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Student and School Concentrated Poverty in Maryland: What are the Long-term High School, College, and Career Outcomes?

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Executive Summary

This report examined the roles of student- and school-level poverty and race/ethnicity on long-term educational and career outcomes. Prior research indicates that poverty has negative effects on academic and career outcomes, and in the United States, concentrated levels of poverty occur within neighborhoods and subsequently schools. The current study builds on past research in several ways. First, poverty was measured using duration of student poverty in 6^{th}-12^{th} grades to reduce some of the limitations typically associated with using student eligibility for free and reduced price meals (FARMS) as a proxy to measure poverty. Second, multiple membership multilevel modeling was used to account for all schools a student attended between middle and high school. Findings indicated that students with longer durations of poverty performed more poorly on academic and workforce outcomes, compared to similar students with shorter durations of poverty in similar schools. Additionally, students attending schools with concentrated levels of poverty typically performed more poorly on academic and workforce outcomes, compared to similar students in similar schools with lower concentrations of poverty. For some outcomes, the gap in outcome due to race/ethnicity disappeared or even reversed after controlling for student and school concentrated poverty. Policy implications and directions for future research are discussed.

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Introduction

Decades of research point to the critical role of childhood poverty in creating, maintaining, and exacerbating inequalities in long-term outcomes (Brooks-Gunn & Duncan, 1997; Jencks & Mayer, 1990; Orfield & Lee, 2005). Above and beyond the critical role of personal experiences with poverty (Brooks-Gunn & Duncan, 1997), increasing residential segregation by income level between 1990 and 2009 has resulted in concentrated levels of poverty within neighborhoods (Bischoff & Reardon, 2014). Since public school boundaries typically follow neighborhood geographic boundaries, disparities in concentrated levels of poverty within schools also exist (Reardon & Owens, 2014). Further compounding the challenges associated with household, neighborhood, and school poverty are the historical patterns of racial discrimination and segregation leading to the disproportionate impoverishment of minority households and high-minority schools (Reardon, 2016). Relatively few studies have focused on disentangling the roles of individual student poverty, school poverty, student race/ethnicity, and school racial/ethnic composition on long term educational and career outcomes (Michelmore & Dynarski, 2016; Reardon & Owens, 2014), highlighting a pressing need to better understand and address the multifaceted role of poverty in contributing to long-term educational and career outcomes.

Data available from the Maryland State Department of Education (MSDE) highlight these critical education issues in Maryland. For example, among Maryland's Class of 2017 cohort, students living in poverty dropped out of school more frequently than students not living in poverty (14% vs. 5%), were less likely to graduate from high school within four years (79% vs. 92%), received lower mean total SAT scores (949 vs. 1113), and had lower rates of meeting college readiness benchmarks (22% vs. 56%; MSDE, 2018; College Board, 2018). Furthermore, Black (8%) and Hispanic (20%) students had higher dropout rates than White students (5%) and Black (85%) and Hispanic students (74%) had lower on-time graduation rates than White students (93%) (MSDE, 2018).

This study builds upon prior research to disentangle the roles of student- and school-level poverty and race/ethnicity on long-term educational and career outcomes.[1] We build on prior research in several ways. First, we measure poverty using duration of student poverty to reduce some of the limitations typically associated with using student eligibility for free and reduced price meals (FARMS) as a proxy to measure poverty (explained in detail below). Second, we apply multiple membership multilevel modeling (Chung & Beretvas, 2012) to account for all schools a student attended between middle and high school. Third, we start our panel of data in 6th grade and we are able to examine college and workforce outcomes in the year following high school.

[1] This research was conducted in response to a request from Senator Bill Ferguson. The preliminary findings from this study were presented to the Maryland Commission for Innovation and Excellence in Education in the Summer of 2018 (Henneberger & Rose, 2018a; 2018b).

Background

The Relation between Student Poverty and Outcomes

Recent data from the National Center for Children in Poverty (NCCP) indicate that about 15 million children—21% of all children—in the United States live in families with incomes below the federal poverty threshold (Jiang, Granja, & Koball, 2017). Poverty has been linked to poor physical health, poor academic achievement, poor social and emotional functioning, and higher levels of sexual activity, teenage pregnancy, internalizing, and externalizing problems (Leventhal & Brooks-Gunn, 2000; McLoyd, 1998). Children growing up in poverty perform poorly on standardized tests, complete fewer years of education, and go on to earn less in the workforce as adults, when compared to their better off peers (Duncan, Magnuson, Kalil, & Ziol-Guest, 2012). Additionally, children who are exposed to persistent poverty have more detrimental outcomes than children exposed to transitory poverty (McLoyd, 1998).

Studies conducted on student achievement from elementary through secondary schools demonstrate similarities in the impact of student poverty on individual academic achievement. Walker, Greenwood, Hart, and Carta's (1994) longitudinal study followed students from age 7 months to 10 years in order to examine the long-term impact of household income on elementary achievement. It was found that students from low-income homes scored lower on standardized reading and spelling achievement tests throughout elementary school (Walker et al., 1994). Pungello, Kupersmidt, Burchinal, & Patterson (1996) focused on students beginning in second through fourth grade and followed those students for four years. This study also found that students from low-income households had lower standardized test scores than students who were not from low-income households through upper elementary and middle school. Caldas and Bankston (1997) and Schultz (1993) found that students who participated in the federal free/reduced-price lunch program had worse outcomes on achievement tests in upper elementary school and tenth grade, respectively. Secondary students from higher income families had higher initial achievement and achievement growth on a composite measure of standardized achievement scores when compared to students with lower family incomes, even when controlling for academic background (Rumberger & Palardy, 2005). Consistently, student-level poverty has a negative effect on students' academic achievement through elementary and secondary school.

Students in the lowest-income group are 24% less likely to complete qualifications needed to attend college than the national average (Cabrera & La Nasa, 2000). In terms of college attendance, low-income students are underrepresented in the college population and are less likely to persist in college (Walpole, 2003). These differences continue after college and into the workforce. Students from low-income backgrounds are less likely to attend graduate school and have lower income levels than their high-income peers (Mulligan, 1997; Walpole, 2003).

The Relation between School Concentration of Poverty and Outcomes

A ground-breaking re-analysis of the data from the Equality of Educational Opportunity (EEO) study or the "Coleman Report" (Coleman et al., 1966) found that the social class composition of the student's school was more important for educational outcomes than the student's own social class (Borman & Dowling, 2010). Students' educational outcomes depend on the schools they attend because the education provided by each school reflects the available resources, curriculum, and student body composition of the school (Borman & Dowling, 2010). For example, an analysis of the educators in high-poverty and low-poverty schools in Maryland published by the U.S. Department of Education (USDE) showed that high-poverty schools, compared to low-poverty schools, have higher rates of first-year teachers (7.3% vs. 3.1%) and uncertified teachers (5.1% vs. 1.9%), and lower adjusted average teacher salaries ($54,480 vs. $61,208; USDE, 2014).

School-level poverty has been measured in a variety of ways and has consistently shown negative relations with academic outcomes. For example, Caldas and Bankston (1997) measured school-level poverty using the percentage of students who participated in the federal free/reduced priced lunch program as a measure of school poverty, as well as a school-level indicator of average family social status. They found that both school-level indicators of poverty have a significant effect on individual academic achievement on tenth grade achievement tests. Borman and Dowling (2010) used mean family income and mean parental education as indicators of school-level poverty and found that both indicators have a significant effect on ninth grade verbal achievement scores (Borman & Dowling, 2010). Both Konstantopoulos and Borman's (2011) and Rumberger and Palardy's (2005) studies of achievement growth from 8th to 12th grade used the mean student poverty composite variable to indicate school-level poverty. Rates of student growth in academic achievement, measured as scores on achievement tests in four subjects, are positively associated with school-level poverty (Rumberger & Palardy, 2005).

Much less is known about the relation between school-level poverty and long-term outcomes, including college and career outcomes. A recent report published by the U.S. Government Accountability Office (USGAO) reported that students in high-poverty public high schools were less likely to have access to the math and science courses that fulfill colleges' expectations (USGAO, 2018). Furthermore, school-level poverty was associated with disparities in access to more advanced courses, like calculus, physics, and those that help students to earn college credits, such as advanced placement (AP) courses (USGAO, 2018). This means that high-poverty schools were less likely to offer courses that four-year colleges may expect for college entry. School officials reported that a lack of resources and teaching staff contributed to not being able to offer these advanced courses (USGAO, 2018).

Most of the research on concentrated levels of poverty and long-term outcomes comes from the neighborhood composition literature. For example, evidence from observational studies suggests that prolonged residence in poor neighborhoods is detrimental to educational outcomes (Burdick-Will et al., 2011; Harding, 2003; Sampson, Sharkey, & Raudenbush, 2008; Wodtke, Harding, & Elwert, 2011). Recent experimental evidence from the Moving to

Opportunity (MTO) study, where a random sample of low-income residents were offered housing vouchers to move to higher income neighborhoods, indicated that moving to a lower poverty neighborhood early in life (before age 13) significantly improved college attendance rates and increased future incomes in the mid-twenties (Chetty, Hendren, & Katz, 2016).

The Overlap between Poverty and Race/Ethnicity

In the U.S., racial and ethnic minority status is intertwined with poverty. That is, a disproportionately high number of racial and ethnic minorities live in poverty (Reardon, 2016), and schools with higher rates of minority students tend to have higher rates of poor students (Reardon, 2016). While some research suggests that the racial gaps in test scores may be more accurately explained by student poverty (Walton & Spencer, 2009) and that the poverty composition of schools has even more of an impact on individual outcomes than the racial composition (Rumberger & Palardy, 2005), other research suggests that school racial composition has a sizeable effect on achievement (Hanushek, Kain, & Rivkin, 2009).

The exact mechanisms of the relation of race/ethnicity with academic and other outcomes are not well understood (Hanushek et al., 2009). Extant literature has documented the profound effects of poverty on minority groups, so that observed minority-majority achievement gaps may simply be artifacts of poverty; however, racial/ethnic differences in academic achievement may be attributed to systemic race-related causes, such as stereotype threats. In essence, stereotype threats reference individuals' tendencies to perform worse when reminded about weaknesses or deficits associated with groups in which they hold membership (Alter, Aronson, Darley, Rodriguez, & Ruble, 2010). In academic settings, stereotype threats are negative psychological messages that undermine the performance of minorities (Walton & Spencer, 2009). These stereotypes increase doubt in the minds of children belonging to minority groups, inhibiting their ability to perform well on standardized tests. As a result, the true ability of minority children is not measured by these tests, but rather is underestimated (Walton & Spencer, 2009). To test the effects of the stereotype threat condition, Alter and colleagues (2010) conducted an experiment with Black children finding those who reported their race prior to taking an exam to perform worse than those reporting their race after the exam. These effects were also observed in another study finding the intellectual ability of Black and Hispanic students to be underestimated in SAT Math and Verbal tests by as much as 39 to 41 points (Walton & Spencer, 2009).

The Current Study

The purpose of this study is to examine the relation between student-level poverty and race/ethnicity and school-level poverty and racial/ethnic composition on students' long-term educational and career outcomes. Multiple membership multilevel models (Chung & Beretvas, 2012) are used to help disentangle student and school factors to determine the relevant importance of each across a number of outcomes, including high school dropout and graduation, standardized test scores, college enrollment, and annual workforce wages. This study expands prior research on this topic in several key ways. First, it uses students' history of eligibility for FARMS between 6th and 12th grades to measure duration of student poverty to help reduce some of the limitations typically associated with using student FARMS as a proxy to measure poverty. Second, multiple membership multilevel modeling was used to account for all schools a student attended between middle and high school. Third, the panel of data began in 6th grade and extends to examine the college and workforce outcomes of students in the year following high school.

Research Questions

This study aimed to address the following research questions: What is the relation of school concentration of poverty to students' long-term educational and workforce outcomes? Does school poverty play an independent role in outcomes over and above that of individual student poverty? Do these relations persist after accounting for students' racial/ethnic backgrounds and the racial compositions of the schools they attend? Do the roles of student and school poverty vary across outcomes?

This report responds to the Maryland Longitudinal Data System Center (MLDS) Center Research Agenda questions: *Are Maryland students academically prepared to enter postsecondary institutions and complete their programs in a timely manner?* and *What are the workforce outcomes for Maryland students who earn a high school diploma (via high school graduation or GED®) but do not transition to postsecondary education or training?*

Methods

The data used for this report are from the Maryland Longitudinal Data System (MLDS), which contains linked longitudinal data from three State agencies.[2] The Maryland State Department of Education (MSDE) provides data for public PreK-12 students and schools. The Maryland Higher Education Commission (MHEC) provides data for Maryland public and private college students and colleges. The Department of Labor Licensing and Regulation (DLLR) provides data for Maryland employees who work for employers who are subject to Maryland's Unemployment Tax law. The workforce data do not include information for federal employees, military employees, individuals who are self-employed, or private contractors. Out-of-state college enrollments and degrees are obtained by MSDE through the National Student Clearinghouse (NSC; Dynarski, Hemelt, & Hyman, 2015).

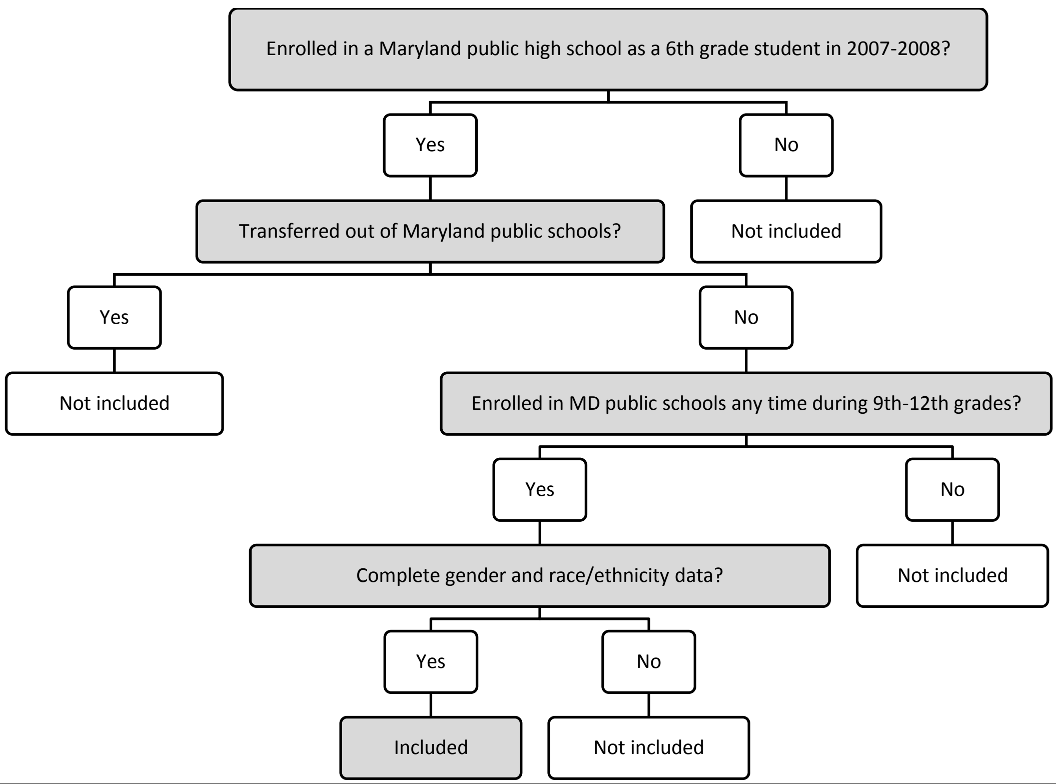
Sample Selection

The initial sample for this study included the cohort of students enrolled in 6th grade in Maryland public schools during the 2007-08 academic year (N = 63,282). Students whose last

[2] For more information on the sources and data elements included in the MLDS, see mldscenter.maryland.gov.

record indicated that they transferred out of the Maryland public school system (n = 7,811) and students who were never enrolled in any Maryland public school at any point between 9th and 12th grade, regardless of exit code (n = 955), were excluded. Additionally, students missing demographic data were excluded (n = 51). Therefore, the final analytic sample for this study was 54,465 students. This report focuses on the earliest cohort of 6th grade students available in the MLDS because using data from this cohort enabled us to measure the long-term duration and timing of poverty between 6th and 12th grades and to identify their long-term academic and career outcomes (one year past the 12th grade). Figure 1 displays the selection criteria used for this study.

