ANNENBERG
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EdWorkingPaper No. 19-137

Trends in Children's Academic Skills at School Entry: 2010 to 2017

Megan Kuhfeld
NWEA

James Soland
University of Virginia

Christine Pitts
NWEA

Margaret Burchinal
Frank Porter Graham Child Development Institute

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VERSION: September 2019

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Megan Kuhfeld
Research Scientist, NWEA

James Soland
Assistant Professor, University of Virginia Curry School of Education

Christine Pitts
Policy Advisor, NWEA

Margaret Burchinal
Senior Scientist, Frank Porter Graham Child Development Institute

CONTACT INFORMATION:

Megan Kuhfeld
121 N.W. Everett Street
Portland, OR 97209
Ph. 503-548-5295
megan.kuhfeld@nwea.org

KEYWORDS:

School readiness; achievement gap; early childhood; descriptive analysis

ACKNOWLEDGEMENTS:

We are grateful to Christine Yankel, Angela Johnson, Beth Tarasawa, and Elizabeth Barker for their feedback on the paper.

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Abstract

Students' level of academic skills at school entry are a strong predictor of later academic success, and focusing on improving these skills during the preschool years has been a priority during the past ten years. Evidence from two prior nationally representative studies indicated that incoming kindergarteners' math and literacy skills were higher in 2010 than 1998, but no national studies have examined trends since 2010. This study examines academic skills at kindergarten entry from 2010 and 2017 using data from over 2 million kindergarten students. Results indicated kindergarteners in 2017 have slightly lower math and reading skills than in 2010, but that inequalities at school entry by race/ethnicity and school poverty level have decreased during this period.

Introduction

The first five years of a child's life lay the foundation for all subsequent learning and development. The academic skills of preschoolers are highly predictive of future academic success and earnings (Duncan et al., 2007; Chetty et al., 2011, Yoshikawa, 2013). Further, disparities related to income and race emerge during infancy (Halle et al., 2009) and are nearly as large when children enter kindergarten as in subsequent years (Burchinal et al., 2018; von Hippel, Workman, and Downey, 2018). A report by the National Academies of Sciences, Engineering, and Medicine (2019) highlighted "disparities in academic readiness" as a key indicator of educational inequity, while acknowledging the limitations in comparing readiness skills across districts and states due to differences in assessments. Accordingly, state and federal policies have focused on improving these skills for all children, especially for low-income children and traditionally underrepresented minorities (URMs).

The level of academic skills and the achievement gaps at school entry have been documented through 2010 with large national datasets such as the Early Childhood Longitudinal Survey-Kindergarten Cohort (ECLS-K). While some evidence suggests that children showed higher levels of skills in 2010 than in 1998 and low-income and URM children showed larger gains (Bassok & Latham, 2017), much less is known about academic skills at entry to school during the past decade. In this study, we use newly available data to describe trends in early math and reading skills at school entry between 2010 and 2017, including racial/ethnicity, gender, and school poverty achievement gaps. Additionally, we examine whether the rise in state pre-kindergarten (pre-K) enrollment during the last decade is associated with trends in academic skills. Specifically, we address three research questions:

Research Question 1: What are the trends in children's math and reading achievement at school entry between 2010 and 2017?

Research Question 2: How have achievement gaps at school entry by race/ethnicity, gender, and school poverty level changed between 2010 and 2017?

Research Question 3: Are changes across time in school districts' pre-K enrollment associated with trends in students' math and reading skills when students enter kindergarten?

Background

School entry reading and math skills are both strongly predictive of academic achievement in later grades (Duncan et al., 2007; Pace et al., 2019), as well as much later outcomes such earnings and home ownership (Chetty et al., 2011). Early reading skills include the identification of letters and decoding skills such as associating sounds with letters, while early math skills consist of the ability to recognize numbers and shapes followed by counting and sequencing skills (National Academies of Sciences, Engineering, and Medicine, 2019). Children from low-income families and traditionally underrepresented minorities enter school with lower levels of reading and math skills than do their more advantaged peers (Duncan & Murnane, 2011). Accordingly, state and federal policies have focused on promoting early care and education programs to improve academic skills in early childhood for all children, especially targeting low-income children (Burchinal et al., 2015). Thus, it is important to examine the extent to skills levels and differences in skills levels by race/ethnicity and income have changed over time.

School Readiness Trends Between 1998 and 2010

Considerable evidence describes changes in school readiness skills from 1998 to 2010, primarily through analyses of the nationally representative ECLS-K collected first with children entering kindergarten in 1998 and subsequently with children entering kindergarten in 2010. Bassok and Lathom (2017) found ECLS-K teachers reported that students entered kindergarten with stronger math and literacy skills in 2010 than 1998, with particularly strong improvements among Black children. Bassok and Lathom (2017) were not able to compare direct measures of math and reading skills because the scaling of the math and reading tests differed between the two ECLS-K cohorts (Tourangeau et al., 2015). As a result, we have no existing national data source on overall trends in students' math and reading skills at school entry have changed across time based on student performance on standardized assessments.

In contrast, the race/ethnicity and income achievement gaps in the direct assessments of math and reading skills could be compared because they were computed within a given cohort. Reardon and Portilla (2016) reported that racial/ethnic achievement gaps in math and reading at school entry were somewhat smaller in 2010 than 1998. They reported a reduction in Black-White school readiness gaps in math and reading skills of 0.08 standard deviations (SDs) and in the Hispanic-White gap in math skills of 0.11 SDs (note: comparisons of Hispanic-White reading gaps over time were not possible due to differences in how Spanish-speaking students were screened into the reading assessment between the two tests).

Trends in income school readiness gaps are less clear. Reardon and Portilla (2016) reported that school readiness gaps by parent income (e.g., comparing children whose family incomes are at the 90th and 10th percentile of the family income distribution) narrowed, declining from 1998 to 2010 by 0.13 SDs in math and 0.21 SDs in reading. However, Wolf, Magnuson, and Kimbro (2017) examined gaps in academic skills between poor and nonpoor children stratifying by neighborhood poverty level and found that achievement gaps between poor and non-poor students actually increased between 1998 and 2010. Specifically, the gap between poor and nonpoor children's reading scores in high-poverty neighborhoods increased from 0.23 SDs to 0.34 SDs during that period.

Demographic Factors that Might Contribute to Change in Academic School Readiness Since 2010

There are many demographic reasons for which the levels of academic skills at entry to school (including gaps in those skills by student subgroup) may have changed during the past decade. Though children growing up in poverty tend to have lower academic skills at school entry (Burchinal et al., 2018), the percentage of children under age 18 in families living in poverty has decreased from 18% in 2010 to 15% in 2016 (National Center for Education Statistics, 2019a). Further, parental investments contribute to acquisition of school readiness skills (Bornstein & Bradley, 2016), and parents are investing more time and money on enrichment activities for young children now than in previous decades (Bassok et al., 2016). Thus, one might hypothesize that such demographic shifts have contributed to positive trends in school readiness.

At the same time, there are also demographic changes that might be associated with widening academic readiness gaps. Income inequality has continued to grow modestly throughout the decade, with the ratio of the 90^{th} percentile of the income distribution to the 10^{th} percentile having grown from 11.70 to 12.59 between 2010 and 2017 (Fontenot, Semega, Kollar, 2018) as have discrepancies in achievement between those groups (Reardon, 2011). Similarly, the proportion of school-age children whose parents immigrated to the US and/or who speak a language other than English at home has also increased for 11% in 1990 to 23% in 2015

(Camarota, Griffith, Zeigler, 2017), and these children typically enter school with lower reading and math skill levels than other children (Espinosa, 2013).

