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Quantifying and Exploring Elementary School Excellence Gaps Across Schools and Time

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Abstract

Despite considerable reform activity surrounding K-12 education over the past 20 years, racial and socioeconomic disparities among students who achieve at advanced levels have received little attention. This study examined how excellence gaps, defined as differences in performance at the 90th percentile of subgroups, change over time and their potential antecedents. We analyzed Measure of Academic Progress achievement data in reading and mathematics from a cohort of approximately 60,000 students from third to fifth grade in 742 elementary schools. Multilevel modeling results indicate that Black/Hispanic and White/Asian excellence gaps were relatively stable in reading. However, excellence gaps in mathematics increased during the school year and across time, and higher achieving schools demonstrated larger excellence gaps than lower achieving schools.

Keywords

excellence gaps, achievement gaps, gifted and talented, MAP, equity

At least since the passage of the No Child Left Behind Act in 2002, much of the policy emphasis in public schools has been on bringing students up to minimal, grade-level proficiency (Jolly & Makel, 2010). Although this goal is purported to have benefits from equity and economic perspectives, several scholars have argued (Kim &

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Sunderman, 2005; Neal & Schanzenbach, 2010) that the focus on minimal proficiency has diverted attention from an individualized approach to learning needs, especially when those needs are above standardized "grade-level" learning objectives (Dee & Jacob, 2011; Domina, Penner, & Penner, 2017; Kim & Sunderman, 2005; Neal, 2010; Neal & Schanzenbach, 2010; Peters, Makel, Matthews, Rambo-Hernandez, & Plucker, 2017). This lack of attention is even more problematic for students from low-income or racial/ethnic minority families who often do not have access to supplemental resources and thus rely on public schools to have their talents fostered (Plucker & Peters, 2016). In the absence of such talent development opportunities, economically vulnerable students rarely reach advanced levels of student achievement.

Literature Review

High-achieving students can be identified using any number of state, national, or international assessments and given a range of labels (e.g., above grade level, above average, advanced, exceeds expectations). Regardless of which assessment is referenced, the rates at which American students are identified as "high achieving" are relatively low when compared with peer nations. Results on the 2017 National Assessment of Educational Progress (NAEP) found that only 9% of Grade 4 and 4% of Grade 8 students scored advanced in reading (identical levels from 2015); in Mathematics, only 8% of Grade 4 and 10% of Grade 8, students scored advanced (slight increases from 2015). On the 2015 NAEP Science assessments, 1% of Grade 4, 2% of Grade 8, and 2% of Grade 12 students scored advanced. Results for other NAEP assessments (e.g., civics, writing) are similar or slightly better than the Science results. Overall, American rates of excellence in terms of advanced achievement are low when compared with peer nations, despite the fact that American rates of advanced achievement are the highest they have been in the past 30 years (Plucker & Peters, 2016).

Although American students score advanced on some international assessments at world-leading rates in Grade 4 (Trends in International Mathematics and Science Study [TIMSS] Science subscale, Progress in International Reading Literacy Study [*PIRLS*]), students scoring advanced by Grade 8 are far higher in many other countries (Organisation for Economic Co-operation and Development [OECD]; Plucker, 2015). For example, on the 2015 TIMSS Grade 4 mathematics assessment, top-performing countries had over 30% of their students scoring at or above the advanced benchmark, including Hong Kong (45%), South Korea (41%), Taiwan (35%), and Japan (32%). With only 14% scoring advanced, American students performed near the bottom of industrialized countries, similar to Russia (20%) and the United Kingdom (17%). Grade 8 math results exhibited the same pattern (e.g., Taiwan 44% and South Korea 43% vs. United States and United Kingdom at 10%).

None of these data are encouraging, but what is more concerning are the differential rates of advanced achievement that can be observed across various student subgroups. These students show both differing rates of advanced achievement as well as have shown different rates of growth in their progress toward greater rates of advanced achievement (Plucker, Burroughs, & Song, 2010; Plucker, Hardesty, & Burroughs, 2013).

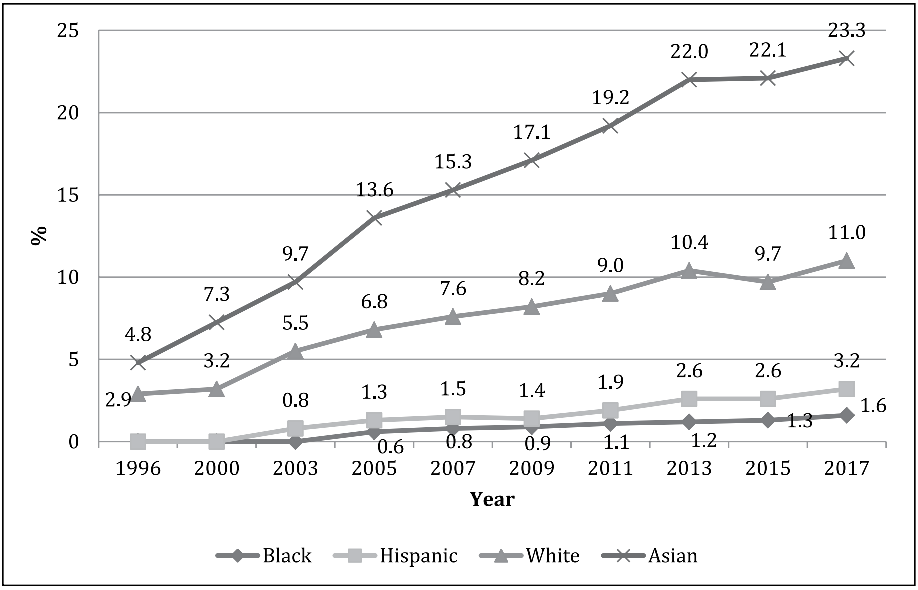

Figure 1. Percentage of students scoring advanced by race—Fourth-grade math NAEP.
Note. NAEP = National Assessment of Educational Progress.

Defining Excellence Gaps

In contrast to grade-level proficiency, excellence gaps, as defined by Plucker et al. (2010), are the difference between proportions of student subgroups performing at the highest levels of achievement. These excellence gaps are largely independent of the basic proficiency gaps that drive American education policy. As an example of excellence gaps, in Wisconsin, as of the 2016 to 2017 school year, 1.7% of Black students scored "advanced" in English language arts. Comparing this with 12.5% of White students scoring advanced results in an excellence gap of nearly 11 percentage points or 7 times more White students scoring advanced than their Black peers. Although much attention has been paid to researching and understanding minimal proficiency gaps (see Reardon, Robinson, & Weathers, 2008), less is known about the nature of excellence gaps.

As noted above, 9% of American Grade 4 students scored advanced in reading on the 2017 NAEP. However, when broken down by race and ethnicity, 3% of African American students, 21% of Asian students, 4% of Hispanic students, 3% of Native American students, and 13% of White students scored advanced. Figure 1 presents similar NAEP data, but for Grade 4 math. As a concept, excellence gaps are very similar to minimal proficiency gaps, but in a key way they are even more troubling because (a) they are growing much more rapidly in size and (b) because the groups less frequently reaching advanced levels of achievement are also the fastest growing segments of the U.S. school population (National Center for Education Statistics, 2016). Furthermore, Ferguson (2007) and Wagner (2014), among many others, argued that achieving minimal proficiency is not likely to be sufficient for success in the 21st century economy. As a case in point, the United States currently has nearly 5.9 million job openings, more than a 30% increase since the pre-Great Recession peak of 4.5 million open positions (OECD, 2019). Many of these positions require advanced problem-solving, communication, or other specialized skills. In addition, the wages of people who have achieved minimal proficiency or leave K-12 schools with a basic level of skills have stagnated over the past 30 years, even as the skills required for jobs and the cost of living have increased substantially. Although we again reiterate that raising student achievement to minimal proficiency is indeed important, it should be seen as necessary but insufficient as a major benchmark for educational quality or long-term economic and cultural development. Nor would it help assure that the wide range of learning needs that exist within every classroom are being sufficiently addressed.

There are a few key implications from Figure 1. Overall, aside from Asian students, a small percentage of American students are scoring at advanced levels in Grade 4 math, and for the most part, the rates for African American and Hispanic students have been stable since the late 1990s, with White students also showing a moderate degree of growth. Although the rapidly increasing rates of advanced achievement for Asian students are certainly positive, they also led to even larger excellence gaps because of differing rates of growth in the percentage of students scoring advanced. African American and Hispanic students have demonstrated an increase in advanced achievement; however, these increases have not come close to keeping pace with those of Asian and White students, thereby leading to even larger racial excellence gaps in the post–No Child Left Behind era (Plucker et al., 2013).