Figure 1. Criteria for Inclusion in the Study



Attrition analyses revealed that students excluded from the study were significantly different from students included in the study, with respect to gender, race, and education experiences (all p values ≤ .05). Excluded students were disproportionately male, Black, and Hispanic. In addition, excluded students displayed higher rates of English Learner (EL) and special education experiences.

Table 1 displays the characteristics of the sample included in this study. Forty-five percent of students were White, 35% were Black, and 10% of students were Hispanic. Just under 50% of the sample was eligible for free or reduced-price meals (FARMS) between 6th and 12th grades (see Figure 2).

Table 1. Descriptive Statistics for Study Sample – Students

Variable	%
Male	50
Asian	5
Black	35
Hispanic	10
Other	4
White	45
Ever eligible for FARMS 6th-12th grade	49
Ever English Learner (EL) 6th-12th grade	3
Ever Special Education 6th-12th grade	14
Ever Homeless 6th-12th grade	4

Note. Data from the 6th grade cohort of students enrolled in Maryland public schools during the 2007-2008 academic year who did not transfer out of the Maryland public school system (N = 54,465). FARMS = free/reduced price meals.

Table 2 presents descriptive statistics for the schools attended by the study cohort. These statistics reflect the mean composition of all schools attended by the students in the study cohort for school years 2007-2008 through 2015-2016. Twenty three percent of schools were Title I Schoolwide (SW) at least once over the time period (they may also have been Title I Targeted Assistance [TA] at some point), 5% were never SW but were TA at least once, and 72% were never SW or TA.

Measures

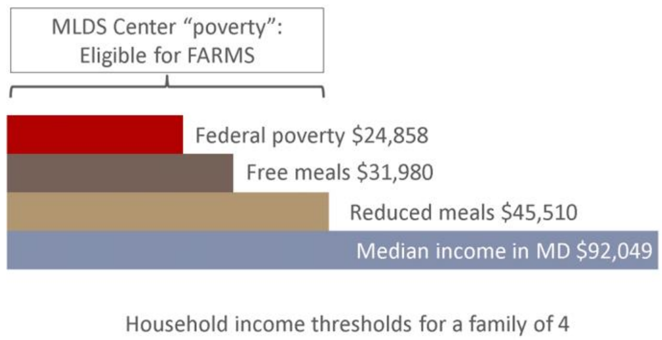
Student poverty duration: The only available measure of students' household socioeconomic background comes from data collected in accordance with the National School Lunch Program, an income-based eligibility program that provides low-income students with improved access to meals at school. Students with household incomes at or below 130% of the federal poverty level were eligible for free meals, while students with household incomes between 130% and 185% of the federal poverty level were eligible for reduced-priced meals (U.S. Department of Agriculture, 2017; see Figure 2). The free and reduced-price meals (FARMS) indicator associated with each school enrollment record in the MLDS data does not distinguish between eligibility for free meals and eligibility for reduced-price meals, which means that this variable merely indicates that the student's household income was below 185% of the poverty line at that particular point in time. For this study, we constructed a variable capturing the *total proportion of time* the student spent in poverty between 6th and 12th grades. We refer to this as *student poverty duration* or simply *student poverty*. This measure ranges from 0 for a student who was never in poverty to 1 for a student who was always in poverty ($M = 0.36$, $SD = 0.42$).

Table 2. Descriptive Statistics for Study Sample – Schools

Variable	*Mean* (*Standard Deviation*)
Percent Asian	0.04 (0.05)
Percent Black	0.50 (0.35)
Percent Hispanic	0.10 (0.14)
Percent Other	0.02 (0.02)
Percent White	0.33 (0.33)
Mean proportion of time eligible for FARMS 6th-12th grade	0.49 (0.25)

Note. Data from the schools (N = 819) attended by the 6th grade cohort of students enrolled in Maryland public schools during the 2007-2008 academic year who did not transfer out of the Maryland public school system (N = 54,465). FARMS = free/reduced price meals.

Figure 2. MLDS Center Definition of Eligibility for FARMS in Comparison to the Federal Poverty Level and Median Income in Maryland



Using students' poverty duration rather than FARMS eligibility at a single point in time enables us to capture students' experiences with poverty that might have been missed if we had chosen to measure poverty only at a specific point in time. For example, about 14% of the sample were not eligible for FARMS during the last school enrollment but had previously been eligible at some point between 6th and 12th grades. Using the measure of students' poverty duration, we capture these students' experiences with poverty. Additionally, using students' duration of FARMS provides the ability to make more nuanced comparisons among students who were never, sometimes (less than 50% of enrollments), usually (50% or more of enrollments), and always in poverty. Overall, 51% of the analytic sample were never eligible for FARMS, 11% were sometimes eligible, 19% were usually eligible, and 19% were always eligible.

Student race and ethnicity: Student race and ethnicity were categorized as Asian (non-Hispanic), Black or African-American (non-Hispanic), Hispanic (of any race), White (non-Hispanic), or other (this includes non-Hispanic Pacific Islander and American Indian/Native American). Figure 3 provides a graphical depiction of the mean proportion of time eligible for FARMS by race/ethnicity. Black students and Hispanic students have the highest mean proportion of time eligible for FARMS, with an average of just under 60% of their time in grades 6-12 spent eligible for FARMS.

***School concentrated poverty*:** School concentration of poverty, or school poverty, was assessed for each school and each school year based on the mean proportion of time students enrolled in the school as of that school year had been eligible to receive FARMS up to that point in time. Each student's overall school context was then measured by taking the mean school poverty across all schools attended over the course of their enrollment in grades 6 through 12.

School racial/ethnic composition: For each academic year, for each school, the percent White, percent Black, percent Hispanic, percent Asian, and percent Other were calculated. Then for each student in the analytic sample, the mean of each of these was taken for all the schools they attended across their entire school history from grades 6-12. The average student in the analytic sample attended a school that was 46% White, 37% Black, 10% Hispanic, 6% Asian, and 3% Other. Figure 4 displays school-level racial composition by school-level poverty. Black students are disproportionately clustered within schools with higher levels of school-poverty, and White students are disproportionately clustered within schools with lower levels of school-poverty.

Figure 3. Proportion of Time Eligible for FARMS in 6th-12th Grade by Student Race/Ethnicity

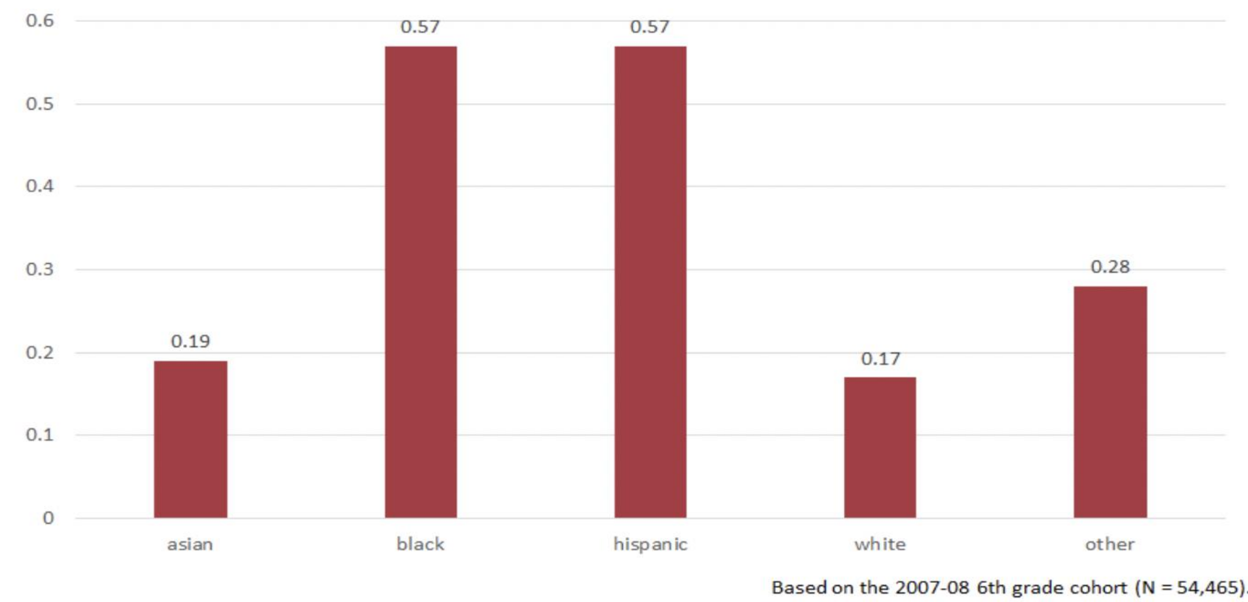
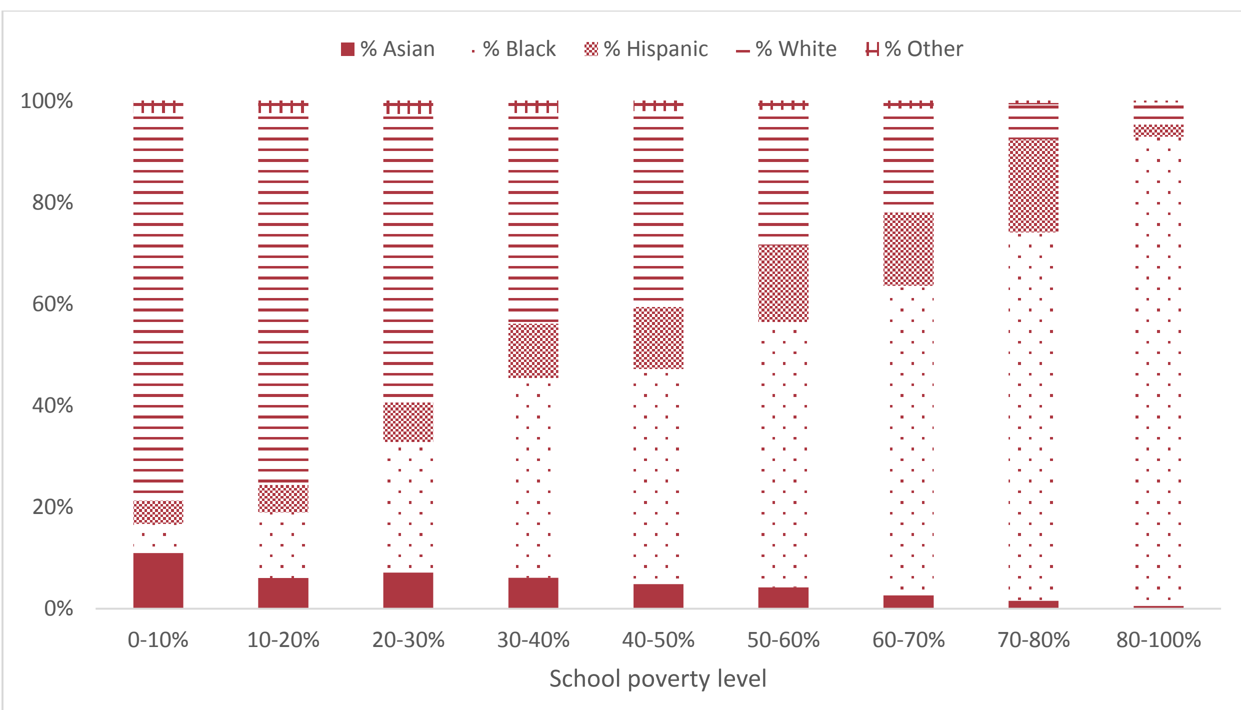


Figure 4. Average School-Level Racial/Ethnic Composition by School-Level Poverty



Outcome Measures

This study examined a variety of educational and workforce outcome measures in order to assess the relation between student and school poverty with high school attainment, standardized tests, college enrollment, and workforce wages. Each of these was constructed specifically for this study using available data from the MLDS. This section provides details on how these were measured. Descriptive statistics for the outcome variables included in this study are presented in Appendix A.

High school attainment: Three measures of high school completion and degree attainment were used for this study: on-time high school graduation, ever graduating from high school, and dropping out of school. This study defined "on-time high school graduation" for the study cohort as attainment of a regular high school diploma in or before academic year 2013-2014. Students' "ever graduating high school" was measured by examining whether students graduated with a regular high school diploma prior to the final year of data included in the MLDS (academic year 2016-2017 at the time this report was written).[3] Students' high school dropout was measured by examining whether students formally withdrew from school prior to the end of academic year 2016-2017. Students whose last enrollment record did not indicate formal withdrawal or transfer out of Maryland public schools but for whom no subsequent record was found were considered dropouts.

Standardized test scores: Algebra and English High School Assessment (HSA), and Math and Verbal PSAT and SAT scores were used for each student. The HSAs were Maryland's end-of-course assessments for high school students at the time this cohort was in high school. This cohort was required to pass these assessments, or obtain a minimum combined score, in order to graduate with a regular high school diploma.[4] The highest score achieved on each test was used in this study. The SAT is a test administered by the College Board and is widely taken for college admission in the U.S. The PSAT is the preliminary SAT test and is taken by some high school students prior to taking the SAT. Each student's highest SAT and PSAT scores on the math and verbal components of the tests were used. Score availability is limited to the students who voluntarily took the test, and likely represents a relatively high achieving subsample of the cohort.

College enrollment: For students who graduated from high school on time (by the end of the 2013-2014 academic year), enrollment in Maryland and out-of-state public and private 2-year and 4-year colleges was measured for the first four quarters after high school graduation (for most students, the 2014-2015 academic year).[5] Students were considered as enrolled in college if any record of postsecondary enrollment (not necessarily degree-seeking) was found during this period. The MLDS does not contain data on non-credit postsecondary enrollments or apprenticeship programs.

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[3] Appendix D includes analyses to expand this definition to include graduating with a diploma via the GED program.

[4] Students who took the MHSA English 10 and MHSA Algebra I in the school years before the 2016-2017 school year needed only to participate, but not pass.

[5] If the only college enrollment for the student began prior to high school graduation (i.e., dual enrollment), the college enrollment was not considered for this analysis.

Workforce wages: For students who graduated from high school on time, available workforce wages in the first four quarters after finishing high school were summed. Wages for students who were enrolled in postsecondary during this time and those who were not enrolled in postsecondary during this time were examined separately. Analyses used log wages in order to adjust for skewness in this variable. The MLDS does not contain wage information for federal employees, military employees, self-employed individuals, or private contractors.

