic district calendar records needed for the estimation of summer learning rates for most districts prior to the 2015-16 school year. We utilize six waves of data: fall and spring of 2015-16, fall and spring of 2016-17, and fall and spring of 2017-18.

Reading and Math Skills

We predict students' reading and mathematics scores on *NWEA's* MAP Growth assessment. Each test takes approximately 40 to 60 minutes depending on the grade and subject area. The MAP Growth assessments are computerized, adaptive tests. Each test begins with a question appropriate for the student's grade level, and then adapts throughout the test in response to student performance. Students respond to assessment items in order (without the ability to return to previous items), and a test event is finished when a student completes all the test items (typically 40-53 items). Importantly, MAP Growth scores are scaled using the Rasch item response theory (IRT) model; evidence suggests that they can be treated as interval measures of skills (Thum, 2018). The assessments also adapt beyond a student's current grade level, which means that (a) floor/ceiling effects are highly unlikely and (b) spring and fall tests from different grade levels are not restricted to measuring different grade-specific standards.

Independent Variables

Beyond exposure to school years and summers (elaborated below), our main independent variables are indicators of students' race/ethnicity. We code students as White (the reference category), Black, Asian, or Hispanic. One of the limitations of the *NWEA* data is that they lack an individual-level measure of students' SES. In order to account for SES as best as we can, we control for *district* SES in our conditional growth model using a composite variable constructed by the *Stanford Education Data Archive* (*SEDA*). *SEDA's* district SES variable is a composite of six measures that reflect the socioeconomic composition of families who live within the geographic borders of the district and have children enrolled in public schools: (1) median family income, (2) percent of adults with a bachelor's or higher degree, (3) poverty rate, (4) unemployment rate, (5) Supplemental Nutritional Assistance Program (SNAP) eligibility rate, and (6) the percent of families headed by a single mother.

Weights

Our sample of 20,000 schools is very large but not representative of all U.S. public schools. To make our results nationally representative, we create school-level weights using a set of school and district characteristics from the 2015-16 Common Core of Data from the *National Center of Educational Statistics* (*NCES*) and data collected by the *American Community Survey* (*ACS*) and reported by *SEDA* Version 2.1 (Reardon et al., 2018). The NCES school characteristics included in the weights are the percentage of students receiving free or reduced-price lunch (FRPL), urbanicity, and school racial/ethnic composition. *SEDA* provides information both on district resources and the characteristics of the community residing within the school district geographic boundaries (for details, see Fahle et al., 2018). The *SEDA* variables on which the weights are based include the percentage of adults in the geographic area with at least a bachelor's degree, the 50th percentile income level, the percent of households with children ages 5 to 17 living in poverty, and the percent of unemployed adults. Appendix A describes the creation of the school-level weights that we use to weight our sample of schools to resemble the U.S. population of public schools that serve K-8 students, as well as the weighted descriptive statistics for the schools used in the analytic sample compared with the U.S. population of schools.

School Calendars and Test Dates

Schools using MAP Growth assessments set their own testing schedules, resulting in considerable variation around when students take the tests. To account for time in school before testing, we draw on district calendars from participating school districts.

We have information on 5,411 district calendars, primarily for the 2016-17 and 2017-18 school years, representing 35% of the total number of districts in our sample. For districts that did not provide a school calendar for a given year, we compute start and end dates based on the average dates in the corresponding state and year. Based on the school start/end dates and the test administration dates, we calculate "months of exposure" to each school year and summer break. For example, a hypothetical student testing at the beginning of September in first grade may have 9.3 months of exposure to kindergarten, 2.7 months exposure to summer break following kindergarten, and 2 weeks of exposure to first grade. As we describe in more detail below, we use these estimates as predictors in the growth models to account for differences in testing schedules between students.

Analytic Strategy

We estimate school-year and summer learning rates using a multilevel growth model (Raudenbush & Bryk, 2002), a three-level hierarchical linear model specification similar to that used in prior seasonal studies of learning (Downey et al., 2004; von Hippel et al., 2018). By conditioning on months of exposure, our modeling approach adjusts for variation in the test dates and school-year start/end dates. The MAP Growth test scores (level 1) are nested within students (level 2) and schools (level 3). To account for the non-random selection of schools in our sample, all models were estimated using the school-level weights described in Appendix A. We assume test scores are missing at random (MAR) and include any student who has at least one MAP Growth score, even if he or she did not test in all waves. We describe below the model specification in the context of the kindergarten cohort; the analytic approach for the third and sixth grade cohorts is identical.

Unconditional growth model. We first estimate the monthly learning rates during each school year and summer from kindergarten to second grade. At level 1, the growth model is:

$$y_{tij} = \pi_{0ij} + \pi_{1ij}G0_{ij} + \pi_{2ij}S1_{ij} + \pi_{3ij}G1_{ij} + \pi_{4ij}S2_{ij} + \pi_{5ij}G2_{ij} + e_{tij}. \qquad (1)$$

We view each test score y_{tij} as a linear function of the months that student *i* in school *j* has been exposed to kindergarten ($G0_{ij}$), first grade ($G1_{ij}$), and second grade ($G2_{ij}$); and the number of months that the student has been exposed to the summer after kindergarten ($S1_{ij}$) and first grade ($S2_{ij}$). As von Hippel and colleagues (2018) note, this model "implicitly extrapolates beyond the test dates to the scores that would have been achieved on the first and last day of the school year" (p. 335). Appendix B provides additional details on the coding of months of exposure. The intercept (π_{0ij}) is the predicted score for of student *i* in school *j* testing on the first day of kindergarten. The slopes ($\pi_{1ij}, \ldots, \pi_{5ij}$) are the monthly learning rates of student *i* during each school year and summer. Since the number of level-1 parameters (one intercept plus five growth terms) is equal to the number of time points used to estimate the model, the model as written is not identified. To identify the model, we set the level-1 error variance equal to the square of the standard error of measurement that is reported with each student's MAP score.