Public Policies Factors that Might Contribute to Change in Academic School Readiness Skills Since 2010

Another reason that academic readiness at school entry may have changed is increased funding for pre-K programs, which has greatly increased pre-K enrollment. Over the last 20 years, many pre-K programs were implemented in districts across the nation that focused on improving the transition from preschool or pre-K to kindergarten. By 2017, there were 60 state-funded pre-K initiatives in 43 states and DC, which enrolled 33% of four-year-olds in the United States, an increase of 9% in a decade (Friedman-Krauss et al., 2018). State-funded pre-Ks are programs funded by states with mandatory performance standards designed to improve children's school readiness skills (Phillips et al, 2017). These programs are often administered by school districts or other local education authorities, such as counties or towns. Most state pre-K programs target children from low-income families, though there is a fair amount of variability across states in terms of the income threshold for eligibility, and some state programs target children who have developmental delays or other risk factors regardless of income (Friedman-Krause, 2018). In short, state investment in closing readiness gaps has increased substantially during the period in question, oftentimes with a focus on supporting underserved students.

A large number of studies have examined the relationship between students' academic achievement and state pre-K preschool program enrollment (e.g., Gormley et al., 2005; Phillips et al., 2017; Wong et al., 2008; Early et al., 2005). An expert panel concluded by consensus that state pre-K programs vary greatly across states in the quality of their services, but on average have positive impacts on school entry skills among states that conducted evaluations (Phillips et al., 2017). The panel acknowledged that both the quality of the pre-K programs and the rigor of the studies examining those impacts varies widely, and lamented the lack of evaluations across all, or at least most, states with pre-K programs. One of the more innovative approaches involved using students' access to pre-K based on where they live as a proxy for participation. For example, Fitzpatrick (2008) used data from the National Assessment of Educational Progress (NAEP) to evaluate Georgia's universal pre-K program, finding positive impacts on being on-grade level in 4th grade relative to other states that did not implement universal pre-K. Ladd, Muschkin, and Dodge (2014) compared counties in North Carolina with different pre-K access and found significant positive impacts of participation on 3rd grade test scores. However, very few studies have compared the impacts of enrollment in state pre-K programs on academic outcomes across states with wide ranging pre-K program quality ratings.

Summary

In spite of a growing recognition of the importance of early childhood education and the significant investment that has accompanied that recognition, little is known about how academic skills at school entry have changed over the last decade based on data collected throughout the US. Evidence suggests that school readiness skills increased and racial/ethnic gaps decreased between 1998 and 2010, and that demographic and policy changes since 2010 could result in changes in overall readiness skills or differences in skills between demographic groups.

In this study, we examine math and reading test scores from a diverse sample of kindergartners collected each year between 2010 and 2017 (over two million students in total). Using these data, we investigate trends in students' math and reading skills at school entry, as well as whether early skill gaps by race/ethnicity, gender, and school poverty level have widened or narrowed during this eight-year period. Lastly, we examine whether enrollment patterns in district-run pre-K programs are related to trends in school entry academic skills using data from students from over 3,400 school districts across 47 states.

Data, Measures, and Methods

Analytic Sample

The data for this study are from the Growth Research Database (GRD) at *NWEA*. School districts partner with NWEA to monitor K-8 students' reading and math growth throughout the school year. We use the fall test scores of over two million unique students in 10,960 schools who entered kindergarten between the fall of 2010 and the fall of 2017. The GRD also includes demographic information, including student race/ethnicity, gender, and age at assessment, though student level socioeconomic status was not available. Table 1 provides the counts of students per year as well as the unweighted demographic characteristics of kindergarteners in 2010 to 2017. As shown, the number of kindergarteners testing with NWEA per year greatly increased from 2010 to 2017, going from 88,000 to 451,000 students per year in reading and from 89,000 to 479,000 in math. During the latter three years of the study, our sample consisted of over 10% of the total population of public school kindergartners in the country.

Additionally, the sample of students became more diverse across time, with the percentage of White students decreasing from 54% to 46% in math (54% to 44% in reading) across the course of the study. Post stratification weighting, which is described in further detail below, was used to account for the dramatic changes in sample characteristics across time.

Measures of Achievement

Student test scores from NWEA's MAP Growth K-2 reading and math assessments are used in this study. The MAP Growth assessments are computer-based tests typically administered three times a year in the fall, winter, and spring. In this study, we only focus on students' fall of kindergarten test scores. The fall test is typically administered between two to eight weeks after starting school. MAP Growth tests, which are aligned to state content standards, begin with a question appropriate for the student's grade level, and then adapts throughout the test in response to student performance. In kindergarten and 1st grade, MAP Growth includes engaging items, interactive elements, and targeted audio supports to accurately engage and assess students who are learning to read. Test scores are reported in the RIT scale[1], where RIT stands for Rasch Unit and is $200 + 10 \times \theta$, where θ refers to the logit scale units of the Rasch item response theory model.

School and District Characteristics

Demographic Characteristics. In our study, we use a set of school and district characteristics reported by the Common Core of Data (CCD) from the National Center for Education Statistics (NCES) and the Stanford Education Data Archive (SEDA; Reardon et al., 2018) for two purposes: (a) to produce school-level weights to match our sample of schools to the population of public schools serving kindergarten in each year, and (b) as covariates within Research Questions 2 and 3. At the time of analysis, the CCD variables used in this study (e.g., school percentage of Free or Reduced Price Lunch (FRPL) receipt, racial/ethnic composition of the school, and geographic locale) were available from the CCD for each school year up until 2016-17. For the 2017 fall estimates, we carry forward the 2016-17 estimates, including associated weights (see Appendix A for school-level descriptive statistics as well as the cross-time stability of the school-level characteristics). Additionally, following categories used in the NCES Condition of Education report (National Center for Education Statistics, 2019b) we define

[1] To ensure that scores can be compared across time on the same scale, MAP Growth items are checked periodically for scale stability across time and student subgroups. A large majority of MAP Growth items have been found to be stable over time, and the small amount of drift observed was found to have minimal impact on student test scores and scale stability (NWEA, 2019).

high-poverty schools as public schools where more than 75% of the students are eligible for FRPL, mid-poverty schools as those where 25.1 to 75.0% of the students are eligible for FRPL, and low-poverty schools with 25% or less FRPL eligibility.

In our Research Question 3, we use a district-level residential poverty measure from SEDA, which were calculated from the US Census Bureau's American Community Survey (ACS). The SEDA data provide information both on district resources and the characteristics of the communities residing within the school district geographic boundaries (for details, see Fahle et al., 2018). Specifically, we control for SEDA's district-level percent of households with children ages 5 to 17 living in poverty.

Pre-K Availability. To quantify the availability of public school district pre-K programs in a student's area, we used pre-K enrollment data from the CCD reported for each school district between 2009-10 to 2016-17. This strategy of using local differences in pre-K availability to study the relationship between pre-K enrollment and later academic outcomes has been previously employed in multiple studies. For example, Bartik and Hersbein (2018) matched 4th grade test scores from NAEP to school district pre-K enrollment reported by the CCD. Additionally, in one of their analyses, Andrews, Jargowsky, & Kuhne (2012) used an indicator of whether the student lived in a district that offered the pre-K to evaluate the impact of Texas's targeted pre-K program on subsequent academic performance.