Analyses

In order to answer the research questions as to the roles of student and school poverty in long-term educational and workforce outcomes, an analytic approach that correctly accounted for both student and school factors was required. Thus, data analyses used a multilevel modeling approach (Raudenbush & Bryk, 2002) with students (level 1) nested within schools (level 2). Multilevel random effects models were used for continuous outcomes, including workforce wages and standardized test scores. Multilevel logistic random effects models were used for binary outcomes, including high school graduation, dropout, and college enrollment. Random intercepts and fixed slopes were modeled. Multiple membership was accounted for in the multilevel models to correctly account for the variation attributable to each middle and high school the students attended (see Chung & Beretvas, 2012). In this approach, enrollment in more than one school (cluster) is modeled by assigning each student a weight for each school attended, then multiplying the school-level variance for each cluster by that weight, and summing the results, for each student. A detailed description of the analytic approach is provided in Appendix B.

First, an unconditional model (Model 1 below) was run to attribute school-level and student-level variance in the outcome. This enables us to understand how much of the variance in the outcome is due to differences between schools and how much is due to differences between students. Second, the main effects of poverty were examined by adding student-level poverty at level 1 and school-level poverty at level 2 (Model 2 below).[6] For these analyses, we standardized the student and school poverty variables to have a mean of zero and a standard deviation of one. Thus, the resulting coefficients can be interpreted as the predicted change in outcome for a student who is one standard deviation above average in their experience with (student or school) poverty. Third, race and ethnicity at the student- and school-levels were added to determine the effects of poverty above and beyond race and ethnicity (Model 3 below).[7,8] School racial composition variables were also standardized (Mean = 0; Standard

[6] This report uses the term "effects" to refer to the role of poverty and race in accounting for variance in educational outcomes, in keeping with most research that uses multilevel modeling. The research design for this study was not experimental or quasi-experimental and no strictly causal inferences can be made.
[7] For both student race/ethnicity and school racial/ethnic composition, White was the omitted reference group. Student race/ethnicity was grand-mean centered to improve model accuracy.
[8] Additional models controlling for 6th grade student and school-level academic achievement (measured using scores on the middle school assessment [MSA] at the student level and % proficient at the school level) were conducted. All results were similar to those reported here. Full modeling results are available upon request.

deviation = 1), so that the coefficients for these variables can be interpreted as the predicted change in outcome for a student whose school(s) composition for this racial/ethnic group was one standard deviation above average.

Findings

This section describes results of the series of multilevel models for each outcome: high school attainment, standardized tests, college enrollment, and workforce wages. Here we present model estimates in the form of coefficient tables followed by charts with predicted likelihoods for ease of interpretation. Corresponding odds ratios and effect sizes are provided in Appendix C. For logistic outcomes, coefficients represent log odds. Continuous outcome coefficients are in the scale of the original measure. Findings for each area are briefly summarized here, and implications are more thoroughly discussed in the sections that follow.

High School Attainment

The first set of outcomes related to high school attainment: graduating on time, ever graduating, and dropping out of school. Results using the expanded measure of graduation to include graduation via the GED can be found in Appendix D.

On-Time High School Graduation. Results for the multilevel model predicting on-time high school graduation are presented in Table 3. The unconditional multilevel model showed that 75% of the total variance in on-time high school graduation was at the school level (between schools).[9] The intercept in the unconditional model (i.e. no adjustments for poverty or race) can be interpreted as the log odds of on-time graduation for the average student; the average student is predicted to have 1.34 log odds of graduating on time. This corresponds to nearly 4-to-1 odds (see table C1b).

In the next model, adjusting for the main effects of poverty, student and school poverty were significantly and negatively associated with on-time high school graduation, such that students who experienced above-average durations of poverty and students in high-poverty schools were less likely to graduate high school on time. The intercept in the poverty main effects model is interpreted as the log odds of on-time graduation for students with average experiences of individual and school poverty. The coefficient for student poverty duration is the predicted change from that intercept for students experiencing household poverty for longer periods of time, and the coefficient for school poverty is the predicted change from that intercept for students attending higher-poverty schools.

The effects of student and school poverty remained significant even after adjusting for student race/ethnicity and school racial/ethnic composition. Additionally, the school poverty effect was significantly worse than the student poverty effect, χ^2 (1 df) = 35.75, p<0.001. After

[9] Calculation of the intraclass coefficient for logistic models assumed level-1 variation of 3.29.

adjusting for poverty, Hispanic, Black, Asian, and other students were more likely to graduate high school on time compared to White students with similar poverty experiences.

Table 3. Multilevel Modeling Results Predicting On-Time High School Graduation			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	1.34***(0.14)	1.99***(0.13)	2.03***(0.15)
Student poverty duration		-0.54***(0.02)	-0.55***(0.02)
Hispanic			0.15*(0.06)
Black			0.25***(0.05)
Asian			1.23***(0.12)
Other			0.34***(0.09)
School mean poverty duration		-0.86***(0.10)	-1.31***(0.12)
School percent Hispanic			0.28***(0.08)
School percent Black			0.53***(0.11)
School percent Asian			-0.13(0.11)
School percent Other			0.03(0.07)
Model fit (Bayesian DIC)	34984.59	33927.02	33752.81
Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 54,465.			

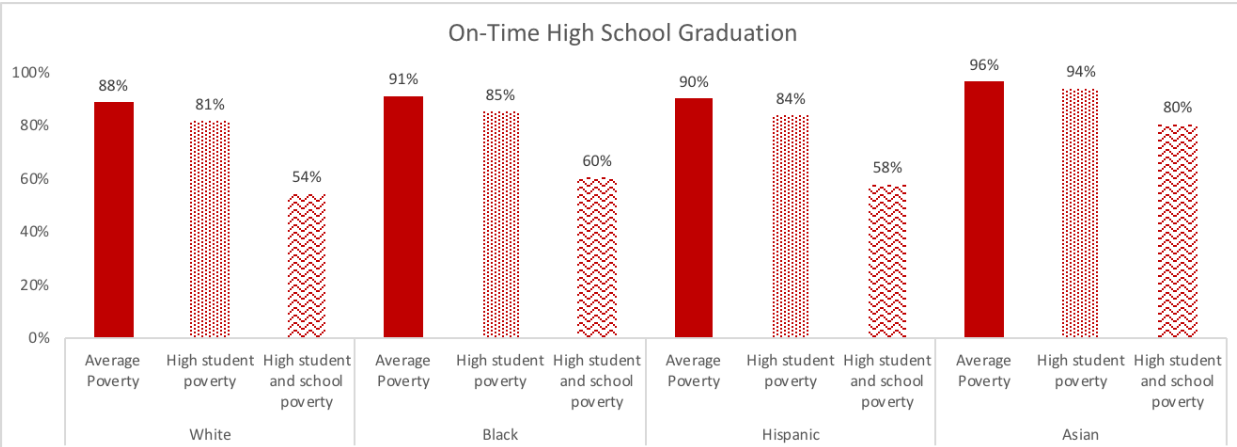
Figure 5 shows the predicted likelihood, based on these model results, of on-time high school graduation for specific subgroups of students characterized by race/ethnicity and poverty. After controlling for student race/ethnicity and school racial/ethnic composition, comparing the solid, dotted, and wavy bars below provides an understanding of the effects of student-level poverty and school concentrated poverty. For White students (left side of graph), those with average duration of poverty in average poverty schools (solid bar) were predicted to have an 88% likelihood of on-time high school graduation, those with above-average duration of poverty who attended average poverty schools (dotted bar) were 81% likely to graduate on time, and white students with above-average duration of poverty who attended high-poverty schools (wavy bar) had only a 54% probability of on-time high school graduation. Patterns are similar for each racial/ethnic group.[10]

High School Graduation (Ever). Results for the multilevel model predicting whether students would ever graduate from high school are displayed in Table 4. The unconditional multilevel model showed that 71% of the total variance in this outcome was at the school level (i.e. due to differences between schools). In the poverty main effects model, both student and school poverty were negatively associated with the outcome such that students with high poverty duration or in high poverty schools were less likely to ever graduate from high school. However, school poverty became non-significant after adjusting for race/ethnicity and school-

[10] Our models did not examine whether the roles of student and school poverty varied across racial/ethnic groups.

level racial/ethnic composition, whereas student poverty remained significant.[11] Hispanic, Black, Asian, and other students were more likely to ever graduate high school when compared to White students with similar poverty experiences.

Figure 5. Predicted Likelihood of On-Time High School Graduation



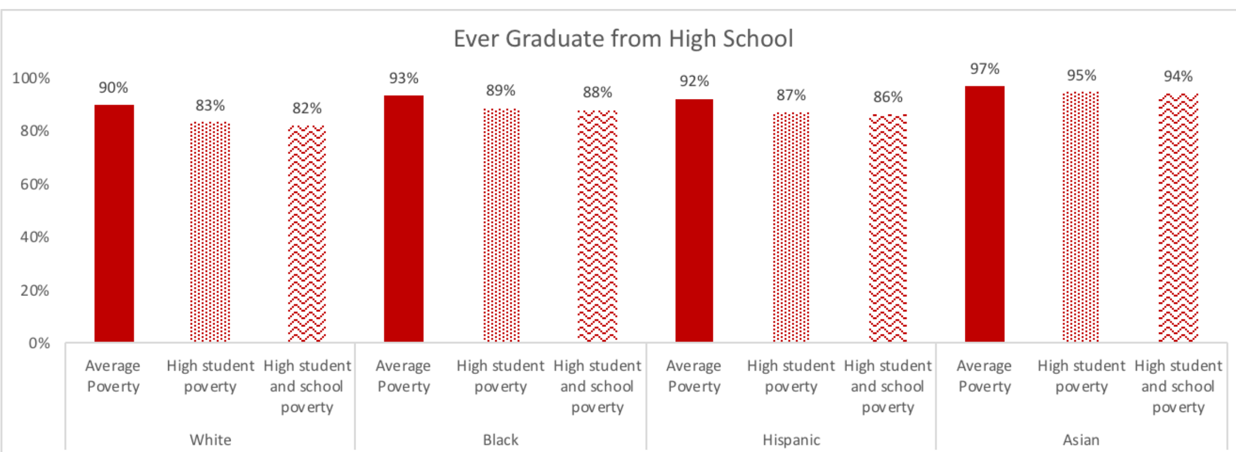
Note. Chart shows model-based predicted outcomes, not actual outcomes, for students in schools with average racial/ethnic composition, based on the 2007-08 6th grade cohort. Average student poverty = 0.36; Average school poverty = 0.37.

Figure 6 shows the predicted likelihood of high school graduation (ever) for subgroups of students characterized by race/ethnicity and poverty. After controlling for student race/ethnicity and school racial/ethnic composition, comparing the solid, dotted, and wavy bars below provides an understanding of the effects of student-level poverty and school concentrated poverty. Students with average levels of poverty in average poverty schools (solid bars) had the highest predicted likelihood of ever graduating, and students with high levels of poverty in average poverty schools (dotted bars) and in high poverty schools (wavy bars) had the lowest predicted likelihood.

[11] Models presented here restrict the relation between school-level poverty and the outcome to be linear. Follow-up analyses indicated that school-level poverty had a non-linear relation with the likelihood of ever graduating high school such that students attending schools in the middle of the poverty distribution had the lowest predicted likelihood of ever graduating. These findings will be presented in a supplemental report.

Table 4. Multilevel Modeling Results Predicting High School Graduation (Ever)			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	1.78***(0.09)	2.19***(0.09)	2.17***(0.12)
Student poverty duration		-0.53***(0.02)	-0.57***(0.02)
Hispanic			0.31***(0.07)
Black			0.46***(0.05)
Asian			1.26***(0.13)
Other			0.40***(0.10)
School mean poverty duration		-0.39***(0.08)	-0.07(0.15)
School percent Hispanic			0.22*(0.09)
School percent Black			-0.07(0.12)
School percent Asian			0.03(0.12)
School percent Other			0.70***(0.08)
Model fit (Bayesian DIC)	30183.36	29439.91	29093.30
Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 54,465.			

Figure 6. Predicted Likelihood of High School Graduation (Ever)



Note. Chart shows model-based predicted outcomes, not actual outcomes, for students in schools with average racial/ethnic composition, based on the 2007-08 6th grade cohort. Average student poverty = 0.36; Average school poverty = 0.37.

High School Dropout. Table 5 presents results for the multilevel model predicting high school dropout. The unconditional multilevel model showed that 65% of the total variance in high school dropout was at the school level (between schools). In the poverty main effects model, students with high poverty or students in high poverty schools were significantly more likely to drop out of high school. However, only student poverty remained significant and school poverty became non-significant after adjusting for student race/ethnicity and school racial/ethnic composition.[12] In addition, Hispanic, Black, Asian, and other students were significantly less likely to drop out of high school compared to White students with similar poverty experiences.

Table 5. Multilevel Modeling Results Predicting High School Dropout

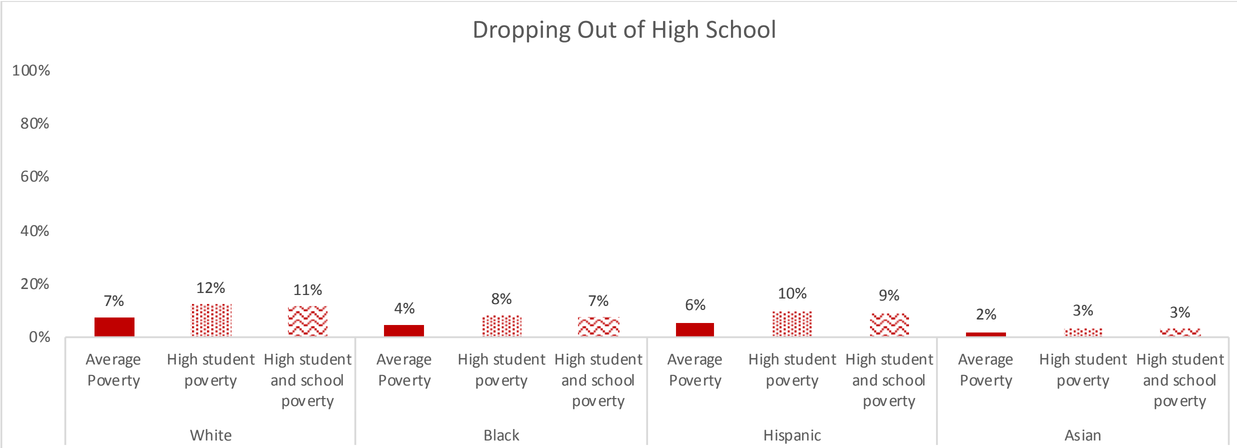
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	-2.14***(0.10)	-2.55***(0.10)	-2.56***(0.10)
Student poverty duration		0.55***(0.02)	0.59***(0.10)
Hispanic			-0.28***(0.07)
Black			-0.51***(0.06)
Asian			-1.45***(0.16)
Other			-0.39***(0.10)
School mean poverty duration		0.41*** (0.07)	-0.08(0.10)
School percent Hispanic			-0.12(0.08)
School percent Black			0.21*(0.09)
School percent Asian			-0.17(0.10)
School percent Other			-0.73***(0.07)
Model fit (Bayesian DIC)	28501.16	27768.73	27363.03

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 54,465.

Figure 7 shows the predicted likelihood of high school dropout for specific subgroups of students characterized by race/ethnicity and poverty. After controlling for student race/ethnicity and school racial/ethnic composition, students with average levels of poverty in average poverty schools (solid bars) had the lowest predicted likelihood of high school dropout, whereas students with high levels of poverty in average poverty schools (dotted bars) and in high poverty schools (wavy bars) had the highest predicted likelihood of high school dropout.