At level 2 and 3, the growth parameter vector is allowed to vary among students within schools and between schools:

$$\begin{bmatrix}\pi_{0ij}\\ \pi_{1ij}\\ \pi_{2ij}\\ \pi_{3ij}\\ \pi_{4ij}\\ \pi_{5ij}\end{bmatrix} = \begin{bmatrix}u_0\\ u_1\\ u_2\\ u_3\\ u_4\\ u_5\end{bmatrix} + \begin{bmatrix}r_{0j}\\ r_{1j}\\ r_{2j}\\ r_{3j}\\ r_{4j}\\ r_{5j}\end{bmatrix} + \begin{bmatrix}r_{0ij}\\ r_{1ij}\\ r_{2ij}\\ r_{3ij}\\ r_{4ij}\\ r_{5ij}\end{bmatrix}. \quad (2)$$

Here $\boldsymbol{u}$ is a parameter vector (e.g., the "fixed effects") representing the grand mean of $\boldsymbol{\pi}_{ij}$, while $\boldsymbol{r_j}$ and $\boldsymbol{r_{ij}}$ are random effect vectors representing school-level residual from the school-level grand mean and student-level residual from the school mean. These random effect vectors have covariance matrices $\boldsymbol{T_{St}}$ and $\boldsymbol{T_{Sch}}$, which represent the student (within-school) and school-level variance and covariances. This model is estimated separately for each subject and cohort using HLM Version 7 (Raudenbush, Bryk, & Congdon, 2013).

Conditional growth model. We next estimate a conditional growth model that examines the associations between race/ethnicity, district SES, and skill growth rates. Due to small sample sizes for Native Hawaiian, American Indian, and multiracial students, we do not report their estimates (although they are included in the model as an "other race" category). In the conditional growth model, level-1 remains unchanged from the previous model but a set of race/ethnicity indicators is included at level 2 and district SES (grand-mean centered) is included at level 3:

$$\begin{bmatrix}\pi_{0ij}\\ \pi_{1ij}\\ \pi_{2ij}\\ \pi_{3ij}\\ \pi_{4ij}\\ \pi_{5ij}\end{bmatrix} = \begin{bmatrix}u_0\\ u_1\\ u_2\\ u_3\\ u_4\\ u_5\end{bmatrix} + \begin{bmatrix}\beta_{01j} & \beta_{02j} & \beta_{03j} & \beta_{04j} & \beta_{05}\\ \beta_{11j} & \beta_{12j} & \beta_{13j} & \beta_{14j} & \beta_{15}\\ \beta_{21j} & \beta_{22j} & \beta_{23j} & \beta_{24j} & \beta_{25}\\ \beta_{31j} & \beta_{32j} & \beta_{33j} & \beta_{34j} & \beta_{35}\\ \beta_{41j} & \beta_{42j} & \beta_{43j} & \beta_{44j} & \beta_{45}\\ \beta_{51j} & \beta_{52j} & \beta_{53j} & \beta_{54j} & \beta_{55}\end{bmatrix}\begin{bmatrix}Black\\ Hispanic\\ Asian\\ Other\\ District\ SES\end{bmatrix} + \begin{bmatrix}r_{0j}\\ r_{1j}\\ r_{2j}\\ r_{3j}\\ r_{4j}\\ r_{5j}\end{bmatrix} + \begin{bmatrix}r_{0ij}\\ r_{1ij}\\ r_{2ij}\\ r_{3ij}\\ r_{4ij}\\ r_{5ij}\end{bmatrix}. \quad (3)$$

With these characteristics included, the intercept $\boldsymbol{u}$ is the kindergarten fall status and growth estimate for non-Hispanic White students in an average SES district. The first four columns of the $\boldsymbol{\beta}$ matrix represent the expected difference in status and learning rates between White students and Hispanic, Black, Asian, and Other race/ethnicity students, holding constant the average SES of the individuals living within the district geographic boundaries.

Results

Before turning to the multilevel growth models, we present in Table 1 weighted descriptive statistics by cohort and race/ethnicity for the full analytic sample within each subject. A glimpse at mean test scores over time by racial/ethnic group allows us to examine trends in achievement gaps. We calculated Asian-White and Black-White achievement gaps by subtracting the White mean from the minority group's mean and then dividing the difference by the overall standard deviation (SD) within a grade/term. We excluded Hispanic-White achievement gaps from the figures because, as we elaborate below, their seasonality is less clear than that of the Asian-White and Black-White gaps. Figures 1 and 2 display the achievement gap trends across grades and seasons for math and reading respectively.

[Table 1 here]

Four patterns emerge from Figures 1 and 2. First, the Black-White gaps are larger among eighth graders than they are among kindergartners. At the beginning of kindergarten, Black students trail White students by –.54 SD in math and –.41 SD in reading. Among students finishing eighth grade, the math gap is –.70 SD and the reading gap is –.57 SD. Put differently, the Black-White math gap is 30% larger at the end of eighth grade than it is at the beginning of kindergarten while the reading gap is 39% larger[2]. Second, we see a general pattern of Black-White gaps widening during school years and narrowing during summers. Third, not only are the Asian-White gaps positive, but these gaps increase substantially over time. In the fall of kindergarten, Asian students are just barely ahead of White students, .10 SD in math and .09 SD in reading. At the end of eighth grade, Asians are .45 SD ahead in math and .21 SD ahead in reading. The Asian advantage in math is 339% larger at the end of eighth grade than it is at the beginning of kindergarten while the reading advantage is 145% larger. Fourth, Asian students appear to pull ahead of White students primarily during summers, especially during the early years. Importantly, Figures 1 and 2 do not adjust for variation in students' exposure to schooling. The growth models to which we now turn do just that and provide more finely-grained estimates of when achievement gaps are growing.