Following Bartik and Hershbein (2018), we calculated percent enrollment in the pre-K program by dividing the count of students enrolled in pre-K in a given year by the count of 1st grade students in the same district/year. This ratio allows us to approximate the share of potentially eligible students in each district enrolled in a district pre-K program.[2] We use the

[2] We used first grade enrollment in the denominator instead of the more proximal kindergarten enrollment because of differences across states in requirements to attend kindergarten. In the small number of cases where the ratio between the number of students

lagged pre-K enrollment in our model. For example, for the students who entered kindergarten in the fall of 2010, students' math and reading skills in 2010 are regressed on the district pre-K enrollment during the 2009-10 school year (the pre-K year). It is important to note that these enrollment percentages do not account for pre-K programs that are publicly-funded but not operating in school districts or enrollment in private pre-K programs, but nevertheless capture an important aspect of the availability of pre-K programs in a local area.

Weighting Approach

As already described, our sample of kindergarten students is quite large, including between 2 and 12% of all of the kindergarteners in U.S. public schools between 2010 and 2017. However, the sample is not nationally representative. We use post-stratification weights to account for the large increases in the sample size over the years and to make our sample more closely match the target population of all kindergartens in U.S. public schools in each school year. Specifically, we use an entropy balancing weighting approach first presented by Hainmueller (2012). Our entropy balancing approach minimizes the absolute standard difference between the sub-population (schools using MAP Growth) and the national population of schools offering kindergarten on multiple school and district characteristics reported by the CCD and SEDA. The CCD school characteristics included in the weights are the percentage of students receiving FRPL, urbanicity, and school racial/ethnic composition. The SEDA district-level variables included in the weights are 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. We calculate a separate set

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enrolled in pre-K to the number of students in first grade exceeded 1.1, we excluded the district from our analyses. As a sensitivity check, Bartik and Hershbein (2018) compared the pre-K enrollment ratio from the CCD (aggregated to the state-level) to other data sources, including the National Institute for Early Education Research (NIEER) state-funded pre-K rate and the ACS public enrollment rate of four-year-olds, and found strong correlations among the approaches.

of post-stratification weights within each school year based on the CCD and SEDA data available for that year. As a result, while the composition of our school sample changes across time, we reduce the impact of the changing sample by matching the set of schools in each year to the target national population of schools for that year.

Appendix A in the supplemental materials provides more detail on the school-level post-stratification weights as well as the weighted descriptive statistics for the schools used in the analytic sample compared with the U.S. population of schools. The standardized differences between the weighted sample characteristics and the population characteristics are less than 0.01 across all years and variables. Appendix B provides a comparison of the unweighted and weighted model estimates to examine the impact of our weighting approach.

Analytic Plan

Question 1. Overall Trends. For our first set of analyses, we estimated the weighted mean and standard deviation of the fall test scores within each year for reading and math separately (as noted previously, we also provide unweighted estimates in Appendix B for those interested primarily on results specific to our large sample). Additionally, we examined the mathematics and reading trends for five selected percentiles to show the progress made by lower- (10^{th} and 25^{th} percentiles), middle- (50^{th} percentile), and higher- (75^{th} and 90^{th} percentiles) achieving students. These analyses describe change over time of the eight cohorts of children who entered kindergarten between 2010 and 2017, and as such they describe change across time among cohorts, not change across time among individual students. Given the interest in trends over time, we report results using the RIT scale rather than standardize within year.

Question 2. Estimating Achievement Gaps. For each year and subject separately, we produced achievement gap estimates in both RIT and standard deviation units. To produce the latter, we standardized achievement score y_{its} for student i in year t and subject s such that:

$$Z_{its} = \frac{y_{its} - \bar{y}_{ts}}{\sigma_{ts}} \tag{1}$$

where $\bar{y}_{ts}$ is the mean test score in year t and subject s, and σ_{ts} is the standard deviation of the test scores in that subject and year. Racial/ethnic achievement gaps for kindergarteners were estimated within a regression framework by year and subject:

$$Z_{its} = \beta_0 + \beta_1 \text{Black}_\text{i} + \beta_2 \text{Hispanic}_\text{i} + \beta_3 \text{Asian}_\text{i} + \beta_4 \text{Other}_\text{i} + \epsilon_{its}. \tag{2}$$

A vector of race/ethnicity dummy variables were included (with non-Hispanic White students as the omitted group) indicating whether a student is Black, Hispanic, Asian or "Other race" (due to low counts in the number of students identified as American Indian, Pacific Islander, and multiracial, these categories were combined). The coefficient for each race/ethnicity indicator is interpreted as the standardized achievement gap between that group and White students for the given year/subject. The analyses reported in the paper incorporate the school-level weights and adjust the standard errors to account for the nesting of students in schools.

One potential concern with such models is that the racial/ethnic achievement gaps may be driven primarily by differences across groups in socioeconomic status (SES). To account for this potential source of bias, we re-estimated our gaps model to control for a set of school-level poverty variables such that:

$$\begin{aligned} Z_{its} = \beta_0 + \beta_1 \text{Black}_\text{i} + \beta_2 \text{Hispanic}_\text{i} + \beta_3 \text{Asian}_\text{i} + \beta_4 \text{Other}_\text{i} \\ + \beta_5 \text{MidPov}_\text{i} + \beta_6 \text{HighPov}_\text{i} + \epsilon_{its,} \end{aligned} \tag{3}$$

where MidPov_i indicates that student *i* is in a school of students receiving between 25-75% FRPL and HighPov_i indicates that student *i* is in a school receiving between over 75% FRPL.

While we would have ideally controlled for students' SES rather than school poverty, such covariates were not available in our data.

Additionally, we estimated gender achievement gaps within each year and subject

$$Z_{its} = \beta_0 + \beta_1 \text{Male}_\text{i} + \epsilon_{its}, \quad (4)$$

where Male_i is coded as 1 if the student is reported as male, and 0 if the student is female. Lastly, since we do not have a student-level indicator of poverty, we examined achievement gaps between students in low-poverty schools with students in mid-poverty and high-poverty schools:

$$Z_{its} = \beta_0 + \beta_1 \text{MidPov}_\text{i} + \beta_2 \text{HighPov}_\text{i} + \epsilon_{its}. \quad (5)$$

To examine the significance of the change in gaps over time, we followed the approach of Reardon and Portilla (2016) and computed the standard error of the difference between each of the 2010 and 2017 gaps. Using these standard errors, we conducted *t*-tests to see if we can reject the null hypothesis that the gap is unchanged from 2010 and 2017.

Finally, we performed several sensitivity checks for each set of models to ensure our estimates were robust to assumptions about the scale used, the number of days that had elapsed between the beginning of school and when the test was taken, use of weights, or some combination of those factors. For example, to ensure results were not sensitive to an assumption of an equal-interval test scale, which has been shown to bias achievement gap estimates (Ho, 2009), we estimated "metric-free" *V* gaps detailed in Ho (2009), which rely on only the rank orderings of students based on their achievement test scores. Appendix B provides more detail for each sensitivity check conducted as well as the gap estimates from each model.