For reasons that are not completely clear, excellence gaps vary widely across schools even within the same district or state or schools within the same district. Part of this is due to the fact that racial and socioeconomic isolation has been getting worse since the mid-1980s (Reardon & Owens, 2014). Reardon and Owens noted that the percentage of Black students attending schools where 90% or more of students are Black has grown in all regions of the United States since the mid-1980s. As schools become more homogeneous in terms of population demographics, this increasing across-building heterogeneity also manifests in achievement heterogeneity across buildings.

Yaluma and Tyner (2018) sought to better understand how a school's population demographics correlate with their identified gifted population. What they found was that while high-poverty schools were just as likely as low-poverty schools to have gifted programs, far more students from low-poverty schools were enrolled in those programs. The authors found similar trends with regard to race or ethnicity. High racial/ethnic minority schools were just as likely to have gifted programs, but fewer African American or Hispanic students were identified for them compared with students from other racial/ethnic groups. Although this research described some clear relationships between race/ethnicity and income and gifted student identification, the relationship between these student and school-level variables and excellence gaps has not yet been investigated.

Predictors of Achievement Gaps

The achievement gap literature, which largely has examined mean differences in achievement between Black and White students or Hispanic and White students, has seen some consistent trends and potential explanations. For example, Black–White achievement gaps in reading and mathematics narrowed from the early 1970s until the late 1980s, before widening in the 1990s, which was then followed again by narrowing since the early 2000s (Reardon et al., 2008). The Hispanic–White gap has narrowed slightly over the past 20 years (Reardon, Valentino, Kalogrides, Shores, & Greenberg, 2013), and the Hispanic–White gaps tend to mimic the Black–White gaps over time (Reardon et al., 2008). The early decreases are largely attributed to desegregation, whereby minority students began to see greater access to higher quality education. Another pattern observed over multiple studies is that the gap between Black and White students' achievement grows during elementary school (e.g., Murnane et al., 2006; Reardon et al., 2008), leading us to wonder if a similar trend existed in excellence gaps.

Racial composition of schools. Both the racial composition of schools and the socioeconomic level of schools are associated with the variability in academic achievement and achievement gaps (e.g., Hanushek, Kain, Markman, & Rivkin, 2003; Hanushek, Kain, & Rivkin, 2009). The racial composition of schools is often a function of individual family decisions and factors such as government interventions (e.g., the way school attendance areas are drawn; Saporito and VanRiper, 2016). Thus, disentangling the effect of the racial composition on achievement from other student ability and background is not an easy task. Hanushek et al. (2009) used panel data available in Texas to separate the effects of racial composition on achievement and achievement gaps from other factors using multiple statistical models. The results suggested that Black students being educated with a higher percentage of Black students had a negative effect on their achievement, but White students being educated with a high proportion of Black students had little to no effect on their achievement. This points to the overall racial demographics of a school as a potentially important variable for seeking to better understand excellence gaps.

Student socioeconomic status. The overall socioeconomic composition of a school also appears to have an impact on achievement and achievement gaps (van Ewijk & Sleegers, 2010; Allington et al., 2010). A meta-analysis of the relationship between student test scores and peer socioeconomic status indicated that dichotomous measures such as free and reduced lunch status explained less variability than multidimensional estimates of socioeconomic status. In other words, their results indicated that measures that account for parental education and family income provided more information than free and reduced lunch status of peers. Furthermore, classroom-level multidimensional estimates of peer socioeconomic status explained more variability in student test scores than school-level multidimensional estimates of peer socioeconomic status. Even after accounting for academic achievement, students from low socioeconomic families are still less likely to be identified as gifted (Hamilton et al., 2018). And again, after controlling for achievement, schools that serve students from lower socioeconomic status have fewer students identified as gifted than schools that served students from higher socioeconomic status (Hamilton et al., 2018).

The relationship between income and achievement has strengthened dramatically over the past 50 years, and over this same time, income inequality has also steadily increased (Reardon, 2011). However, socioeconomic achievement gaps have not been examined in as much detail as those across racial ethnic groups, but some study results indicate that the gaps between lower and higher income students have grown over the past few decades, as much as 40% (Reardon, 2011). The most likely reason for this growth, according to Reardon (2011), is increased income inequality and changes in how parents invest in their children. With regard to this latter point, Kornrich and Furstenberg (2013) found that parents in the lowest two income deciles spent US$750 and US$900, respectively, on their children in 2006 to 2007 compared with US$3,701 and US$6,573 spent by the highest two deciles. This differential investment finding provides additional insight into why gaps emerge and why they are difficult to close.

Although the gaps in achievement between children from low and high socioeconomic families have steadily grown, there is evidence that students from all types of families are engaging in more educational experiences. For example, Bassok, Finch, Lee, Reardon, and Waldfogel (2016) found evidence that, over a 30-year period, families "increasingly structured their kindergarteners' lives to be more explicitly focused on engaging learning experiences" (p. 13). However, families across *all* socioeconomic levels experienced similar or larger increases in enriching educational experiences. Of note, although all students were engaging in more learning experience, over the same time, a socioeconomic gap grew in preschool participation. Bassok et al. hypothesized that low-income students may benefit more from the increased resources and intellectual engagement, but Kalil, Ziol-Guest, Ryan, and Markowitz (2016) found evidence that the across-the-board increases in enriched early childhood experiences lead to growing achievement gaps as upper-income students benefit more than lower-income students.

Plucker and Peters (2018), in an examination of research on poverty-based excellence gaps, noted that many of the associations mentioned above between socioeconomic factors and proficiency-based achievement gaps *probably* apply to advanced achievement. However, they also noted that little empirical evidence has been provided to determine the degree to which these other studies apply to excellence gaps.

Average school achievement. One possible predictor of achievement gaps that has not been explored is the average achievement level at each school. Students perform better when they are in classes with higher achieving students, and students typically perform more poorly when they are educated in classes with lower achieving students (Hanushek et al., 2003; Marks, 2010). If these findings are extended to the excellence gap, then high-achieving schools should see smaller excellence gaps than low-achieving schools—a rising tide lifting all boats. There are several possible antecedents to this effect, both at the student level (e.g., motivation, effort; (Harker & Tymms, 2004;

Stäbler, Dumont, Becker, & Baumert, 2017) and classroom level (e.g., teacher expectations, content coverage; (Harker & Tymms, 2004; Stäbler et al., 2017).

Seasonal changes in gaps. The ebb and flow of student achievement across the school year and summer has long been of interest to researchers. In a meta-analytic review, Cooper, Nye, Charlton, Lindsay, and Greathouse (1996) established that students tended to lose academic ground over the summer, and this loss was more pronounced in mathematics than in reading. Downey, von Hippel, and Hughes (2008) noted that "the amount learned in a year [in school] is still heavily influenced by children's time outside of school" (p. 245). In fact, Hofferth and Sandberg (2001) found that high-socioeconomic-status students grew in their summer (out of school) reading achievement at a rate of about 15 points, whereas their middle- and low-socioeconomic-status peers lost about 3 points each. Such differences in summer achievement change alone have significant implications for any type of achievement gap as some students make gains, whereas others stagnate or lose ground over the summer. In a more recent analysis using nationally representative ECLS-K:2011 data, Quinn, Cooc, McIntyre, and Gomez (2016) found that time in school does tend to equalize achievement and to a larger degree in math than in reading.

Rambo-Hernandez and McCoach (2015) evaluated differential reading growth between average and high-achieving students using the Northwest Evaluation Association's (NWEA) Measure of Academic Progress (MAP®) assessment. This study was particularly relevant as it utilized a computer adaptive assessment allowing for a better measure of above-grade-level performance and growth. The authors found that average students showed marked increases in reading achievement during the school year and flat achievement over the summer, whereas high-achieving students showed much slower growth during the school year than average students that persisted at the same rate over the summer. These differential growth patterns—both over the summer and during the school year—will aggregate over time and influence all types of achievement gaps.

Evaluating excellence gaps over time allows for an estimate of the impact of school-level variables (Downey et al., 2008). How the gaps change in the summer serves as a counterfactual for the impact of schools on the excellence gap. For example, if gaps increase over the summer but decrease during the school year, then schools are helping to ameliorate inequality across subgroups. If gaps decrease over the summer but increase during the school year, then the two groups of students benefit differentially from their time in school. By comparing how excellence gaps are changing during the school year with how the gaps are changing during the summer, new insights could be gained into how disparities in advanced achievement change for specific groups of students over time and how various factors may mitigate or exacerbate them.