[Figures 1 and 2 here]

Before turning to the conditional model's estimates of racial/ethnic gaps by season, we present in Table 2 results from the unconditional growth model in order to assess the overall seasonal learning patterns. The model includes the intercept (the predicted score on the first day of school) and the estimates of the school year and summer monthly learning rates. Across all cohorts, the average monthly learning rates are positive during school years and negative during summers. The school-year learning rates and summer drops are largest in magnitude within the kindergarten cohort and slow

[2] Figures 1 and 2 contain results from three different cohort of students. As a result, the percentage growth in gaps is a function of both changes over time and any cohort differences.

progressively across the grade levels. During kindergarten, students increase an average of 2.10 points per month in reading and 2.26 points per month in math, whereas by eighth grade students gain an average of 0.48 points per month in reading and 0.72 points per month in math. Similarly, summer learning drops are largest in the early grades (a drop of 1.14 points per month after third grade in reading and 1.89 points per month after first grade in math) and smallest following seventh grade (a drop of 0.41 points per month in reading and 0.85 points per month in math).

[Table 2 here]

Correlations among initial scores and the school-year and summer learning rates appear in the second set of columns in Table 2. The estimated student-level correlations indicate that there is a low correlation between initial fall status and summer drop/gains. However, there is a strong and negative correlation between the gains within the school year and the subsequent summer learning, ranging from –.36 to –.56 in reading and –.44 to –.58 in math. These correlations indicate that summer is acting as a sort of "correction;" students who show larger gains during the school year show larger drops on average the following summer. Similarly large correlations are observed between summer drops and the subsequent school year gains, indicating students with larger summer drops are likely to have higher than average gains the next school year. The results of the unconditional model show several expected patterns and give us confidence in our model, but to understand how racial/ethnic gaps change across seasons we next expand the model to include covariates for race/ethnicity and district SES.

Table 3 displays the results of the conditional models. Within each subject, we can track students over school years and summers by first reading down the “K-2 Cohort” column, then down the “G3-5 Cohort” column, and then down the “G6-8 Cohort” column. We begin with the Black-White gap, which shows a consistent seasonal pattern behind the general increase over time noted above. Black students gain fewer points per month than do White students in 16 of the 18 school-year estimates across both subjects. In contrast, in 11 of the 12 summer estimates the Black coefficient is positive, suggesting that Black students experience less of a summer drop compared to White students nearly across the board (the exception is Summer 2016 for the Grade 6-8 cohort). It thus appears that schooling contributes to Black-White disparities in math and reading skills as children progress through the elementary years and into middle school. The coefficients also reveal that the math gap grows at a fairly consistent rate across grade levels while the reading gap grows notably faster during the first few school years before the rate declines beginning in third grade and even equals zero during fifth and eighth grades.

[Table 3 here]

When it comes to the Hispanic-White gaps, the conditional growth models produce estimates that are smaller in magnitude (often statistically indistinguishable from zero) and seasonally less clear compared to the Black-White pattern. In Table 3, the Hispanic slope is negative and significant in 10 school years (mostly in math), but that compares to 16 negative/significant school-year coefficients for Black students and the negative/significant Hispanic school-year coefficients are very small. Like Black students, Hispanic students tend to lose fewer skills compared to White students during the summers. In reading it is clear that Hispanic students gain ground on White students during school years 5-8. In the end, Hispanic students close the gap with White students slightly over time (Figures 1 and 2); this narrowing traces primarily to summer for math and school years 5-8 for reading.

Finally, the conditional models show that the growth of Asian students' skill advantages over White students traces to both school years and summers, but summers in particular. While Asian students gain more than White students in 14 of the 18 school years, the monthly rates of those school-year gains are generally modest compared to the rates during 10 of the 12 summers. And, Asians gain less than Whites during four school years. The most dramatic example comes from the summer after first grade, when Asian students gained 1.06 points per month more than White students in reading. In contrast, during first grade they gained only 0.04 points per month more than White students and during second grade they *lost* 0.16 points per month. In general, Asian students pull ahead of White students during summers and either pull ahead slower or even lose ground during school years. Throughout Table 3, the evidence suggests that exposure to schooling *tempers* the rate of summer growth in Asians' math and reading advantages.[3]

Discussion

Previous seasonal studies of racial/ethnic achievement gaps either lacked vertically-aligned, interval measures of skills based on adaptive testing, relied on non-representative samples, or covered only the first few years of schooling. Our analysis of

[3] Although not our focus, the district-level SES patterns are consistent with past seasonal studies that generally find that individual-level SES gaps grow faster when school is out than in (Downey et. al. 2004; von Hippel et. al 2018).

over two and a half million U.S. children in kindergarten through eighth grade overcomes each of these limitations and produces three major conclusions.

First, we find significant evidence consistent with the position that exposure to schooling exacerbates Black-White inequalities in math and reading skills. This conclusion may seem unremarkable given the school practices that disadvantage Black children such as tracking (Lucas & Berends, 2007; Lucas 1999; Oakes, Gamoran, & Page, 1992; Gamoran, 1992), teacher expectations (Delpit, 2012), disproportionality in discipline (Gordon, 2018; Noguera, 2013), and the role of parents' background when interacting with teachers/schools (e.g., Horvat, Weininger, & Lareau, 2003; Lareau, 1989). But the existence of school mechanisms that disadvantage Black students does not preclude the possibility that schools could operate in a compensatory manner.

The patterns for socioeconomic status highlight the distinction between identifying exacerbatory school processes and estimating schools' overall effect. Scholars also have uncovered many school processes that disadvantage low-SES children (e.g., funding, teacher discrimination, curriculums, class size), and yet the seasonal patterns (from previous studies and our own) indicate that exposure to school tends to reduce SES-based achievement gaps. In the case of socioeconomic status, it appears that schools do more to reduce than increase gaps in math and reading. It was possible that the Black-White gaps would follow this same pattern and it is noteworthy that we found that they did not.