[12] Models presented here restrict the relation between school-level poverty and the outcome to be linear. Follow-up analyses indicated that school-level poverty had a non-linear relation with the likelihood of dropout such that students attending schools in the middle of the poverty distribution had the highest predicted likelihood of dropping out. These findings will be presented in a supplemental report.

Figure 7. Predicted Likelihood of High School Dropout



Note. Chart shows model-based predicted outcomes, not actual outcomes, for students in schools with average racial/ethnic composition, based on the 2007-08 6th grade cohort. Average student poverty = 0.36; Average school poverty = 0.37.

Standardized Tests

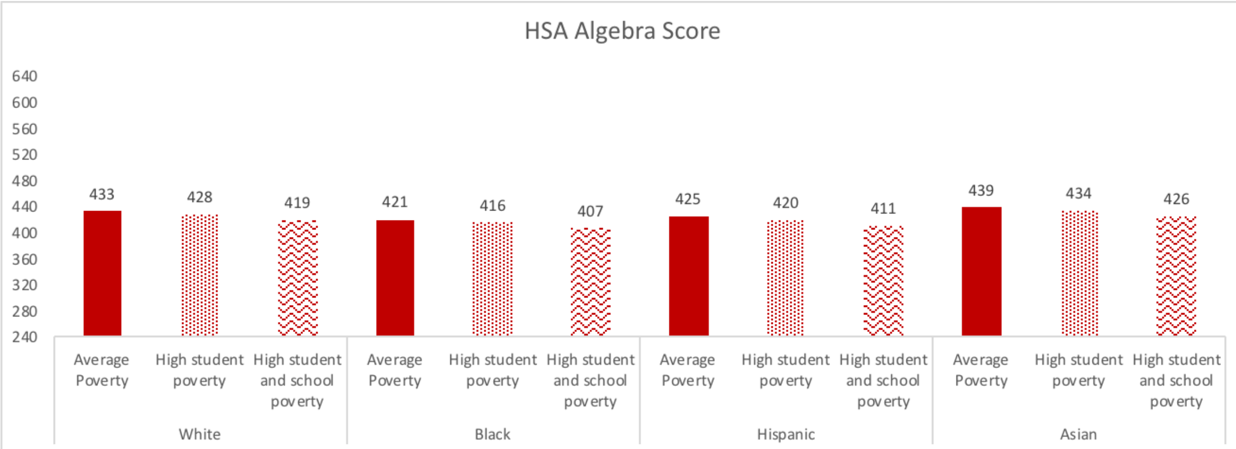
The next set of outcomes included standardized assessments of academic achievement: high school end-of-course assessments required for graduation and administered by the State (presented here), and college readiness exams administered by the College Board (presented in Appendix D). For all assessments, scale scores were used as the outcome measure.

HSA Algebra. Table 6 presents results for the multilevel model predicting HSA Algebra score. The unconditional multilevel model showed that 56% of the total variance in HSA Algebra score was at the school level (between schools). In the poverty main effects model, students with high poverty or students in high poverty schools showed significantly lower HSA Algebra scores. The effects of student and school poverty on HSA Algebra scores remained significant even after adjusting for student race/ethnicity and school racial/ethnic composition, and the school poverty effect is significantly worse than the student poverty effect, χ^2 (1 df) = 14.83, p<0.001. In addition, Hispanic, Black, and other students had significantly lower HSA Algebra scores compared to White students with similar poverty experiences, whereas Asian students had significantly higher HSA Algebra scores.

Table 6. Multilevel Modeling Results Predicting HSA Algebra Score			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	424.89***(1.29)	432.07***(0.70)	433.15***(0.72)
Student poverty duration		-6.40***(0.14)	-5.15***(0.14)
Hispanic			-7.96***(0.45)
Black			-12.24***(0.36)
Asian			6.10***(0.54)
Other			-2.43***(0.56)
School mean poverty duration		-12.31***(0.58)	-8.58***(0.87)
School percent Hispanic			1.54*(0.66)
School percent Black			-0.84(0.78)
School percent Asian			3.35***(0.73)
School percent Other			0.77(0.50)
Model fit (Bayesian DIC)	488681.65	486611.00	485061.48
Note. **p* < 0.05, ***p* < 0.01, ****p* < 0.001. N = 52,261.			

Figure 8 shows the predicted HSA Algebra scores for specific subgroups of students characterized by race/ethnicity and poverty. After controlling for student race/ethnicity and school racial/ethnic composition, comparing the solid, dotted, and wavy bars below provides an understanding of the effects of student-level poverty and school concentrated poverty. Students with average levels of poverty in average poverty schools (solid bars) had the highest predicted HSA Algebra score, students with high levels of poverty in average poverty schools (dotted bars) had the second highest predicted HSA Algebra score, and students with high levels of poverty in high poverty schools (wavy bars) had the lowest predicted HSA Algebra score.

Figure 8. Predicted HSA Algebra Score



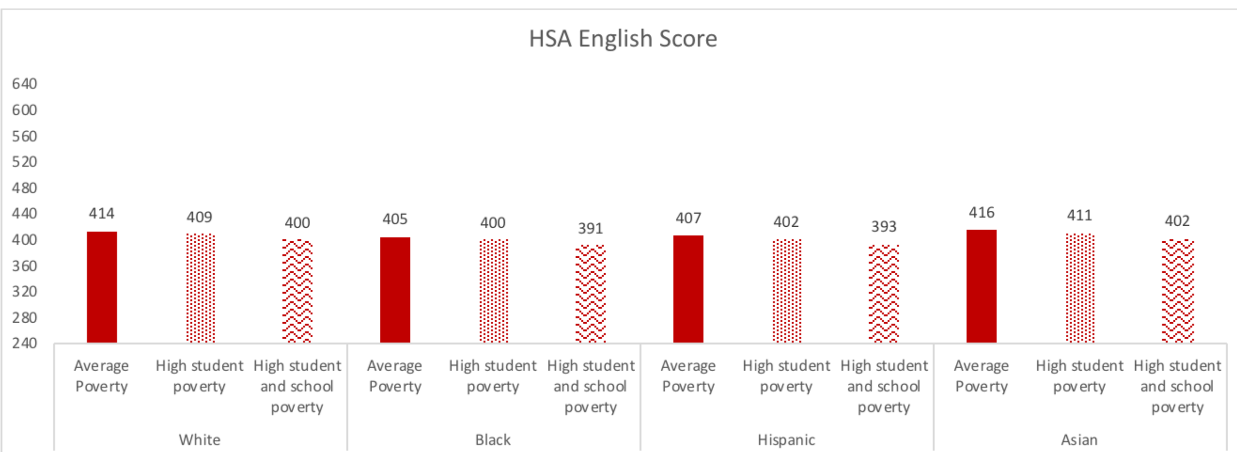
Note. Chart shows model-based predicted outcomes, not actual outcomes, for students in schools with average racial/ethnic composition, based on the 2007-08 6th grade cohort. Average student poverty = 0.36; Average school poverty = 0.37.

HSA English. Table 7 presents results for the multilevel model predicting HSA English score. The unconditional multilevel model showed that 53% of the total variance in HSA English score was at the school level (between schools). In the poverty main effects model, students with high poverty or students in high poverty schools showed significantly lower HSA English scores. The effects of student and school poverty remained significant after adjusting for race/ethnicity and school racial/ethnic composition, and the school poverty effect is significantly worse than the student poverty effect, χ^2 (1 df) = 17.72, p<0.001. Hispanic and Black students showed significantly lower HSA English scores compared to White students with similar poverty experiences, whereas Asian students showed significantly higher HSA English scores than White students with similar poverty experiences.

Figure 9 depicts the predicted HSA English scores for specific subgroups of students characterized by race/ethnicity and poverty. After controlling for student race/ethnicity and school racial/ethnic composition, comparing the solid, dotted, and wavy bars below provides an understanding of the effects of student-level poverty and school concentrated poverty. Students with average levels of poverty in average poverty schools (solid bars) had the highest predicted HSA English score, students with high levels of poverty in average poverty schools (dotted bars) had the second highest predicted HSA English score, and students with high levels of poverty in high poverty schools (wavy bars) had the lowest predicted HSA English score.

Table 7. Multilevel Modeling Results Predicting HSA English Score			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	407.17***(0.88)	412.78***(0.67)	413.59***(0.61)
Student poverty duration		-5.93***(0.12)	-4.94***(0.12)
Hispanic			-7.09***(0.38)
Black			-9.04***(0.31)
Asian			2.15***(0.45)
Other			-0.67(0.48)
School mean poverty duration		-8.79***(0.49)	-8.57***(0.85)
School percent Hispanic			2.44***(0.58)
School percent Black			1.91*(0.76)
School percent Asian			2.94***(0.71)
School percent Other			-0.86*(0.44)
Model fit (Bayesian DIC)	456128.59	453668.20	452592.86
Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 50,681.			

Figure 9. Predicted HSA English Score



Note. Chart shows model-based predicted outcomes, not actual outcomes, for students in schools with average racial/ethnic composition, based on the 2007-08 6th grade cohort. Average student poverty = 0.36; Average school poverty = 0.37.

Results for PSAT and SAT Math and Verbal demonstrated similar patterns and are included in Appendix D.

Enrollment in College within First Year of On-Time High School Graduation

Results for the multilevel model predicting college enrollment within 1st year of on-time high school graduation are displayed in Table 8. The unconditional multilevel model showed that 38% of the total variance in college enrollment within 1st year of on-time high school graduation was at the school level (between schools). In the poverty main effects model, student and school poverty were significantly associated with college enrollment, such that students with high poverty or students in high poverty schools were less likely to enroll in college within 1st year of on-time high school graduation. The effects of student and school poverty remained significant, even after adjusting for student race/ethnicity and school racial/ethnic composition; the difference in size between the student and school poverty coefficients is not statistically significantly different from zero. In addition, Black, Asian, and other students were significantly more likely to enroll in college within the 1st year of on-time high school graduation compared to White students with similar poverty experiences.

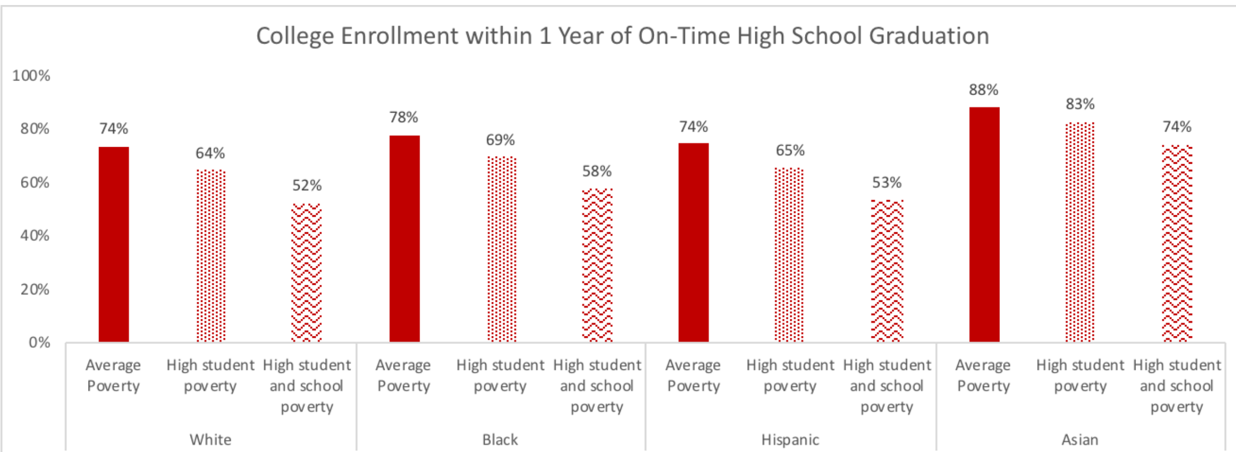
Table 8. Multilevel Modeling Results Predicting Enrollment in College within 1st Year of On-Time High School Graduation

	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	0.67***(0.07)	0.94***(0.04)	1.02***(0.04)
Student poverty duration		-0.41***(0.01)	-0.43*** (0.01)
Hispanic			0.04 (0.05)
Black			0.22*** (0.04)
Asian			0.96*** (0.08)
Other			0.40*** (0.06)
School mean poverty duration		-0.46***(0.04)	-0.51***(0.05)
School percent Hispanic			0.12**(0.04)
School percent Black			0.14**(0.05)
School percent Asian			0.35***(0.05)
School percent Other			-0.06(0.04)
Model fit (Bayesian DIC)	49270.48	48320.14	48096.08

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 46,581.

Figure 10 depicts the predicted likelihood of college enrollment within 1st year of on-time high school graduation for specific subgroups of students characterized by race/ethnicity and poverty. After controlling for student race/ethnicity and school racial composition, comparing the solid, dotted, and wavy bars below provides an understanding of the effects of student-level poverty and school concentrated poverty. Students with average levels of poverty in average poverty schools (solid bars) had the highest predicted likelihood of college enrollment, students with high levels of poverty in average poverty schools (dotted bars) had the second highest predicted likelihood of college enrollment, and students with high levels of poverty in high poverty schools (wavy bars) had the lowest predicted likelihood of college enrollment.

Figure 10. Predicted Likelihood of College Enrollment within 1st Year of On-Time High School Graduation



Note. Chart shows model-based predicted outcomes, not actual outcomes, for students in schools with average racial/ethnic composition, based on the 2007-08 6th grade cohort. Average student poverty = 0.36; Average school poverty = 0.37.

Annual Wages in First Year after On-Time High School Graduation

Annual Wages for Non-College Enrollees. Table 9 presents results for the multilevel model predicting annual wages in 1st year after on-time high school graduation for those who did not enroll in college. The unconditional multilevel model showed that 8% of the total variance in annual wages for non-college enrollees was at the school level (between schools). In the poverty main effects model, students not enrolled in college with high poverty or in high poverty schools showed significantly lower annual wages. However, only student poverty remained significant and school poverty became non-significant after adjusting for student race/ethnicity and school racial/ethnic composition.[13] In addition, Black students not enrolled in college showed significantly lower annual wages compared to White students not enrolled in college with similar poverty experiences. On the other hand, Hispanic students not enrolled in

[13] Models presented here restrict the relation between school-level poverty and the outcome to be linear. Follow-up analyses indicated that school-level poverty was significantly related to annual wages in the first year after on-time high school graduation for non-college enrollees for specific levels of school poverty.

college earned significantly higher annual wages than White students not enrolled in college with similar poverty experiences.