Question 3. Examining trends by pre-K enrollment. Lastly, we examined the degree to which longitudinal trends in academic achievement at school entry are associated with trends in district pre-K enrollment. We estimated a series of hierarchical linear models (HLM) by subject, where multiple cohorts of students (level-1) are nested in schools (level-2) within districts (level-3). That is to say, each school may have up to eight cohorts of incoming kindergarten students across eight years included at level-1 of the model. The reading data consist of 2,229,390 kindergarteners nested in 10,509 schools within 3,414 districts, whereas the math data consists of 2,339,900 kindergarteners in 10,690 schools within 3,437 districts. We first fit an unconditional HLM (shown in Equation 6) to quantify the within- and between-district variation in both student scores in 2010 as well as the score trends across time:

$$\begin{aligned}
y_{ijd} &= \pi_{0jd} + \pi_{1jd}(\mathrm{Cohort}_{ijd} - 2010) + \epsilon_{ijd} \\
\pi_{0jd} &= \beta_{00d} + r_{0jd} \\
\pi_{1jd} &= \beta_{10d} + r_{1jd} \\
\beta_{00d} &= \gamma_{000} + u_{00d} \\
\beta_{10d} &= \gamma_{100} + u_{10d}
\end{aligned} \tag{6}$$

where y_{ijs} is the test score of student i in school j in district d, and $\mathrm{Cohort}_{\mathrm{ijd}}$ is the year that student i entered kindergarten. This model contains a random intercept (γ_{000}) and a random slope for the linear trend across years (γ_{100}). The level-1 residual error ϵ_{ijs} is normally distributed with mean zero and variance σ^2, the school-level residuals r_{0jd} and r_{1jd} have a multivariate normal distribution with zero means and covariance matrix $\boldsymbol{\tau_j}$, and the district-level residuals u_{00d} and u_{10d} have a multivariate normal distribution with zero means and covariance matrix $\boldsymbol{\tau_d}$. From this model, we are able to estimate the percentage of variance between districts (e.g., the intraclass correlation or ICC) in both (a) initial achievement and (b) score trends over time.

After fitting the unconditional model, we examined whether district-level achievement trends are moderated by trends in the percent enrollment in districts' pre-K programs, controlling for the percentage of children 5 to 17 in the district that are in poverty ($\mathrm{Poverty}_d$). We do this by including an interaction term between cohort and enrollment. In practical terms, this interaction sheds light on whether the association between achievement and enrollment in district pre-K programs changes as the years go by. For instance, a positive coefficient would mean that the association between enrollment and mean RIT scores increases, on average, with each subsequent group of students. One could imagine such a scenario if, hypothetically, the district infrastructure created around pre-K and the quality of associated programs improved over time such that every additional student enrolled each year meant an even larger RIT score gain. The model is as follows:

$$
\begin{aligned}
y_{ijd} &= \pi_{0jd} + \pi_{1jd}(\mathrm{Cohort_{ijd}} - 2010) + \pi_{2jd}\mathrm{PS\_Enroll_{ijd}} + \pi_{3jd}\left(\mathrm{Cohort_{ijd}} - 2010\right) * \mathrm{PS\_Enroll_{ijd}} + \epsilon_{ijd} \\
\pi_{0jd} &= \beta_{00d} + r_{0jd} \\
\pi_{1jd} &= \beta_{10d} + r_{1jd} \\
\pi_{2jd} &= \beta_{20d} + r_{2jd} \\
\pi_{3jd} &= \beta_{30d} + r_{3jd} \\
\beta_{00d} &= \gamma_{000} + \gamma_{001}\mathrm{Poverty}_d + u_{00d} \\
\beta_{10d} &= \gamma_{100} + u_{10d} \\
\beta_{20d} &= \gamma_{200} + u_{20d} \\
\beta_{30d} &= \gamma_{300} + u_{30d}
\end{aligned}
\tag{7}
$$

The unconditional and conditional growth models were estimated separately for each subject and using HLM Version 7 (Raudenbush, Bryk, & Congdon, 2013).

Results

Research Question 1: Trends in Academic Skills at School Entry

Figure 1 presents the trends of kindergarten academic skills in math (top panel) and reading (bottom panel) by score percentile. We find that students’ achievement levels at school entry were mostly flat in the first half of the decade but slightly decreased between 2014 and 2017. In total, the median math score has dropped approximately four RIT points, which corresponds to 0.24 standard deviations (SDs), and the median reading score has dropped two RIT points (0.14 SD) during the 8-year time span. In 2017, math and reading scores were slightly lower at all five selected percentiles compared to 2010. That is to say, we do not see differences in trends between low-, middle-, and high-achieving students across time.

Research Question 2: Trends in Achievement Gaps by Race/Ethnicity, Gender, and School Poverty

Racial/Ethnic Gaps. Racial/ethnic achievement gaps at school entry have narrowed modestly over the last eight years (see Figure 2). In 2010, the average math score for White kindergarteners was 0.64 SD higher than their Black peers, which is significantly larger than the 0.53 SD difference in 2017. In reading, the Black-White gap significantly narrowed from 0.51 to 0.42 SD over the eight year span. The Hispanic-White gap at school entry has similarly significantly narrowed, dropping from 0.68 to 0.59 SD in math and from 0.64 to 0.53 SD in reading. The Asian-White gap has fluctuated somewhat over time without a clear overall pattern. By 2017, Asian students at school entry scored an average of 0.15 SD higher than White students in math and 0.10 SD higher than White students in reading. However, the Asian-White gaps appeared to be sensitive to the use of weights (as seen in Appendix Tables B1 and B2), and therefore we have less confidence in these findings than the other racial/ethnic gaps reported.

Does School Poverty Level Explain Racial/Ethnic Gaps? Figure 3 shows the racial/ethnic achievement gaps after controlling for school poverty level. After controlling for school-level poverty, the Black-White and Hispanic-White achievement gaps were greatly reduced (an average reduction of approximately 0.18 SD in math and 0.16 SD in reading). However, even after controlling for school poverty, racial/ethnic gaps at school entry were still statistically significant across all years in both math and reading, with the only exception of the Asian-White gap in math in 2010. The patterns of narrowing Black-White and Hispanic-White achievement gaps (as shown in Figures 2 and 3) were consistent whether or not we include controls for school poverty.

Gender Gaps. In each year since 2010, female students have scored higher than male students in math and reading at school entry (see Figure 4). The 2017 reading achievement gap between male and female kindergarteners (0.16 SD) was not significantly different from the male-female gaps in 2010. The math male-female gap has narrowed slightly from 0.09 SD in 2010 to 0.05 SD in 2017, indicating the small female advantage at school entry has shrunk.

School Poverty Gaps. Lastly, we examined trends in achievement gaps by school poverty level (right panels of Figure 4). For parsimony, we only discuss the gaps between low-poverty and high-poverty schools here, and differences between low- and mid-poverty are provided in the supplemental materials. In 2017, the average math RIT score in high-poverty schools (133) was lower than the average scores of kindergarteners in low-poverty schools (144). Specifically, the math gap between students at high-poverty and low-poverty schools (0.90 SD) was modestly but significantly smaller than the corresponding achievement gaps in 2010 (0.95 SD). The low-high poverty gap in reading significantly narrowed from 0.88 SD in 2010 to 0.77 SD in 2017. For both subjects, the primary years in which achievement gaps narrowed (2013-2017) correspond to the same period in which the trends for both groups are negative. That is, gaps are narrowing, but overall achievement for both groups is declining.

Research Question 3: Do Achievement Trends Differ Between Districts that do and do not Offer Pre-K Programs?

We begin by using the unconditional model to examine overall district-level trends in early math skills, as well as how much of the variance in achievement trends is at the district level. We present the results of the unconditional HLM model in Table 2. The results mirror the estimates shown in Figure 1, with districts showing a statistically significant yearly drop in RIT scores in both math and reading. Additionally, we found that a sizable amount of the variance in math and reading skills at school entry in 2010 is between districts (rather than between schools within districts). The district ICC for scores in 2010 is .47 in reading and .48 in math. That is to say, 47% of variation in reading scores in 2010 is between districts while 53% is between schools within districts. Less of the variance in the linear slope across time is between districts. In reading, the district ICC for the linear trend is .35 in math and .39 in reading.

