Expanding the Understanding of School Concentrated Disadvantage Using Free and Reduced-Price Meals Data: Links to College and Labor Market Outcomes in Maryland

Corresponding Author:
Angela K. Henneberger
University of Maryland School of Social Work
525 W. Redwood St.
Baltimore, MD 21201
ahenneberger@ssw.umaryland.edu

Bess A. Rose
University of Maryland School of Social Work

Dawnsha R. Mushonga
University of Baltimore

Boyoung Nam
Yonsei University

Alison M. Preston
University of Maryland School of Social Work

Suggested Citation:

Henneberger, A.K., Rose, B.A., Mushonga, D.R., Nam, B., & Preston, A.M. (in press). Expanding the understanding of school concentrated disadvantage using free and reduced-price meals data: Links to college and labor market outcomes in Maryland. *Journal of Education for Students Placed at Risk.*

Acknowledgement: This research was supported by the Maryland Longitudinal Data System (MLDS) Center. We are grateful for the assistance provided by the MLDS Center. Prior versions of this manuscript were published by the MLDS Center and findings were presented to multiple local and statewide stakeholder audiences. We appreciate the feedback received from the MLDS Center and its stakeholder partners. Additionally, we thank the panelists and attendees at multiple academic conferences and the anonymous reviewers of the current journal for helpful feedback on this manuscript. All opinions are the authors' and do not represent the opinion of the MLDS Center or its partner agencies.

Abstract

School concentrated disadvantage has been linked to poorer academic achievement and psychosocial functioning in prior research. The current study expands upon prior examinations of school concentrated disadvantage by applying a measurement approach first described by Michelmore and Dynarksi (2017), where eligibility for free and reduced-price meals (FRPM) is examined over time and the duration of eligibility serves as the key indicator of student disadvantage. We used data from a linked longitudinal administrative data system in Maryland, and we measured disadvantage using the proportion of years a student was eligible for FRPM between 6th and 12th grades (see Michelmore & Dynarski, 2017). This measure was aggregated to the school level to measure school concentrated disadvantage. We found that school-level concentrated disadvantage was uniquely, and more strongly related to college enrollment than individual student-level disadvantage. However, early labor market outcomes tended to be more strongly linked to race/ethnicity than experiences with disadvantage. We highlight the need for additional targeted resources for students in schools with high concentrations of disadvantaged students.

Keywords: disadvantage; concentrated disadvantage; eligibility for free and reduced-price meals; college enrollment; labor market outcomes

Student disadvantage, traditionally measured using student eligibility for free or reduced-price meals (FRPM), has long been a factor for identifying students who are at risk for poorer educational outcomes (Caldas & Bankston, 2005; Coleman, 1968). Early seminal analyses (e.g., Coleman, 1968) brought attention to the importance of school factors for identifying risk, and school concentrated disadvantage, traditionally measured by aggregating the student-level FRPM measure to the school-level, was of keen interest (Borman & Dowling, 2010; Caldas & Bankston, 1997; Crosnoe, 2009; Gollner et al., 2018; Konstantopoulos & Borman, 2011; Rumberger & Palardy, 2005). However, concerns with the FRPM measure in education sciences call into question its validity and reliability for identifying students at risk (Bass, 2010; Domina et al., 2018; Fazlul et al., 2021; Harwell & LeBeau, 2010; Michelmore & Dynarski, 2017). The current study expands upon prior examinations of school concentrated disadvantage by applying an approach that was first described by Michelmore and Dynarksi (2017), where students' FRPM eligibility was examined over time and the duration spent receiving FRPM was the key predictor of interest. Here, we aggregate that measure to the school level, leveraging linked administrative data from Maryland to examine the role of middle and high school concentrated disadvantage on academic outcomes, including college enrollment, and early labor market outcomes, including early labor market earnings.

Concentrated Disadvantage and Long-term Academic and Early Labor Market Outcomes

Bronfenbrenner's (1992) ecological systems theory underscores the importance of the developmental context in producing developmental outcomes, above and beyond the role of individual-level factors. The school and the neighborhood are two of the most proximal contexts for development (Bronfenbrenner & Morris, 1998). Public school boundaries typically follow neighborhood geographic boundaries, and as a result, measures of school context are often confounded with measures of neighborhood context. Historically, increasing residential segregation by income level between 1990 and 2009 has resulted in concentrated levels of disadvantage within neighborhoods (Bischoff & Reardon, 2014) and within schools (Reardon & Owens, 2014).

A substantial body of research examines the role of concentrated disadvantage by linking neighborhood composition to future child cognitive development, social and emotional development, and educational outcomes (Brooks-Gunn et al., 1997; Duncan et al., 1994; Klebanov et al., 1998; Jencks & Mayer, 1990; Leventhal & Brooks-Gunn, 2000; Mayer, 2002). Evidence from observational studies suggests that prolonged residence in poor neighborhoods is detrimental to educational outcomes, including significant links to lower academic achievement scores, lower verbal ability, and higher rates of high school dropout (Burdick-Will et al. 2011; Harding 2003; Sampson et al., 2008; Wodtke et al., 2011). Recent experimental evidence from the Moving to Opportunity (MTO) study, an experimental study where a random sample of low-income residents were offered housing vouchers to move to higher income neighborhoods, initially showed few significant long-term impacts of moving to a higher income neighborhood on long-term educational and career outcomes (Kling et al., 2007; Ludwig et al. 2013). However, more recent evidence from the MTO study indicates 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 et al., 2015). Additionally, a recent study conducted by Levy (2019) used data from the National Study of Adolescent Health and reported little evidence that neighborhood concentrated poverty was linked to college matriculation, but concentrated poverty had a robust linkage with the odds of graduating from college. School composition played a role in the mechanisms through which neighborhood concentrated poverty was linked to college outcomes (Levy, 2019).

A large body of research also examines concentrated disadvantage by examining school-level composition. A seminal re-analysis of the data from the Equality of Educational Opportunity (EEO) study, or the “Coleman Report” (Coleman, 1968) found that, across a national sample of schools, the social class composition of a student’s school was more than 1¾ times more important than a student’s individual social class for understanding educational outcomes (Borman & Dowling, 2010). Concentrated levels of disadvantage within a school have been consistently linked to negative student outcomes, including academic achievement and psychosocial problems (Caldas & Bankston, 1997; Crosnoe, 2009; Gollner et al., 2018; Konstantopoulos & Borman, 2011; Rumberger & Palardy, 2005), despite variations in structure of studies and how school-level disadvantage, is measured.

In the United States, a disproportionately high number of Black, Indigenous, People of Color (BIPOC) and Latinx children experience disadvantage in terms of income (Drake & Rank, 2009; Koball & Jiang, 2018), and schools with larger minority populations tend to have higher rates of disadvantage (Reardon, 2016). BIPOC and Latinx children experience historical and systemic biases and discrimination that are interwoven into the educational and labor market institutions in this country, producing inequalities that concentrate disadvantage among minority families, and subsequently within the schools they attend (Borman & Dowling, 2010; Wilson & Rodgers, 2016). Some research evidence suggests that the achievement gaps between minority and majority students may be more accurately explained by income (Walton & Spencer, 2009) and that the composition of student disadvantage within schools is the driving factor linking school racial composition to academic outcomes (Rumberger & Palardy, 2005).

Measuring Disadvantage and School Concentrated Disadvantage

Disadvantage, including experiences with poverty, is consistently linked to poorer physical health, academic achievement, and social, emotional, and behavioral functioning (Alexander et al., 2014; Leventhal & Brooks-Gunn, 2000). In educational studies, student disadvantage is traditionally measured using students' eligibility for FRPM at a single point in time using data from the National School Lunch Program (U.S. Department of Agriculture [USDA], 2017). Students can qualify through submitting applications to their schools, in which case, eligibility for reduced-price meals indicates a monthly household income below 185% of the poverty line and eligibility for free meals indicates a monthly household income below 130% of the poverty line. Relative to the federal poverty level of $24,858 for the 2017-2018 school year, a family of four must have had annual earnings below $31,980 to qualify for free meals and below $45,510 to qualify for reduced-price meals. Students can also qualify for FRPM through direct certification, the result of data sharing through which school systems identify students in households that receive other income-based federal benefits, including the Supplemental Nutrition Assistance Program (SNAP; formerly known as Food Stamps), the Special Supplemental Nutrition Program for women, infants, and children (WIC), or welfare services. Student eligibility for FRPM at a point in time is typically aggregated to the school level to calculate the percentage of students eligible for FRPM to create a measure of school concentrated disadvantage (Caldas & Bankston, 1997; Hanushek et al., 2003; Kim & Sunderman, 2005).

A key limitation for using FRPM in educational sciences is that FRPM is traditionally used as a proxy for poverty, but research shows a misalignment between FRPM and poverty in the United States (Bass, 2010; Domina et al., 2018; Fazlul et al., 2021; Harwell & LeBeau, 2010). The eligibility for FRPM indicator is a crude categorical variable that reduces the variation in student and school poverty experiences. Nearly half of students in the U.S. are eligible for FRPM, yet only a quarter of children in the U.S. live in poverty, highlighting a misalignment in the use of FRPM at a point in time as the sole measure of poverty (Michelmore & Dynarksi, 2017). Domina and colleagues (2018) linked IRS income tax data to school administrative records for eighth graders in California and Oregon and reported substantial variation in household income among students in the same FRPM category. Furthermore, two students who were not eligible for FRPM at the start of a research study may have two very different FRPM histories. For example, a student who was never eligible for FRPM prior to the study could have the same value on the FRPM indicator as a student who was intermittently eligible for FRPM prior to the study. Prior developmental research shows that children who experience persistent disadvantage have more detrimental outcomes than children who experience transitory disadvantage (McLoyd, 1998; Najman et al., 2009), and children who experience disadvantage earlier in life have more detrimental outcomes than those who experience disadvantage later in life (Duncan et al., 2012). These nuances are lost when measuring disadvantage using FRPM at a single point in time.

