Gender, Racial/Ethnic, and Socioeconomic Inequalities in U.S. High Schools: How School Resources Affect Disparities in Educational Achievement and Attainment

By

Hannah Kathleen Miller

A dissertation submitted in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

(Sociology)

at the

UNIVERSITY OF WISCONSIN-MADISON

2016

Date of final oral examination: 5/12/2016

This dissertation is approved by the following members of the Final Oral Committee:

Myra Marx Ferree, Professor, Sociology
Adam Gamoran, Emeritus Professor, Sociology and Educational Policy Studies
Sara Goldrick-Rab, Professor, Educational Policy Studies and Sociology
Monica Grant, Assistant Professor, Sociology
Jee-Seon Kim, Professor, Department of Educational Psychology

TABLE OF CONTENTS

ABSTRACT

This dissertation examines how the relation between students' demographic characteristics and their educational outcomes varies across U.S. high schools, as well as the school resources associated with more equitable outcomes by gender, socioeconomic status, and race/ethnicity. I use data from the Education Longitudinal Study of 2002 to examine multiple outcomes (math achievement, high school graduation, and two measures of postsecondary enrollment) that may require different resources for schools to influence. After constructing latent class models of five school resources (instruction, teachers' qualifications and satisfaction, physical resources, student-staff relationships, and student-peer relationships), I use multilevel models with a slopes-as-outcomes approach to examine the relation between the degree of differentiation in outcomes across schools and these resources, both independently and jointly in common "school types."

The first empirical chapter shows that male students' average advantage in math achievement is larger in schools with more academically-oriented instruction, positive student-staff relationships, and academically-oriented students. In contrast, male students' average disadvantage in high school graduation is smaller in schools with more positive student-staff relationships, more satisfied teachers, and fewer physical resource problems. Thus, whether better-resourced schools exhibit smaller or larger gender inequalities depends on the outcome.

The second empirical chapter finds that, for the more differentiating outcomes of math achievement and on-time four-year enrollment, schools with more experienced teachers, academically-oriented instruction, and positive student-staff relationships have both higher average outcomes and smaller SES-based inequalities. Results for less differentiating outcomes do not follow this pattern of higher average values associated with less SES-based inequality.

The third empirical chapter shows that, among schools with relatively diverse student bodies, less well-maintained but academically advantaged schools have higher rates of postsecondary enrollment but greater enrollment inequalities between White and Black or Hispanic students, perhaps because White students are privileged when resources are limited. On average, students from all racial/ethnic backgrounds have better outcomes in schools with more positive student-staff relationships and academically-oriented instruction, but Black and Hispanic students' outcomes are particularly high.

Overall, demographic inequalities in outcomes are not constant across schools, and the types and levels of resources schools provide are associated with the degree of inequality.

ACKNOWLEDGEMENTS

I am very grateful to Myra Marx Ferree for her mentoring and guidance, starting with an early graduate school class paper and continuing through this dissertation. Myra has provided such constructive and detailed feedback on my work, and I have learned so much from that feedback as well as from observing her as a scholar in other settings. I am especially appreciative that Myra continued to help me make progress on my goals during her sabbatical year. Thank you also to Adam Gamoran. While working on Adam's research projects, I learned a great deal both from him as well as from other students. I appreciate all of the feedback, advice, and funding Adam has provided to me over the years. I am grateful for the opportunity I had to take a class from Sara Goldrick-Rab and collaborate with her on a project, as well as for her comments on my dissertation. Thank you to Monica Grant and Jee-Seon Kim for serving on my dissertation committee.

I also appreciate the support, assistance, and critical perspectives provided on this dissertation as well as other projects by my fellow graduate students and colleagues, including Jeremy Fiel, Michael Halpin, Annabel Ipsen, Nicole Kaufman, Lily Liang, Alyn Turner McCarty, Johanna Quinn, Megan Shoji, and Jessa Lewis Valentine. I am exceptionally grateful to Jared Knowles who talked through all of my dissertation-related ideas multiple times, encouraged me to be a bit bolder in my interpretation of results, solved many an R programming challenge, and repeatedly reassured me that completion was possible.

The research reported here was supported by a dissertation grant from the American Educational Research Association and by the Institute of Education Sciences, U.S. Department of Education, through Award # R305B090009 to the University of Wisconsin-Madison. The opinions expressed are my own and do not represent views of the American Educational Research Association or the U.S. Department of Education.