Current Study and Hypotheses

The current study examines excellence gaps from the beginning of third grade to the end of fifth grade and explores how the excellence gaps change during the school year and over the summer. We also examine potential explanations of why excellence gaps expand or contract over time, such as the influence of poverty on excellence gaps. Thus, this study sought to test the accuracy of the following hypotheses:

1. Excellence gaps will increase over the course of students' elementary years.
2. The average school-level racial/ethnic composition, income, and achievement demographics of a school will explain some of the between school variability in the size of the excellence gaps and changes in the excellence gap during the school year and over the summer.

Methods

Sample

The MAP® reading and math assessments, which are produced and maintained by Northwest Evaluation Association (NWEA), were used as the data sources for this study. The data were provided via a data grant from NWEA. Our base sample included 59,353 students in reading and 64,801 students in mathematics nested within 742 schools nested in 35 states (Table 1). Of note, NWEA collected data on the demographics of the students using variables such as Black, White, Asian, and Hispanic. Thus, in the methods and results, we maintain these demographic labels. The full data set included student-level reading and math scores, which were collected from students twice yearly (early fall and late spring) from fall 2011 to spring 2014, for a maximum of six testing events per student. Both the reading and mathematics data sets had approximately 284,000 observations, which indicated an average of four to five observations per student (see Tables 2 and 3 for more details). Because the data were de-identified, this study was deemed nonhuman subjects and was not subjected to review from Institutional Review Board review by the first author's university.

As described above in past research, any achievement gap involves comparing two groups of students—often one that is historically higher achieving with one that is historically lower achieving. Just as when a group of students all receive the same score, there is zero variance, when the entire population of a school is from a single group, then differences between group achievement rates (at any level) cannot be computed. Because there must be two groups to calculate an excellence gap, the first step was to remove any schools that had 100% Black and Hispanic students or 100% White and Asian students from the data. Approximately 23% of the original 742 schools fell into this category—with 85% of the omitted schools served only White or Asian students and 15% served only Black or Hispanic students—a finding in its own right. The final analytic sample was 569 schools for the reading data and 568 for the mathematics data. The excluded schools had slightly slower NSLP percentages than included schools (44% vs. 49%).

Based on prior research showing growing excellence gaps in Grade 4 (Plucker et al., 2013; Plucker & Peters, 2016), for this study, we focused on Grades 3 (fall 2011) through 5 (spring 2014) to test our hypotheses regarding excellence gaps growing as

Table 1. Number of Schools in the Sample by State.

State	Frequency	Percent of total	State	Frequency	Percent of total
AK	1	0.13	NC	3	0.40
AZ	10	1.35	ND	33	4.45
CA	4	0.54	NE	3	0.40
CO	57	7.68	NH	19	2.56
DE	2	0.27	NM	11	1.48
FL	1	0.13	NV	3	0.40
IA	33	4.45	OH	3	0.40
ID	11	1.48	OR	2	0.27
IL	47	6.33	PA	5	0.67
IN	28	3.77	SC	139	18.73
KS	21	2.83	SD	2	0.27
KY	16	2.16	TX	20	2.70
MA	13	1.75	UT	1	0.13
MD	9	1.21	WA	59	7.95
ME	10	1.35	WI	39	5.26
MI	20	2.70	WV	1	0.13
MN	80	10.78	WY	15	2.02
MT	21	2.83	Total	742	100

Table 2. Number of Total Students Disaggregated by Minority and Nonminority Status.

	Frequency	%
Reading		
Black or Hispanic	15,697	26.4
Not specified or other	8,425	14.2
White or Asian	35,231	59.4
Total	59,353	100.0
Mathematics		
Black or Hispanic	17,080	26.4
Not specified or other	9,126	14.1
White or Asian	38,595	59.6
Total	64,801	100.0

students move through school. Furthermore, based on research by Plucker and colleagues (2013; Plucker & Peters, 2016) showing similar, flat rates of advanced achievement, we grouped them together into a composite Black/Hispanic variable. These students were then compared with the combined group of White and Asian students. In addition to being based on prior research, we also chose to group certain demographics together because of sample size. If we calculated the excellence gap

Table 3. Linear and Quadratic Variables Included in Each Model to Account for Time.

	Piece 1: School year linear time	Piece 2: Summer linear time	Piece 3: School year quadratic time
Fall 2011	0	0	0
Spring 2012	1	0	1
Fall 2012	1	1	1
Spring 2013	2	1	4
Fall 2013	2	2	4
Spring 2014	3	2	9

separately for Black and Hispanic students (compared with Asian or White students), another 40% of the schools would have been dropped from the analyses because of an inability to calculate an excellence gap. Students who were not identified in one of these four groups were not included in analyses (approximately 14% of the sample—see Table 2).

Measure

The MAP® is a vertically scaled computer adaptive assessment based on Rasch Measurement Theory and was explicitly designed to measure individual student academic growth. Students typically take the MAP® test for each subject at the beginning of the school year and again near the end of the academic year. This allows for the evaluation of within academic year growth as well as any growth or regression that occurs over the summer (e.g., comparing spring with fall scores). Because of the computer adaptive nature of the test, the MAP® test is able to determine the achievement level of students who typically score near the top of achievement measures with a high degree of accuracy (McCall, Kingsbury, & Olson, 2004), making this an ideal assessment to examine excellence gaps over time. The reading MAP® assesses students in three areas: (a) reading strategies and comprehending literary text, (b) comprehending informative and persuasive text, and (c) word meaning and relationships (NWEA, 2011; Wang, McCall, Jiao, & Harris, 2012). The mathematics MAP® assesses students in seven areas: (a) number systems, (b) number operations, (c) equations, (d) measurement, (e) problem-solving, (f) statistics and probability, and (g) applications (Wang, Jiao, & Zhang, 2013).

For each state in which NWEA administers the MAP test, NWEA also conducts and publishes a linking study. This helps test users see the alignment between the MAP test to the state's mandated accountability test and to the states content standards. For example, in 2016, NWEA conducted a linking study between the MAP and the Partnership for Assessment of Readiness for College and Careers (PARCC) in English language arts and math (NWEA, 2016). This allows MAP users to connect a given student's score back to specific state learning standards. In 2010 and 2017, NWEA also aligned its assessments to the Common Core State Standards such that sufficient item pools were created to measure each goal area. A single student score can then be traced back to learning standards over which the student has or has not demonstrated mastery.

All MAP tests report an overall Rasch Unit Scale (RIT) score. This RIT is on an equal-interval scale that is also the same for all grade levels tested. Math and reading scores can range from 100 to 300, with "grade-level" cut scores varying based on the particular state's content standards. For example, in states that utilize the Smarter Balanced Summative Assessment, scores of 202 in reading and 204 in mathematics are the minimum threshold for meeting standards for Grade 3 (NWEA, 2017). The internal consistency of the MAP® test scores as measured by marginal reliability is consistently high (.93 to .95; NWEA, 2011) with each individual score showing a standard error close to 3 points. In reading, an average third-grade student's score is predicted to increase 10.5 points from fall to spring, and fifth grade student is expected to increase approximately 6 points. In mathematics, an average third-grade student's mathematics score is predicted to increase, on average, 13 points from fall to spring, and fifth-grade student is expected to increase approximately 10 points (Thum & Hauser, 2015). Concurrent validity estimates of the MAP® score and state-based achievement tests are all around $r = .80$; however, these correlations drop if the state assessment includes subjectively scored items (NWEA, 2011). The scale of the MAP® test and the constructs assessed have remained extremely stable and consistent across time (Kingsbury & Wise, 2011; Wang et al., 2013).

In addition to reporting published alpha reliability levels for the MAP, we also computed conditional reliability levels based on MAP scores based on our data set. We did this to check that extreme scores, such as those at the 90th percentile, did not show larger standard errors than those at the 50th percentile. If this were the case, it might influence our findings. An examination of mean standard errors for scores in the middle decile compared with upper decile showed they all only varied by 10% or less suggesting scores were highly reliable regardless of where they fell on the achievement spectrum.

Variables

Our primary dependent variable of interest was the size of the Black/Hispanic and White/Asian excellence gap in reading and math. Any time a "gap" is calculated, it must be within a given context, such as a nation, state, district, or school. Because of the nested nature of the data (students within school educational contexts), we used the student-level data described above to compute school building-level excellence gaps. These building gaps were then summarized to estimate average excellence gaps as students moved through school in response to Hypothesis 1. Because the instructional experiences of students happen in the context of a given school, we chose to compute school-level excellence gaps rather than aggregate all students together and compute an overall "national" excellence gap over time. To do so would have attributed individual learning experiences in a given school to an average effect and ignored the individual students' context for learning. School-level gap calculations allowed us to address our hypotheses while considering the individual student context, but did not come without downsides. Specifically, as previously noted, including the most proximal setting to the individual student, the school setting did result in a quarter of the schools being removed from the data set because students in these schools were either all Black or Hispanic or all White or Asian.