That point in time measure of FRPM is typically aggregated to the school-level to create a measure of school concentrated disadvantage (see van Ewijk & Sleegers, 2010 for a meta-analytic review of limitations in measuring effects of peers' socio-economic status). However, Domina and colleagues (2018) found that the degree to which FRPM captured student disadvantage across schools was highly variable. That is, for some schools the traditional FRPM measure aligned very well with household income; however, in other schools, the measures of FRPM and household income were misaligned. Subsequently, the school aggregated measure of concentrated disadvantage may be an imprecise measure of school-level disadvantage and may be more or less precise for certain types of schools (Domina et al., 2018). An additional key obstacle to examining school concentrated disadvantage using education data since 2013-14 has been the introduction of the community eligibility provision (CEP), which allows eligible schools to serve all enrolled children free meals, regardless of household income (Koedel & Parsons, 2021). A further complication is that CEP schools may or may not continue to administer FRPM application forms, which may blur the understanding of student disadvantage in later years after the introduction of CEP.

To address these limitations, Michelmore and Dynarksi (2017) leveraged the longitudinal nature of administrative data in Michigan to develop a new measure of disadvantage by measuring the proportion of years the student was eligible for FRPM over time. This measure was validated using data from the Early Childhood Longitudinal Study-Kindergarten Class of 1998-1999 to provide evidence that the number of years a child spends eligible for FRPM was a reasonable proxy for household income, with children who were persistently disadvantaged being more likely to live with a single parent, have more siblings residing in the household, and have parents with lower levels of education when compared to children who were never disadvantaged. There are several advantages of this measure over the traditional point in time measure of student disadvantage, including increased variation and the ability to differentiate students who were persistently disadvantaged, transitorily disadvantaged, or never disadvantaged. Michelmore and Dynarski reported that children who spent all their school years in kindergarten through eighth grade eligible for FRPM had the lowest scores on standardized tests in eighth grade, and children who spent none of their school years eligible for FRPM had the highest scores. Children who were persistently eligible for FRPM scored nearly one standard deviation below students who were never disadvantaged, whereas, using the traditional point in time measure of student disadvantage, the gap was only about 0.69 standard deviations.

The Current Study

This study used statewide administrative data from secondary, postsecondary, and labor market records for a single cohort of students who were in 6th grade in the 2007-08 academic year. These data are of policy importance, as states, including Maryland, continue to use early K-12 experiences to understand risk in terms of experiencing more negative college and career outcomes. Many states are focusing on concentrations of student disadvantage in particular, and in Maryland, the state was considering updating funding formulas for at-risk students to include increased funding for each student in a school with high levels of concentrations of student disadvantage, as measured by a threshold indicator. The goal of the current study was to extend the prior research of Michelmore and Dynarksi (2017) to research on school concentrated disadvantage by aggregating student-level disadvantage calculated using the proportion of enrollment records since sixth grade in which the student was eligible for FRPM to the school level. We applied multilevel multiple membership modeling to nest students in each school they attended between 6th and 12th grades. We answer the following research question: *What is the association between school concentrated disadvantage between 6th and 12th grades and (i) college enrollment; (ii) workforce participation in Maryland; and (iii) early labor market earnings in Maryland?* We provide evidence for a link between school concentrated disadvantage and college enrollment and early labor market outcomes. These quantitative findings can be used to help other users of administrative data address challenges with the use of FRPM to measure concentrated disadvantage in schools.

Method

Data and Cohort

This study used population-level linked longitudinal administrative data from the Maryland Longitudinal Data System (MLDS). The MLDS links State PreK-12 data records with postsecondary and workforce data to support decision makers regarding students' education experience and career achievement. Longitudinal data records are obtained from three state agencies; PreK-12 student and school data are obtained from the Maryland State Department of Education (MSDE). Maryland public and private college student and college data are obtained from the Maryland Higher Education Commission (MHEC). Data for out-of-state college enrollments and degrees are obtained by MSDE through the National Student Clearinghouse. Workforce data are obtained from the Maryland Department of Labor for Maryland employees who work for employers who are subject to Maryland's Unemployment Insurance (UI) law. Federal employees, military employees, individuals who are self-employed, and private contractors are excluded from the workforce data. Research with the MLDS was approved by the University of Maryland Institutional Review Board and no consent or assent was necessary.

The cohort of students who were in 6th grade in the 2007-2008 academic year (the first year of MLDS data; N=63,282) was used for the current study. This provided a reliable measure of student eligibility for free/reduced price meals (across students' entire middle and high school years) as well as a full year of postsecondary and workforce data post-high school (for those who graduated on time in 2013-2014). Students (n=10,672) were excluded from the final sample for the following reasons: (1) transferring out of the Maryland public school system (n=7,811); (2) never enrolled in any Maryland public school at any time during 9th through 12th grade despite not being recorded as transfers out of Maryland public schools (n=955); and (3) missing values for race/ethnicity (*n*=414) or 6th grade academic performance data (*n*=1,492). Thus, the final analytic sample consisted of 52,610 students.

Measures

Student disadvantage. Student disadvantage was defined and measured as the duration of time eligible for free and reduced-price meals (FRPM) between 6th and 12th grade.[1] Students living in households with incomes at or below 130% of the federal poverty level were eligible for free meals, while students living in households with incomes between 130% and 185% of the federal poverty level were eligible for reduced-priced meals (USDA, 2017).[2] The MLDS includes annual records for each K12 enrollment for each student (with multiple records per year for students who changed schools during the school year). These enrollment records indicate whether the student was eligible for FRPM (below 185% of the poverty line) at that point in time. For this study, for each student in grades 6 through 12, the entire database of enrollment records in which the student was indicated as FRPM eligible as of the end of each school year, from 2007-2008 through 2015-2016, was summarized to create a cumulative proportion. The final measure reflected the cumulative proportion of enrollments in 6th through 12th grades that indicated the student was eligible for FRPM. For most students this reflected their FRPM duration between 6th and 12th grades. For dropouts, this measure reflected their FRPM duration as of their last year in school. This student disadvantage variable ranged from 0 (never disadvantaged) to 1 (always disadvantaged). For the multilevel analyses (see section on analytic strategy, below), the variable was multiplied by 10 to create a range from 0 to 10, and as such, a 1-unit change reflects the change in outcome for a 10-percentage point change in student disadvantage duration.

Student race/ethnicity. Student race and ethnicity[3] was recoded into dummy variables for non-Hispanic White, non-Hispanic Black/African American, and Other (including Hispanic of any race, American Indian, Asian, Pacific Islander, two or more races).

Student baseline academic performance. Students' achievement in reading and math at baseline (6th grade) was measured using their scale scores on the 2008 Maryland School Assessments (MSA) in Reading and Math. The MSA tests, part of Maryland's accountability system under No Child Left Behind, were developed by MSDE and Pearson with the involvement of a National Psychometric Council as well as committees that reviewed for content, bias, and vision accessibility. The tests were aligned to the Maryland reading and math standards set forth in the Voluntary State Curriculum and were administered statewide in April 2008.

School concentrated disadvantage. School concentrated disadvantage was measured by creating a school-by-year measure calculating the mean of the student-by-year cumulative annual disadvantage duration measure for each school for each school year. This reflected the mean disadvantage duration of all students in grades 6-12 in the school as of the end of each year. For the study cohort, this school-by-year measure was then linked to each student's enrollment record(s) in each school. Each cohort member's overall school context was then assessed by taking the mean school disadvantage across all schools attended over the course of their enrollment in grades 6 through 12. The initial school disadvantage variable ranged from near 0 (average student in the school experienced nearly no disadvantage) to near 1 (average student in the school experienced nearly constant disadvantage). Like the scaling of the student disadvantage variable, for the multilevel analyses, the school disadvantage variable was rescaled by multiplying by 10.

School racial/ethnic composition. The proportion of White, Black, and Other students for each school for each academic year was obtained first by linking compiled school-by-year MLDS data with public data from the Common Core of Data provided by the National Center for Educational Statistics. For each student, the mean of each of these proportions was calculated from all the schools each student attended from grades 6 to 12. This value was rescaled by multiplying by 10.

School baseline academic performance. The academic performance of each school at baseline was measured using the school mean 2008 MSA Reading and Math Grade 6 scores. Due to high collinearity between school mean reading scores and school mean math scores, the two mean scores for each school were averaged to obtain a single measure of school baseline academic performance.

College enrollment. Enrollment records in Maryland and out-of-state public and private 2-year and 4-year colleges were used to indicate college enrollment among those who graduated from high school on time (2013-2014 academic year). Students with any record of postsecondary enrollment including non-degree programs were considered as enrolled.

Labor market participation. Students who appeared in the Maryland labor data in any of the first four quarters after on-time high school graduation were assigned 1 to indicate participation in the Maryland labor market, and those who did not appear were assigned 0.

Labor market earnings. The sum of Maryland quarterly earnings in the first four quarters after on-time high school graduation was calculated for each student. The earnings variable was log-transformed due to high skewness.

Analytic Strategy

Multiple membership multilevel modeling was used to examine the link between school-level disadvantage (and other school-level factors) and student-level disadvantage (and other student-level factors) and academic and labor market outcomes, while also accounting for the fact that most students attended more than one school over the study time frame (6^{th} through 12^{th} grades). 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; Raudenbush & Bryk, 2002). 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 6^{th} grade through leaving high school, 22% of students attended three schools, and 3% attended 6 or more. Less than one percent of the analytic sample attended one school for the entire period. Therefore, a multiple membership approach[4] (Beretvas, 2011) was used to nest students in all schools attended over the period of the study.

A sequential modeling approach was used where, first, each outcome of interest was modeled with an unconditional model (Model 1). In model 2, terms for student and school disadvantage were added. In model 3, student race/ethnicity (White is the omitted reference category) and school racial/ethnic composition were added. In model 4, student's grade 6 MSA Reading and Math scores and school mean MSA were added. All level 1 variables were group-mean centered, and all level 2 variables were grand-mean centered (Bell et al., 2018; Enders & Tofighi, 2007). The full model was a random intercept model.

At Level 1 (students) the outcome Y of student i who attended the set of schools $\{j\}$ was modeled as the mean outcome for average students attending the set of schools $\{j\}$, $\beta_{0\{j\}}$. β_1, β_2, β_3, β_4, and β_5 estimate the association between student disadvantage, Black or Other-race, and

MSA scores in Reading and Math and the outcome, respectively. A student residual, $e_{i\{j\}}$, represents the distance of the individual student's outcome from the mean.