Specifically, as students advance through the elementary and middle-school years, the Black-White gap expands by 30% in math and 39% in reading. This gap growth does not occur during summers; Black students overall lose fewer skills over summer breaks compared to White students, net of the economic status of their school district. But Black students' math and reading skills fall behind those of their White counterparts during every single school year, kindergarten through eighth grade. Although a few other seasonal studies suggest a pernicious role of schools in shaping Black-White gaps (Downey et al., 2004; Fryer & Levitt, 2004; Quinn et al., 2016), those studies had data on only one or two summers to compare to two or three school years during early childhood. Those limitations made it difficult to establish a pattern because those summers/school years might be anomalous and unrepresentative of what occurs in the long run. Our analysis, however, reveals a consistent pattern of Black-White gap growth tracing to school years over nine school years and six summers.

Second, Hispanic-White gaps decline slightly over time and lack a clear seasonal pattern. The conditional growth models mostly yield small coefficients, so it is not surprising that the gaps are about the same size in eighth grade as they were in kindergarten. There is some evidence that Hispanic students catch up to White students during school years, but that evidence is limited to school years 5-8 and to reading. Overall, we find very little action surrounding Hispanic-White gaps – they are present before kindergarten, change little over time, and generally cannot be traced to a particular season.

Third, we find that Asian students generally pull ahead of Whites at a faster rate during summers than during school years. Exposure to school, therefore, is related to a relative weakening of the Asian advantage in learning rates. This is true for both math and reading, but especially reading. Yoon and Merry (2018) note that this pattern may indicate mechanisms within schools that obstruct Asian students' progress relative to Whites students. The possibility that school mechanisms impede the success of Asian students may seem odd given how well Asian students perform on average, but our seasonal models suggest that Asians' skill advantages would be even greater if children were exposed to school less.

Our findings also raise a question about how racial gaps form during the pre-kindergarten period versus the summers. Note that for both Black-White and Asian-White skill comparisons, the patterns observed at the beginning of kindergarten do not persist in the summers after school begins. For example, Black-White skill disparities widen during school years and not summers, but the presence of Black-White gaps at kindergarten entry suggests that non-school environments generated those initial gaps. In fact, most of the Black-White skill disparities in our data are present before kindergarten. At kindergarten entry, the Black-White math gap is –.54 SD while the reading gap is –.41 SD. These gaps suggest a strong role of non-school environments in creating disparities in skills and predict that Black students will fall behind White students during summers too. But they do not. Similarly, the faster summertime growth of Asian students' skill advantages suggests that non-school environments play a strong role, but the Asian-White gaps at kindergarten entry are negligible. Both of these puzzles suggest that the pre-kindergarten and summer time periods may affect racial/ethnic skill gaps in different ways, an issue that warrants further attention as scholars explore the pre-kindergarten mechanisms that promote gaps.

The school mechanisms that slow the growth of Asian students' skill advantages and widen Black students' disadvantages also warrant further attention. Seasonal studies like this one are well-suited for revealing the overall summer/school-year comparisons, but they do not identify the season-specific mechanisms that explain those patterns. To move in that direction, we need a data source that has both seasonally-collected data and detailed information on students' summer and school-year environments over an extended period of time.

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Table 1.

Weighted Descriptive Statistics by Race/Ethnicity and Wave

		Overall			Black			Hispanic			Asian			White		
Wave	Coh.	M	SD	N	M	SD	N	M	SD	N	M	SD	N	M	SD	N
Math																
Fall K	1	138.19	12.61	384,251	134.84	11.19	73,568	133.71	11.26	67,376	142.91	15.8	13,771	141.63	12.45	177,065
Spring K	1	159.03	15.4	459,888	154.24	14.89	87,851	154.1	14.7	80,103	164.72	17.1	18,137	163.1	14.49	213,047
Fall 1	1	160.39	15.47	524,099	155.73	14.37	93,959	155.09	14.71	91,168	167	17.72	22,717	164.38	14.66	247,129
Spring 1	1	180.99	16.37	544,887	174.99	15.85	96,891	175.91	15.79	95,036	188.81	17.93	24,334	185.24	15.15	256,462
Fall 2	1	176.59	14.73	594,436	171.6	13.8	100,391	172.58	13.96	102,852	184.71	16.01	26,825	179.74	14.22	283,947
Spring 2	1	192.04	15.02	609,168	186.2	14.59	102,543	188.29	14.89	109,063	200.02	15.63	28,082	195.54	13.9	287,479
Fall 3	2	189.03	13.59	721,575	183.35	12.94	113,634	184.51	12.78	126,247	197.36	14.26	29,121	192.47	12.71	363,487
Spring 3	2	202.01	14.04	710,703	195.76	13.73	115,946	197.96	13.4	129,284	210.94	14.81	29,144	205.6	12.88	348,856
Fall 4	2	200.58	14.34	687,218	194.49	13.69	106,413	196.17	13.64	118,384	210.06	15.39	29,272	204.05	13.29	348,537
Spring 4	2	211.98	15.81	666,051	204.98	15.1	106,820	207.53	15.19	120,350	222.87	16.93	28,698	215.9	14.49	328,247
Fall 5	2	209.77	15.59	648,966	202.82	14.84	103,710	205.24	14.75	116,170	220.35	16.98	28,660	213.7	14.35	320,839
Spring 5	2	219.88	17.56	608,991	211.82	16.52	98,866	215.22	16.61	113,292	232.32	18.45	26,806	224.2	16.28	294,970
Fall 6	3	215.02	15.6	654,971	207.14	14.84	96,449	209.65	14.5	107,267	225.27	16.72	25,605	219.02	14.41	343,116
Spring 6	3	223.35	17.31	640,506	214.79	16.49	97,804	217.62	16.56	110,457	236.61	18.09	27,763	227.63	15.71	326,521
Fall 7	3	221.14	17.79	627,053	212.43	16.65	92,618	214.99	16.83	105,931	232.99	18.82	25,676	225.74	16.38	323,281
Spring 7	3	227.93	18.96	589,667	219.26	17.77	90,402	221.72	18.24	106,186	241.2	19.95	24,038	232.74	17.44	298,614
Fall 8	3	226.54	18.77	552,474	217.56	17.44	84,859	220.1	17.73	96,754	238.83	20.24	21,888	231.61	17.27	277,743
Spring 8	3	232.31	19.98	493,482	223.37	18.37	79,835	226.45	19.02	91,417	246.26	21.68	19,723	237.35	18.62	245,241
Reading																
Fall K	1	140.73	10.67	363,609	138.73	9.91	68,715	137.23	9.95	60,913	143.99	13.61	12,948	143.07	10.4	170,085
Spring K	1	158.06	13.77	428,147	154.54	13.3	80,467	153.51	12.78	70,088	162.19	15.96	15,689	161.38	13.28	203,272
Fall 1	1	159.47	14.27	490,173	156	13.32	88,947	154.48	13.32	80,240	164.15	16.65	19,346	162.88	13.85	235,668
Spring 1	1	177.11	15.78	513,098	172.23	15.01	91,986	171.53	15.23	84,278	182.73	16.82	20,885	181.23	14.84	246,571
Fall 2	1	174.16	16.46	564,149	169.81	15.27	94,886	168.96	15.15	93,434	181.55	17.08	23,732	177.6	16.31	274,238
Spring 2	1	188.17	16.02	583,277	183.11	15.54	98,302	182.86	15.61	100,834	194.48	15.66	25,253	192.17	15.02	278,814