Next, we examined the extent to which enrollment in district pre-K programs (net of district poverty) is associated with students' skills at school entry in 2010, as well as whether districts' across-time trends in skills at school entry were moderated by percent pre-K enrollment. These results are also presented in Table 2. While district poverty level is significantly associated with average district RIT score in 2010, the percentage of students enrolled in district pre-K programs was not associated with either the average RIT score in 2010 or change in scores over time. That is to say, districts with high pre-K enrollment showed similar overall drops across time as districts that did not offer pre-K programs.

Discussion

This study provides the first national examination of trends in academic skills and gaps at school entry for students who entered kindergarten between 2010 and 2017 using a diverse sample of over two million children. There were three findings: (a) relatively stable trends between 2010 to 2014 followed by small declines in entry-to-school reading and math skills, (b) modest narrowing of the racial/ethnic achievement gaps, and (c) no evidence that state-funded pre-K enrollment was associated with districts' trends in academic skills between 2010 and 2017. These findings are discussed below.

Our first major finding was that academic skills at school entry were mostly flat between 2010 and 2014 followed by small declines between 2014 and 2017, particularly in math. Given that Bassok and Lathom (2017) reported increases in teacher-reported math and literacy skills between 1998 and 2010, it is unclear whether these small negative trends seen in our data reflect (a) a true flattening in student achievement at school entry subsequent to the most recent kindergarten cohort of ECLS-K or (b) differences between teacher-reported and standardized assessments of students' academic skills.

Although no other large-scale studies we are aware of examine kindergarten trends during this past decade, these recent drops are mostly consistent with NAEP's 4th grade results. Between 2011 and 2013, US 4th graders showed small increases on NAEP, followed by small drops (statistically significant in mathematics, not in reading) between 2015 and 2017 (Petrilli, 2018). We are unable to say based on our descriptive study whether drops that the two tests (MAP Growth and NAEP) reflect the same underlying phenomena, but future research should explore broader educational mechanisms associated with these trends.

Our second key finding is the narrowing of racial/ethnic gaps with respect to academic skills at school entry during the past decade. In particular, the Black-White gap in math narrowed by roughly 0.11 SDs between 2010 and 2017, and the same gap in reading narrowed by about 0.09 SDs, both statistically significant. Similarly, the Hispanic-White gap at school entry went from 0.68 to 0.59 SDs in math and from 0.64 to 0.53 SDs in reading. All told, these results indicate that the narrowing of racial/ethnic achievement gaps between 1998 and 2010 reported by Reardon and Portilla (2016) has continued in the most recent decade.

Additionally, since our study starts in the same year as the most recent cohort of ECLS-K students entered school, we can compare the magnitude of our achievement gaps with the nationally representative sample collected by the ECLS-K. The Black-White achievement gaps on the MAP Growth assessment (0.64 SD in math and 0.51 SD in reading) were larger than those reported based on the 2010 ECLS-K data (0.55 SD in math and 0.32 SD in reading) by Reardon and Portilla (2016), though the Hispanic-White gap in math was fairly comparable (0.68 SD on MAP Growth and 0.67 SD on the ECLS-K test). It is unclear whether the differences in the Black-White gaps reflect differences in test content or format, samples used, or some other factor.

Finally, our study is among the first to examine the association between pre-K enrollment and academic skills at school entry using data from state pre-K programs across the country. Our results indicate that enrollment in state-funded programs run by school districts was not associated with the observed drops in students' academic skills across time. These findings are consistent with Bassok and Latham (2017), who found that their measures of preschool participation within the ECLS-K did not account for any of the differences between 1998 and 2010 in teacher-reported math or literacy skills.

The failure to see associations between pre-K experiences and entry-to-school reading and math skills was surprising given the relatively consistent reporting of positive impacts of state and local pre-K programs (Phillips et al., 2017). There are at least three possible explanations. First, the reports of pre-K impacts are from evaluations of pre-K programs, typically commissioned by states or cities with programs that meet the highest quality standards (Phillips et al., 2017). As a state or local initiative, there are over 60 state or local pre-K programs in this country in 43 states and D.C. (Friedman-Krauss et al., 2018). The performance standards of these programs differ dramatically, creating programs with very different levels of quality (Friedman-Krause et al., 2018). Therefore, generalizing findings from the evaluated pre-

K programs to all programs is questionable. Second, the pre-K evaluations relied on widely used achievement tests, such as the Woodcock-Johnson Tests of Cognitive Abilities, that tend to focus on whether children learned basic decoding and numeracy skills such as letter and number recognition, recognizing short words, counting, and cardinality. MAP Growth K-2, which is aligned to state content standards, tests students on foundational skills, but also covers more abstract and higher-level concepts as well. It is possible that this difference in focus could account for the differences in findings to the extent the pre-K programs focus mainly on teaching the rote skills. Third, about 53% of children ages 3 to 5 attend either full- day or part-day preschool prior to entry to kindergarten (Child Trends Databank, 2019), including the 60 publicly funded pre-K programs, so it is likely that many children are acquiring these early skills even if they do not attend a state-funded pre-K program.

Our study is descriptive and cannot provide explanations for the trends we observed. However, there are a set of potential explanations for the overall downward trends in academic skills at school entry. For instance, declines in achievement could represent delayed effects from the Great Recession, which occurred during the early formative years for most of the cohorts of students in our study. Additionally, overall declines may reflect changing demographics of school age children, who are increasingly likely to have parents who have immigrated to this country and may not speak English as a first language (Child Trends, 2018; 2019). Furthermore, during the study period, the Common Core State Standards (CCSS) were adopted across many states, and as a result, the expectations for what skills kindergarten students should be able to demonstrate have gotten more rigorous in many settings. It is possible that there is a widening disconnect between preschool and kindergarten standards, which is potentially leading to reduced scores.

Limitations

This study provides a unique perspective on recent academic trends at school entry that are unavailable in other national data sources such as ECLS-K and NAEP. However, this study has several notable limitations. First, our results are purely descriptive and cannot answer questions about why gaps are widening or narrowing. Second, while we are able to examine students' math and reading skills at school entry, we are unable to study other important early skills, such as students' self-regulation and social skills. Third, our sample of incoming kindergarteners changed substantially over time, with each subsequent cohort growing in size as well as becoming increasingly racial/ethnically diverse. The across-time comparisons presented in this study are dependent on the degree to which our post-stratification weighting procedure corrects for the non-random selection of schools into the NWEA sample across time. The post-stratification reweighted the data to be consistent with national proportions in each year across a number of school and district characteristics, including school racial/ethnic breakdown, urbanicity, FRPL receipt, and district socioeconomic measures. To understand the sensitivity of our results to the choice of weights, we provide supplemental tables in Appendix A comparing our (unweighted and weighted) school sample to the population of US schools serving kindergarten children across time, as well as a comparison between the weighted and unweighted achievement gaps in Appendix B.

Furthermore, the substantially larger and more diverse sample in the later years means that we are much more confident in the estimates for those years than for the earlier years. Between 2014 and 2017, our sample consists of approximately one in every 10 kindergarteners in US public schools. While our weights are meant to help account for some of these differences in the sample across years, it is not clear they sufficiently accomplish that goal, especially in the earlier years of the sample. Even if this sample does not perfectly mirror the national population of US kindergarteners, we believe there is great value of understanding the trends of such a substantial portion of kindergarten students in the country.