Level 1 (students):

$$Y_{i\{j\}} = \beta_{0j} + \beta_{1j}StDisadvantage_{i\{j\}} + \beta_{2j}Black_{i\{j\}} + \beta_{3j}Other_{i\{j\}} + \beta_{4j}MSAR_{i\{j\}} + \beta_{5j}MSAM_{i\{j\}} + e_{i\{j\}}$$

At Level 2 (schools) the level 1 intercept, $\beta_{0\{j\}}$, was modeled as the overall mean, γ_{00}, plus the sum of the weighted between-school contributions of school disadvantage, school percentages of Black and Other-race students, and school mean MSA scores, γ_{01}, γ_{02}, γ_{03}, and γ_{04}, respectively, and weighted school residuals across all schools in the set *{j}* (Beretvas, 2011). There is a single parameter for each school-level factor, e.g., γ_{01} for school disadvantage, because we assume that the relationship between the school characteristic and the outcome is constant across schools, but we used a weighted average of the values of the school-level variables across the set of *{j}* schools attended by student *i* (Beretvas, 2011).

Level 2 (schools):

$$\begin{aligned}\beta_{0j} = \gamma_{00} + \sum_{h\epsilon\{j\}} & [w_{ih}(\gamma_{01}(SchDisadvantage_h - MeanSchDisadvantage_{..}) + \gamma_{02}(PctBlack_h \\ & - MeanPctBlack_{..}) + \gamma_{03}(PctOther_h - MeanPctOther_{..}) + \gamma_{04}(MeanMSA_h \\ & - MeanMeanMSA_{..}) + u_{0h})]\end{aligned}$$

For model parsimony all level-1 variables were constrained as fixed at level 2 (preliminary analyses indicated very small, though statistically significant, level-2 variation in student disadvantage slopes for some outcomes).

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

$$\beta_{2j} = \gamma_{20}$$

$$\beta_{3j} = \gamma_{30}$$

$$\beta_{4j} = \gamma_{40}$$

$$\beta_{5j} = \gamma_{50}$$

Binary outcomes (e.g., 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 (Browne, 2017; Charlton et al., 2017) from Stata/SE version 15 using runmlwin (Leckie & Charlton, 2012). This Bayesian approach enables estimation of models that are not otherwise estimable due to limited computing power (Browne, 2017). Informative priors were used based on single membership models. Defaults were used for the burn-in period (500 iterations) and the monitoring chain period (5,000 iterations). Models for Maryland labor market participation and earnings were conducted separately for students who enrolled in postsecondary in Maryland colleges and students who did not enroll in postsecondary.

Results

Descriptive Statistics

Descriptive statistics for the final analytic sample can be found in Table 1 (Panel A). The mean duration of FRPM eligibility was 0.35 (*SD* = 0.42; i.e., the average student in our study was eligible for FRPM about 35% of the time from 6th through 12th grade). Forty-six percent of students were White and 35% were Black. Nineteen percent of students were Other-race. The mean school-level duration of FRPM eligibility was 0.36 (*SD* = 0.22; i.e., the average school enrolled students who were eligible for FRPM about 36% of the time from 6th through 12th grade). We provide descriptive statistics by two measures of student disadvantage. First, students were categorized based on their duration of disadvantage as *never* (none of their school enrollment records indicated they were eligible for FRPM), *sometimes* (eligible for FRPM at least once but less than 50 percent of the time), *usually* (eligible for FRPM more than 50 percent of the time but less than 100 percent), or *always* (eligible for FRPM on all their school enrollment records). Second, students were categorized in terms of the final point-in-time measure of FRPM using students' last middle school record. Demographic characteristics differed among categories of student disadvantage using both measures. Black and Other-race students and students with lower standardized test scores were disproportionately represented in higher-disadvantage categories (see Figure 1).

Sample characteristics also differed among school disadvantage categories (see Table 2, panel A). We provide descriptive statistics by two measures of school concentrated disadvantage. First, school contexts were categorized based on the aggregate FRPM duration of enrolled students into low (M = 0.01 – 0.24), medium (M = 0.24 – 0.46), or high (M = 0.46 – 0.96) concentrated disadvantage. Second, school contexts were categorized based on the aggregate final point-in-time measure of FRPM using students' last middle school record into low (M = 0.01 – 0.18), medium (M = 0.18 – 0.39), or high (M = 0.39 – 0.96) concentrated disadvantage. Schools with higher levels of concentrated disadvantage, whether measured by mean FRPM duration or the percentage of students who were eligible for FRPM at the final middle school record, had disproportionate enrollment of Black students and had poorer average MSA reading and math scores (see Figure 2).

Figure 3 shows the correlations between the two measures of school concentrated disadvantage: (i) aggregate FRPM duration on the X axis and (ii) aggregate FRPM at the final middle school record on the Y axis. The two measures are positively correlated with a correlation coefficient ranging from 0.91 in 2015 to 0.96 in 2009. Descriptive statistics also indicate that both measures show increasing school concentrated disadvantage between 2008 and 2015. The mean for FRPM duration increased from 0.41 (SD = 0.24) in 2008 to 0.54 (SD = 0.28) in 2015.

Similarly, the mean for aggregate FRPM at the final middle school record increased from 0.42 (*SD* = 0.26) in 2008 to 0.51 (*SD* = 0.28) in 2015.

Descriptive statistics for all dependent variables examined in this study are also included in Table 1 (Panel B). Overall, 90 percent of students graduated from high school by 2017 (on-time graduation for this cohort would have been in 2014) and 9 percent dropped out of school. Seventy-three percent enrolled in college within the first year of high school graduation (only on-time high school graduates are included in this measure due to data availability). Among students who were not enrolled in college, 75% appeared in the Maryland labor market and these students earned on average about $8,161 in total earnings in the first year after graduating from high school. Among students who were enrolled in Maryland colleges (46% of our sample), 76% appeared in the Maryland labor market and these students earned on average about $5,286.

Multilevel Analyses

College enrollment. Table 3 presents the results of the multilevel modeling approach predicting college enrollment within the first year of on-time high school graduation. The unconditional model (Model 1) showed that the model intercept, or the average log odds of enrolling in college, was 0.68; exponentiating this value converts to odds of 1.97 and converting to a probability 1.97/ (1+1.97) = 0.66, indicating that the overall average probability of enrolling in college is 66%. The odds of enrolling in college varies across schools; this variation is represented by the level-2 variance component which was 2.05. In multilevel models with a binary outcome, the dependent variable is assumed to follow a logistic distribution with level-1 variance equal to $\pi^2/3$ or approximately 3.29 (Hedeker, 2003; Hox et al., 2018). Thus, the intra-class correlation coefficient, calculated by dividing the level-2 variance component (2.05) by the level 1 variance plus the level 2 variance (i.e., the total variance; 3.29 + 2.05 = 5.34) was 0.38, indicating that 38% of the variance in college enrollment was at the school level (i.e., due to differences between schools).

Model 2 indicated that higher levels of student- (B = -0.10, $p < .001$) and school-level (B = -0.32, $p < .001$) disadvantage were significantly associated with lower likelihood of enrolling in college. Model 3 indicated that the significant associations between student- and school-level disadvantage remained after adding student race and school-level racial composition. Black students (B = 0.27, $p < .001$) and Other-race students (B = 0.33, $p < .001$) had significantly higher likelihoods of enrolling in college when compared to White students at similar levels of disadvantage and in similar schools. The percentage of Black students in the school (B = 0.10, $p < .001$) and the percentage of Other-race students in the school (B = 0.23, $p < .001$) were significantly associated with higher likelihood of enrolling in college. Model 4 indicated that results remained significant even after adjusting for student- and school-level scores on the 6^{th} grade MSA. Results were similar for graduating from high school and drop out, and these results are available from the first author upon request.

Labor market participation and earnings. Table 4 presents the results of the final multilevel models (Model 4) predicting labor market participation and logged annual earnings within the first year after on-time high school graduation, separately for non-college enrollees and for students who enrolled in college in Maryland. For the earnings models, only individuals with some positive earnings were included in the models. Models 1-3 for each outcome are available from the first author upon request. Panels 1 and 2 present results for non-college enrollees. Panel 1 indicates that school-level disadvantage (B = 0.07, $p < .01$), but not student-level disadvantage (B = 0.01, $p > .05$), was significantly associated with higher likelihood of labor market participation for students who were not enrolled in college. Additionally, for students who were not enrolled in college, Other-race students (B = -0.69, $p < .001$) and students attending schools with higher proportions of Black (B = -0.11, $p < .001$) and Other-race students (B = -0.22, $p < .001$) had lower likelihoods of labor market participation. Panel 2 displays the results from the multilevel model predicting early labor market earnings for students not enrolled in college. Panel 2 indicates that student-level disadvantage (B = -0.01, $p <.05$), but not school-level disadvantage (B = -0.01, $p > .05$) was significantly negatively associated with earnings within the first year after on-time high school graduation for students who were not enrolled in college. Black-race at the student-level (B = -0.27, $p < .001$) and the school-level (B = -0.06, $p < .001$) were significantly negatively associated with earnings.

Panels 3 and 4 present results for cohort members who were enrolled in a Maryland college during the first year after on-time high school graduation. Panel 3 indicates that both student-level (B = 0.03, $p < .001$) and school-level (B = 0.08, $p < .001$) disadvantage were related to significantly higher odds of participation in the labor market for students who were enrolled in a Maryland college. Black-race (B = -0.25, $p < .001$) and Other-race (B = -0.59, $p < .001$) at the student-level and school-levels (B = -0.15, $p < .001$ for % Black and B = -0.24, $p < .001$ for % Other) were related to significantly lower odds of participation in the labor market for students who were enrolled in a Maryland college. Panel 4 indicates that student-level disadvantage (B = 0.02, $p <.001$) and school-level disadvantage (B = 0.10, $p < .001$) were significantly associated with higher earnings within the first year after on-time high school graduation for students who were enrolled in college. Black-race at the student-level (B = -0.32, $p < .001$) and school-level Black- (B = -0.09, $p < .001$) and Other- (B = -0.08, $p < .001$) racial composition were significantly associated with lower earnings.