Chapter 1: Introduction

In the U.S., housing prices rise and fall with the perceived quality of local schools, policymakers focus on giving families more choices in the schools they can attend, and neighborhood schools mean that schools can be as homogeneous – or diverse – as the communities they serve. "Good" schools usually are seen as those with high average test scores, high rates of enrollment in selective colleges, socioeconomically advantaged families, a strong tax base, and an abundance of curricular resources (Attewell 2001; Harris 2007; Klugman 2013). But, as Lewis and Diamond (2015) point out, such schools often contain stark inequalities for students from different demographic groups. Of course, students bring much of this inequality *into* schools because of inequalities in home lives, neighborhoods, and U.S. society as a whole (Reardon and Owens 2014). However, schools also shape, mitigate, and exacerbate particular forms of inequality (Downey, von Hippel and Broh 2004; Lewis and Diamond 2015) and the extent to which being low-SES, Black or Hispanic, or male or female is a liability for one's education may vary in different schools (Bryk and Schneider 2002; Gamoran 1992; Grubb 2008; Jennings et al. 2015).

This dissertation seeks to answer a series of questions about the extent to which the relation between students' ascribed characteristics – their gender, race/ethnicity, and SES – and their educational outcomes varies across a nationally representative sample of high schools. In doing so, it seeks to shed light on what types of schools and school resources are associated with more equitable outcomes and with smaller gender, racial/ethnic, and socioeconomic disparities in achievement and attainment. I focus on the high school years, a period of time during which "adolescents make some of the most significant choices in their lives and develop their sense of self and their place in the world" (Fletcher 2011: 267). Rather than focusing on average gender, racial/ethnic, or class differences in high school achievement, graduation, or college enrollment, I ask how these differences vary across contexts. In what school contexts is inequality in educational outcomes particularly pronounced? What types of schools, and school-based resources, are related to greater or lesser gender, racial/ethnic, and socioeconomic inequality? Are the same types of schools and school-based resources linked to relatively equal educational outcomes across different outcomes and student subgroups?

RESEARCH ON SCHOOL EFFECTS

Most parents, practitioners, and policymakers believe that the schools students attend – and the peers with whom they attend these schools – shape students' achievement, attainment, and life trajectory (Attewell 2001; Klugman 2012; Lewis-McCoy 2014; Palardy 2013; Payne and Biddle 1999), but education researchers have long been less sure about the extent to which schools matter for students' outcomes. In the sociology and economics of education literature, there is a significant body of research suggesting that the effects of schools on student outcomes are trivial in the face of the large effects of students' background characteristics, and that apparent effects of school resources stem from poor measurement of family SES and selection into schools (Coleman et al. 1966; Elliott 1998; Hanushek 1996; Hanushek 1997; Harris 2007; Jencks et al. 1972; Ludwig and Bassi 1999). In the 1960s, the Coleman Report was designed to show that school resource availability differed in predominantly Black versus predominantly White schools and that these resource differences were related to differences in student achievement (Coleman et al. 1966). The Coleman Report, however, provided little evidence that differential resource availability explained variation in student achievement, though part of this finding stemmed from statistical limitations in accurately partitioning variation at the student and school levels (Borman and Dowling 2010).

Much of the initial school effects research focused on differences between private (or specifically Catholic) schools and public schools, finding higher academic achievement after controlling for students' background characteristics in Catholic and other private schools (Bryk, Lee and Holland 1993; Bryk and Schneider 2002; Carbonaro and Covay 2010; Lee et al. 1998; Watt 2003).[1] Although not universally the case, the balance of evidence – particularly more recent evidence – suggests that *particular* school resources do matter for student achievement (Billings, Deming and Rockoff 2012; Greenwald, Hedges and Laine 1996; Palardy 2013). For example, some of the school resources that have been repeatedly found to be associated with higher achievement or achievement growth include smaller class sizes, higher rates of academic math course-taking and a greater percentage of students in the college-preparatory track, greater staff cooperation and higher perceived responsibility on the part of teachers for students' success, and more time in instruction and higher graduation requirements (Camburn and Han 2011; Carbonaro and Gamoran 2002; Finn and Achilles 1999; Harris and Herrington 2006; Lee, Croninger and Smith 1997; Lee and Smith 1996). As a result, research now has largely shifted from asking *whether* schools affect achievement to asking *which* school resources matter, *how*, and *for whom* (Cohen, Raudenbush and Ball 2003; Gamoran and An 2016).

School Effects on Student Attainment

Most research on how K-12 schools affect student outcomes has focused on test scores, with few studies examining the effects of high schools on postsecondary outcomes (for exceptions, see Black et al. 2014; Engberg and Wolniak 2010a; Jennings et al. 2015; Palardy

[1] This "Catholic school advantage" was explained in part by sector differences in school resources, including course-taking patterns (controlling for students' background and academic preparation, Catholic school students took more advanced academic courses and fewer vocational courses), Catholic schools' conception of the school as a community, expectations for teachers, and high levels of social support and control.

2013; Perna and Titus 2005; Pike and Saupe 2002; Wolniak and Engberg 2010). However, school effects may differ across outcomes (cf. Rumberger and Palardy 2005b) given that some outcomes may be easier to influence than others, schools may prioritize different outcomes, or particular resources may affect some outcomes but not others. For example, Grubb (2008) argued that efforts to increase students' attachment to school are likely to improve students' attainment but not their achievement. Thus, "studying a broader range of school outcomes may change the conclusions we draw about the relationship between schools and inequality" (Jennings et al. 2015: 57).