Lastly, we are unable to systematically link our student test records at school entry with their preschool care arrangements. Therefore, we can only track preschool availability in a students' area rather than compare groups of students who did or did not attend local pre-K programs. Given that many district pre-K programs are targeted to certain groups (e.g., low-income students and/or students with developmental delays), district pre-K enrollment may be a poor proxy for overall availability of pre-K programs in a local area. Further work should be conducted to tie MAP Growth data to better measures of pre-K availability in a local area, such as the census tract-level child care desert data collected by the Center for American Progress (Malik, Hamm, Schochet, Novoa, Workman, & Jessen-Howard, 2018).

Future Directions

These findings raise several important issues. It is not clear the extent to which earlier findings of increased skills over time based on teacher ratings reflect changes only in basic skills or also in more abstract skills. Fade-out of Head Start and pre-K effects (Phillips et al., 2017) could be due to focus on those basic skills in preschool program. More focus on the alignment between pre-K curriculum and the state standards taught in kindergarten may be important for ensuring publicly funded programs have long-term impacts (Keily, Evans, & Atchison, 2019).

Conclusions

Our study produces somewhat mixed findings on the state of students' academic skills at school entry, including trends in kindergarten achievement over the last decade. On one hand, we find that overall academic achievement at school entry has slightly dipped in the past few years, and that negative trends in achievement are not associated with the percent of students enrolled in district pre-K. On the other, we find that achievement gaps by race/ethnicity and school poverty have shown promising reductions during the same period. Additional investigation into potential policy and practice mechanisms underlying these differing trends is warranted.

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Table 1

Descriptive Statistics for the Study Sample Across Years

Fall Year	N Students	% of K Pop[a]	RIT M (SD)	Prop. Male	Racial/Ethnic Percentages[b] White	Black	Hispanic	Asian	School Avg. FRPL[c]
Reading									
2010	88,165	2%	142.86 (10.54)	0.51	0.54	0.14	0.11	0.04	0.51
2011	123,293	3%	143.83 (9.81)	0.51	0.54	0.13	0.12	0.03	0.53
2012	218,085	6%	142.66 (10.61)	0.52	0.50	0.17	0.15	0.04	0.57
2013	285,341	7%	142.80 (10.54)	0.51	0.52	0.17	0.14	0.04	0.55
2014	324,215	9%	142.62 (10.80)	0.51	0.49	0.17	0.16	0.04	0.57
2015	382,392	10%	141.51 (10.90)	0.51	0.46	0.19	0.17	0.04	0.59
2016	413,415	11%	140.90 (10.75)	0.52	0.45	0.20	0.16	0.03	0.58
2017	451,845	12%	141.02 (10.45)	0.51	0.46	0.19	0.16	0.03	—
Math									
2010	88,943	2%	141.89 (12.20)	0.51	0.54	0.14	0.11	0.04	0.52
2011	127,351	3%	143.09 (11.58)	0.51	0.53	0.13	0.12	0.04	0.52
2012	228,944	6%	142.63 (11.73)	0.51	0.50	0.17	0.16	0.04	0.56
2013	298,219	8%	141.53 (12.68)	0.51	0.52	0.17	0.14	0.04	0.54
2014	350,526	9%	141.08 (12.78)	0.51	0.48	0.18	0.17	0.04	0.57
2015	401,866	11%	139.22 (12.88)	0.51	0.45	0.19	0.17	0.04	0.59
2016	443,278	12%	138.58 (12.80)	0.51	0.44	0.20	0.18	0.04	0.58
2017	478,660	13%	138.20 (12.55)	0.51	0.44	0.19	0.17	0.04	—
US population of kindergarteners									
2010	3,682,092	—	—	0.51	0.50	0.15	0.26	0.04	0.53
2011	3,746,415	—	—	0.51	0.49	0.15	0.26	0.04	0.53
2012	3,830,982	—	—	0.51	0.48	0.15	0.27	0.04	0.55
2013	3,833,526	—	—	0.51	0.48	0.15	0.27	0.05	0.55
2014	3,772,413	—	—	0.52	0.47	0.15	0.27	0.05	0.56
2015	3,713,104	—	—	0.52	0.47	0.15	0.27	0.05	0.56
2016	3,726,656	—	—	0.52	0.46	0.15	0.28	0.05	0.51
2017	3,696,525	—	—	—	—	—	—	—	—

Note. FRPL = Free or Reduced Price Lunch, Pop.=Population, M=Mean, SD=Standard deviation. The reported M/SD values are estimated using our post-stratification weights.

[a] These percentages represents the number of all kindergarteners in public schools who took the MAP Growth assessment in a given year. The numerator is the number of students testing on MAP Growth reported in the adjacent column, and the denominator in this estimate is the total number of students enrolled in kindergarten according to the Table 203.10 in the 2017 Digest of Education, which are reported in the bottom third of the table. In 2017, projected enrollment numbers are used.

[b] Race/ethnicity within our analytic sample is reported using student-level NWEA data, whereas the US population percentages represent authors' calculations using racial/ethnic enrollment counts for kindergarten students relative to total enrollment in kindergarten.
[c] In 2016-17, the reporting of FRPL counts by NCES changed, with community eligibility now reported as a different field. As a result, this percentage is not directly comparable to the prior year estimates.

Table 2

Results from Unconditional and Conditional HLM Models

	Math		Reading	
	Unconditional Model	Conditional Model	Unconditional Model	Conditional Model
Fixed Effects				
Intercept (2010 Fall Score)	145.67 (0.21)***	145.49 (0.29)***	145.64 (0.17)***	145.68 (0.37)***
District Poverty	—	-25.40 (1.16)***	—	-18.53 (1.19)***
Year	-0.91 (0.04)***	-0.94 (0.06)***	-0.55 (0.03)***	-0.64 (0.06)***
Enrollment in Pre-K (%)	—	-0.88 (0.86)	—	-1.01 (0.94)
Year by Enrollment	—	0.07 (0.17)	—	0.24 (0.16)
Random effects				
Intercept SD (School)	4.46	4.42	4.25	4.22
Intercept SD (District)	4.72	3.78	4.45	3.86
Intercept ICC	0.47	—	0.48	—
Year SD (School)	0.55	0.55	0.56	0.56
Year SD (District)	0.75	0.72	0.70	0.67
Year ICC	0.35	—	0.39	—

Note. SD=Standard deviation, ICC=Intraclass correlation.