Discussion

This study is among the first to extend the Michelmore and Dynarksi (2017) measure of disadvantage, examining the proportion of enrollment years eligible for FRPM in secondary school, aggregating to the school-level to create a measure of school concentrated disadvantage. We demonstrated negative links between school-level concentrated disadvantage and college enrollment, above and beyond the links between student disadvantage, race/ethnicity, and baseline academic achievement and college enrollment. In the fully adjusted models, we found that a 10-percentage point increase in school concentrated disadvantage was associated with a 27 percent reduction (*OR* = 0.73; 1-0.73 = 0.27) in the likelihood of enrolling in college. Additionally, we found that school concentrated disadvantage was not related to early labor market earnings for students who were not enrolled in college in the year following high school. However, school concentrated disadvantage was associated with higher early labor market earnings for students who were enrolled in college. A 10-percentage point increase in school concentrated disadvantage was associated with a 0.08 *SD* (*B* = 0.10; *SD* for earnings was 1.25; 0.10/1.25 = 0.08) increase in earnings for students enrolled in college in the year after high school.

School-level concentrated disadvantage was uniquely associated with college enrollment, above and beyond the association between student-level disadvantage and college enrollment, consistent with Borman & Dowling's (2010) re-analysis of data from the seminal EEO study. In the current study, school-level concentrated disadvantage was negatively related to college enrollment, even after controlling for student-level race and disadvantage, school racial composition, and student and school-level baseline academic performance. These findings indicate a unique mechanism linking school-concentrated disadvantage to long-term outcomes, above and beyond the mechanisms typically associated with student-level disadvantage, academic achievement, and school composition. Additionally, after controlling for disadvantage experiences and school-level concentrated disadvantage, Black students were more likely to enroll in college than White students with similar experiences with disadvantage. Traditionally, BIPOC students have disproportionately lower rates of college enrollment when compared to White students (Baker et al., 2018), and our findings may indicate that this gap is driven by differences in experiences with disadvantage and concentrated disadvantage between BIPOC and white students.

This study did not seek to determine the specific mechanisms through which school-concentrated disadvantage was related to college enrollment. However, prior research indicates that schools with higher levels of disadvantaged students often have limited or no access to quality educational resources, fewer qualified teachers, more overcrowded classrooms, and poorer facilities (Morgan, 2012). Student disadvantage tends to co-occur with several other risk factors, including homelessness, child maltreatment, and single parenting, which likely lead to fewer opportunities and greater family instability and stress (Fantuzzo et al., 2014). Schools with higher concentrations of disadvantage may have overall school climates that reflect cumulative disadvantage, stress, and instability. For example, students from low socioeconomic status (SES) families are more likely than higher-SES students to experience school mobility (Hanushek et al., 2004; Rumberger & Larson, 1998). Low-income students may be more vulnerable to the negative outcomes associated with mobility (DuBois et al., 1994), including experiences with declining academic performance and increased dropout (South et al., 2007), particularly in the year immediately following a move (Hanushek et al., 2004). Mobility can be a challenge for schools and teachers, making it difficult to meet the instructional and social-emotional needs of incoming students and to establish and maintain stable relationships and processes (Bryk et al., 2010; Lash & Kirkpatrick, 1990; U.S. GAO, 2010). Additionally, in schools with higher levels of disadvantage, teacher expectations and bias may play a role (Bomer et al., 2008). Prior research indicates that teachers may favor students from higher socioeconomic backgrounds and may have lower expectations of lower SES students, impacting 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 nature of these problems may contribute to the school environment and educational experiences for all students in the school, even those not directly experiencing student disadvantage.

Prior research on college enrollment indicates that enrollment patterns are shaped more by the application stage than the admissions stage, and lower-SES high-achieving students are less likely to apply to the most selective colleges (Radford, 2013), highlighting the importance of disadvantage in college decision-making. Additionally, differences in college enrollment by school-level concentrated disadvantage may be attributed to academic preparation and/or informational barriers (Roderick et al., 2009). Schools with higher concentrations of student disadvantage may not have the resources available to offer college preparatory coursework to students (GAO, 2018). Additionally, there may be fewer enrichment experiences, such as dual enrollment programs that allow students to enroll in college coursework while in high school and help to prepare students for college (Henneberger et al., 2020). Informational barriers may exist such that guidance counselors in higher disadvantage schools provide insufficient guidance about the pathways into college, need-based financial aid, and the benefits of attending more selective colleges (Radford, 2013; Roderick et al., 2009). Individuals living in concentrated disadvantage are also likely to be living in areas that have high concentrations of individuals who are not college educated. Students indicate a preference for colleges that are familiar to them, and this familiarity often comes from knowing someone who attended the college (Radford, 2013). Students in schools with high concentrations of disadvantage may be less likely to have a parent, older peer, or peers' parent who went to college, providing an additional informational barrier that may contribute to lower likelihood of eventual college enrollment.

The link between school-level concentrated disadvantage and early labor market outcomes was not as strong as the link with college enrollment. However, we found that, for students who were not enrolled in college, higher levels of student disadvantage, but not school concentrated disadvantage, were related to slightly lower earnings in the year following high school. The lack of a significant relation between school concentrated disadvantage and earnings for students not enrolled in college was counterintuitive, but promising, and may indicate that these schools are supporting students who are moving directly into careers. Vocational programming may be a viable alternative, as an international study examining career-technical education showed that participation in occupation specific vocational programming increased earnings seven years after high school but did not reduce college enrollment rates (Bishop & Mane, 2007).

For students who were attending college during the first year after high school, both student and school concentrated disadvantage were associated with higher earnings. Although the positive link indicates higher earnings, this is not necessarily a desirable outcome for students enrolled in college. Higher earnings may reflect a financial need to work during college, and financial aid alone may not be enough to cover college-related expenses in the presence of the high tuition and non-tuition (e.g., textbooks, living expenses) costs of postsecondary education (Long & Riley, 2007).

Early labor market outcomes were more strongly linked with race and ethnicity when compared to disadvantage, which is consistent with prior research indicating persistent racial discrimination in U.S. labor markets over the past 30 years (Bertrand & Mullainathan, 2004; Pager et al., 2009; Quillian et al., 2017). Discrimination in the hiring process may be prevalent because little information is known about the applicant, but the employer often knows the name and race of the applicant. Additionally, discrimination is not easily detected in the hiring process and it is harder to hold employers accountable during hiring, when compared to later in the employer-employee relationship (Quillian et al., 2017). Two possible mechanisms for racial disparities in the labor market likely work in tandem to perpetuate discrimination. First, present discrimination in certain jobs may lead BIPOC and Latinx applicants to refrain from seeking jobs from employers that are more likely to discriminate (Pager et al., 2009). Second, BIPOC and Latinx job seekers may suffer following an experience of discrimination and opt to not continue the job search (Pager et al., 2009), which may lead to lower labor market participation rates for BIPOC and Latinx individuals and/or lower participation in some employment industries.

The findings of this study should be interpreted within the context of the following data limitations. First, students who transferred out of the Maryland public school system were excluded from analyses, and excluded students were slightly more likely to be Black and Other-race and poorer performers on the MSA reading and math tests. Additionally, excluded students had slightly higher levels of disadvantage duration when compared to included students and were slightly more likely to attend schools with higher mean disadvantage durations and higher proportions of Black students. Second, the workforce data did not include federal employment, military employment, independently contracted employment, self-employment, informal (under the table) employment, and out-of-state employment. Our early labor market results would be biased to the degree that students in disadvantage and/or students attending schools with high concentrations of disadvantage disproportionately work in one of these sectors. For non-college enrollees, we found that higher durations of FRPM eligibility predicted lower early labor market earnings, and this relation would be overestimated in this study if disadvantaged students disproportionately worked for sectors missing from the MLDS data. For college enrollees, we found that higher durations of FRPM eligibility predicted higher early labor market earnings, and this relation would be underestimated in this study if disadvantaged students disproportionately worked for sectors missing from the MLDS data. Third, our study is limited due to the availability of complete postsecondary data only through the 2014-2015 academic year. As such, college enrollment outcomes could only be determined for students who graduated from high school on time (i.e., in the 2013-2014 academic year), and the only outcome that could be assessed was enrolling in college within the first year after leaving high school. The limitation on college data also limited our ability to assess longer-term labor market outcomes, because our analysis of earnings required us to account for whether students were also enrolled in college at the time. The volatility of earnings for this cohort was likely particularly pronounced due to the 2008 Great Recession (Crosnoe & Smith, 2017; Schoon & Bynner, 2017).

Additionally, since school boundaries in Maryland follow neighborhood lines very closely, but not perfectly, our measurement of school concentrated disadvantage is confounded by neighborhood disadvantage. The generalizability of our results may be limited to students and schools with similar student populations and school boundaries to Maryland. There is great value to replicating the results from the current study with data from other states and localities, both with similar populations to Maryland and with populations that are distinct from Maryland's demographic and school population. Toward the latter, future research using data where school and neighborhood boundaries do not overlap may help to disentangle school concentrated disadvantage from neighborhood disadvantage, further clarifying their distinct relations with college enrollment and early labor market outcomes. Finally, we cannot draw causal conclusions from our analyses. As such, unmeasured confounders that are correlated with disadvantage at the student- and school-levels could be contributing to relations we observed between disadvantage and outcomes.

Implications

Policymakers and practitioners can use the findings from this study to better target resources to help support the students and schools who need them most. We underscore the importance of the school context, and specifically, school concentrated disadvantage, as a unique developmental mechanism associated with long-term educational (i.e., college enrollment) and early labor market outcomes. The primary federally funded intervention aimed at addressing the needs of disadvantaged students and schools is Title I, a federal aid program that allocates funding to local school systems and public schools with high percentages of low-income families to assist all children in meeting state academic achievement standards. In Maryland, Title I funds are distributed by the local school systems, who choose to allocate funds to elementary and middle schools, even though some high schools are also eligible to receive Title I funds in the state. Although we recognize the importance of early prevention and intervention, additional Title I funds that could help to serve high schools may help to alleviate the longer-term secondary, postsecondary, and early labor market disparities associated with concentrated disadvantage.

Our findings suggest that schools with high concentrations of students who were persistently disadvantaged may need additional resources to help serve the student population.

Recent research from the economics literature shows a strong positive relation between additional per pupil funding and student outcomes, including academic achievement (Lafortune et al., 2018), high school graduation (Candelaria & Shores, 2019), college enrollment (Hyman, 2017), and annual earnings (Rothstein & Whitmore, 2021), particularly for lower-income students (Jackson et al., 2016). However, it is not just the amount of money that is spent per pupil, but also what the money is used for that helps to determine efficiency and adequacy in resources (King, 2004).