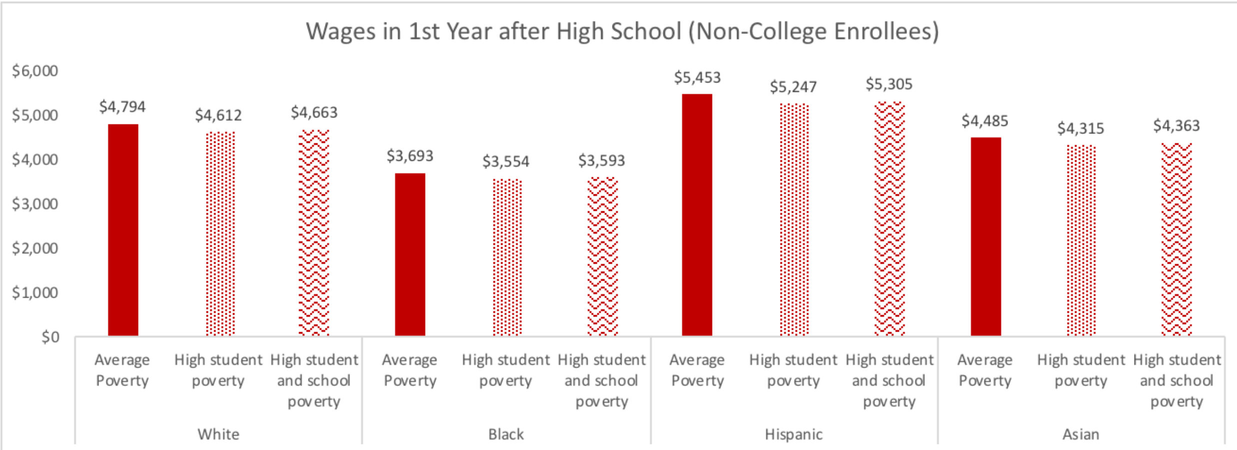
Table 9. Multilevel Modeling Results Predicting Annual Wages in 1st Year after On-Time High School Graduation (For Non-College Enrollees)

	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	8.45***(0.02)	8.49***(0.02)	8.48***(0.02)
Student poverty duration		-0.05**(0.01)	-0.04*(0.02)
Hispanic			0.13*(0.06)
Black			-0.26***(0.04)
Asian			-0.07(0.14)
Other			-0.13(0.08)
School mean poverty duration		-0.07***(0.02)	0.01(0.03)
School percent Hispanic			0.00(0.02)
School percent Black			-0.08**(0.03)
School percent Asian			-0.09**(0.03)
School percent Other			-0.02(0.02)
Model fit (Bayesian DIC)	28137.30	28122.44	28029.43

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 8,693.

Figure 11 presents the predicted annual wages in 1st year after on-time high school graduation (non-college enrollees) for specific subgroups of students characterized by race/ethnicity and poverty. After controlling for student race/ethnicity and school racial/ethnic composition, comparing the solid, dotted, and wavy bars below provides an understanding of the effects of student-level poverty and school concentrated poverty. For students not enrolled in college, those students with average levels of poverty in average poverty schools (solid bars) had the highest predicted annual wages and students with high levels of poverty in average poverty schools (dotted bars) had the lowest predicted annual wages.

Figure 11. Predicted Annual Wages in 1st Year after On-Time High School Graduation (For Non-College Enrollees)



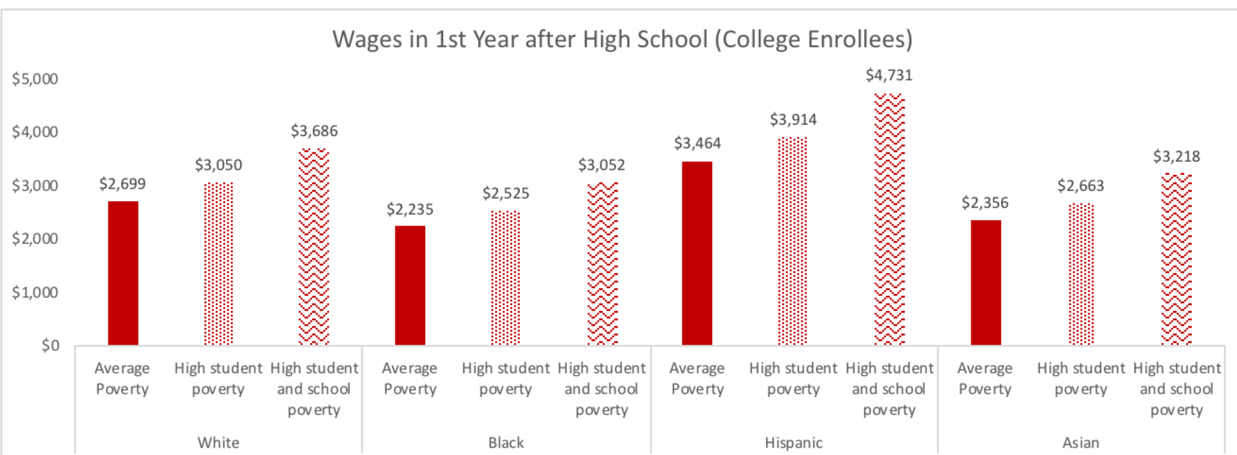
Note. Chart shows model-based predicted outcomes, not actual outcomes, for students in schools with average racial/ethnic composition, based on the 2007-08 6th grade cohort. Average student poverty = 0.36; Average school poverty = 0.37.

Annual Wages for College Enrollees. Table 10 presents results for the multilevel model predicting annual wages in the 1st year following on-time high school graduation for those students who enrolled in college. The unconditional multilevel model showed that 9% of the total variance in annual wages for college enrollees was at the school level (between schools). In the poverty main effects model, students enrolled in college who had high poverty or were in high poverty schools showed significantly higher annual wages. Contrary to non-college enrollees, the effects of student and school poverty remained significant, even after adjusting for race/ethnicity and school racial/ethnic composition, such that students with high poverty or those attending high poverty schools showed significantly higher annual wages. The school poverty effect is significantly worse than the student poverty effect, χ^2 (1 df) = 5.44, $p<0.05$. In addition, for college enrollees, Black students showed significantly lower annual wages compared to White students with similar poverty experiences. On the other hand, Hispanic college enrollees earned significantly higher annual wages than White students with similar poverty experiences.

Figure 12 shows the predicted annual wages in the 1st year after on-time high school graduation (college enrollees) for specific subgroups of students characterized by race/ethnicity and poverty. After controlling for student race/ethnicity and school racial/ethnic composition, comparing the solid, dotted, and wavy bars below provides an understanding of the effects of student-level poverty and school concentrated poverty. Students with average levels of poverty in average poverty schools (solid bars) had the lowest predicted annual wages while enrolled in college, students with high levels of poverty in average poverty schools (dotted bars) had the second lowest predicted annual wages while enrolled in college, and students with high levels of poverty in high poverty schools (wavy bars) had the highest predicted annual wages while enrolled in college.

Table 10. Multilevel Modeling Results Predicting Annual Wages in 1st Year after On-Time High School Graduation (College Enrollees)			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	7.90***(0.02)	7.91***(0.02)	7.90***(0.01)
Student poverty duration		0.12***(0.01)	0.12*** (0.01)
Hispanic			0.25*** (0.03)
Black			-0.19*** (0.03)
Asian			-0.14*** (0.04)
Other			-0.10*(0.04)
School mean poverty duration		0.04*(0.02)	0.19*** (0.02)
School percent Hispanic			-0.08*** (0.02)
School percent Black			-0.16*** (0.02)
School percent Asian			-0.10*** (0.02)
School percent Other			0.01(0.02)
Model fit (Bayesian DIC)	75380.31	75252.45	75034.64
Note. *p < 0.05, **p < 0.01, ***p < 0.001. N = 23,005.			

Figure 12. Predicted Annual Wages in 1st Year after On-Time High School Graduation (College Enrollees)



Note. Chart shows model-based predicted outcomes, not actual outcomes, for students in schools with average racial/ethnic composition, based on the 2007-08 6th grade cohort. Average student poverty = 0.36; Average school poverty = 0.37.

Variation in Findings by Student and School Level of Poverty

The results presented here examine the linear relation between poverty and outcomes, restricting the relation between school poverty and outcomes to be the same at each level of student poverty, and the relation between student poverty and outcomes to be the same at each level of school poverty. Follow-up analyses relaxed these restrictions and examined variation in the relations by levels of student and school poverty.[14] Results indicated that school poverty played a particularly negative role for students who themselves experienced longer durations of poverty. Academic and career outcomes for students who never experienced poverty were relatively positive regardless of the concentration of poverty of their schools, but outcomes worsened dramatically at higher school concentrations of poverty for those who were usually or always in poverty. Surprisingly, it was the students who were usually, but not always, eligible for FARMS who had the worst outcomes and for whom school concentration of poverty mattered the most.

Results also indicated a non-linear relation of school concentration of poverty with outcomes. In the current study, the linear relations between school-level poverty and the likelihood of ever graduating from high school, the likelihood of dropping out of high school, and annual wages in the first year after on-time high school graduation for non-college enrollees were no longer significant after controlling for student race/ethnicity and school racial/ethnic composition. However, follow-up analyses found that relations were significant for students in schools with specific levels of school poverty, with students in schools between 20% and 60% of concentrated poverty typically experiencing the worst outcomes.

Variation in Findings by Local School System

The results presented here examine average relations Statewide, with no examination of the variation in relations by local school system. Follow up analyses indicated that relations do vary by local school system.[15] In most local school systems, the relations between poverty and outcomes were negative. However, in a few local school systems, the relation between poverty and outcomes was positive. That is, higher levels of poverty were related to more positive outcomes for some local school systems. In depth analyses of these specific school systems may provide insight into resources, programs, and practices that may be particularly beneficial for students living in poverty.

[14] Results of models examining relations by student- and school-level of poverty will be presented in a follow-up research report.

[15] Results of models examining relations by local school system will be presented in a follow-up research report.

Summary of Findings

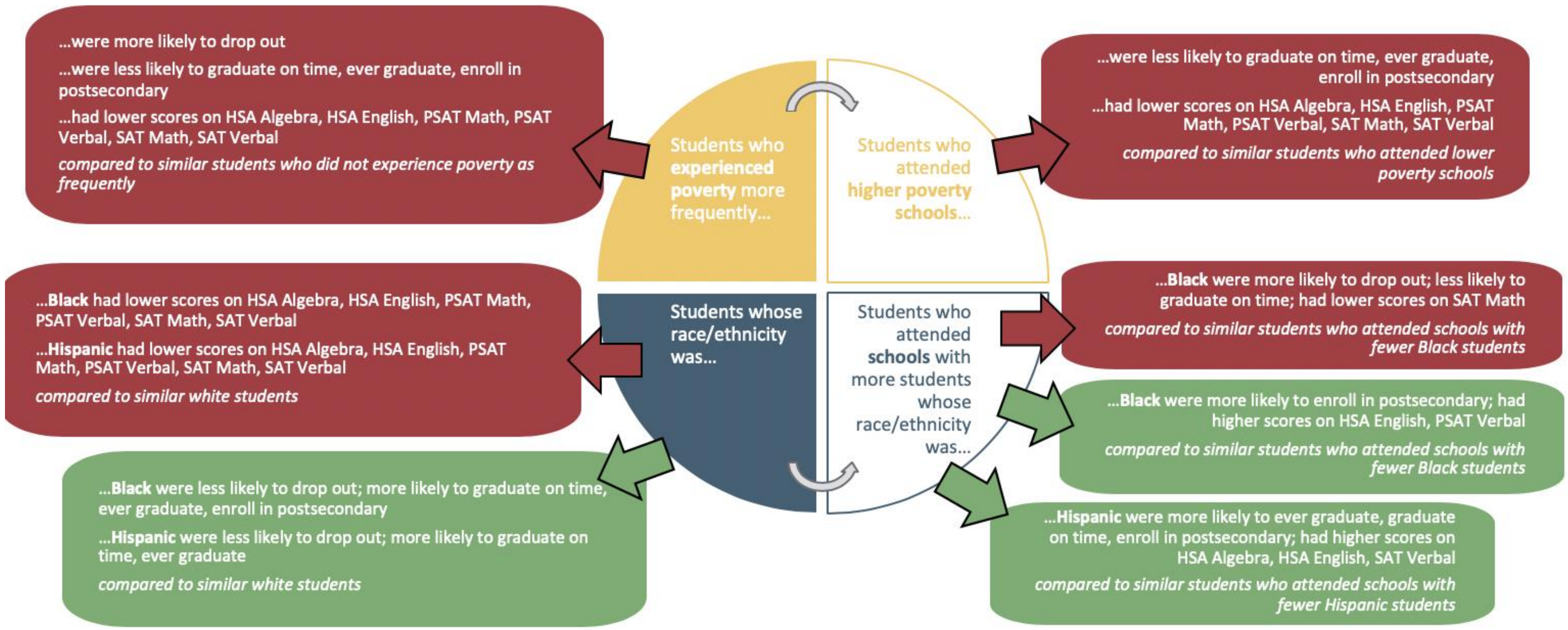
In sum, this study found that both student and school-level poverty were related to long-term academic outcomes, even after controlling for individual student race/ethnicity and school racial/ethnic composition. Figure 13 displays a summary of findings for all outcomes examined in this study. Students who experienced poverty for longer periods of time had worse educational outcomes, including lower predicted likelihoods of high school graduation, higher predicted likelihoods of high school dropout, lower predicted standardized assessment scores, and lower predicted likelihoods of enrolling in postsecondary education. School concentration of poverty, regardless of an individual student's poverty experience and race, usually predicted worse educational outcomes. Racial and ethnic gaps in standardized test scores persisted regardless of student and school-level poverty. However, racial and ethnic gaps in student dropout, high school graduation, and postsecondary enrollment disappeared or reversed when controlling for student and school-level poverty and school racial/ethnic composition. Student and school-level poverty were associated with lower annual wages for students who did not enroll in college and higher annual wages for students who did enroll in college immediately following high school. Relations varied by student poverty level, school poverty level, and local school system.

Discussion

This study used administrative statewide population data from the MLDS to disentangle the roles of student-level and school-concentrated poverty on long-term academic and workforce outcomes. Multilevel multiple membership models (Chung & Beretvas, 2012) were used to account for students nested within schools and to allow for students to attend more than one middle and high school. Student poverty was measured by calculating the total proportion of school enrollments between 6th and 12th grades that students were eligible for FARMS. This measure was aggregated to the school level to calculate school concentrated poverty. Findings indicated that students' experiences with household poverty and school concentration of poverty had significant negative relations with most outcomes examined. Racial and ethnic gaps in most educational outcomes disappeared or were reversed after controlling for poverty. However, racial and ethnic gaps persisted for standardized test scores and wages, even after controlling for poverty.

The current study expands upon prior research in several ways: (1) the use of students' history of eligibility for FARMS between 6th and 12th grade to measure duration of student poverty helped to reduce some of the limitations typically associated with using student FARMS as a proxy to measure poverty; (2) the use of multiple membership multilevel modeling to account for all schools a student attended between middle and high school helped to disentangle the role of students' own experiences with poverty from the role of school concentration of poverty; and (3) the use of longitudinal data following a cohort of students beginning in 6th grade and extending to college and workforce helped to distill the role of students' middle and high school experiences on post-K12 outcomes.

Figure 13. Summary of Findings about Student and School Concentrated Poverty and Race/Ethnicity and Long-term Academic and Workforce Outcomes



The Role of Student Poverty in Long-Term Academic Outcomes

Consistent with prior research, this study found that student poverty was negatively associated with academic and career outcomes (Caldas & Bankston, 1997; Mulligan, 1997; Rumberger & Palardy, 2005; Walpole, 2003). Students experiencing poverty for longer durations were less likely to graduate from high school or enroll in college within the first year following on-time high school graduation, were more likely to drop out, and performed worse on standardized tests, than similar students with shorter experiences of poverty. This study provides further support that persistent poverty results in more detrimental outcomes (Duncan et al., 2012; McLoyd, 1998). Children exposed to poverty experience a wide array of stressors, including poor living conditions, poor nutrition, limited access to health care, reduced access to quality childcare and safe, reduced access to cognitive-stimulating environments, higher levels of family violence and disruption, higher levels of crime in the neighborhood, and greater residential mobility and environmental hazards (Duncan et al., 2012; Malat, Oh, & Hamilton, 2005; Morrissey, Hutchison, & Winsler, 2013; Wagmiller & Adelman, 2009). Increased exposure to poverty-related stressors has severe implications for children's academic and workforce trajectories, especially since the income-related academic achievement gap is well established by kindergarten and remains throughout K-12 education (Williams, Bryan, Morrison, & Scott, 2017). Throughout children's lives, living in poverty for longer durations creates a cumulative effect of the stressors associated with living in poverty (Wagmiller & Adelman, 2009). This cumulative effect of poverty extends into adulthood and may help to explain why early poverty is associated with long-term college outcomes.