The excellence gap–dependent variable. The first step in this process was to operationalize level of "excellence" and to decide how to best measure the gap in rates of achievement of excellence. Reardon and Robinson (2007) described three ways to calculate achievement gaps: (a) differences in average scale scores, (b) differences in standardized standard deviation units, and (c) differences in average ranks. The first option, differences in scale scores, is only appropriate when scores are available that meet the scale score assumption. The last two options are useful when the assessment scores are not vertically scaled. Because the MAP assessment uses an interval scaled metric with a computer adaptive test, test scores across different occasions and at different relative positions on the scale are comparable. Therefore, we used the differences in average scale score approach, with one change. Because we were interested in excellence gaps not achievement gaps, rather than calculating differences in average scale scores at the 50th percentile like Reardon and Robinson (2007), we calculated differences between groups at the 90th percentile.

To compute the 90th percentile difference scores, we first calculated the mean achievement score (math and reading) and standard deviation separately for Black/Hispanic and White/Asian students within each school for each time point. Then, we used the mean and standard deviation of each group to calculate separate predicted scores for the 90th percentile for Black/Hispanic and White/Asian students within a school (i.e., 90th percentile $\text{score}_{\text{subgroup}} = M_{\text{subgroup}} + 1.285_{z\ \text{score}} * SD_{\text{subgroup}}$). Finally, we subtracted the predicted 90th percentile score for Black/Hispanic students from White/Asian students at the same school to calculate the excellence gap between the two groups (Excellence Gap = 90th percentile $\text{score}_{\text{White/Asian students}}$ – 90th percentile $\text{score}_{\text{Black/Hispanic students}}$). Thus, each school had a maximum of six excellence gap observations: excellence gap between groups in fall 2011, spring 2012, fall 2012, spring 2013, fall 2013, and spring 2014.

We chose the 90th percentile for a few reasons, but primarily because it was a common criterion in past excellence gap research (e.g., Plucker et al., 2010). Selecting a norm-based criterion was also necessary for this present research because there are no national cut scores for "advanced" on MAP like there are on TIMSS or NAEP.

Following prior examples of longitudinal research in gifted education that examine changes in achievement during the school year and over the summer (Rambo-Hernandez & McCoach, 2015; McCoach, Rambo, & Welsh, 2013), we coded the time using three piecewise variables to account for time in school and time in the summer (Table 3). The first two pieces, school year linear time and summer linear time, were used to account for the anticipated differences in the changes in the excellence gap between fall and spring (each school year) and spring to fall (each summer). To account for a potential acceleration or deceleration of the excellence gap during the school year, we used a third piecewise variable, school year quadratic time. For example, if the school year linear time and the quadratic time estimates are both positive, this pattern would indicate the excellence gap gets larger as time passes. However, if the school year linear time is positive while the quadratic time estimate is negative, this pattern would indicate the gap starts to close over time. Because of the number of observations and the piecewise modeling of the data, we were only able to model quadratic effects of time on the excellence gap during the school year but not the summer.

Finally, the literature indicated three potential school-level variables that may be associated with the excellence gap: peer socioeconomic status (Reardon, Robinson, & Weathers, 2008; van Ewijk & Sleegers, 2010; Allington, et al., 2010), peer racial composition (Hanushek et al., 2009), and average school achievement. Thus, we tested the impact of three school-level variables on initial excellence gaps and changes in the excellence gap during the school year and summer. The three school-level variables were (a) the average percentage of students in the school who qualified for free or reduced lunch, (b) the average percentage of students in the school who were Black/Hispanic, and (c) the average reading or mathematics achievement percentile of all students within a school. We aggregated each of the variables from every time point (e.g., the average percentage of free or reduced lunch was entered as the mean of the three available observations of percent of students receiving free or reduced lunch in third, fourth, and fifth grade for each cohort). We considered modeling each as time-varying variables at Level 1, repeated measures, but there was very little variability across the time points. For example, we looked at the variability within a school in the percentage of minority students in a school. The median standard deviation of the percentage of minority students within a school was 2, meaning half of the schools had a standard deviation of less than 2 points on a 100-point scale across 6 time points. To further determine the effect of Black/Hispanic and White/Asian composition of schools, we also examined a fourth categorical variable which indicated whether the school had more Black/Hispanic or White/Asian students, that is, *high_minority* = 0.50 for schools with more Black/Hispanic students, *high_minority* = 0 for schools with equal proportions, or *high_minority* = –0.50 for schools with more White/Asian students than Black/Hispanic students.

Analyses

We analyzed two different dependent variables to test each of the hypotheses. First, we examined the *excellence gap* to understand the size of the excellence gap and how the gap changes over time. The excellence gap is a difference score and ranged from –9 to 25 approximately. Second, we examined the *90th percentile predicted scores* of both groups of students, which is on the metric of the MAP® assessment and range 200 to 250 approximately, to understand why the excellence gap exists and why it changes over time. In the analyses described here, we go into detail about the models for the two dependent variables, the excellence gap and predicted 90th percentile predicted scores for both groups, for both hypotheses and conclude the analyses section with the description of how we model the second dependent variable to address the hypotheses.

Modeling the excellence gap. Following an examination of the descriptive statistics, the data were analyzed using HLM v7 (Raudenbush & Bryk, 2002) in a three-level multilevel model. Level 1 modeled the within-school excellence gap at each time point, Level 2 modeled between school variability in the initial excellence gap and change in excellence gap over time, and Level 3 modeled between state variability in the initial excellence gap and change over time.

Regardless of the size of the school, each school had a maximum number of six observations. However, the precision of the estimate of the excellence gap is only as good as the smaller count of the two groups, White/Asian students or Black/Hispanic students. Many researchers have suggested different approaches for how to adjust for sample size using weights (Li, Thomas, & Li, 2018; Stapleton, 2002). In our study, if two schools had the same number of White/Asian students (e.g., $n = 100$) but different numbers of students who were Black/Hispanic (e.g., School A, $n = 90$ and School B, $n = 5$), the excellence gap at the School A would have a more accurate estimate of the excellence gap because it is based on a larger number of Black/Hispanic students and less susceptible to random variation or outliers than the excellence gap estimate for School B. Therefore, to account for school size in our models, we entered frequency weights in HLM at Level 2 (Stapleton, 2002). Specifically, we weighted our model estimates by using the smaller of the two: either the number of Black/Hispanic students in the school or the number of White/Asian students. In this way, School A above would be given the frequency weight 90, and School B would be given the frequency weight 5. Thus, School A would carry more statistical weight in the model estimates than School B. By weighting the Level 2 estimates by the smaller group, we were able to account for variability in the precision of the excellence gap estimates and also for extreme variability likely to occur due to estimates based on very few students (Li et al., 2018).

A major focus of this study was the effect being in school had on excellence gaps. Therefore, we used changes in the excellence gaps in the summer for each school as the counterfactual for what would had happened to school-level excellence gaps had the students not been in school. By comparing school year with summer changes in the excellence gap, we could obtain an estimate of what changes were due to school-based factors as opposed to other conditions.

Hypothesis 1: To address our first hypothesis, we fit separate models for reading and mathematics that modeled the excellence gap across each of the six observations. These models included separate linear slopes for the school year and summer and a school year quadratic slope (see Equation 1 below).