Fall 3	2	187.19	17.02	711,371	181.68	16.29	111,358	180.94	16.12	124,729	195.2	16.29	28,461	191.36	16.22	359,213
Spring 3	2	197.68	16.39	697,718	191.88	16.19	113,011	191.9	16.16	126,277	204.99	15.67	28,142	202.01	15.02	344,610
Fall 4	2	197.31	16.78	674,337	191.73	16.36	104,066	191.53	16.41	116,180	204.93	16.13	28,153	201.32	15.68	342,729
Spring 4	2	205.37	16.34	656,795	199.77	16.14	105,060	199.89	16.28	118,650	212.71	15.81	27,824	209.54	14.88	324,217
Fall 5	2	204.54	16.38	640,902	198.93	16	102,680	199.21	16.22	113,780	211.72	15.98	27,546	208.57	15.13	317,924
Spring 5	2	210.95	15.67	604,671	205.53	15.4	99,187	206.08	15.69	111,780	217.98	15.31	26,203	214.83	14.29	293,007
Fall 6	3	210.03	16.37	649,141	203.59	16.49	94,859	203.97	16.4	106,247	217.42	15.76	26,110	214.03	14.82	341,100
Spring 6	3	214.91	16.04	625,109	208.74	16.09	95,079	209.14	16.39	108,184	222.51	15.54	25,555	218.93	14.36	320,238
Fall 7	3	214.26	16.76	616,872	207.74	16.75	90,015	208.41	16.92	102,856	221.89	16.13	25,480	218.26	15.24	321,002
Spring 7	3	218.47	16.61	578,927	212.57	16.38	87,826	212.82	17.13	103,180	226.26	16.21	24,238	222.43	14.98	294,741
Fall 8	3	218.19	16.43	558,126	212.11	16.1	84,322	212.64	16.66	95,978	225.62	16.3	23,485	222.12	14.95	283,699
Spring 8	3	221.71	16.12	493,093	216.3	15.64	79,118	217.06	16.39	90,397	228.82	16.2	20,349	225.42	14.76	247,039

Note. Coh=Cohort, M=Mean, SD=Standard Deviation, N=Number of students.

Table 2

Mean and Variability of Achievement and Learning

		Random effect variation			Student-level Correlations				
	Mean (SE)	School SD	Student SD	ICC	Initial	Points 2015-16	Points Summer 2016	Points 2016-17	Points Summer 2017
Reading K-2 Cohort									
Initial Points (K)	136.21 (0.05)	4.04	9.62	0.17					
Points per month									
Kindergarten	2.10 (0.01)	0.48	1.05	0.15	-0.25				
Summer 2016	-1.00 (0.02)	1.09	2.84	0.11	0.12	-0.47			
First Grade	2.11 (0.01)	0.39	0.97	0.12	0.02	0.01	-0.43		
Summer 2017	-1.06 (0.02)	1.21	2.96	0.10	0.02	0.03	0.09	-0.36	
Second Grade	1.80 (0.00)	0.37	0.95	0.10	-0.07	-0.04	-0.02	0.01	-0.50
Reading 3-5 Cohort									
Initial Points (3rd)	185.05 (0.08)	7.65	12.51	0.19					
Points per month									
Third Grade	1.39 (0.00)	0.37	0.94	0.09	-0.41				
Summer 2016	-1.14 (0.01)	1.10	2.75	0.09	0.15	-0.55			
Fourth Grade	1.06 (0.00)	0.31	0.91	0.07	-0.13	0.04	-0.48		
Summer 2017	-0.88 (0.01)	0.95	2.64	0.08	0.05	-0.03	0.11	-0.56	
Fifth Grade	0.83 (0.00)	0.26	0.91	0.06	-0.14	0.03	-0.04	0.03	-0.47
Reading 6-8 Cohort									
Initial Points (6th)	207.56 (0.11)	7.84	14.11	0.20					
Points per month									
Sixth Grade	0.68 (0.01)	0.36	0.96	0.09	-0.37				
Summer 2016	-0.75 (0.02)	1.11	2.99	0.09	0.13	-0.54			
Seventh Grade	0.57 (0.01)	0.35	0.98	0.08	-0.07	0.02	-0.51		
Summer 2017	-0.41 (0.02)	0.99	2.89	0.08	0.01	-0.02	0.11	-0.56	
Eighth Grade	0.48 (0.01)	0.30	0.94	0.07	-0.07	0.02	-0.03	0.01	-0.47

Rates

Note. SE=standard error, ICC=intraclass correlation, SD=standard deviation. All fixed effects and variation around the random effects (reported as SD) estimates are statistically significant.