The Role of School Concentration of Poverty in Long-Term Academic Outcomes

Also consistent with prior research, the results of this study showed a negative association between school poverty and academic outcomes, regardless of the student's race or poverty experience. This finding is consistent with previous research highlighting that school poverty matters, above and beyond student poverty (Borman & Dowling, 2010). In the present study, students attending higher poverty schools were less likely to graduate (on-time or ever) or enroll in college, and performed worse on standardized tests, compared to similar students attending lower poverty schools. Higher poverty schools often have limited or no access to quality educational resources, fewer qualified teachers, more overcrowded classrooms, and poorer facilities (Morgan, 2012). Additionally, teacher bias may play a role, such that teachers may favor students from higher socioeconomic (SES) backgrounds and have lower expectations of students living in poverty (Borman & Dowling, 2010). This bias may impact teachers' interactions with students and teachers' instructional practices, such that both favor the academic growth of higher SES students over lower SES students (Borman & Dowling, 2010). The associations between school-level poverty and academic outcomes extend into college and may be due to lower levels of preparation for college at high poverty schools. For example, schools with high concentrations of student poverty may not have the resources available to offer college preparatory coursework to students (GAO, 2018).

The Role of Race/Ethnicity in Long-Term Academic Outcomes

Prior research documents the detrimental role of poverty in creating and exacerbating racial/ethnic gaps in academic outcomes (Bali & Alvarez, 2004; Duncan & Magnuson, 2005; Fram, Miller-Cribbs, & Van Horn, 2007; Reardon & Portilla, 2016). In the current study, while racial/ethnic gaps were observed in descriptive statistics for on-time high school graduation and postsecondary enrollment, these observed racial/ethnic gaps either disappeared or reversed after controlling for student poverty, school poverty, and school racial/ethnic composition. Black and Hispanic students were predicted to be *more* likely to graduate from high school (on-time and ever), and *less* likely to drop out, after poverty and school membership were taken into account. Black students were also predicted to be more likely to enroll in college after poverty and school membership were taken into account. While Black and Hispanic students in reality do have lower graduation rates and higher dropout rates than White students, our findings suggest that this may be due to the fact that minority students are disproportionately poor and often clustered within high poverty schools (Borman & Dowling, 2010).

Minorities experience poverty at a rate that is two to three times higher than White children in the U.S. (Drake & Rank, 2009). The findings of the current study suggest that the negative educational and career outcomes seen for minority students may be attributable to poverty. The disappearance and reversal of racial/ethnic gaps in some outcomes after controlling for poverty was unexpected, yet consistent with cultural differences in achievement motivation (e.g., the source of motivation for students to achieve goals; Trumbull & Rothstein-Fisch, 2011). Achievement motivation is linked to academic success and is influenced by culture (Trumbull & Rothstein-Fisch, 2011). For example, if a student's culture values education, his/her family will emphasize education in the home setting through reinforcing homework, study schedules, and additional learning opportunities. After poverty is accounted for, the historic and systemic oppression experienced by minority families in the U.S. may lead to particularly high achievement motivation, with extra effort needed to "get ahead" in terms of educational and workforce outcomes.

Additionally, results also show racial/ethnic gaps to persist for standardized tests, regardless of the student's individual or school poverty experience. Previous research highlights the prominence of stereotype threat for possibly explaining the racial/ethnic gaps in test scores (Alter et al., 2010; Walton & Spencer, 2009). Due to uncertainty in why these trends were observed, the persistence of racial/ethnic gaps in academic achievement remain a perpetual concern for the public education system (Bali & Alvarez, 2004).

The Role of Poverty and Race in Workforce Outcomes

Students' experiences with poverty during their middle and high school years did not predict future wages as strongly as they predicted students' educational outcomes. Rather, wage patterns appeared to be primarily driven by race and ethnicity. This is consistent with findings indicating persistent racial discrimination in US labor markets (Quillian, Pager, Hexel, &

Midtboen, 2017). We analyzed wages for those enrolled in college separately from those not enrolled in college. For those *not* enrolled in college, individuals who had experienced higher levels of student poverty were predicted to have slightly lower wages in the first year after high school; however, the concentration of poverty at the schools they attended during middle and high school did not predict post-high school wages. This finding is consistent with previous research indicating that students in poverty for longer durations have lower annual wages (Duncan et al., 2012), particularly for those without any college education. Students with a high school diploma or less are more likely to occupy lower paying jobs (Oreopoulos & Petronijevic, 2013), whereas higher levels of education are associated with increased annual wages, as education promotes economic success and social mobility (Engle, 2007; Long & Riley, 2007).

For those who *were* attending college during the first year after high school, both student and school poverty were associated with *higher* wages. Financial aid alone is often not enough to cover college-related expenses, leaving many students needing to work long hours or more than one job due to rising tuition costs (Long & Riley, 2007; Pike, Kuh, & Massa-McKinley, 2008). The data available in the MLDS reflect only total wages, not hours worked or hourly wage, so this study was unable to determine whether the higher wages were due to more hours worked or higher pay. The finding that attending a higher poverty school was associated with higher wages may also be due to a peer or cultural effect, whereby students are motivated to earn wages due to observing that their peers are working. Alternatively, school poverty may be confounded with geographic location, which in turn may be correlated with higher college costs, spurring students in these areas to earn higher wages.

Variation by Level of Poverty and Local School System

The current study only examined the *linear* relationship between student and school poverty and outcomes. The models assumed that as student or school poverty increased, outcomes would either increase, or decrease, or stay the same. A future report will examine what happens when this assumption is relaxed. This will be done by estimating the relation between school poverty and outcomes for separate groups of students based on the duration of their experiences with poverty (never, sometimes, usually, or always in poverty) and by estimating the relation between student poverty and outcomes for separate groups of schools based on the school mean poverty duration. Furthermore, the current study examined these relations Statewide. A future report will examine the roles of poverty and race/ethnicity in each local school system in Maryland. Preliminary analyses indicate that relations vary by level of student poverty, level of school poverty, and local school system.

Limitations

The findings of this study should be interpreted within the context of the following limitations. First, this study measured poverty using students' eligibility for FARMS over the duration of the 6^{th} through 12^{th} grade years. The MLDS data do not provide the ability to differentiate between students' eligibility for free meals and students' eligibility for reduced meals. Furthermore, the entire range of socioeconomic status (SES) above the poverty line is collapsed. A more nuanced scale for measuring the full range of students' SES backgrounds would provide the ability to more precisely examine the role of family resources in contributing to long-term educational and career outcomes. A proxy for household income could be obtained by linking students' home address (not currently available in the MLDS) with neighborhood median income data from the Census. Second, the MLDS data begin in academic year 2007-2008, so in order to examine college and workforce outcomes, the earliest available panel of data for this study started with the 6^{th} grade cohort of students. A more complete understanding of students' duration of poverty would begin in pre-school or kindergarten at the time the students begin formal schooling. Third, the MLDS data only contain workforce data for those students employed in the state of Maryland. Workforce data were unavailable for students employed by the federal government, the military, and for students employed out of state. Additionally, workforce data for private contractors and for those who were self-employed were not included in the MLDS. Furthermore, the MLDS data reflect total wages only and does not provide information on hours worked or whether employment was full- or part-time. Fourth, there are several correlates of poverty and educational outcomes that have not been measured in this study; their exclusion from our models could bias our estimates of the roles of student and school poverty. For example, prior research provides strong evidence that minorities and low-income students are disciplined in schools at higher rates than White students and higher income students (Gregory, Skiba, & Noguera, 2010; Theriot, Craun, & Dupper, 2010). Additionally, students who are suspended and expelled from school are disproportionately more likely to experience worse long-term educational and career outcomes (Theriot et al., 2010). It is possible that the behavioral issues leading to discipline and the resulting exclusion from school could confound the association we see between poverty and student outcomes. Not including student discipline information in the statistical models likely creates an overestimate of the relation between poverty and race and long-term academic and career outcomes.

Policy Implications

This study found that both longer duration of household poverty and higher school concentrations of poverty were negatively related to long-term educational outcomes, even after controlling for student race and school racial composition. These findings support the implementation of programs and policies for students living in poverty and for schools with high concentrations of poverty. For example, community schools, which focus resources within the school while taking community needs into account, are one approach that has worked well for students living in poverty (Maier, Daniel, Oakes, & Lam, 2017). Additional supports such as tutoring and summer and after-school programs may be beneficial to students living in poverty, given their association with more positive educational outcomes, particularly in low-income students (Knopf et al., 2015; Vandell, Reisner, & Pierce, 2007). Also, since school poverty had stronger relations with most outcomes than student poverty did in our study, it is important to examine school-level factors. For example, it may be beneficial to equip teachers working in high poverty schools with additional training and support. Higher quality, more experienced teachers often work in lower poverty schools (USDE, 2014). Policy initiatives that incentivize more experienced teachers to teach in high poverty schools may be beneficial.

The primary federally funded intervention aimed at addressing the needs of children in poverty is Title I. Our findings of persistent effects of student and school poverty suggest that current Title I funding is not sufficient to meet the needs of all high-poverty schools. Title I is a federal aid program that allocates funding to local educational agencies and public schools with high percentages of low-income families to assist all children in meeting state and student academic achievement standards (USDE, 2018). Title I was created in an effort to ameliorate the effects of poverty and improve academic achievement, especially among low-achieving students. Title I eligibility is designated to schools with poverty rates above 40% (35% for targeted assistance programs). Eligible schools must use Title I funds to target children who are failing or most at risk of failing to meet the academic standards of the state unless they are operating a schoolwide program (USDE, 2015). Due to insufficient funding to serve all eligible schools, districts must select their most impoverished schools as recipients of the Title I funds. Additionally, grade span groupings are often used to ensure that eligible elementary schools have precedence over middle and high schools. Thus, many Maryland schools that are eligible for Title I funds do not receive them, and no high schools in Maryland receive Title I funds at all. Our findings indicate that additional school-level resources and interventions for students in schools with high concentrations of poverty may be beneficial.

Future Research

Future research examining the role of student and school-level poverty on long-term educational and career outcomes will examine the protective role of individual student (e.g., academic achievement), classroom (e.g., average level of academic achievement in the classroom; teacher characteristics), and school (e.g., average level of academic achievement in the school) characteristics that may aid in reducing the negative effects of poverty. This research would help to inform the types of programs and supports that schools could implement for students living in poverty and that districts could implement for schools with concentrated levels of student poverty. Furthermore, additional years of longitudinal data incorporated into the MLDS would enable future research examining poverty in elementary, middle, and high schools. This would aid in identifying points of intervention for students experiencing various poverty levels within homes and schools across the entire K-12 experience. Additionally, it would provide an increased understanding of the detriments of early poverty on long-term academic success. Future research should also examine additional college and career outcomes with additional years of longitudinal data that enable examination of poverty in relation to college persistence, degree attainment, and workforce trajectories. This would inform policy pertaining to additional funding and supports provided to students experiencing high levels of student and school poverty to increase economic success and social mobility. Lastly, this study used duration of FARMS in 6^{th} through 12^{th} grades as a proxy for poverty; however, future research should assess how well FARMS compares to other measures of poverty, including linking MLDS data to data from the United States Census Bureau.

Conclusion

This report disentangled the roles of student and school poverty and race in contributing to long-term educational and workforce outcomes. Consistent with prior research, this study found that the duration of students' experiences with household poverty and school concentrations of poverty were associated with worse educational outcomes. The results of this study can be used to inform policy that directs appropriate resources for students experiencing poverty and schools with high concentrations of poverty in order to improve students' likelihoods of attaining high school diplomas and being prepared for college and career.

References

Alter, A. L., Aronson, J., Darley, J. M., Rodriguez, C., & Ruble, D. N. (2010). Rising to the threat: Reducing stereotype threat by reframing the threat as a challenge. *Journal of Experimental Social Psychology, 46*, 166-171.

Bali, V. A., & Alvarez, R. M. (2004). The race gap in student achievement scores: Longitudinal evidence from a racially diverse school district. *Policy Studies Journal*, *32*(3), 393-415.

Bischoff, K., & Reardon, S. F. (2014). Residential segregation by income, 1970-2009. In J. R. Logan (Ed.), *Diversity and Disparities: America Enters a New Century* (pp. 208-233). New York: Russell Sage Foundation.

Borman, G., & Dowling, M. (2010). Schools and inequality: A multilevel analysis of Coleman's equality of educational opportunity data. *Teachers College Record, 112*, 1201-1246.

Brooks-Gunn, J., & Duncan, G. J. (1997). The effects of poverty on children. *The Future of Children*, 55-71.

Burdick-Will, J., Ludwig, J., Raudenbush, S. W., Sampson, R. J., Sanbonmatsu, L., & Sharkey, P. (2011). Converging evidence for neighborhood effects on children's test scores: An experimental, quasi-experimental, and observational comparison. In G. J. Duncan & R. J. Murnane (Eds.), *Whither Opportunity: Rising Inequality, Schools, and Children's Life Chances* (pp. 255-276). New York: Russell Sage Foundation.

Cabrera, A. F., & La Nasa, S. M. (2000). Overcoming the tasks on the path to college for America's disadvantaged. *New Directions for Institutional Research, 107*, 31-43.

Caldas, S. J., & Bankston, C. (1997). Effect of school population socioeconomic status on individual academic achievement. *The Journal of Educational Research, 90*, 269-277.

Chetty, R., Hendren, N., & Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment. *American Economic Review, 106*, 855-902.

Chung, H., & Beretvas, S. N. (2012). The impact of ignoring multiple membership data structures in multilevel models. *British Journal of Mathematical and Statistical Psychology, 65*, 185-200.

Coleman, J. S., et al. (1966). *Equality of educational opportunity*. Washington, DC: U.S. Government Printing Office. ED012275.

College Board. (2018). SAT Suite of Assessments Annual Report - Maryland. https://reports.collegeboard.org/pdf/2018-maryland-sat-suite-assessments-annual-report.pdf

Duncan, G. J., & Magnuson, K. A. (2005). Can family socioeconomic resources account for racial and ethnic test score gaps? *The Future of Children, 15*, 35-54.

Duncan, G. J., Magnuson, K., Kalil, A., & Ziol-Guest, K. (2012). The importance of early childhood poverty. *Social Indicators Research*, *108*, 87-98.

Dynarski, S. M., Hemelt, S. W., & Hyman, J. M. (2015). The missing manual: Using National Student Clearinghouse data to track postsecondary outcomes. *Educational Evaluation and Policy Analysis, 37*(1_suppl), 53S-79S.

Engle, J. (2007). Postsecondary access and success for first-generation college students. *American Academic*, *3*(1), 25-48.

Gregory, A., Skiba, R. J., & Noguera, P. A. (2010). The achievement gap and the discipline gap: Two sides of the same coin?. *Educational Researcher*, *39*(1), 59-68.

Hanushek, E. A., Kain, J. F., & Rivkin, S. G. (2009). New evidence about Brown v. Board of Education: The complex effects of school racial composition on achievement. *Journal of Labor Economics, 27*, 349-383.