Level 1:

$$y_{tij} = \pi_{0ij} + \pi_{1ij}\left(time\ in\ school\right) + \pi_{2ij}\left(time\ in\ summer\right) + \pi_{3ij}\left(time\ in\ school^2\right) + e_{tij} \tag{1}$$

Level 2:

$$\pi_{0ij} = \beta_{00j} + r_{0ij}$$

$$\pi_{1ij} = \beta_{10j} + r_{1ij}$$

$$\pi_{2ij} = \beta_{20j} + r_{2ij}$$

$$\pi_{3ij} = \beta_{30j} + r_{3ij}$$

Level 3:

$$\beta_{0ij} = \gamma_{000} + u_{00j}$$

$$\beta_{1ij} = \gamma_{100} + u_{10j}$$

$$\beta_{2ij} = \gamma_{200} + u_{20j}$$

$$\beta_{3ij} = \gamma_{300} + u_{20j}$$

The dependent variable (y_{tij}) was the difference in the 90th percentile performance at each of the time points. The intercept (π_{0ji}) is the predicted initial excellence gap at the beginning of third grade in school i in state j. The slope for time in school (π_{1ij}) is the expected instantaneous change in the excellence gap during the school year, and the quadratic change over time (π_{3ji}) captures the amount of acceleration or deceleration of the excellence gap during the school year for school i in state j. Finally, the slope for time in summer (π_{2ji}) is the predicted change in the excellence gap over the summer school i in state j. These effects are aggregated at Level 2 so that the β estimates are the average estimates across all schools in state j and again at Level 3 so the γ estimates are the average estimates across states. The differences between the observed differences and predicted differences are captured by e_{tij} at Level 1, $r_{oij} - r_{3ij}$ at Level 2, and $u_{0ij} - u_{30j}$ at Level 3. We address Hypothesis 1 by examining the initial excellence gap (γ_{000}) to establish the excellence gap at the beginning of third grade and by examining the pattern of the growth estimates. For example, a positive school year slope (γ_{100}) and a positive school year quadratic slope (γ_{300}) would indicate the excellence gap grows during school and increases as time in school passes. A nonstatistically significant summer linear slope (γ_{200}) would indicate no changes in the excellence gap over the summer.

Hypothesis 2: To address our second hypothesis, for reading and then mathematics, we fit four models (White/Asian students—90th percentile predicted scores in reading, Black/Hispanic students—90th percentile predicted scores in reading, White/Asian students—90th percentile predicted scores in mathematics, Black/Hispanic students—90th percentile predicted scores in mathematics) separately to test the relationship of the four school-level variables (i.e., average NLSP, average Black/Hispanic, average achievement [all grand mean centered], and high Black/Hispanic school [effect coded]) entered at Level 2 to determine which explained differences in the size of the excellence gap and changes in the excellence gap during the school year and summer. Grand mean centering was used to facilitate interpretation, such that the intercept would be the predicted value for a typical school, for example, a school with an average number of students receiving free or reduced lunch or approximately 49%. For all competing models, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) were examined to determine the best fitting model. Equation 2 below is an example for the Level 1 and Level 2 models that tested the effects of average NLSP on the Level 2 estimated parameters (Level 3 is omitted for space constraints).

Level 1:

$$\begin{aligned} y_{tij} &= \pi_{0ij} + \pi_{1ij}\left(time\ in\ school\right) + \pi_{2ij}\left(time\ in\ summer\right) \\ &\quad + \pi_{3ij}\left(time\ in\ school^{2}\right) + e_{tij} \end{aligned} \tag{2}$$

Level 2:

$$\pi_{0ij} = \beta_{00j} + \beta_{01j}\left(average\ NSLP\right) + r_{0ij}$$
$$\pi_{1ij} = \beta_{10j} + \beta_{11j}\left(average\ NSLP\right) + r_{1ij}$$
$$\pi_{2ij} = \beta_{20j} + \beta_{21j}\left(average\ NSLP\right) + r_{2ij}$$
$$\pi_{3ij} = \beta_{30j} + \beta_{31j}\left(average\ NSLP\right) + r_{3ij}$$

The interpretations are similar to the interpretations in the model for Hypothesis 1 but now these parameter estimates account for average percentage NLSP. Because average NLSP was grand mean centered, the intercept β_{00j} represents the average initial excellence gap across schools which have an average percentage of students receiving NLSP in state j, and the slope β_{01j} represents the expected change in the initial excellence gap for a one unit change in the percentage of students who receive NLSP. The remaining parameter estimates follow the same pattern, namely, for schools with average NLSP percentages, β_{10j} is the instantaneous change in the excellence gap for time in school, β_{30j} is the quadratic change in the excellence gap over time in school, and β_{20j} is the expected change in the excellence gap over each summer. Parameter estimates β_{11j}, β_{31j}, and β_{21j} represent the expected change in each of the effects of school time, school quadratic time, and summer time for a one unit change in percentage of students receiving NLSP, respectively.

Modeling the predicted scores. Finally, differences in excellence gaps over time could be due to several reasons, such as (a) steady performance by Black/Hispanic student but increasing performance by White/Asian students, (b) steady performance by White/Asian students but decreasing performance by Black/Hispanic students, or (c) decreasing performance by Black/Hispanic and increasing performance by White/Asian students. Thus, we followed up both final models of reading and mathematics with statistical models of 90th percentile achievement scores (instead of excellence gaps) by Black/Hispanic and White/Asian students. These models indicated the predicted scores of each group (White/Asian or Black/Hispanic) instead of the difference between the predicted 90th percentile performance of each group. In the predicted 90th achievement score models, we used frequency weights at Level 2 based on the average number of White/Asian students in each school for the White/Asian 90th percentile achievement models and the average number of Black/Hispanic students in each school for the Black/Hispanic 90th percentile achievement models.

Results

The initial descriptive statistics indicated that, on average, the excellence gap between White/Asian and Black/Hispanic students slightly decreased across time in reading but demonstrated a clear increase in mathematics (Table 4).

An examination of the distribution of the excellence gap at each time point indicated that the excellence gap appeared to be normally distributed but with steep peaks around the mean. Reading difference scores across time points: skew ranged from 0.05 to .64, kurtosis ranged from 0.44 to 5.70; mathematics difference scores across time points: skew ranged from –0.09 to 0.63, kurtosis ranged from 1.24 to 3.08. An examination of the residuals for the final reading and mathematics multilevel models indicated that the residuals were also normally distributed.

Prior to adding any predictor variables to the student level, the proportion of variance in reading excellence gaps within schools was 19%, between schools was 58%, and between states was 23%. The proportion of variance in mathematics excellence gaps within schools was 24%, between schools was 56%, and between states was 20%.

Hypothesis 1

Reading. The weighted HLM results indicated that the initial excellence gap (fall 2011) was approximately 6.3 points across schools. As reported in Table 5 and illustrated in Figure 2, the reading excellence gap initially decreased in third grade (γ_{100}) and then remained stable over the summers (γ_{200}). However, the excellence gap increased almost back to its original value during fifth grade (γ_{300}). This suggests that, on average, gaps are in place very early on in elementary school and tend to linger as students progress through school. Of note, there was statistically significant variability

Table 4. Descriptive Statistics for the Achievement of White/Asian and Black/Hispanic Students in Reading and Mathematics and Their Difference for Each Semester.

	90th percentile reading				90th percentile mathematics			
		White/Asian	Black/Hispanic	Difference		White/Asian	Black/Hispanic	Difference
	N	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*N*	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)
Fall 2011	520	210.65 (6.30)	203.27 (8.78)	7.38 (9.25)	522	209.12 (5.82)	202.17 (7.21)	6.95 (7.63)
Spring 2012	527	219.46 (5.56)	212.64 (7.50)	6.82 (7.65)	526	222.57 (6.50)	215.08 (7.19)	7.49 (7.14)
Fall 2012	499	219.29 (6.06)	212.53 (8.82)	6.76 (9.44)	493	220.73 (6.37)	213.71 (7.49)	7.03 (8.13)
Spring 2013	507	226.54 (6.34)	219.99 (7.47)	6.55 (8.06)	498	234.07 (8.19)	226.46 (8.54)	7.61 (8.09)
Fall 2013	494	226.37 (5.39)	219.46 (7.68)	6.91 (8.19)	495	232.18 (7.13)	224.38 (8.06)	7.79 (8.42)
Spring 2014	513	232.51 (5.65)	225.47 (7.28)	7.05 (7.20)	516	245.12 (8.68)	236.06 (10.02)	9.07 (9.08)

Table 5. Multilevel Model Results Predicting the Excellence Gap in Reading and Mathematics.

	Reading	Mathematics	
Fixed effect	Final model	Final Level 1 model	Final Level 2 model
Initial excellence gap, π_0			
For intercept, β_{00}			
Intercept, γ_{000}	6.28 (0.66)***	6.42 (0.64)***	6.44 (0.61)***
For average achievement, β_{01}			
Intercept, γ_{010}			0.08 (0.03)**
For school linear slope, π_1			
For intercept, β_{10}			
Intercept, γ_{100}	−0.80 (0.32)*	−0.06 (0.3)	−0.07 (0.3)
For summer linear slope, π_2			
For intercept, β_{20}			
Intercept, γ_{200}	0.00 (0.66)	−0.04 (0.41)	−0.05 (0.41)
For school quadratic slope, π_3			
For intercept, β_{30}			
Intercept, γ_{300}	0.25 (0.17)	0.27 (0.11)*	0.27 (0.11)*
Random effects			
Level 1 (within schools)			
Temporal variation, e_{tij}	11.31	9.72	9.72
Level 2 (between schools)			
Initial status, r_{0ij}	28.41***	21.07***	20.73***
School year change, r_{1ij}	1.90	0.16	0.15
Summer change r_{2ij}	2.97***	1.56**	1.56*
School year quadratic change, r_{3ij}	0.22*	0.16	0.16
Level 3 (between states)			
Initial status, u_{00j}	5.05***	5.55***	4.75***
School year change, u_{10j}	0.09	0.16	0.17
Summer change, u_{20j}	7.65***	2.24**	2.22***
School year quadratic change, u_{30j}	0.41***	0.07	0.07

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

between schools in the initial gap and in the summer slope and quadratic effects for time in school on the excellence gap during the school year. In addition, there was also statistically significant variability between states in the initial excellence gap, summer linear slope, and school year quadratic effect for time in school. This variability indicated that there are differences in the size of the excellence gap and how the excellence gap changes between schools and between states.