Table 2

Mean and Variability of Achievement and Learning Rates (continued…)

		Random effect variation			Student-level Correlations				
	Mean (SE)	School SD	Student SD	ICC	Initial	Points 2015-16	Points Summer 2016	Points 2016-17	Points Summer 2017
Math K-2 Cohort									
Initial Points (K)	139.05 (0.06)	4.69	9.90	0.19					
Points per month									
Kindergarten	2.26 (0.01)	0.50	1.24	0.19	-0.24				
Summer 2016	-1.19 (0.02)	1.17	3.41	0.14	0.10	-0.48			
First Grade	2.21 (0.00)	0.39	1.17	0.14	-0.02	-0.02	-0.44		
Summer 2017	-1.89 (0.02)	1.30	3.79	0.16	-0.01	-0.01	0.09	-0.44	
Second Grade	1.90 (0.00)	0.36	1.16	0.12	-0.05	0.00	-0.03	0.02	-0.51
Math 3-5 Cohort									
Initial Points (3rd)	186.56 (0.07)	6.48	16.07	0.21					
Points per month									
Third Grade	1.70 (0.00)	0.34	1.18	0.12	-0.30				
Summer 2016	-1.72 (0.01)	0.97	3.49	0.11	0.12	-0.55			
Fourth Grade	1.45 (0.00)	0.35	1.11	0.13	0.07	0.04	-0.44		
Summer 2017	-1.58 (0.01)	0.93	3.29	0.11	-0.01	-0.03	0.12	-0.58	
Fifth Grade	1.27 (0.00)	0.34	1.03	0.12	0.13	0.04	-0.03	0.07	-0.42
Math 6-8 Cohort									
Initial Points (6th)	212.14 (0.10)	7.87	15.59	0.24					
Points per month									
Sixth Grade	1.07 (0.01)	0.38	1.12	0.14	-0.10				
Summer 2016	-1.44 (0.02)	1.11	3.58	0.12	0.08	-0.54			
Seventh Grade	0.86 (0.01)	0.37	1.14	0.13	0.08	0.05	-0.47		
Summer 2017	-0.85 (0.02)	1.02	3.46	0.11	-0.03	-0.04	0.11	-0.57	
Eighth Grade	0.72 (0.01)	0.33	1.07	0.11	0.09	0.05	-0.03	0.05	-0.45

Table 3

Coefficients from the Conditional Growth Model

	Math						Reading					
	K-2 Cohort		G3-5 Cohort		G6-8 Cohort		K-2 Cohort		G3-5 Cohort		G6-8 Cohort	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Initial Points, Fall 2015												
Reference Group	141.31***	(0.05)	189.13***	(0.06)	215.30***	(0.09)	137.94***	(0.05)	188.11***	(0.07)	210.83***	(0.09)
Black	-3.93***	(0.07)	-6.24***	(0.07)	-7.94***	(0.11)	-2.62***	(0.06)	-6.15***	(0.09)	-6.94***	(0.12)
Asian	-1.08***	(0.12)	2.52***	(0.12)	3.71***	(0.19)	-1.19***	(0.12)	0.91***	(0.14)	0.48**	(0.17)
Hispanic	-5.04***	(0.07)	-5.21***	(0.07)	-6.44***	(0.12)	-4.21***	(0.06)	-6.99***	(0.09)	-7.39***	(0.13)
District SES	1.82***	(0.05)	2.61***	(0.05)	3.00***	(0.07)	1.51***	(0.04)	3.09***	(0.06)	2.92***	(0.08)
R^2	4.59		5.33		6.91		3.21		3.82		4.78	
Points per month, 2015-16												
Reference Group	2.30***	(0.01)	1.71***	(0.00)	1.12***	(0.01)	2.16***	(0.01)	1.39***	(0.00)	0.68***	(0.01)
Black	-0.19***	(0.01)	-0.09***	(0.01)	-0.15***	(0.01)	-0.21***	(0.01)	-0.05***	(0.01)	-0.02**	(0.01)
Asian	0.07***	(0.01)	0.03***	(0.01)	0.12***	(0.01)	0.02*	(0.01)	-0.06***	(0.01)	0.04***	(0.01)
Hispanic	-0.07***	(0.01)	-0.01	(0.00)	-0.09***	(0.01)	-0.15***	(0.01)	0.03***	(0.01)	0.03***	(0.01)
District SES	-0.03***	(0.01)	-0.03***	(0.00)	-0.02***	(0.01)	0.02**	(0.01)	-0.04***	(0.00)	-0.06***	(0.01)
R^2	0.56		0.14		0.57		0.61		0.06		0.02	
Points per month, Summer 2016												
Reference Group	-1.20***	(0.02)	-1.74***	(0.01)	-1.44***	(0.02)	-1.01***	(0.02)	-1.16***	(0.01)	-0.74***	(0.02)
Black	0.15***	(0.02)	0.12***	(0.02)	0.04*	(0.02)	0.11***	(0.02)	0.04*	(0.02)	-0.06**	(0.02)
Asian	0.19***	(0.03)	0.25***	(0.02)	0.15***	(0.02)	0.14***	(0.03)	0.29***	(0.02)	0.15***	(0.02)
Hispanic	0.01	(0.02)	0.02	(0.01)	-0.01	(0.02)	-0.01	(0.02)	0.05**	(0.02)	-0.04*	(0.02)
District SES	0.23***	(0.02)	0.23***	(0.01)	0.23***	(0.02)	0.16***	(0.02)	0.22***	(0.02)	0.20***	(0.02)
R^2	0.09		0.10		0.03		0.04		0.05		0.03	
Points per month, 2016-17												
Reference Group	2.23***	(0.01)	1.50***	(0.00)	0.89***	(0.01)	2.16***	(0.01)	1.07***	(0.00)	0.56***	(0.01)
Black	-0.13***	(0.01)	-0.16***	(0.01)	-0.11***	(0.01)	-0.16***	(0.01)	-0.05***	(0.01)	-0.01*	(0.01)
Asian	0.11***	(0.01)	0.08***	(0.01)	0.13***	(0.01)	0.04***	(0.01)	-0.02**	(0.01)	0.04***	(0.01)
Hispanic	-0.01	(0.01)	-0.07***	(0.00)	-0.06***	(0.01)	-0.09***	(0.01)	0.01	(0.01)	0.03***	(0.01)
District SES	-0.01	(0.01)	0.01**	(0.00)	-0.05***	(0.01)	0.04***	(0.01)	-0.05***	(0.00)	-0.08***	(0.01)
R^2	0.44		0.61		0.39		0.39		0.05		0.02	
Points per month, Summer 2017												
Reference Group	-2.06***	(0.02)	-1.65***	(0.01)	-0.89***	(0.02)	-1.25***	(0.02)	-0.93***	(0.01)	-0.44***	(0.02)
Black	0.39***	(0.02)	0.25***	(0.02)	0.14***	(0.02)	0.41***	(0.02)	0.12***	(0.02)	0.06**	(0.02)
Asian	0.64***	(0.03)	0.14***	(0.02)	0.02	(0.03)	1.06***	(0.03)	0.19***	(0.02)	0.04	(0.03)
Hispanic	0.30***	(0.02)	0.10***	(0.01)	0.06**	(0.02)	0.29***	(0.02)	0.08***	(0.02)	0.07***	(0.02)
District SES	0.18***	(0.02)	0.10***	(0.01)	0.18***	(0.02)	0.16***	(0.02)	0.14***	(0.01)	0.18***	(0.02)
R^2	0.53		0.16		0.05		0.60		0.03		0.00	
Points per month, 2017-18												
Reference Group	1.94***	(0.00)	1.32***	(0.00)	0.74***	(0.01)	1.85***	(0.01)	0.83***	(0.00)	0.46***	(0.01)
Black	-0.13***	(0.01)	-0.17***	(0.01)	-0.10***	(0.01)	-0.13***	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Asian	-0.03***	(0.01)	0.16***	(0.01)	0.15***	(0.01)	-0.16***	(0.01)	0.02**	(0.01)	0.05***	(0.01)
Hispanic	-0.05***	(0.01)	-0.08***	(0.01)	-0.04***	(0.01)	-0.06***	(0.01)	0.04***	(0.01)	0.06***	(0.01)
District SES	-0.01**	(0.00)	0.03***	(0.00)	-0.03***	(0.01)	-0.01	(0.00)	-0.05***	(0.00)	-0.07***	(0.01)
R^2	0.26		0.87		0.43		0.22		0.04		0.07	