Community school initiatives, which consider specific community needs to help focus resources within the school, have been shown to have promise in prior studies with students in schools with high concentrations of disadvantage (Blank et al., 2003; Dryfoos, 2000; 2005; Dryfoos & Maguire, 2019). Additionally, high school counselors are instrumental in increasing students' access to college, particularly for disadvantaged students, who often lack college-related social capital (e.g., college knowledge and resources from social relationships; Bryan et al., 2011; Paolini, 2019; Stephan, 2013). Consequently, disadvantaged students may require additional support in college-readiness; however, the same schools that tend to serve large concentrations of disadvantaged students often have fewer school counselors available to assist students with college-related matters (Paolini, 2019; Woods & Domina, 2014), highlighting a mismatch between the needs of students and schools and the resources available. Programs that specifically aim to introduce students to college during high school (e.g., dual enrollment; early college initiatives) may help to smooth the transition into college (Edmunds et al., 2017; Henneberger et al., 2020).

High school counselors are also instrumental in supporting students' financial aid, especially for first-generation college students, who disproportionately come from socioeconomically disadvantaged backgrounds (Bryan et al., 2011; Redford & Hoyer, 2017). For students from disadvantaged backgrounds, securing adequate financial aid is pivotal to postsecondary enrollment and persistence (Redford & Hoyer, 2017). For example, recent programs that mandate and provide help with filing of the Free Application for Federal Student Aid (FAFSA) are meant to improve students' access to financial resources and reduce the barriers financial problems may cause for enrolling and persisting in college (Deneault, 2021). Without additional financial resources, students from disadvantaged backgrounds may be forced to work during college, which has been associated with poor academic outcomes, including low GPAs, limited social interactions, and decreased rates of persistence and graduation (Lundberg, 2004; Neyt et al., 2017; Riggert et al., 2006). Improved focus on financial aid for schools serving large concentrations of students experiencing disadvantage may help to reduce the need to work during college, providing increased opportunities to focus on academic performance and degree attainment (Broton et al., 2016), ultimately improving long-term success for this population.

Conclusion

This study extended the Michelmore and Dynarksi (2017) measure of disadvantage, examining the proportion of enrollment years eligible for FRPM in secondary school, aggregating to the school-level to create a measure of school concentrated disadvantage. In doing so, we aimed to alleviate some of the limitations that have been associated with measuring disadvantage using data from students' eligibility for FRPM (see Domina et al., 2018). We found a negative link between school-level concentrated disadvantage and college enrollment, above and beyond the links between student disadvantage, race/ethnicity, and baseline academic achievement and college enrollment. Additionally, we found that school concentrated disadvantage was not related to early labor market earnings for students who were not enrolled in college in the year following high school but was associated with higher early labor market earnings for students who were enrolled in college. Our findings point to the need for additional targeted resources that can help schools serving high concentrations of disadvantaged students successfully enter college and the labor market.

Data Availability Statement: The data that support the findings of this study are available from the Maryland Longitudinal Data System (MLDS) Center. Restrictions apply to the availability of these data, which were used under contract for this study. Access to the restricted use data is available with permission from the MLDS Center.

Notes

[1] Nationally, the utility of FRPM data as a measure of disadvantage has become more limited due to the implementation of the Community Eligibility Provision (CEP), which allows schools to provide free meals to all enrolled students regardless of household income (see Koedel & Parsons, 2021 for a review). CEP did not begin to be implemented in Maryland, beyond a few small sites, until the 2015-2016 academic year, and did not affect this cohort of students.

[2] The FRPM qualification process usually requires parents or guardians to complete a form that documents household composition and income. Some students qualify for free meals through direct certification, a mechanism by which students who are in certain programs (e.g., homeless, foster care) or who live in households receiving need-based services (e.g., SNAP) qualify for free meals without completing application forms (USDA, 2017). All local school systems in Maryland were required by federal law to have a direct certification process by academic year 2008-2009. Students who are directly certified through need-based services are likely more disadvantaged since the income threshold for these programs is lower than 185% of the federal poverty line.

[3] A small percentage of students reported different race/ethnicities over time. For this study, we used the most recently reported race/ethnicity. Additionally, the data collection methods for student race/ethnicity changed in 2011 based on federal reporting guidance from the U.S. Department of Education. Before the change, race/ethnicity was a single measure with 5 categories (White, Black, Asian, Hispanic, Native American). After the change, students were first asked whether they were Hispanic (yes/no) and then they were asked for their race.

[4] For each student i, for each school h in the set of schools they attended $\{j\}$, a weight w was created for each school and summed to 1. An equal weighting approach was used that did not

consider the length of time students attended each school. For example, in Maryland there are 180 days in an academic year. If student *i* spent 30 days in school 1, 60 days in school 2, and 90 days in school 3, the school residuals would be weighted: school 1 = 0.333; school 2 = 0.333; and school 3 = 0.333. Wolff Smith & Beretvas (2014) found that the choice between equal weighting, used in the current study, and proportional weighting, where schools are weighted by the proportion of time spent in each school, did not greatly impact parameter or residual estimates.

References

Alexander, K., Entwisle, D., & Olson, L. (2014). *The long shadow: Family background, disadvantaged urban youth, and the transition to adulthood*. New York: Russell Sage Foundation.

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*(1), 166-171.

Baker, R., Klasik, D., & Reardon, S. F. (2018). Race and stratification in college enrollment over time. *AERA Open, 4*(1), 2332858417751896.

Bass, D. N. (2010). Fraud in the lunchroom? Federal school-lunch program may not be a reliable measure of poverty. *Education Next, 10*(1), 67-72. Retrieved from https://www.educationnext.org/fraud-in-the-lunchroom/

Bell, A., Jones, K., & Fairbrother, M. (2018). Understanding and misunderstanding group mean centering: a commentary on Kelley et al.'s dangerous practice. *Quality & Quantity, 52*(5), 2031-2036.

Beretvas, S. N. (2011). Cross-classified and multiple membership models. In J. J. Hox & J. K. Roberts (Eds.), *Handbook of Advanced Multilevel Analysis* (pp. 313-334). New York: Routledge.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *American Economic Review*, *94*(4), 991-1013.

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.

Bishop, J. H., & Mane, F. (2004). The impacts of career-technical education on high school labor market success. *Economics of education Review, 23*(4), 381-402.

Blank, M. J., Melaville, A., & Shah, B. P. (2003). *Making the Difference: Research and Practice in Community Schools*. Washington, DC: Coalition for Community Schools, Institute for Educational Leadership.

Bomer, R., Dworin, J. E., May, L., & Semingson, P. (2008). Miseducating teachers about the poor: A critical analysis of Ruby Payne's claims about poverty. *Teachers College Record, 110*(12), 2497-2531.

Borman, G., & Dowling, M. (2010). Schools and inequality: A multilevel analysis of Coleman's equality of educational opportunity data. *Teachers College Record, 112*(5), 1201-1246.

Bronfenbrenner, U. (1992). *Ecological systems theory*. Jessica Kingsley Publishers.

Bronfenbrenner, U., & Morris, P. A. (1998). The ecology of developmental processes. In W. Damon & R. M. Lerner (Eds.), *Handbook of child psychology: Theoretical models of human development* (pp. 993-1028). Hoboken, NJ: John Wiley & Sons Inc.

Brooks-Gunn, J., & Duncan, G. J. (1997). The effects of poverty on children. *The Future of Children*, *7*(2), 55-71.

Brooks-Gunn, J., Duncan, G., & Aber, J. L. (Eds.). (1997). *Neighborhood poverty, Volume 2: Policy implications in studying neighborhoods*. New York: Russell Sage Foundation.

Broton, K. M., Goldrick-Rab, S., & Benson, J. (2016). Working for college: The causal impacts of financial grants on undergraduate employment. *Educational Evaluation and Policy Analysis*, *38*(3), 477-494.

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

Bryan, J., Farmer-Hinton, R., Rawls, A., & Woods, C. S. (2017). Social capital and college-going culture in high schools: The effects of college expectations and college talk on students' postsecondary attendance. *Professional School Counseling, 21*(1), 1096-2409.

Bryk, A. S., Sebring, P. B., Allensworth, E., Luppescu, S., Easton, J. Q. (2010). Organizing schools for improvement: Lessons from Chicago. Chicago: The University of Chicago Press.

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. *Whither Opportunity*, 255-276.

Caldas, S. J., & Bankston, C. (1997). Effect of school population socioeconomic status on individual academic achievement. *The Journal of Educational Research, 90*(5), 269-277.

Candelaria, C. A., & Shores, K. A. (2019). Court-ordered finance reforms in the adequacy era: Heterogeneous causal effects and sensitivity. *Education Finance and Policy, 14*(1), 31-60.

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

Chetty, R., Hendren, N., & Katz, L. F. (2015). The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment. *American Economic Review*, *106*(4), 855-902.

Coleman, J. S. (1968). Equality of educational opportunity. *Integrated Education, 6*(5), 19-28.

Crosnoe, R. (2009). Low-income students and the socioeconomic composition of public high schools. *American Sociological Review, 74*(5), 709-730.

Crosnoe, R., & Smith, C. (2017). Structural advantages, personal capacities, and young adult functioning during the Great Recession. In I. Schoon & J. Bynner (Eds.), *Young People's Development and the Great Recession* (pp. 129-153). New York: Cambridge University Press.

Deneault, C. (2021). College Enrollment and Mandatory FAFSA Applications: Evidence from Louisiana. (EdWorkingPaper: 21-425). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/m28g-5v80

Domina, T., Pharris-Ciurej, N., Penner, A. M., Penner, E. K., Brummet, Q., Porter, S. R., & Sanabria, T. (2018). Is free and reduced-price lunch a valid measure of educational disadvantage?. *Educational Researcher, 47*(9), 539-555.

DuBois, D. L., Felner, R. D., Meares, H., & Krier, M. (1994). Prospective investigation of the effects of socioeconomic disadvantage, life stress, and social support on early adolescent adjustment. *Journal of abnormal psychology*, *103*(3), 511.