*** < .001; ** <.01; *<0.05

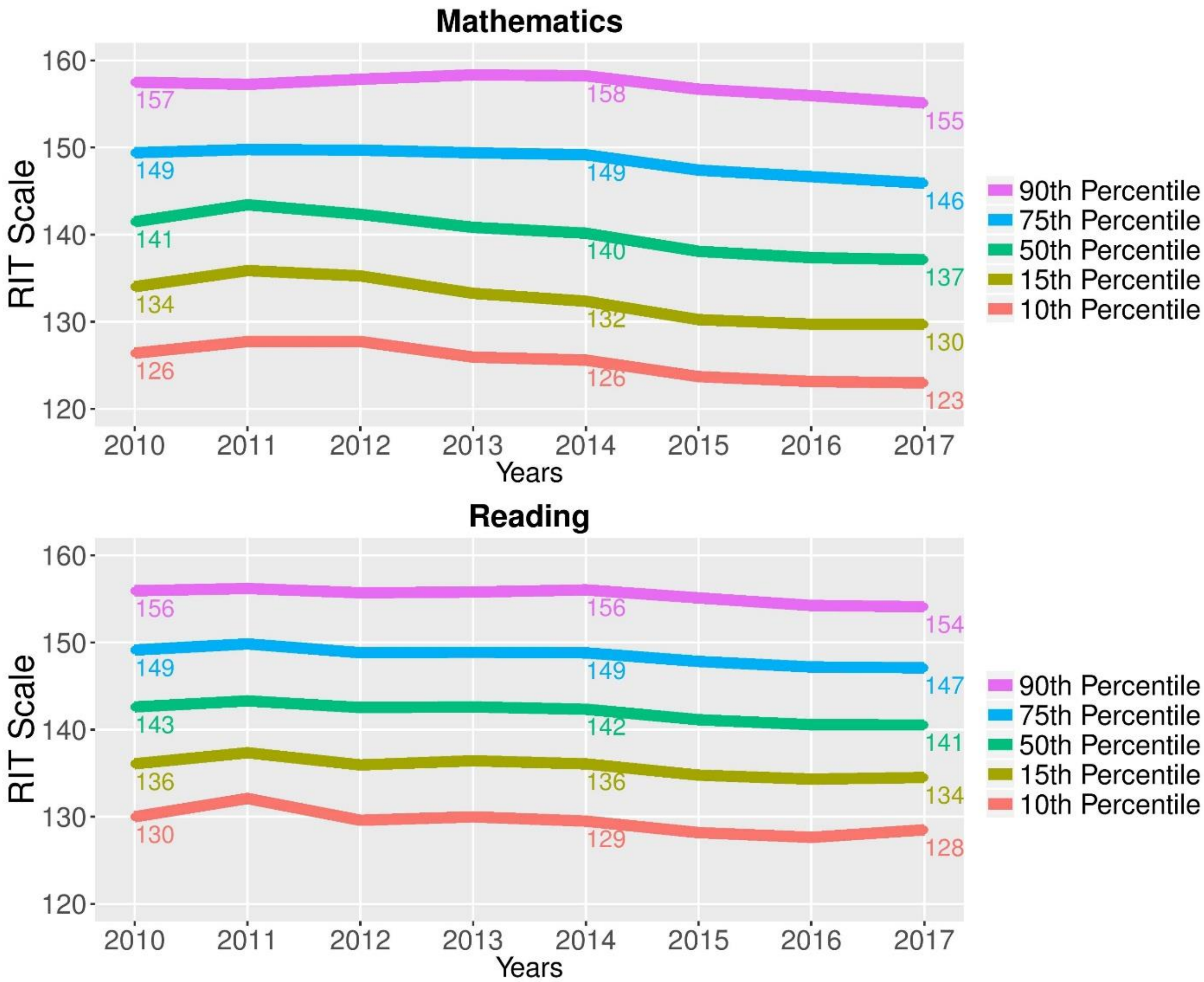

Figure 1. Trends in math and reading ability at school entry between 2010 and 2017 by score percentile.

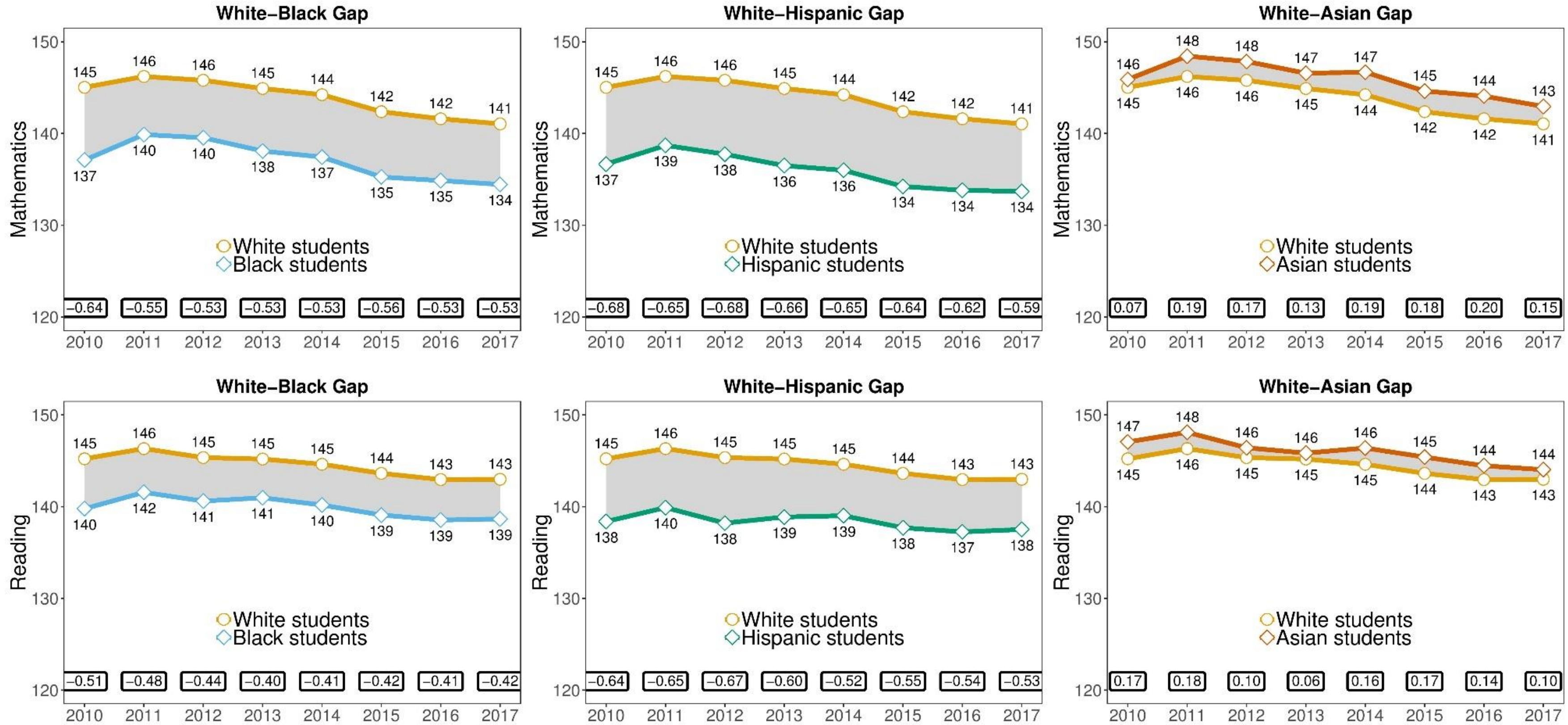

Figure 2. Trends in racial/ethnic achievement gaps at school entry in math and reading between 2010 and 2017. The top row displays gaps in math while the bottom row displays gaps in reading. Gaps in a standardized metric (relative to the standard deviation of the spring scores in each school year) are reported in boxed at the bottom of each panel.