Note. The proportion of variance explained (R^2) values are presented as percentages and can range from 0 to 100 percent.

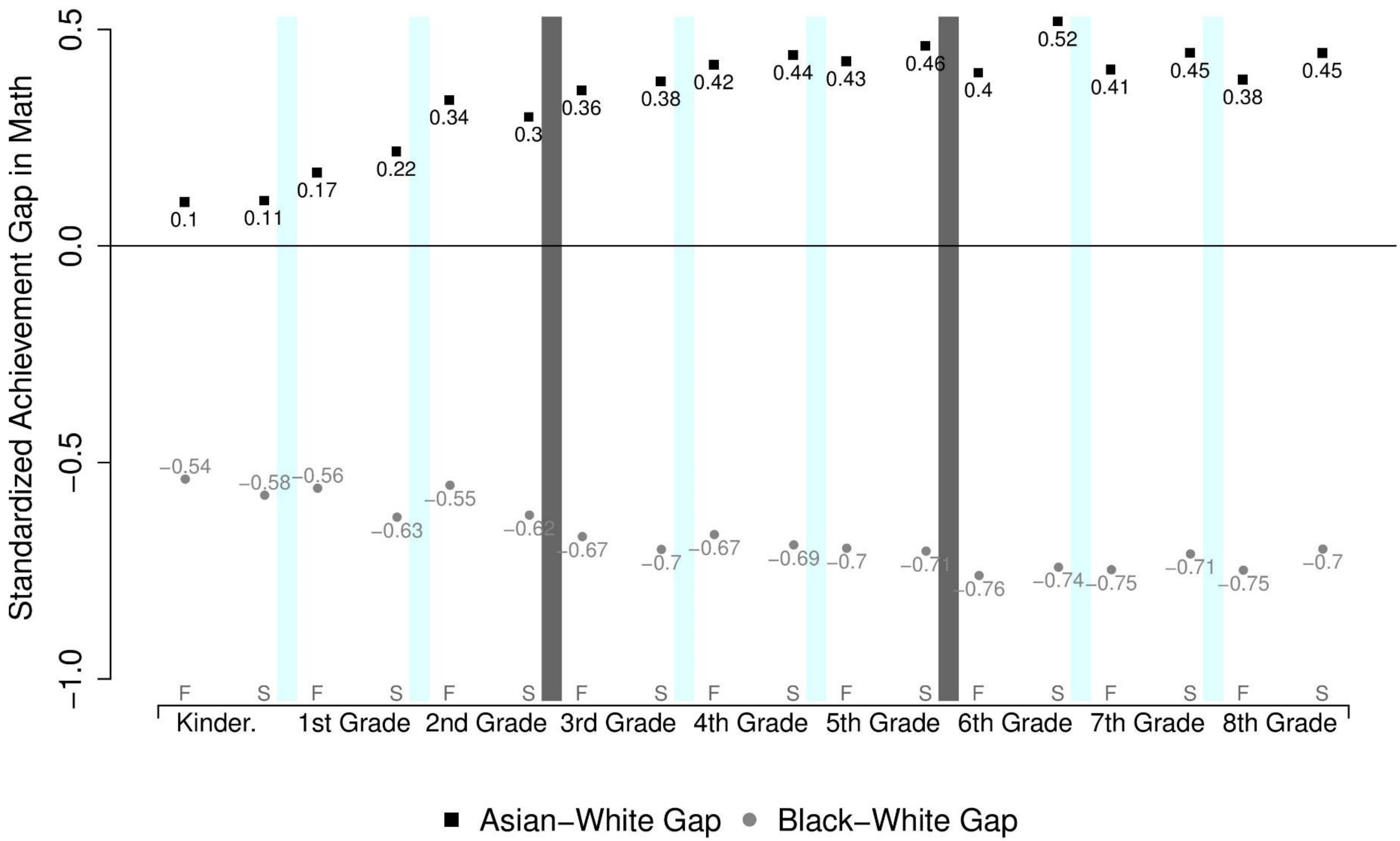

Figure 1. Standardized Black-White and Asian-White achievement gaps in math for the three cohorts. The dark vertical bars represent the switch between Cohorts 1 and 2 and Cohorts 2 and 3, and therefore the estimates between 2nd grade spring and 3rd grade fall and between 5th grade spring and 6th grade fall should not be compared. The standardized achievement gaps reported in this figure are based on the group means and overall standard deviations reported in Table 1, which are not adjusted for the months that students have been in school prior to testing. As a result, there are some discrepancies between these findings and the model-based estimates that adjust for time in school.