Duncan, G. J., Brooks-Gunn, J., & Klebanov, P. K. (1994). Economic deprivation and early childhood development. *Child Development*, *65*(2), 296-318.

Duncan, G. J., Magnuson, K., Kalil, A., & Ziol-Guest, K. (2012). The importance of early childhood poverty. *Social Indicators Research*, *108*(1), 87-98.

Drake, B., & Rank, M. R. (2009). The racial divide among American children in poverty: Reassessing the importance of neighborhood. *Children and Youth Services Review*, *31*(12), 1264-1271.

Dryfoos, J. G. (2000). Evaluation of community schools: Findings to date. Washington, DC: Coalition for Community Schools.

Dryfoos, J. (2005). Full-service community schools: a strategy--not a program. *New directions for youth development*, (107), 7-14.

Dryfoos, J., & Maguire, S. (2019). *Inside full-service community schools*. Simon and Schuster.

Dynarski, S., & Berends, M. (2015). Introduction to special issue. *Educational Evaluation and Policy Analysis, 37,* 3S-5S.

Eccles, J. S., Midgley, C., Wigfield, A., Buchanan, C. M., Reuman, D., Flanagan, C., & Mac Iver, D. (1993). Development during adolescence: The impact of stage-environment fit on young adolescents' experiences in schools and in families. *American Psychologist, 48*(2), 90–101.

Edmunds, J. A., Unlu, F., Glennie, E., Bernstein, L., Fesler, L., Furey, J., & Arshavsky, N. (2017). Smoothing the transition to postsecondary education: The impact of the early college model. *Journal of Research on Educational Effectiveness, 10*(2), 297-325.

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods, 12*(2), 121-138.

Fantuzzo, J. W., LeBoeuf, W. A., & Rouse, H. L. (2014). An investigation of the relations between school concentrations of student risk factors and student educational well-being. *Educational Researcher, 43*(1), 25-36.

Fazlul, I., Koedel, C., & Parsons, E. (2021). Free and reduced-price meal eligibility does not measure student poverty: Evidence and policy significance. (EdWorkingPaper: 21-415). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/ytaf-nc39

Göllner, R., Damian, R. I., Nagengast, B., Roberts, B. W., & Trautwein, U. (2018). It's not only who you are but who you are with: High school composition and Individuals' attainment over the life course. *Psychological science, 29*(11), 1785-1796.

Hanushek, E. A., Kain, J. F., Markman, J. M., & Rivkin, S. G. (2003). Does peer ability affect student achievement?. *Journal of Applied Econometrics, 18*(5), 527-544.

Hanushek, E. A., Kain, J. F., & Rivkin, S. G. (2004). Disruption versus Tiebout improvement: The costs and benefits of switching schools. *Journal of public Economics*, *88*(9-10), 1721-1746.

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*(3), 676-719.

Harwell, M., & LeBeau, B. (2010). Student eligibility for a free lunch as an SES measure in education research. *Educational Researcher 39*(2), 120-131.

Hedeker, D. (2003). A mixed-effects multinomial logistic regression model. *Statistics in Medicine, 22*, 1433-1446.

Henneberger, A.K., Witzen, H., & Preston, A.M. (2020). A longitudinal study examining dual enrollment as a strategy for easing the transition to college and career for emerging adults. Emerging Adulthood, 1-12. https://doi.org/10.1177/2167696820922052

Hox, J. J., Moerbeek, M., & van de Schoot, R. (2018). *Multilevel Analysis: Techniques and Applications (3rd ed.)*. New York: Routledge.

Hyman, J. (2017). Does money matter in the long run? Effects of school spending on educational attainment. *American Economic Journal: Economic Policy, 9*(4), 256-80.

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

Kim, J. S., & Sunderman, G. L. (2005). Measuring academic proficiency under the No Child Left Behind Act: Implications for educational equity. *Educational Researcher, 34*(8), 3-13.

Klebanov, P. K., Brooks-Gunn, J., McCarton, C., & McCormick, M. C. (1998). The contribution of neighborhood and family income to developmental test scores over the first three years of life. *Child Development*, *69*(5), 1420-1436.

Kling, J. R., Liebman, J. B., & Katz, L. F. (2007). Experimental analysis of neighborhood effects. *Econometrica*, *75*(1), 83-119.

Koball, H., & Jiang, Y. (2018). Basic facts about low-income children: Children under 9 years, 2016. National Center for Children in Poverty. Retrieved from: https://academiccommons.columbia.edu/doi/10.7916/d8-t97p-bf73.

Koedel, C., & Parsons, E. (2021). The effect of the Community Eligibility Provision on the ability of free and reduced-price meal data to identify disadvantaged students. *Educational Evaluation and Policy Analysis, 43*(1), 3-31.

Konstantopoulos, S., & Borman, G. (2011). Family background and school effects on student achievement: A multilevel analysis of the Coleman data. *Teachers College Record*, *113*(1), 97-132.

Lafortune, J., Rothstein, J., & Schanzenbach, D. W. (2018). School finance reform and the distribution of student achievement. *American Economic Journal: Applied Economics, 10*(2), 1-26.

Lash, A. A., & Kirkpatrick, S. L. (1990). A classroom perspective on student mobility. *Elementary School Journal, 91*, 171-191.

Leventhal, T., & Brooks-Gunn, J. (2000). The neighborhoods they live in: The effects of neighborhood residence on child and adolescent outcomes. *Psychological Bulletin*, *126*(2), 309-337.

Levy, B. L. (2019). Heterogeneous impacts of concentrated poverty during adolescence on college outcomes. *Social Forces, 98*(1), 147-182.

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

Ludwig, J., Duncan, G. J., Gennetian, L. A., Katz, L. F., Kessler, R. C., Kling, J. R., & Sanbonmatsu, L. (2013). Long-term neighborhood effects on low-income families: Evidence from Moving to Opportunity. *American Economic Review*, *103*(3), 226-231.

Lundberg, C. A. (2004). Working and learning: The role of involvement for employed students. *Journal of Student Affairs Research and Practice*, *41*(2), 400-414.

Mayer, S. E. (2002). How economic segregation affects children's educational attainment. *Social Forces, 81*(1), 153-176.

McLoyd, V. C. (1998). Socioeconomic disadvantage and child development. *American Psychologist*, *53*(2), 185-204.

Michelmore, K., & Dynarski, S. (2017). The gap within the gap: Using longitudinal data to understand income differences in educational outcomes. *AERA Open, 3*(1), 2332858417692958.

Najman, J. M., Hayatbakhsh, M. R., Heron, M. A., Bor, W., O'Callaghan, M. J., & Williams, G. M. (2009). The impact of episodic and chronic poverty on child cognitive development. *The Journal of Pediatrics, 154*(2), 284-289.

Neyt, B., Omey, E., Verhaest, D., & Baert, S. (2019). Does student work really affect educational outcomes? A review of the literature. *Journal of Economic Surveys*, *33*(3), 896-921.

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

Paolini, A. C. (2019). School Counselors Promoting College and Career Readiness for High School Students. *Journal of School Counseling, 17*(2), n2.

Pager, D., Western, B., & Bonikowski, B. (2009). Discrimination in a low-wage labor market: A field experiment. *American Sociological Review, 74*(5), 777-799.

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.

Radford, A. W. (2013*). Top student, top school?: How social class shapes where valedictorians go to college*. Chicago: University of Chicago Press.

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

Reardon, S. F. (2011). The widening academic achievement gap between rich and poor: New evidence and possible explanations. In G. J. Duncan & R. J. Murnane (Eds.), *Whither opportunity? Rising inequality, schools, and children's life chances* (pp. 91–115). New York: Russell Sage Foundation.

Reardon, S. F. (2016). School segregation and racial academic achievement gaps. *Russell Sage Foundation Journal of the Social Sciences, 2,* 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.

Reardon, S. F., & Portilla, X. A. (2016). Recent trends in income, racial, and ethnic school readiness gaps at kindergarten entry. *AERA Open*, *2*(3), 1-18.

Redford, J., & Hoyer, K. M. (2017). First-generation and continuing generation college students: A comparison of high school and postsecondary experiences. Washington, DC: National Center for Education Statistics. Retrieved from https://nces.ed.gov/pubs2018/2018009.pd

Rice, J. K. (2004). Equity and efficiency in school finance reform: Competing or complementary goods?. *Peabody Journal of Education, 79*(3), 134-151.

Riggert, S. C., Boyle, M., Petrosko, J. M., Ash, D., & Rude-Parkins, C. (2006). Student employment and higher education: Empiricism and contradiction. *Review of Educational Research*, *76*(1), 63-92.

Roderick, M., Nagaoka, J., & Coca, V. (2009). College readiness for all: The challenge for urban high schools. *The future of children*, 185-210.

Rothstein, J., & Whitmore, D. (2021). Does money still matter? Attainment and earnings effects of post-1990 school finance reforms. NBER Working Paper 29177. Retrieved from: https://www.nber.org/papers/w29177.

Rumberger, R. W., & Larson, K. A. (1998). Student mobility and the increased risk of high school dropout. *American Journal of Education, 107*, 1-35.

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*(9), 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*(3), 845-852.

Schoon, I., & Bynner, J. (2017). Conceptualizing youth transitions in times of economic upheaval and uncertainty. In I. Schoon & J. Bynner (Eds.), *Young People's Development and the Great Recession* (pp. 3-22). New York: Cambridge University Press.

South, S. J., Haynie, D. L., & Bose, S. (2007). Student mobility and school dropout. *Social Science Research, 36*, 68-94.

Stephan, J. (2013). Social capital and the college enrollment process: How can a school program make a difference?. *Teachers College Record, 115*(4), 1-39.

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/schoolmeals/fr-041017.

U.S. Government Accountability Office (GAO). (2010, November). Many Challenges Arise in Educating Students Who Change Schools Frequently, GAO-11-40 (Washington, DC: Author). Retrieved from http://www.gao.gov/products/GAO-11-40

Van Ewijk, R., & Sleegers, P. (2010). The effect of peer socioeconomic status on student achievement: A meta-analysis. *Educational Research Review*, *5*(2), 134-150.

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*(9), 1132-1139.

Wilson, V., & Rodgers III, W. M. (2016). Black-white wage gaps expand with rising wage inequality. Economic Policy Institute, 20, 18. Retrieved from: https://www.epi.org/publication/black-white-wage-gaps-expand-with-rising-wage-inequality/ .