Mathematics. The weighted HLM results indicated that the initial excellence gap in mathematics (γ_{000}) was approximately 6.4—very similar to the initial excellence gap

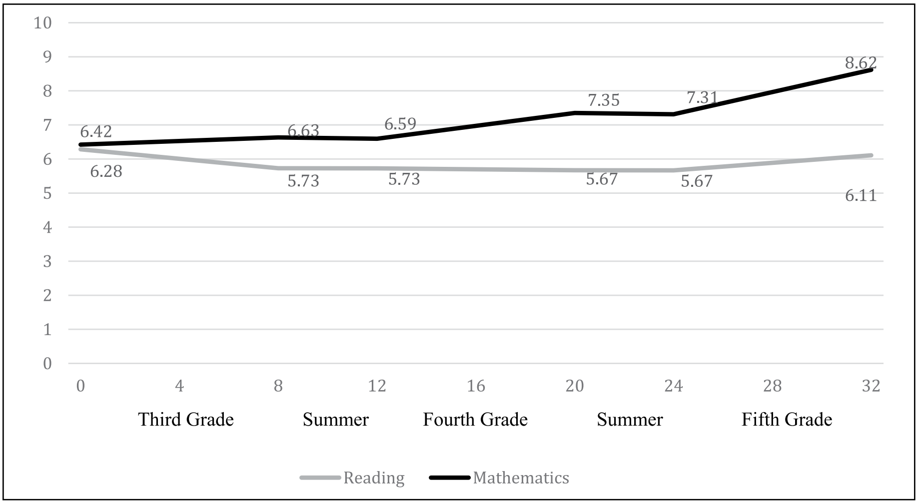

Figure 2. Multilevel model-implied excellence gap in reading and mathematics from the beginning of third grade (0 months) to the end of fifth grade (32 months).

in reading. The parameter estimates (Table 5) and model-implied trajectory (Figure 2) demonstrated that, like reading, excellence gaps did not change over the summer (γ_{200}). However, unlike reading, the excellence gap was expected to increase in third grade, fourth grade, and fifth grade (γ_{100}, γ_{300}). Thus, the excellence gaps were evident at the beginning of third grade, grew during the school year, and remained relatively stable over the summer. Like reading, there was statistically significant variability between schools and between states in the initial excellence gap and in the linear effect of time in summer on the excellence gap but no statistically significant variability existed between schools in the effect of linear or quadratic time in school on the excellence gap. Furthermore, there was statistically significant between state variability in the initial excellence gap and on the effect of time in summer on the excellence gap. Taken holistically, there is between school and state variability in the excellence gaps starting in third grade but those gaps change in similar ways across schools and across states during the school year. However, there is still substantial variability in how the excellence gap changes during the summer both between schools and between states.

In summary, the first hypothesis was fully supported in mathematics but not in reading. Consistent with our hypothesis, excellence gaps grew during school in mathematics. Contrary to our hypothesis, excellence gaps in reading briefly started to close during school but had essentially returned to its original value by the end of fifth grade.

Hypothesis 2

Reading. The second hypothesis addressed different explanatory variables, both related to initial excellence gaps and their change over time. School-level NSLP, percent of Black/Hispanic students, average school achievement, and majority Black/Hispanic school variables were not predictive of the excellence gap in reading (Table 6). Thus, the model from Hypothesis 1 remained the best fitting model. Changes in the excellence gap are more easily visible through the model-implied trajectory, which is provided in Figure 2. The black line illustrates the changes in the reading excellence gap across time. Like the descriptive statistics indicated, the excellence gap was relatively stable across the school year and summer as well as across students' elementary careers.

Next, we examined the predicted 90th percentile achievement of White/Asian students and Black/Hispanic students to understand why the reading gap was remaining relatively stable (Table 6). As illustrated in Figure 3, the black line shows the model-implied trajectory for 90th percentile reading achievement score for White/Asian students, and the gray line shows the model-implied trajectory for 90th percentile reading achievement score for Black/Hispanic students. While there were statistically significant effects (e.g., Black/Hispanic students had steeper declines in reading achievement as evidenced by the larger school quadratic slope parameter estimate), these differences were not practically meaningful. The two trajectories follow similar paths—indicating both Black/Hispanic and White/Asian students grew in reading at roughly the same rates despite being consistently around 7 points apart.

Mathematics. We hypothesized that several variables would be associated with changes in the excellence gaps. The AIC and BIC indicated different best fitting models (Table 7). Because of the discrepancy in model fit indices, we examined the model with average school achievement more closely and observed that average school achievement was only a statistically significant predictor of *size* of the excellence gaps not how the excellence gap changed. Thus, we removed average school achievement as a predictor of changes of the achievement gap during school and over the summer but retained average school achievement as a predictor on the intercept of the excellence gap (Table 5—final Level 2 model). This final model provided the best fit according to both AIC and BIC indices.

In this final model, average school achievement (SD = 11.33) had a statistically significant effect on the size of the excellence gap but not on the linear or quadratic changes in the excellence gap across time. Figure 4 illustrates the model-implied trajectories for schools that were above average in math achievement (depicted as 1 SD above the mean), average (SD = 0), and below average (depicted as 1 SD below the mean). At the beginning of third grade, the difference in excellence gaps between above and below average–achieving school was approximately 2 points—low-achieving schools demonstrated an almost 6-point excellence gap, whereas high-achieving schools demonstrated an almost 8-point excellence gap. Difference between the two types of schools persisted to the end of fifth grade. Furthermore, as with the final Level 1 model, summer appeared to have little effect on the excellence gap, but the excellence gap was predicted to grow during the fourth and fifth grade school years.

We followed the analyses of the excellence gap with two models that predicted the 90th percentile mathematics achievement scores of White/Asian and Black/Hispanic students. The results of the two models are provided in Table 6.

Table 6. Multilevel Model Results Predicting the Achievement in Reading and Mathematics for White/Asian Students and Black/Hispanic Students.

	Reading		Mathematics	
	White/Asian	Black/Hispanic	White/Asian	Black/Hispanic
Fixed effect	Coefficient (*SE*)	Coefficient (*SE*)	Coefficient (*SE*)	Coefficient (*SE*)
For intercept, π_{0ij}				
For intercept, β_{00j}				
Intercept, γ_{000}	211.34 (0.46)***	203.45 (0.71)***	208.34 (0.48)***	203.49 (0.50)***
For school achievement, β_{01j}				
Intercept, γ_{010}			0.39 (0.01)***	0.29 (0.02)***
For school linear slope, π_{1ij}				
For intercept, β_{10j}				
Intercept, γ_{100}	9.12 (0.29)***	10.62 (0.35)***	13.77 (0.45)***	13.81 (0.43)***
For summer linear slope, π_{2ij}				
For intercept, β_{20j}				
Intercept, γ_{200}	0.12 (0.35)	−0.21 (0.30)	−1.86 (0.40)***	−1.58 (0.28)***
For school quadratic slope, π_{3ij}				
For intercept, β_{30j}				
Intercept, γ_{300}	−0.66 (0.11)***	−1.04 (0.09)***	−0.11 (0.12)	−0.50 (0.13)***
Random effects				
Level 1 (within schools)				
Temporal variation, e_{tij}	4.08	7.76	6.17	7.81
Level 2 (between schools)				
Initial status, r_{0ij}	15.5***	24.45***	5.55***	8.61***
School year change, r_{1ij}	5.18***	3.77**	2.73**	2.51*
Summer change r_{2ij}	2.97***	1.37***	1.79***	1.16**
School year quadratic change, r_{3ij}	0.13***	0.26**	0.56***	0.44***
Level 3 (between states)				
Initial status, u_{00j}	3.2***	6.01**	4.29***	3.03***
School year change, u_{10j}	0.6*	0.5	2.99***	1.36**
Summer change, u_{20j}	2.21***	0.79**	3.02***	0.65**
School year quadratic change, u_{30j}	0.21***	0.02*	0.15***	0.12**