Harding, D. J. (2003). Counterfactual models of neighborhood effects: The effect of neighborhood poverty on dropping out and teenage pregnancy. *American Journal of Sociology, 109*, 676-719.

Henneberger, A. K. & Rose, B. A. (2018a). *The role of concentrated poverty and race in long-term academic outcomes.* Legislative testimony for the Maryland Commission on Innovation and Excellence in Education, Annapolis, MD.

Henneberger, A. K. & Rose, B. A. (2018b). *Poverty and long-term educational outcomes: Variation by level of school poverty, student poverty, and local school system.* Legislative testimony for the Maryland Commission on Innovation and Excellence in Education, Annapolis, MD.

Jencks, C., & Mayer, S. (1990). The social consequences of growing up in a poor neighborhood. In L. E. Lynn, & M. F. H. McGeary (Eds.), Inner-city poverty in the United States (pp. 111-186). Washington DC: National Academy Press.

Jiang, Y., Granja, M. R., & Koball, H. (2017). Basic facts about low-income children: Children under 18 years, 2015. Retrieved from http://www.nccp.org/publications/pub_1170.html

Knopf, J. A., Hahn, R. A., Proia, K. K., Truman, B. I., Johnson, R. L., Muntaner, C., ... & Qu, S. (2015). Out-of-school-time academic programs to improve school achievement: A community guide health equity systematic review. *Journal of public health management and practice: JPHMP*, *21*(6), 594-608.

Konstantopoulos, S., & Borman, G. D. (2011). Family background and school effects on student achievement: A multilevel analysis of the Coleman data. *Teachers College Record, 113*, 97-132.

Leventhal, T., & Brooks-Gunn, J. (2000). The neighborhoods they live in: the effects of neighborhood residence on child and adolescent outcomes. *Psychological Bulletin, 126*, 309-337.

Long, B. T., & Riley, E. (2007). Financial aid: A broken bridge to college access?. *Harvard Educational Review*, *77*(1), 39-63.

Malat, J., Oh, H. J., & Hamilton, M. A. (2005). Poverty experience, race, and child health. *Public Health Reports, 120*, 442-447.

Maryland State Department of Education (MSDE). (2018). 2018 Maryland Report Card. Baltimore, MD: Author. reportcard.msde.maryland.gov/CohortDropoutRate.aspx.

McLoyd, V. C. (1998). Socioeconomic disadvantage and child development. *American Psychologist, 53*, 185-204.

Michelmore, K., & Dynarski, S. (2016). *The gap within the gap: Using longitudinal data to understand income differences in student achievement* (No. w22474). National Bureau of Economic Research.

Morgan, H. (2012). Poverty-stricken schools: What we can learn from the rest of the world and from successful schools in economically disadvantaged areas in the US. *Education, 133*, 291-297.

Morrissey, T. W., Hutchison, L., & Winsler, A. (2013). Family Income, School Attendance, and Academic Achievement in Elementary School. Developmental Psychology. Advance online publication. doi: 10.1037/a0033848

Mulligan, C. B. (1997). Work ethic and family background. Employment Policies Institute.

Oreopoulos, P., & Petronijevic, U. (2013). Making college worth it: A review of the returns to higher education. *The Future of Children*, 23(1), 41-65.

Orfield, G., & Lee, C. (2005). Why segregation matters: Poverty and educational inequality. *The Civil Rights Project at Harvard University.*

Pike, G. R., Kuh, G. D., & Massa-McKinley, R. C. (2008). First-year students' employment, engagement, and academic achievement: Untangling the relationship between work and grades. *Naspa Journal*, *45*(4), 560-582.

Pungello, E. P., Kupersmidt, J. B., Burchinal, M. R., & Patterson, C. J. (1996). Environmental risk factors and children's achievement from middle childhood to early adolescence. *Developmental Psychology, 32*, 755.

Quillian, L., Pager, D., Hexel, O., & Midtbøen, A. H. (2017). Meta-analysis of field experiments shows no change in racial discrimination in hiring over time. *Proceedings of the National Academy of Sciences, 114*(41), 10870-10875.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). Thousand Oaks: Sage.

Reardon, S. F. (2016). School segregation and racial academic achievement gaps. *RSF: The Russell Sage Foundation Journal of the Social Sciences, 2*(5), 34-57.

Reardon, S. F., & Owens, A. (2014). 60 years after Brown: Trends and consequences of school segregation. *Annual Review of Sociology, 40*, 199-218.

Rumberger, R. W., & Palardy, G. J. (2005). Does segregation still matter? The impact of student composition on academic achievement in high school. *Teachers College Record*, *107*, 1999-2045.

Sampson, R. J., Sharkey, P., & Raudenbush, S. W. (2008). Durable effects of concentrated disadvantage on verbal ability among African-American children. *Proceedings of the National Academy of Sciences, 105*, 845-852.

Schultz, G. F. (1993). Socioeconomic advantage and achievement motivation: Important mediators of academic performance in minority children in urban schools. *The Urban Review, 25*, 221-232.

Theriot, M. T., Craun, S. W., & Dupper, D. R. (2010). Multilevel evaluation of factors predicting school exclusion among middle and high school students. *Children and Youth Services Review*, *32*(1), 13-19.

U.S. Department of Agriculture. (2017). Child nutrition programs: Income eligibility guidelines (July 1, 2017 – June 30, 2018). Retrieved from https://www.fns.usda.gov/school-meals/fr-041017.

U.S. Department of Education (USDE). (2014). Educator Equity Profile - Maryland. Washington, DC: Author. https://www2.ed.gov/programs/titleiparta/equitable/md.html

U.S. Department of Education (USDE). (2015). Educator Equity Profile - Maryland. Washington, DC. Retrieved from https://nces.ed.gov/fastfacts/display.asp?id=158.

U.S. Department of Education (USDE). (2018). Educator Equity Profile - Maryland. Washington, DC. Retrieved from https://www2.ed.gov/programs/titleiparta/index.html.

U.S. Government Accountability Office (USGAO). (2018). Report to the Ranking Member, Committee on Education and the Workforce, House of Representatives: Public High Schools with More Students in Poverty and Smaller Schools Provide Fewer Academic Offerings to Prepare for College (GAO-19-8). Washington, DC: Retrieved from https://www.gao.gov/products/GAO-19-8

Vandell, D. L., Reisner, E. R., & Pierce, K. M. (2007). Outcomes Linked to High-Quality Afterschool Programs: Longitudinal Findings from the Study of Promising Afterschool Programs. *Policy Studies Associates, Inc.* Retrieved from: https://files.eric.ed.gov/fulltext/ED499113.pdf

Wagmiller, R. L., & Adelman, R. M. (2009). Childhood and intergenerational poverty: The long-term consequences of growing up poor. Retrieved from: https://academiccommons.columbia.edu/doi/10.7916/D8MP5C0Z

Walker, D., Greenwood, C., Hart, B., & Carta, J. (1994). Prediction of school outcomes based on early language production and socioeconomic factors. *Child Development, 65*, 606-621.

Walpole, M. (2003). Socioeconomic status and college: How SES affects college experiences and outcomes. *The Review of Higher Education, 27*, 45-73.

Walton, G. M., & Spencer, S. J. (2009). Latent ability: Grades and test scores systematically underestimate the intellectual ability of negatively stereotyped students. *Psychological Science*, *20*, 1132-1139.

Williams, J. M., Bryan, J., Morrison, S., & Scott, T. R. (2017). Protective factors and processes contributing to the academic success of students living in poverty: Implications for counselors. *Journal of Multicultural Counseling and Development*, *45*(3), 183-200.

Wodtke, G. T., Harding, D. J., & Elwert, F. (2011). Neighborhood effects in temporal perspective: The impact of long-term exposure to concentrated disadvantage on high school graduation. *American Sociological Review, 76*, 713-736.

Appendix A
Descriptive Statistics

Table A.1. Descriptive Statistics for Outcome Variables					
	N	Mean	Standard Deviation	Minimum	Maximum
Graduated from HS on time	54,465	0.86	0.35	0	1
Ever graduated from HS	54,465	0.89	0.31	0	1
Dropped out	54,465	0.10	0.30	0	1
HSA Algebra score	52,261	435.30	31.67	240	650
HSA English score	50,681	415.55	25.42	240	650
SAT Math score	33,534	495.80	129.70	200	800
SAT Verbal score	33,534	490.36	121.22	200	800
PSAT Math score	47,162	44.21	12.02	20	80
PSAT Verbal score	47,193	43.97	11.32	20	80
Enrolled in college within one year of on-time HS graduation	46,581	0.73	0.44	0	1
Non-zero annual wages in 1st year after HS (not enrolled in college)	8,693	8156.59	9225.56	2	481093
Non-zero annual wages in 1st year after HS (enrolled in college)	23,005	4819.07	5527.26	4	151653
Notes. HS = high school; HSA = high school assessment.					

Table A.2. Descriptive Outcomes by Students' FARMS History						
	High School Graduation (on time) (n = 54,465)	High School Graduation (ever) (N = 54,465)	Dropout (n = 54,465)	HSA Algebra Score (n = 52,261)	SAT Math Score (n = 33,534)	College Enrollment
FARMS History	Mean %	Mean %	Mean %	Mean Score	Mean Score	Mean %
Never	0.95	0.97	0.03	448	543	0.83
Sometimes (<50%)	0.83	0.88	0.11	429	449	0.64
Usually (>=50%)	0.69	0.77	0.21	419	414	0.59
Always	0.76	0.82	0.17	418	406	0.56
All	0.86	0.89	0.1	435	496	0.73
Notes. FARMS = eligibility for free/reduced price meals; HSA = high school assessment; college enrollment is measured in the year following on time high school graduation.						

Appendix B
Detailed Analytic Approach

The primary research question for this study was, to what extent does school poverty (the aggregated poverty of all students in schools), apart from student poverty (individual students' experiences with household poverty), predict students' long-term educational and workforce outcomes? In order to answer this question, we needed a way to disentangle the roles of school-level poverty (and other school-level factors) from the role of student-level poverty (and other student-level factors). Multilevel modeling, also called hierarchical linear modeling, gives us a way to do this.

Traditional Multilevel Models

Multilevel or hierarchical modeling can account for the "nesting" of students in larger social contexts such as schools (Bronfenbrenner, 1986, 1994; Raudenbush & Bryk, 2002). Using traditional hierarchical modeling, in which each student is nested within a single school, the outcome of student *i* who attended school *j* can be modeled as:

$$Outcome_{ij} = \beta_{0j} + e_{ij}$$

where β_{0j} is the mean outcome of all students who attended school *j* and e_{ij} is the residual error associated with student *i*. This error is assumed to have a normal distribution with a mean of 0 and level-1 (student level) variance σ^2_e.

The mean outcome β_{0j} of all students who attended school *j* can be modeled as:

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

where γ_{00} is the mean outcome across all schools and u_{0j} is the residual error associated with school *j*. This error is assumed to have a normal distribution with a mean of 0 and level-2 (school level) variance σ^2_u. The level-1 and level-2 equations can be combined:

$$Outcome_{ij} = \gamma_{00} + e_{ij} + u_{0j}$$

Thus, in the multilevel framework, we can estimate the variance in the outcome that is due to differences among students and the variance that is due to differences between the schools those students attended.

Multiple Membership Multilevel Models

Traditional multilevel models assume that each lower-level unit or individual (e.g., student) is nested within only one higher-level cluster (e.g., school). In reality, students often belong to more than one school over the course of their K-12 educational experience. In the present study, most students (63%) belonged to two schools (usually one middle school and one high school) over the course of their educational history from 6th through 12th grade (or whenever they left high school) and 22% of students attended three schools. Less than one percent of the analytic sample attended one school for the entire period, and 3% attended 6 or more. While researchers often drop mobile students from analyses, or nest students in only one school, it is important to model students' membership in all higher-level units because educational outcomes are functions of students' environments across their educational histories (Bronfenbrenner, 1986, 1994; Goldstein et al., 2007; Chung, 2009; Chung & Beretvas, 2012). Figure B1 displays the multiple membership structure of the data. The appropriate method to account for this mobility is to use a multiple membership approach that accounts for the relative influence of all of the higher level units.

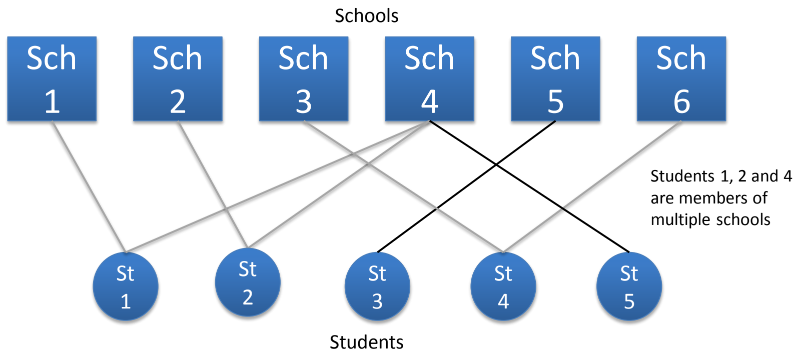


Figure B1. Multiple membership

Unconditional model

Using multiple membership multilevel modeling, we can take into account all the schools attended by each student by first creating, for each student, for each school *h* in the set of schools they attended *{j}*, a weight *w* such that the weights sum to 1 (for example, for a student attending 2 schools, each school's residual is weighted .5), then multiplying each weight by the corresponding school's residual, and summing the result to obtain a total school-level residual for each student. Thus, we can predict the score of student *i* who attended the set of schools {*j*} as a function of the mean outcome across all students in all schools, the residual error associated with each student, and the sum of the weighted school-level residuals for each student:

$$Outcome_{i\{j\}} = \gamma_{00} + e_{i\{j\}} + \sum_{h\epsilon\{j\}} w_{ih}\, u_{0h}$$

We modeled each outcome of interest starting with an unconditional model like this one in order to estimate the school-level variance.

Student and school poverty

For each outcome we then added terms for student and school poverty. These were constrained as fixed. At level 1:

$$Outcome_{i\{j\}} = \beta_{0j} + \beta_{1j} StPov_{i\{j\}} + e_{i\{j\}}$$

And at level 2:

$$\beta_{0j} = \gamma_{00} + SchPov_{0\{j\}} + \sum_{h\epsilon\{j\}} w_{ih}\, u_{0h}$$

$$\beta_{1j} = \gamma_{10}$$

Student race/ethnicity and school racial/ethnic composition

For each outcome we then added dummy variables for student race/ethnicity categories Black, Hispanic, Asian, and Other, with White as the omitted reference category, and school racial/ethnic composition variables for the percentage Black, percentage Hispanic, percentage Asian, and percentage Other (the mean across all schools the student attended). These were also constrained as fixed. At level 1:

$$Outcome_{i\{j\}} = \beta_{0j} + \beta_{1j}StPov_{i\{j\}} + \beta_{2j}Black_{i\{j\}} + \beta_{3j}Hisp_{i\{j\}} + \beta_{4j}Asian_{i\{j\}} + \beta_{5j}Other_{i\{j\}} + e_{i\{j\}}$$

And at level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}SchPov_{0\{j\}} + \gamma_{02}Black_{0\{j\}} + \gamma_{03}Hisp_{0\{j\}} + \gamma_{04}Asian_{0\{j\}} + \gamma_{05}Other_{0\{j\}} + \sum_{h\epsilon\{j\}} w_{ih}\, u_{0h}$$

$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$
$$\beta_{5j} = \gamma_{50}$$

Thus the full model was a random intercept model where, for continuous outcomes, such as test scores and annual wages, outcome *Y* for student *i* who attended the set of schools *{j}* is predicted as a function of the average outcome for all students in the set of schools *{j}*, the student's own experience with household poverty, the student's own race/ethnicity, the average student poverty duration in the school(s) the student attended, the average racial/ethnic composition in the school(s) the student attended, and residual error terms. Binary outcomes, such as graduating from high school or enrolling in postsecondary education, were modeled in a similar fashion but using logistic models. All models were fitted using Markov Chain Monte Carlo (MCMC) procedures in MLwiN version 3.02 (Charlton et al., 2017; Browne, 2017) from Stata/SE version 15 using *runmlwin* (Leckie & Charlton, 2012).