Wodtke, G.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*(5), 713-736.

Wolff Smith, L. J., & Beretvas, S. N. (2014). The impact of using incorrect weights with the multiple membership random effects model. *Methodology, 10*(1), 31-42.

Woods, C., & Domina, T. (2014). The school counselor caseload and the high school-to-college pipeline. *Teachers College Record, 116*(10), 1-30.

Table 1

Descriptive Statistics for Study Variables by Two Student-Level Disadvantage Measures

Variable	Total N=52,610		Student Disadvantage – Duration (Mean across all schools attended grades 6-12)								Student Disadvantage – Last MS record			
			Never n=27,328		Sometimes n=5,744		Usually n=9,535		Always n=10,003		Not FRPM n=32,785		FRPM n=19,825	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Panel A														
Student														
FRPM duration	0.35	0.42	0.00	0.00	0.27	0.12	0.74	0.13	1.00	0.00	0.06	0.16	0.84	0.21
Black, non-Hispanic	0.35	0.48	0.18	0.38	0.44	0.50	0.55	0.50	0.60	0.49	0.22	0.42	0.57	0.49
Other	0.19	0.39	0.17	0.38	0.20	0.40	0.22	0.41	0.22	0.41	0.18	0.38	0.22	0.41
White, non-Hispanic	0.46	0.50	0.65	0.48	0.36	0.48	0.24	0.43	0.18	0.39	0.60	0.49	0.21	0.41
MSA Reading	413.80	36.93	427.40	35.43	407.59	33.13	397.80	32.16	395.47	31.95	424.10	35.81	396.78	32.17
MSA Math	427.31	39.67	442.70	37.01	419.44	36.14	408.59	34.99	407.65	34.84	438.77	37.85	408.36	35.08
School														
Mean FRPM duration	0.36	0.22	0.25	0.16	0.40	0.19	0.50	0.20	0.53	0.20	0.27	0.17	0.51	0.20
% Black, non-Hispanic	0.36	0.30	0.24	0.24	0.42	0.30	0.51	0.30	0.53	0.31	0.27	0.26	0.52	0.31
% Other	0.19	0.15	0.19	0.13	0.18	0.15	0.18	0.16	0.18	0.17	0.19	0.14	0.18	0.17
% White, non-Hispanic	0.46	0.31	0.58	0.27	0.41	0.31	0.32	0.29	0.30	0.29	0.55	0.28	0.31	0.29
Mean MSA Reading	413.53	15.05	420.17	12.46	410.92	13.28	405.83	14.18	404.21	14.39	418.63	13.05	405.09	14.34
Mean MSA Math	426.51	17.90	434.16	14.12	423.48	16.15	417.57	17.79	415.85	18.30	432.40	14.94	416.77	18.15
Mean MSA (reading and math)	420.02	16.02	427.17	12.76	417.20	14.21	411.70	15.48	410.03	15.84	425.51	13.49	410.93	15.74
Panel B														
Outcomes														
Graduated with a HS diploma by 2017	0.90	0.30	0.97	0.17	0.89	0.32	0.79	0.41	0.83	0.38	0.96	0.20	0.81	0.39
	(n=52,610)		(n=27,328)		(n=5,744)		(n=9,535)		(n=10,003)		(n=32,785)		(n=19,825)	
Dropped out	0.09	0.29	0.03	0.16	0.11	0.31	0.20	0.40	0.17	0.38	0.04	0.20	0.18	0.39

Variable	Total N=52,610		Student Disadvantage – Duration (Mean across all schools attended grades 6-12)								Student Disadvantage – Last MS record			
			Never n=27,328		Sometimes n=5,744		Usually n=9,535		Always n=10,003		Not FRPM n=32,785		FRPM n=19,825	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
	(n=52,610)		(n=27,328)		(n=5,744)		(n=9,535)		(n=10,003)		(n=32,785)		(n=19,825)	
Enrolled in college within one year of on-time HS graduation	0.73	0.44	0.83	0.37	0.64	0.48	0.59	0.49	0.56	0.50	0.81	0.40	0.57	0.49
	(n=45,580)		(n=26,265)		(n=4,830)		(n=6,795)		(n=7,690)		(n=30,804)		(n=14,776)	
Labor market participation – not in college	0.75	0.44	0.75	0.43	0.74	0.44	0.75	0.43	0.73	0.44	0.75	0.43	0.74	0.44
	(n=11,441)		(n=3,991)		(n=1,607)		(n=2,651)		(n=3,192)		(n=5,528)		(n=5,913)	
Earnings – not in college	8,161	9,257	9,255	11,807	8,071	7,212	7,605	6,534	7,277	8,263	8,927	10,721	7,438	7,553
	(n=8,529)		(n=2,999)		(n=1,197)		(n=1,997)		(n=2,336)		(n=4,141)		(n=4,388)	
Log earnings – not in college	8.49	1.23	8.61	1.22	8.48	1.24	8.43	1.23	8.37	1.21	8.57	1.23	8.40	1.22
	(n=8,529)		(n=2,999)		(n=1,197)		(n=1,997)		(n=2,336)		(n=4,141)		(n=4,388)	
Labor market participation – in MD college	0.76	0.43	0.75	0.43	0.75	0.43	0.78	0.41	0.76	0.43	0.75	0.43	0.77	0.42
	(n=24,040)		(n=15,113)		(n=2,385)		(n=3,123)		(n=3,419)		(n=17,314)		(n=6,726)	
Earnings – in MD college	5,286	5,501	4,883	5,313	6,091	6,431	6,022	5,746	5,807	5,200	5,040	5,469	5,909	5,535
	(n=18,177)		(n=11,361)		(n=1,788)		(n=2,438)		(n=2,590)		(n=13,026)		(n=5,151)	
Log earnings – in MD college	8.00	1.25	7.91	1.24	8.18	1.22	8.17	1.25	8.13	1.27	7.95	1.24	8.15	1.25
	(n=18,177)		(n=11,361)		(n=1,788)		(n=2,438)		(n=2,590)		(n=13,026)		(n=5,151)	

Note. MS = middle school; FRPM = eligibility for free or reduced-price meals; MSA = Maryland School Assessment; HS = high school; MD = Maryland.

Table 2

Descriptive Statistics for Study Variables by Two School-Level Disadvantage Measures

Variable	Total N=52,610		School Disadvantage – Mean FRPM Duration†						School Disadvantage – Percent FRPM††					
			Low (.01-.24) n=17,860		Medium (.24-.46) n=17,447		High (.46-.96) n=17,303		Low (.01-.18) n=17,614		Medium (.18-.39) n=18,004		High (.39-.96) n=16,831	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Panel A														
Student														
FRPM duration	0.35	0.42	0.10	0.26	0.33	0.41	0.64	0.39	0.12	0.28	0.34	0.41	0.62	0.40
Black, non-Hispanic	0.35	0.48	0.08	0.27	0.37	0.48	0.62	0.49	0.10	0.31	0.37	0.48	0.59	0.49
Other	0.19	0.39	0.18	0.38	0.21	0.40	0.19	0.39	0.17	0.38	0.20	0.40	0.20	0.40
White, non-Hispanic	0.46	0.50	0.74	0.44	0.42	0.49	0.19	0.40	0.72	0.45	0.43	0.49	0.21	0.41
MSA Reading	413.80	36.93	428.11	35.12	413.78	36.37	399.05	33.35	426.54	35.51	413.54	36.28	400.95	34.48
MSA Math	427.31	39.67	443.98	36.52	427.03	38.34	410.39	36.78	442.17	37.02	427.44	38.45	411.93	37.65
School														
Mean FRPM duration	0.36	0.22	0.13	0.06	0.35	0.06	0.62	0.12	0.14	0.09	0.36	0.11	0.59	0.15
% Black, non-Hispanic	0.36	0.30	0.11	0.10	0.38	0.25	0.61	0.28	0.13	0.13	0.38	0.26	0.59	0.29
% Other	0.19	0.15	0.17	0.11	0.20	0.14	0.19	0.19	0.17	0.11	0.20	0.19	0.18	0.19
% White, non-Hispanic	0.46	0.31	0.73	0.17	0.44	0.26	0.21	0.24	0.72	0.17	0.43	0.27	0.23	0.25
Mean MSA Reading	413.53	15.05	426.18	10.04	413.30	9.59	400.70	12.75	425.14	10.99	413.11	10.91	401.91	13.18
Mean MSA Math	426.51	17.90	441.39	10.52	426.06	10.91	411.59	16.99	440.23	11.90	426.44	12.46	412.35	16.80
Mean MSA (reading and math)	420.02	16.02	433.79	9.56	419.68	9.63	406.15	14.30	432.68	10.85	419.77	11.07	407.13	14.42
Panel B														
Outcomes														
Graduated with a HS diploma by 2017	0.90	0.30	0.97	0.18	0.91	0.28	0.82	0.38	0.96	0.19	0.91	0.28	0.83	0.38
	(n=52,610)		(n=17,860)		(n=17,447)		(n=17,303)		(n=17,614)		(n=18,004)		(n=16,831)	
Dropped out	0.09	0.29	0.03	0.17	0.08	0.27	0.17	0.38	0.04	0.19	0.08	0.28	0.16	0.37
	(n=52,610)		(n=17,860)		(n=17,447)		(n=17,303)		(n=17,614)		(n=18,004)		(n=16,831)	
	0.73	0.44	0.83	0.37	0.73	0.45	0.60	0.49	0.82	0.38	0.73	0.44	0.61	0.49