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

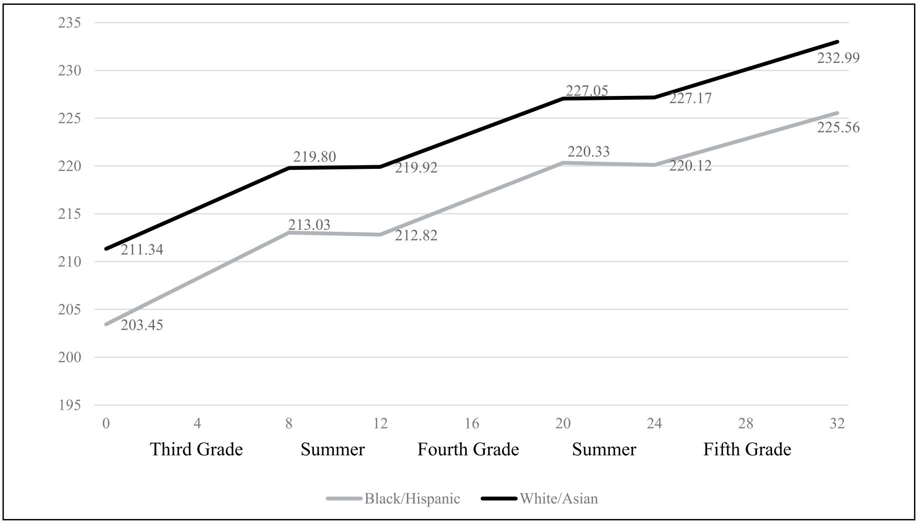

Figure 3. Predicted 90th percentile achievement in reading by Black/Hispanic status from the beginning of third grade (0 months) to the end of fifth grade (32 months).

Table 7. Indications of Model Fit for the Fitted Mathematics and Reading Models.

		Estimated parameters	Deviance	AIC	BIC
Reading					
Level 1 models					
1A	Linear time for school and summer and quadratic time for school	25	17,918.5	17,968.51	18,077.07
Level 2 models					
2A	Best Level 1 model with average achievement on intercept and slopes	29	17,915.6	17,973.6	18,099.52
2B	Best Level 1 model with percent minority in school on intercept and slopes	29	17,917.1	17,975.1	18,101.02
2C	Best Level 1 model with percentage of students receiving free/reduced lunch in school on intercept and slopes	29	17,916.9	17,974.92	18,100.84
Mathematics					
Level 1 models					
1A	Linear time for school and summer and quadratic time for school	25	17,604.98	17,654.98	17,763.53

(continued)

Table 7. (continued)

		Estimated parameters	Deviance	AIC	BIC
Level 2 models					
2A	Best Level 1 model with average achievement on intercept and slopes	29	17,588.2	17,646.22	17,772.14
2B	Best Level 1 with model percent minority in school on intercept and slopes	29	17,604.3	17,662.27	17,788.19
2C	Best Level 1 model with percentage of students receiving free/reduced lunch in school on intercept and slopes	29	17,598.2	17,656.17	17,782.09
Final model					
3A	Best Level 2 model with nonstatistically significant fixed effects removed	26	17,590.7	17,642.73	17,755.62

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion.

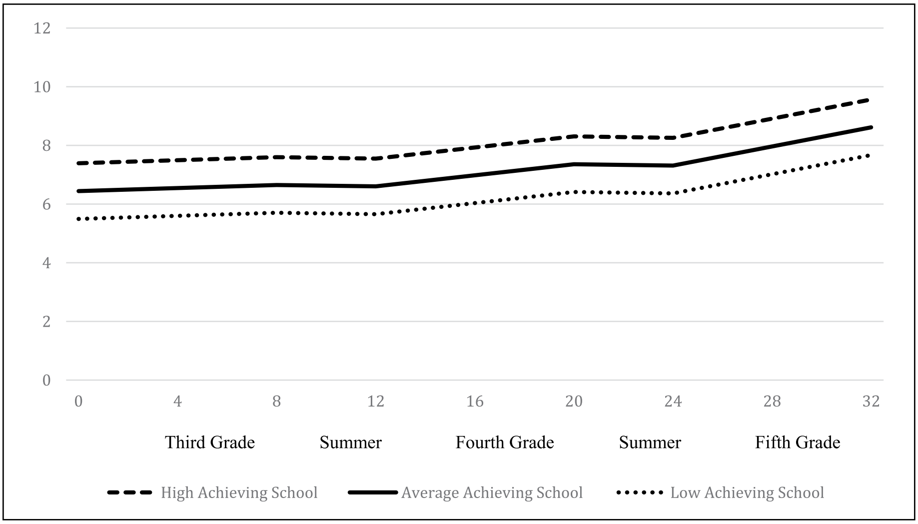

Figure 4. Multilevel model predicted mathematics excellence gap by school achievement from the beginning of third grade (0 months) to the end of fifth grade (32 months).
Note. Above and below average were defined as 1 *SD* above or below average in school achievement (*SD* = 11.33).

For average-achieving schools, White/Asian and Black/Hispanic students started approximately 5 points apart in mathematics. For every one percentage point higher a school's average achievement, the initial excellence gap was expected to increase by 0.10 units (i.e., $\gamma_{010-White/Asian} - \gamma_{010-Black/Hispanic} = 0.39 - 0.29$). For example, a school whose performance is one standard deviation above average would be expected to have an excellence gap that is 2.27 points larger than a school with an average achievement one standard deviation below average.

Both White/Asian and Black/Hispanic students appeared to have approximately identical growth in mathematics during third grade and very similar losses over the summer; however, the growth trajectories of the two groups differed as time in school accumulated. Specifically, the White/Asian quadratic school effect estimate was not statistically significant, which indicated that there was no change in their rate of growth across time in school and White/Asian students continued to grow at the same pace during third, fourth, and fifth grades. But the Black/Hispanic quadratic effect was statistically significant and negative, which indicated a slowing of growth across time in school and indicated these students did not grow as much in fifth grade as they did in third or fourth grade. Thus, the source of the increased excellence gap in mathematics was slowing growth from Black/Hispanic students paired with steady growth from White/Asian students. Also, of note, there was substantially more variability in the Black/Hispanic initial achievement than in White/Asian initial achievement.

As illustrated in Figure 5, the solid lines show the model-implied achievement for White/Asian and Black/Hispanic students in average-achieving schools. At the beginning of third grade, the achievement of Black/Hispanic students in the higher achieving schools was roughly commensurate with the achievement of White/Asian students at average-achieving schools, but by the end of fifth grade, the achievement of Black/Hispanic students in the higher achieving schools was roughly commensurate with the achievement of White/Asian students at the lowest achieving schools. Thus, the excellence gap grew.

To summarize the results of Hypothesis 2, only one variable predicted the size of the excellence gap—average school achievement, and only for mathematics. None of the other explanatory variables were statistically significant predictors of the size of the excellence gap or changes in the excellence gap during the school year of over the summer. Thus, our second hypothesis was only partially supported.

Discussion

This study explored associations with changes in excellence gaps over time. The goals of this study were to understand how time in school and school demographic factors influence excellence gaps. Four important findings stand out: (a) excellence gaps in reading were relatively stable, (b) excellence gaps in mathematics continued to increase during the school year, (c) average school achievement was positively related to the size of the mathematics gap but unrelated to how the excellence gap changes over time, and (d) none of the other predictors were related to either the size or changes in the excellence gap. These results suggest that excellence gaps widen in mathematics as students

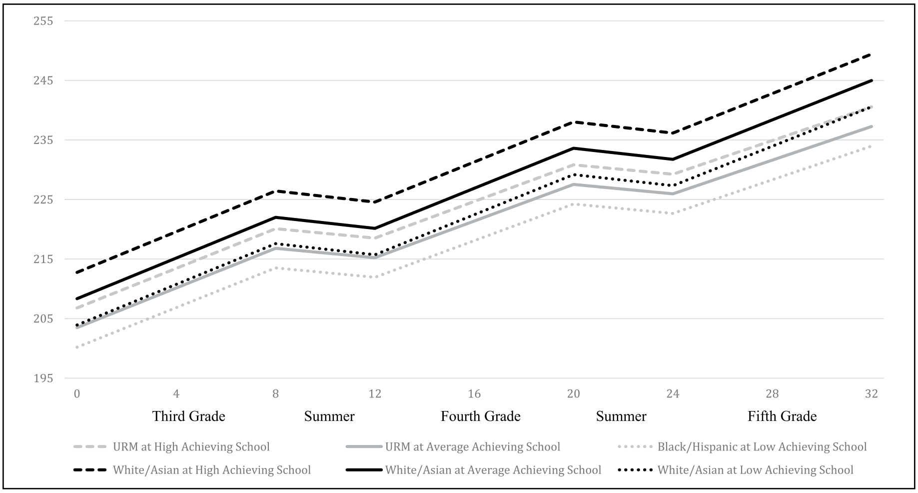

Figure 5. Predicted 90th percentile achievement in mathematics by Black/Hispanic status at high-, average-, and low-achieving schools from third grade (0 months) to the end of fifth grade (32 months).
Note. High-achieving schools were estimated at 1 *SD* above average (*SD* = 11.33). Low-achieving schools were estimated to be 1 *SD* below average on their average school achievement (*SD* = −11.33).

move into middle school and begin to self-select into various mathematics courses, potentially resulting in greater racial and socioeconomic homogeneity within classes.