Estimating the "Effects" of Student and School Poverty

These analyses estimate the degree to which student and school poverty predict students' long-term educational and workforce outcomes, with an emphasis on determining the extent to which school concentration of poverty, over and above individual household poverty, accounts for outcomes. It should be noted that these analyses are not strictly causal but rather correlational. It may be that other factors that are correlated with both student and school poverty and outcomes account for the observed relationships. For example, other research has shown that schools with high levels of poverty tend to hire teachers with fewer years of experience; it may be that the outcomes of students who attend high poverty schools is not due to the high level of poverty in those schools per se but rather the inexperience of their teachers. Future research is needed to explore these additional factors. Future analyses may use additional techniques to strengthen the potential for causal inferences.

Appendix B References

Bronfenbrenner, U. (1986). Ecology of the family as a context for human development: Research perspectives. *Developmental Psychology, 22*, 723-742.

Bronfenbrenner, U. (1994). Ecological models of human development. In *International Encyclopedia of Education, Vol. 3, 2nd Ed*. Oxford: Elsevier. Reprinted in: M. Gauvain & M. Cole (Eds.), *Readings on the development of children, 2nd Ed*. (1993, pp. 37-43). New York: Freeman.

Browne, W. J. (2017). *MCMC Estimation in MLwiN v3.02*. Centre for Multilevel Modelling, University of Bristol.

Charlton, C., Rasbash, J., Browne, W. J., Healy, M., & Cameron, B. (2017). *MLwiN Version 3.02*. Centre for Multilevel Modelling, University of Bristol.

Chung, H. (2009). *The impact of ignoring multiple-membership data structures* (Doctoral dissertation). Retrieved from UT Electronic Theses and Dissertations, http://repositories.lib.utexas.edu/handle/2152/11672

Goldstein, H., Burgess, S., & McConnell, B. (2007). Modelling the effect of pupil mobility on school differences in educational achievement. *Journal of the Royal Statistical Society, 170*, 941-954.

Leckie, G., & Charlton, C. (2012). *runmlwin: A program to run the MlwiN multilevel modeling software from within Stata. Journal of Statistical Software, 52*(11), 1-40.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: SAGE.

Appendix C
Odds Ratios and Effect Sizes for Multilevel Multiple Membership Models

Table C1a. Effect Sizes for Multilevel Model Results Predicting On-Time Graduation from High School

	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.20	-0.20
Hispanic		0.04
Black		0.07
Asian		0.22
Other		0.09
School mean poverty duration	-0.35	-0.60
School Percent Hispanic		0.07
School Percent Black		0.13
School Percent Asian		-0.04
School Percent Other		0.01

Table C1b. Odds Ratios for Multilevel Model Results Predicting On-Time Graduation from High School

	Unconditional	Poverty Main Effects	Poverty and Race
Intercept	3.83	7.32	7.65
Student poverty duration		0.58	0.57
Hispanic			1.16
Black			1.28
Asian			3.43
Other			1.40
School mean poverty duration		0.42	0.27
School Percent Hispanic			1.32
School Percent Black			1.70
School Percent Asian			0.88
School Percent Other			1.03

Table C2a. Effect Sizes for Multilevel Model Results Predicting Graduation from High School (Ever)		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.19	-0.21
Hispanic		0.08
Black		0.11
Asian		0.23
Other		0.10
School mean poverty duration	-0.13	-0.02
School Percent Hispanic		0.06
School Percent Black		-0.02
School Percent Asian		0.01
School Percent Other		0.16

Table C2b. Odds Ratios for Multilevel Model Results Predicting Graduation from High School (Ever)			
	Unconditional	Poverty Main Effects	Poverty and Race
Intercept	5.94	8.95	8.76
Student poverty duration		0.59	0.56
Hispanic			1.36
Black			1.59
Asian			3.52
Other			1.50
School mean poverty duration		0.68	0.93
School Percent Hispanic			1.24
School Percent Black			0.93
School Percent Asian			1.03
School Percent Other			2.02

Table C3a. Effect Sizes for Multilevel Model Results Predicting High School Dropout		
	Poverty Main Effects	Poverty and Race
Student poverty duration	0.16	0.17
Hispanic		-0.05
Black		-0.09
Asian		-0.18
Other		-0.07
School mean poverty duration	0.11	-0.02
School Percent Hispanic		-0.03
School Percent Black		0.05
School Percent Asian		-0.04
School Percent Other		-0.12

Table C3b. Odds Ratios for Multilevel Model Results Predicting High School Dropout			
	Unconditional	Poverty Main Effects	Poverty and Race
Intercept	0.12	0.08	0.08
Student poverty duration		1.74	1.81
Hispanic			0.76
Black			0.60
Asian			0.23
Other			0.68
School mean poverty duration		1.51	0.93
School Percent Hispanic			0.89
School Percent Black			1.23
School Percent Asian			0.84
School Percent Other			0.48

Table C4. Effect Sizes for Multilevel Model Results Predicting HSA Algebra Score		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.20	-0.16
Hispanic		-0.25
Black		-0.39
Asian		0.19
Other		-0.08
School mean poverty duration	-0.39	-0.27
School Percent Hispanic		0.05
School Percent Black		-0.03
School Percent Asian		0.11
School Percent Other		0.02

Table C5. Effect Sizes for Multilevel Model Results Predicting HSA English Score		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.23	-0.19
Hispanic		-0.28
Black		-0.36
Asian		0.08
Other		-0.03
School mean poverty duration	-0.35	-0.34
School Percent Hispanic		0.10
School Percent Black		0.08
School Percent Asian		0.12
School Percent Other		-0.03

Table C6a. Effect Sizes for Multilevel Model Results Predicting Enrollment in College within 1st Year of On-Time High School Graduation		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.20	-0.20
Hispanic		0.02
Black		0.09
Asian		0.32
Other		0.16
School mean poverty duration	-0.23	-0.25
School Percent Hispanic		0.05
School Percent Black		0.06
School Percent Asian		0.14
School Percent Other		-0.03

Table C6b. Odds Ratios for Multilevel Model Results Predicting Enrollment in College within 1st Year of On-Time High School Graduation			
	Unconditional	Poverty Main Effects	Poverty and Race
Intercept	1.96	2.56	2.78
Student poverty duration		0.66	0.65
Hispanic			1.04
Black			1.25
Asian			2.62
Other			1.49
School mean poverty duration		0.63	0.60
School Percent Hispanic			1.13
School Percent Black			1.15
School Percent Asian			1.42
School Percent Other			0.94

Table C7. Effect Sizes for Multilevel Model Results Predicting Annual Wages in First Year after On-Time High School Graduation (For Non-College Enrollees)		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.04	-0.03
Hispanic		0.10
Black		-0.21
Asian		-0.05
Other		-0.11
School mean poverty duration	-0.06	0.01
School Percent Hispanic		0.00
School Percent Black		-0.06
School Percent Asian		-0.07
School Percent Other		-0.02

Table C8. Effect Sizes for Multilevel Model Results Predicting Annual Wages in First Year after On-Time High School Graduation (For College Enrollees)		
	Poverty Main Effects	Poverty and Race
Student poverty duration	0.09	0.10
Hispanic		0.20
Black		-0.15
Asian		-0.11
Other		-0.08
School mean poverty duration	0.03	0.15
School Percent Hispanic		-0.07
School Percent Black		-0.13
School Percent Asian		-0.08
School Percent Other		0.01

Appendix D
Additional Outcomes

Table D1a. Multilevel Modeling Results Predicting Obtaining GED or Ever Graduating from High School			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	2.05***(0.12)	2.52***(0.10)	2.42***(0.09)
Student poverty duration		-0.55***(0.02)	-0.57***(0.02)
Hispanic			0.15*(0.07)
Black			0.28***(0.05)
Asian			1.10***(0.15)
Other			0.30**(0.10)
School mean poverty duration		-0.52***(0.07)	-0.35*(0.14)
School Percent Hispanic			0.26*(0.10)
School Percent Black			0.08(0.13)
School Percent Asian			-0.07(0.10)
School Percent Other			0.65***(0.07)
Model fit (Bayesian DIC)	26959.75	26040.06	26040.06
Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 54,465.			

Table D1b. Effect Sizes for Multilevel Model Results Predicting Obtaining GED or Ever Graduating from High School		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.16	-0.19
Hispanic		0.04
Black		0.06
Asian		0.18
Other		0.07
School mean poverty duration	-0.15	-0.10
School Percent Hispanic		0.06
School Percent Black		0.02
School Percent Asian		-0.02
School Percent Other		0.13

Table D1c. Odds Ratios for Multilevel Model Results Predicting Obtaining GED or Ever Graduating from High School			
	Unconditional	Poverty Main Effects	Poverty and Race
Intercept	7.74	12.49	11.24
Student poverty duration		0.58	0.57
Hispanic			1.17
Black			1.32

Asian			3.01
Other			1.35
School mean poverty duration		0.59	0.70
School Percent Hispanic			1.29
School Percent Black			1.09
School Percent Asian			0.94
School Percent Other			1.92

Table D2a. Multilevel Modeling Results Predicting PSAT Math Score

	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	40.45***(0.34)	42.59***(0.67)	43.04***(0.23)
Student poverty duration		-2.83***(0.06)	-2.27***(0.23)
Hispanic			-3.69***(0.18)
Black			-5.09***(0.14)
Asian			4.81***(0.21)
Other			-0.91***(0.22)
School mean poverty duration		-3.59***(0.25)	-2.17***(0.30)
School percent Hispanic			-0.05(0.24)
School percent Black			0.50(0.29)
School percent Asian			2.85***(0.27)
School percent Other			-0.19(0.21)
Model fit (Bayesian DIC)	350363.81	347856.27	345461.45

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 47,162.

Table D2b. Effect Sizes for Multilevel Model Results Predicting PSAT Math Score

	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.24	-0.19
Hispanic		-0.31
Black		-0.42
Asian		0.40
Other		-0.08
School mean poverty duration	-0.30	-0.18
School Percent Hispanic		0.00
School Percent Black		0.04
School Percent Asian		0.24
School Percent Other		-0.02

Table D3a. Multilevel Modeling Results Predicting PSAT Verbal Score			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	40.73***(0.32)	42.62***(0.27)	42.99***(0.22)
Student poverty duration		-2.83***(0.05)	-2.33***(0.05)
Hispanic			-3.66***(0.17)
Black			-4.54***(0.14)
Asian			2.14***(0.20)
Other			-0.56**(0.21)
School mean poverty duration		-3.03***(0.23)	-2.15***(0.29)
School percent Hispanic			0.28(0.23)
School percent Black			0.82**(0.29)
School percent Asian			2.34***(0.26)
School percent Other			-0.12(0.20)
Model fit (Bayesian DIC)	347244.44	344578.36	343060.13
Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. N = 47,193.			

Table D3b. Effect Sizes for Multilevel Model Results Predicting PSAT Verbal Score		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.25	-0.21
Hispanic		-0.32
Black		-0.40
Asian		0.19
Other		-0.05
School mean poverty duration	-0.27	-0.19
School Percent Hispanic		0.02
School Percent Black		0.07
School Percent Asian		0.21
School Percent Other		-0.01

Table D4a. Multilevel Modeling Results Predicting PSAT Writing Score			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	38.82***(0.38)	40.67***(0.28)	41.07***(0.24)
Student poverty duration		-2.74***(0.05)	-2.29*** (0.06)
Hispanic			-3.12***(0.18)
Black			-4.08***(0.14)
Asian			2.31***(0.21)
Other			-0.61**(0.22)
School mean poverty duration		-2.97***(0.23)	-2.17***(0.32)
School percent Hispanic			0.36(0.25)
School percent Black			1.02***(0.30)
School percent Asian			2.79***(0.28)
School percent Other			-0.06(0.20)
Model fit (Bayesian DIC)	347698.74	345332.27	344119.88
Note. **p* < 0.05, ***p* < 0.01, ****p* < 0.001. N = 46,988.			

Table D4b. Effect Sizes for Multilevel Model Results Predicting PSAT Writing Score		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.24	-0.20
Hispanic		-0.27
Black		-0.35
Asian		0.20
Other		-0.05
School mean poverty duration	-0.26	-0.19
School Percent Hispanic		0.03
School Percent Black		0.09
School Percent Asian		0.24
School Percent Other		-0.01

TableD5a. Multilevel Modeling Results Predicting SAT Math Score			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	449.40***(4.21)	474.79***(2.76)	478.78***(2.22)
Student poverty duration		-25.21***(0.69)	-18.58***(0.70)
Hispanic			-43.28***(2.18)
Black			-64.73***(1.72)
Asian			39.34***(2.21)
Other			-17.39***(2.59)
School mean poverty duration		-54.43***(2.49)	-26.92***(3.51)
School percent Hispanic			3.09(2.33)
School percent Black			-6.69*(3.05)
School percent Asian			23.62***(2.67)
School percent Other			7.33**(2.31)
Model fit (Bayesian DIC)	403046.36	401793.32	399526.02
Note. **p* < 0.05, ***p* < 0.01, ****p* < 0.001. N = 33,534.			

Table D5b. Effect Sizes for Multilevel Model Results Predicting SAT Math Score		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.19	-0.14
Hispanic		-0.33
Black		-0.50
Asian		0.30
Other		-0.13
School mean poverty duration	-0.42	-0.21
School Percent Hispanic		0.02
School Percent Black		-0.05
School Percent Asian		0.18
School Percent Other		0.06

Table D6a. Multilevel Modeling Results Predicting SAT Verbal Score			
	Unconditional	Poverty Main Effects	Poverty and Race
	β (SE)	β (SE)	β (SE)
Intercept	450.33***(3.83)	472.68***(2.52)	475.97***(2.13)
Student poverty duration		-24.81***(0.68)	-19.09***(0.70)
Hispanic			-39.34***(2.16)
Black			-54.45***(1.71)
Asian			11.21***(2.20)
Other			-13.43***(2.57)
School mean poverty duration		-48.37***(2.28)	-29.54***(3.37)
School percent Hispanic			6.81**(2.24)
School percent Black			-0.81(2.94)
School percent Asian			19.62***(2.56)
School percent Other			6.16**(2.23)
Model fit (Bayesian DIC)	401565.00	400290.56	399040.11
Note. *p < 0.05, **p < 0.01, ***p < 0.001. N = 33,534.			

Table D6b. Effect Sizes for Multilevel Model Results Predicting SAT Verbal Score		
	Poverty Main Effects	Poverty and Race
Student poverty duration	-0.20	-0.16
Hispanic		-0.32
Black		-0.45
Asian		0.09
Other		-0.11
School mean poverty duration	-0.40	-0.24
School Percent Hispanic		0.06
School Percent Black		-0.01
School Percent Asian		0.16
School Percent Other		0.05