Variable	Total N=52,610		School Disadvantage – Mean FRPM Duration† Low (.01-.24) n=17,860		Medium (.24-.46) n=17,447		High (.46-.96) n=17,303		School Disadvantage – Percent FRPM†† Low (.01-.18) n=17,614		Medium (.18-.39) n=18,004		High (.39-.96) n=16,831	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Enrolled in college within one year of on-time HS graduation	(n=45,580)		(n=17,091)		(n=15,440)		(n=13,049)		(n=16,700)		(n=15,838)		(n=12,946)	
	0.75	0.44	0.76	0.43	0.76	0.43	0.73	0.45	0.77	0.42	0.75	0.43	0.73	0.44
Labor market participation – not in college	(n=11,441)		(n=2,574)		(n=3,936)		(n=4,931)		(n=2,700)		(n=3,994)		(n=4,699)	
	8,161	9,257	9,232	8,301	8,489	11,245	7,301	7,721	9,145	8,108	8,392	11,260	7,364	7,797
Earnings – not in college	(n=8,529)		(n=1,962)		(n=2,980)		(n=3,587)		(n=2,068)		(n=2,993)		(n=3,431)	
	8.49	1.23	8.60	1.25	8.54	1.22	8.38	1.21	8.61	1.24	8.51	1.22	8.39	1.22
Log earnings – not in college	(n=8,529)		(n=1,962)		(n=2,980)		(n=3,587)		(n=2,068)		(n=2,993)		(n=3,431)	
	0.76	0.43	0.77	0.42	0.75	0.43	0.74	0.44	0.77	0.42	0.75	0.43	0.74	0.44
Labor market participation – in MD college	(n=24,040)		(n=9,631		(n=8,290)		(n=6,119)		(n=9,357)		(n=8,483)		(n=6,163)	
	5,286	5,501	4,952	5,389	5,370	5,442	5,714	5,726	5,043	5,473	5,259	5,312	5,706	5,775
Earnings – in MD college	(n=18,177)		(n=7,399)		(n=6,226)		(n=4,552)		(n=7,210)		(n=6,378)		(n=4,560)	
	8.00	1.25	7.92	1.25	8.03	1.24	8.11	1.25	7.95	1.24	8.00	1.25	8.10	1.25
Log earnings – in MD college	(n=18,177)		(n=7,399)		(n=6,226)		(n=4,552)		(n=7,210)		(n=6,378)		(n=4,560)	

Note. The 2 school-level measures were created by recoding the continuous measure into 3 buckets with the same number of people in each bucket (tertiles). MS = middle school; FRPM = eligibility for free or reduced-price meals; MSA = Maryland School Assessment; HS = high school; MD = Maryland.

† Mean of school mean FRPM duration across all schools attended, grades 6-12.

†† Based on the point-in-time measure of school percent FRPM of the first school attended in 6th grade. This is missing for 161 cohort students in 9 schools.

Table 3

Multi-level Analysis Predicting Enrollment in College within the First Year of On-Time High School Graduation

	Model 1: Unconditional Multilevel			Model 2: FRPM Duration Main Effects			Model 3: FRPM Duration and Race			Model 4: FRPM Duration, Race, and Baseline Academics		
	B	SE	OR	*B*	SE	OR	*B*	SE	OR	*B*	SE	OR
Fixed Effects												
Intercept	0.68***	0.06	1.97	0.94***	0.05	2.57	0.99***	0.04	2.68	1.05***	0.03	2.86
Level 1												
Student FRPM Duration				-0.10***	0.00	0.91	-0.11***	0.00	0.90	-0.18***	0.00	0.93
Black							0.27***	0.04	1.31	0.62***	0.04	1.85
Other							0.33***	0.04	1.39	0.44***	0.04	1.56
MSA Grade 6 Reading										0.01***	0.00	1.01
MSA Grade 6 Math										0.01***	0.00	1.01
Level 2												
School FRPM Duration				-0.32***	0.02	0.73	-0.40***	0.02	0.67	-0.32***	0.02	0.73
% Black							0.10***	0.02	1.11	0.12***	0.02	1.12
% Other							0.23***	0.03	1.26	0.22***	0.03	1.24
School mean MSA										0.02***	0.00	1.02
Random Parameters												
Level 2: All schools												
Var (cons)	2.05***	0.16		0.98***	0.09		0.75***	0.07		0.55***	0.06	
Model fit (Bayesian DIC)	48,078.28			47,124.77			47,039.67			43,936.97		

Notes. N = 45,580; FRPM = eligibility for free or reduced-price meals measured using mean FRPM eligibility duration between 6th and 12th grades; MSA = Maryland School Assessment; **p* < .05; ***p* <.01; ****p* < .001.

Table 4

Multi-level Analysis Predicting Participation in the Maryland Labor Market and Earnings within the First Year after On-time High School Graduation for Students not Enrolled in College and Students Enrolled in Maryland Colleges

	Non-College Enrollees					Maryland College Enrollees				
	Labor Market Participation (*N* = 11,441) (Panel 1)			Earnings (*N* = 8,529) (Panel 2)		Labor Market Participation (*N* = 24,040) (Panel 3)			Earnings (*N* = 22,550) (Panel 4)	
	B	*SE*	*OR*	*B*	*SE*	*B*	*SE*	*OR*	*B*	*SE*
Fixed Effects										
Intercept	1.04***	0.04	2.84	8.49***	0.02	1.27***	0.03	3.57	7.94***	0.01
Level 1										
Student FRPM Duration	0.01	0.01	1.01	-0.01*	0.00	0.03***	0.01	1.03	0.02***	0.00
Black	-0.12	0.07	0.89	-0.27***	0.04	-0.25***	0.05	0.78	-0.32***	0.03
Other	-0.69***	0.07	0.50	0.02	0.05	-0.59***	0.04	0.56	0.00	0.03
MSA Grade 6 Reading	0.00	0.00	1.00	-0.00*	0.00	-0.00	0.00	1.00	-0.00***	0.00
MSA Grade 6 Math	-0.00	0.00	1.00	0.00*	0.00	-0.00***	0.00	1.00	-0.00***	0.00
Level 2										
School FRPM Duration	0.07**	0.02	1.07	-0.01	0.01	0.08***	0.02	1.08	0.10***	0.01
% Black	-0.11***	0.01	0.90	-0.06***	0.01	-0.15***	0.01	0.86	-0.09***	0.01
% Other	-0.22***	0.02	0.80	-0.02	0.01	-0.24***	0.02	0.79	-0.08***	0.01
School mean MSA	-0.00	0.00	1.00	-0.00*	0.00	-0.01***	0.00	0.99	-0.01***	0.00
Random Parameters										
Level 2: All schools										
Var (cons)	0.25***	0.06		0.02	0.02	0.17***	0.03		0.05***	0.01
Level 1: Student										
Var (cons)				1.46***	0.02				1.49***	0.01

Notes. Only individuals with some positive earnings were included in the models. Earnings were log transformed due to skewness. FRPM = eligibility for free or reduced-price meals measured using mean FRPM eligibility duration between 6th and 12th grades; MSA = Maryland School Assessment; Labor data are obtained from the Maryland Department of Labor for Maryland employees who work for employers who are subject to Maryland's Unemployment Insurance (UI) law.

Federal employees, military employees, individuals who are self-employed, and private contractors are excluded from the labor data. *$p < .05$; **$p < .01$; ***$p < .001$.

Figure 1

Student race/ethnicity (left) and mean MSA Reading and Math scores (right) by level of student disadvantage, measured using FRPM eligibility duration between 6th and 12th grades

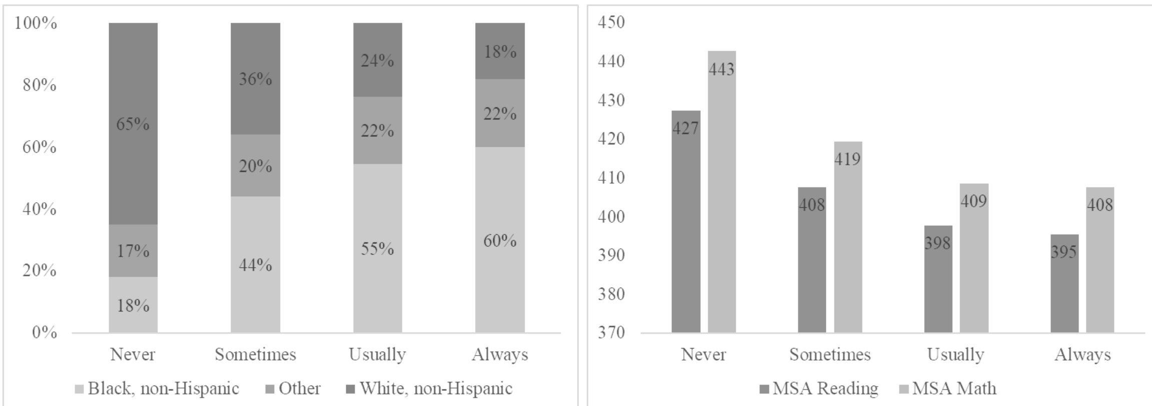

Figure 2

School-level racial/ethnic composition (left) and mean MSA Reading and Math scores (right) by level of school concentrated disadvantage, measured using mean FRPM eligibility duration between 6th and 12th grades

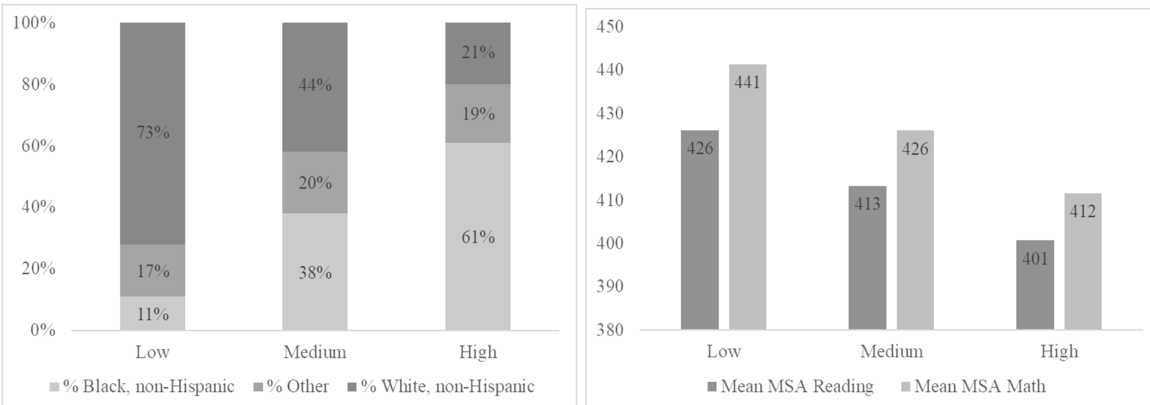

Figure 3

Correlation of Two School-Level Concentrated Disadvantage Measures by Academic Year