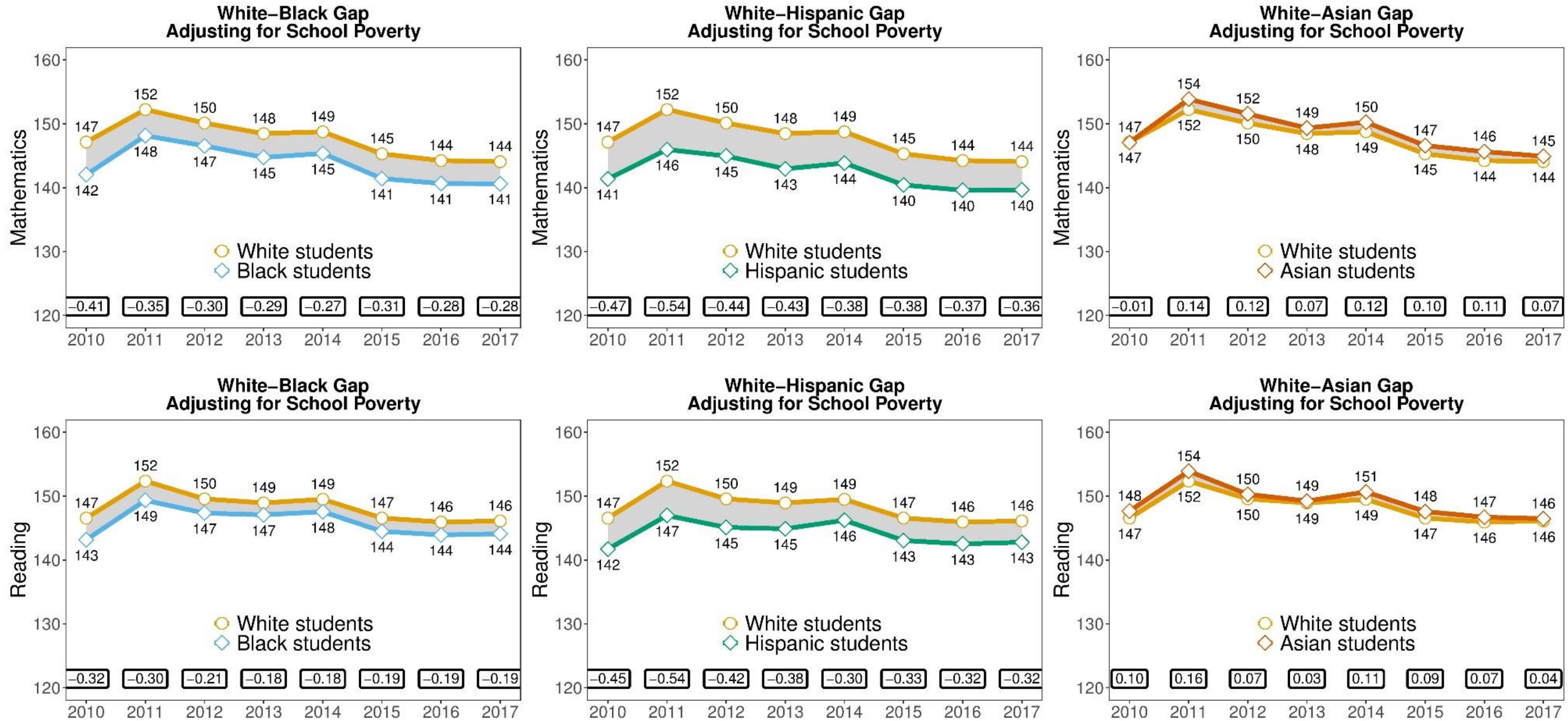

Figure 3. Trends in racial/ethnic achievement gaps at school entry in math and reading between 2010 and 2017. The top row displays gaps in math while the bottom row displays gaps in reading. Gaps in a standardized metric (relative to the standard deviation of the fall scores in each school year) are reported in boxed at the bottom of each panel.

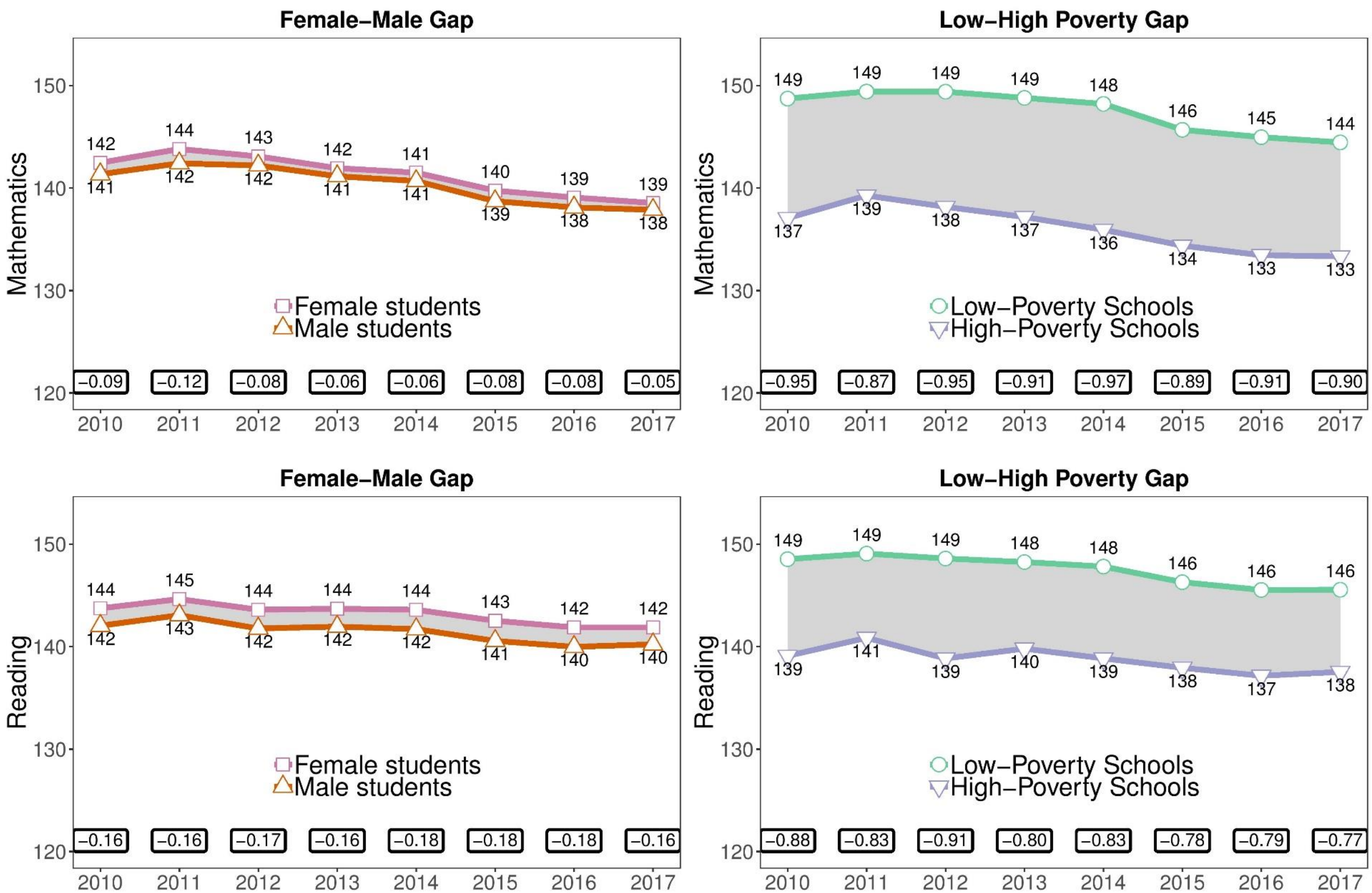

Figure 4. Trends in achievement gaps at school entry by gender and school poverty level in mathematics and reading between 2010 and 2017. The top row displays gaps in mathematics while the bottom row displays gaps in reading. Gaps in a standardized metric (relative to the standard deviation of the fall scores in each school year) are reported in boxed at the bottom of each panel.