Previous research has illustrated that the gaps between majority and minority racial/ethnic groups are widening. Plucker and colleagues (2010; Plucker et al., 2013), looking over 10-year time frames, found that the percentage of Black and Hispanic students scoring at advanced levels was outpaced by the growth in the rate of White and Asian students scoring advanced, thereby increasing excellence gaps (see also Plucker & Peters, 2016; Rutkowski, Rutkowski, & Plucker, 2012). However, in the shorter time frame of the present study, examining a single cohort of students and using a different approach to estimating advanced achievement, reading excellence gaps appeared to be relatively stable—time in schools did not appear to have much of an effect on the size of excellence gaps. Our more nuanced, seasonal approach appears to demonstrate that excellence gaps in reading actually decreased during third grade and then remained stable until the beginning of fifth grade. Despite a slight increase in the excellence gap during fifth grade, the excellence gap in reading was slightly smaller than it was at the beginning of third grade. Furthermore, the excellence gap did not change over the summer, contrary to expectations based on previous research on summer learning loss (e.g., Allington et al., 2010; Slates, Alexander, Entwisle, & Olson, 2012).

Student growth in mathematics and reading is typically greatest from kindergarten to fourth grade but begins to slow from fifth grade to eighth grade, and mathematics gains are typically greater than reading gains over time (Lee, 2010). On this assessment, average third-grade students typically increase their MAP reading score by 10 points. Therefore, a 6-point difference in third grade represents just over half a year of learning difference between Black/Hispanic and White/Asian students. But in fifth grade, students typically increase their MAP reading score by 6 points, representing a full year's difference in performance between Black/Hispanic and White/Asian students. Although the actual excellence gap estimate remained stable, this number could be masking a growing excellence gap in terms of grade-level equivalents.

Reading and mathematics excellence gap trends were distinct. The excellence gap in mathematics consistently widened during the school year and stayed constant during the summer. In third grade, all students—regardless of their ethnicity or type of school—grew at roughly the same rate. However, as illustrated in Figure 5, Black/Hispanic students in all types of schools demonstrated slower growth in fifth grade (gray lines) than their White/Asian counterparts (black lines). In this sense, time in school does appear to widen excellence gaps. Furthermore, the excellence gap widened not because White/Asian students were growing more quickly but because Black/Hispanic students were growing more slowly. In third grade, the difference in 90th percentile performance of White/Asian students and Black/Hispanic students was about half a grade level (e.g., typical gains for average third-grade students are 13 points in mathematics, and the difference observed in our data was 6.4 points). But by the end of fifth grade, the difference in 90th percentile performance of White/Asian students and Black/Hispanic students was nearly an entire grade level (e.g., typical gains in fifth grade are 10 points in mathematics, and the difference in performance was 8.4 points). In terms of typical gains, both the reading and mathematics excellence gap started around half an academic year in third grade but grew to nearly one whole academic year by the end of fifth grade.

A possible explanation of why excellence gaps grew in mathematics but not reading is the more teacher-dependent nature of learning mathematics (Alexander, Entwisle, & Olson, 2001; Cooper et al., 1996) compared with reading. For example, once a student has the basic skills for reading (e.g., decoding and comprehension), he or she may be able to read more complex texts with less teacher support than what would be required to move from mastering operations with whole numbers to mastering mathematical operations with fractions. In a similar vein, teachers and parents may find informal attempts at differentiation easier in reading than mathematics. In addition, Yaluma and Tyner (2018) found that African American and Hispanic students were just as likely to have gifted programs at their schools, but that they were less likely to be served by them. It is possible that this discrepancy in likelihood to receive gifted services could explain some of the slowing of growth among high-achieving students from those particular subgroups over time. Finally, we hypothesized that schools with higher achievement levels would have smaller excellence gaps, which was not the case. There could be other possible explanations for the larger excellence gap between high-achieving Black/Hispanic students and White/Asian students, such as the Matthew Effect (Merton, 1995), which, in the present context, posits that those who are already higher achieving are likely to grow at an even faster rate even when all students are provided with the same instructional experience.

In general, the growth in mathematics excellence gaps supports previous findings regarding an approximate doubling of the size of fourth-grade excellence gaps in math between 2003 and 2011 (Plucker et al., 2013). Of note, the current study examined a cohort of students across time instead of tracking one grade level across time as in all previous excellence gap studies. Thus, we looked at changes in the excellence gap differently. However, only one of the hypothesized predictors was associated with any of these differences—the higher the school's achievement, the greater the excellence gap. Other factors may cause excellence gaps to grow over the course of a school year (i.e., individual school policies or practices), but what is clear is that, on average, excellence gaps in mathematics in elementary school are increasing.

Limitations

One of the earliest findings from this study is also a limitation—the fact that such a large percentage of schools are completely homogeneous—either all Black and Hispanic or all White and Asian (23% of our sample). Although this level of segregation is a finding in its own right, it also limits the ability to calculate any kind of building-level achievement or excellence gap.

Simplistically, excellence gaps are calculated by subtracting the mean of two groups of students. Therefore, our dependent variable was a school-level variable calculated from student-level data. Modeling the dependent variable at the school level prevented modeling specific student characteristics, such as family socioeconomic status. Given how influential family income appears to be based on prior studies, this is a limitation.

Also, because we wanted to retain as many schools in the data set as possible, we aggregated both White and Asian students and then Black and Hispanic students. All four of these groups represent distinct populations with a lot of variability within each population. An even larger data set may be able to provide more nuanced detail on how the excellence gap changes based on the specific populations.

Another limitation is that we modeled the data within schools and states but not within classrooms. Future studies should examine the excellence gap at the classroom level in addition to the school level to determine potential causes for this increase in the excellence gap. Next, this study evaluated excellence gaps using a single measure of academic achievement. Although the MAP is especially well suited for our analyses, no one test can perfectly measure a student's "true" level of achievement, even within a single domain. Finally, we did not have enough time points to model potential acceleration or deceleration of excellence gaps during the summers. Our models assumed identical change in the excellence gaps between the summer after third grade and the summer after fourth grade.

Conclusion

A decade ago, the knowledge base on how to address excellence gaps was limited (see discussion in Worrell, 2014). But recent advances within gifted education, and education and psychology more generally, provide a path forward (e.g., Harris & Plucker, 2014; Plucker & Harris, 2015). For example, Plucker and Peters (2016) recently surveyed the intervention literature and proposed an empirically based intervention model for shrinking excellence gaps. The entire model suggests that frontloading—preparing promising students in advance for advanced education opportunities—is required if these gaps are ever to close in meaningful ways, and the present study provides additional justification for early intervention. Indeed, our results suggest that early interventions are important but need to be maintained throughout elementary school to prevent the relative slowing of learning rates experienced by Black and Hispanic students after third grade. Such interventions are needed due to the wide range of learning experiences and opportunities students bring with them when they first enter formalized education.

If greater equity continues to be a focus of American educational policy as well as at the district and school level, then inequality must be conceptualized beyond that of minimal proficiency to include a much wider range of learner differences in terms of academic need. Advanced achievement is no less important than grade-level achievement and, in fact, some might argue that advanced achievement is far more important (e.g., Ferguson, 2007). As the present study showed, inequality in advanced levels of achievement between students exists as early as third grade, and it stubbornly remains as students progress through school. If policy makers at the national, state, district, and school levels see greater equity as a major goal, then they need to take proactive efforts toward mitigating these gaps and encourage continued growth even among those students who are already at grade level.

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