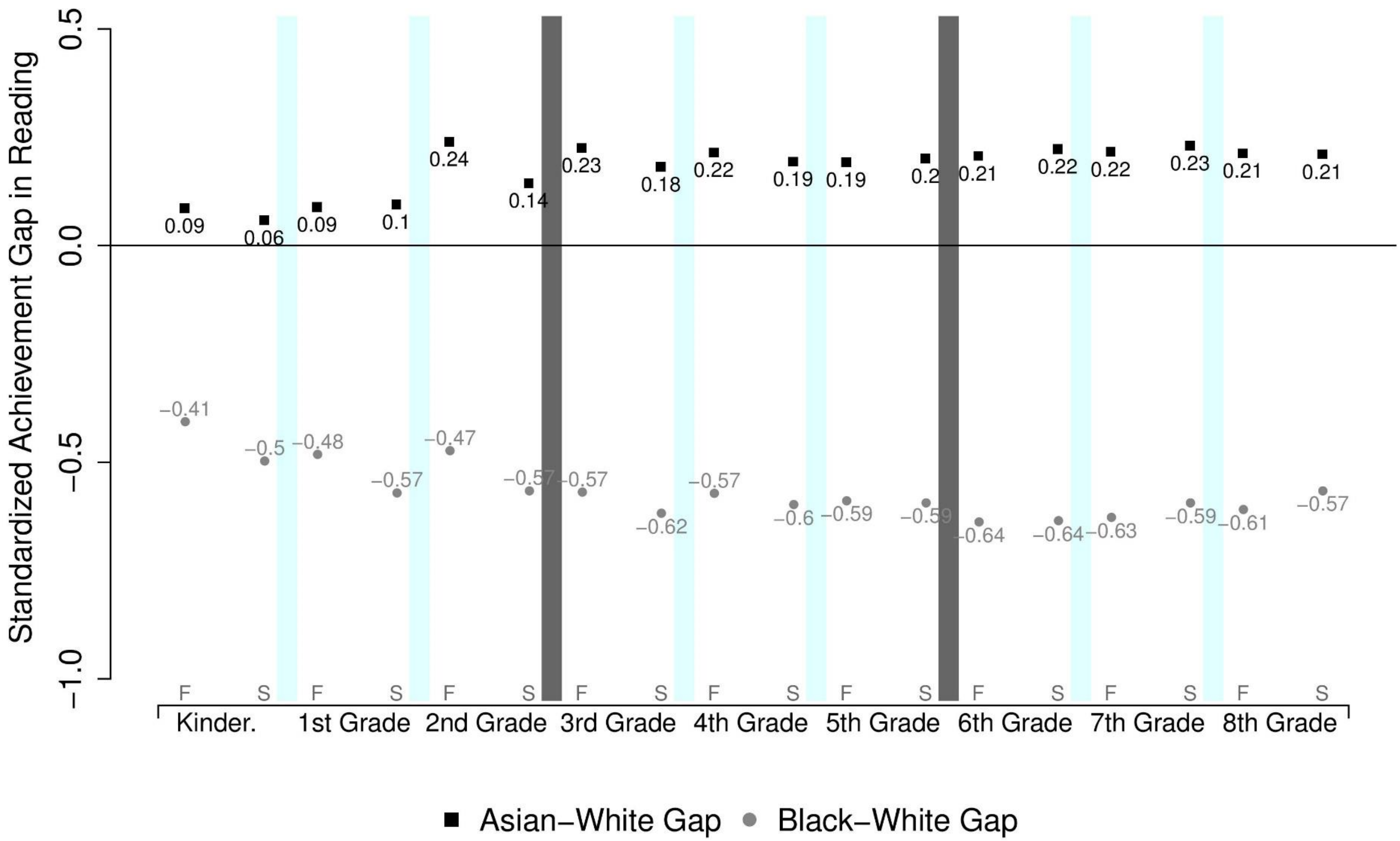

Figure 2. Standardized Black-White and Asian-White achievement gaps in reading for the three cohorts. The dark vertical bars represent the switch between Cohorts 1 and 2 and Cohorts 2 and 3, and therefore the estimates between 2nd grade spring and 3rd grade fall and between 5th grade spring and 6th grade fall should not be compared. The standardized achievement gaps reported in this figure are based on the group means and overall standard deviations reported in Table 1, which are not adjusted for the months that students have been in school prior to testing. As a result, there are some discrepancies between these findings and the model-based estimates that adjust for time in school.