While some research suggests few, if any, effects of high school resources on college enrollment (cf. Betts and Morell 1999), other research indicates that the high school characteristics related to college enrollment include graduation requirements, school-level GPA, math course-taking, Advanced Placement course-taking, and high school SES (Engberg and Wolniak 2010b; Fletcher 2011; Palardy 2013). Relatedly, there is an extensive literature on schools' effects on high school graduation or dropout, though most of this research is less recent (cf. Arum 1998; Bowditch 1993; Bryk and Thum 1989; Fall and Roberts 2012; Goldschmidt and Wang 1999; Guryan 2004). For example, Lee and Burkam (2003) reported lower dropout rates in smaller high schools, schools with a constrained academic curriculum, and schools with more positive student-teacher relationships, but found that, controlling for students' background characteristics and behavior, schools' demographic composition and sector were almost completely unrelated to dropout rates. In an analysis of a district-wide school choice lottery, Deming et al. (2011) found that overall effects on graduation were positive but small. However, effects were larger for students who would otherwise have attended low-quality neighborhood schools; for these students, winning a school choice lottery "clos[ed] nearly 75 percent of the black-white gap in high school graduation" (Deming et al. 2011: 3).

School Effects on Gender, Racial/Ethnic, and Socioeconomic Differentiation in Outcomes

Deming et al.'s (2011) findings point to the possibility that schools – and their resources – may have differing effects for different students. Much of the literature on school effects implicitly assumes that schools and school quality affect all students equally (Jennings et al. 2015), despite a great deal of research showing that students within the same school do not necessarily experience schooling in the same way (cf. Crosnoe 2009; Entwisle, Alexander and Olson 2007; Finn and Achilles 1999; Gamoran 2010; Kalogrides and Loeb 2013; Martinez and Cervera 2012; Oakes 2005; Stanton-Salazar and Dornbusch 1995).

Lee and Bryk pioneered much of the initial research on how the relation between students' characteristics and their outcomes varies across schools, arguing that "the causes of such heterogeneity should be a central concern in research on school effects" (1989: 173). Initial research on variation in schools' differentiating effects found that Catholic or other private schools were more equitable than public schools in terms of achievement by race/ethnicity, SES, and initial ability (Bryk, Lee and Holland 1993; Gamoran 1992; Lee et al. 1998); that schools with more diverse math courses had more inequality in math achievement while schools in which students perceived discipline to be fair and effective had less inequality (Bryk and Schneider 2002); and that achievement growth was more equitable in schools where teachers took collective responsibility for students' academic success or failure (Lee and Smith 1996). In their reanalysis of the Coleman Report's data, Borman and Dowling (2010) reported that achievement differences between Black and White students – and students from more and less economically advantaged family backgrounds – were larger in schools with stronger teacher preferences for working with middle-class students.

In subsequent chapters, I discuss research on variation in schools' differentiating effects by gender, race/ethnicity, and socioeconomic status in more detail. Overall, some research suggests that the relation between educational achievement or attainment and students' demographic characteristics varies across schooling contexts, but this research has been isolated and unconnected, examining the effect of individual resources on different samples for different outcomes. I aim to provide a more comprehensive look at the resource patterns associated with smaller or larger gender, racial/ethnic, and socioeconomic disadvantages in American high schools, examining a number of different outcomes and measuring school resources both independently and as a package or typology.

CHAPTER OUTLINE

In the following chapters, I examine the extent to which gender, racial/ethnic, and socioeconomic differences in math achievement, high school graduation, and postsecondary enrollment vary across high schools, and what school resources – and clusters of resources – are associated with smaller or larger differences. Chapter 2 describes the dataset I use, the Education Longitudinal Study of 2002, as well as the methods I employ to obtain measures of school resources; estimate the degree of within-school gender, racial/ethnic, and socioeconomic inequality; and predict variation in the level of inequality across schools. Chapter 3 describes differences in gender inequalities in educational outcomes across high schools, documenting the extent of inequality as well as the school types and resources associated with greater or lesser inequality. Similar analyses for socioeconomic and racial/ethnic inequality comprise Chapters 4 and 5, respectively. Chapter 6 summarizes the findings, reviewing the extent to which the same types of schools and school-based resources are linked to the greatest equality across different subgroups and educational outcomes.

Chapter 2: Data and Methods

I use data from the Education Longitudinal Study of 2002 (ELS), a nationally representative dataset containing information on U.S. students and the high schools they attend. Beginning in 2002, the ELS followed tenth-grade students as they progressed through high school and entered college or the labor market.

The ELS has many advantages for my dissertation. One advantage is that it permits examination of multiple educational outcomes, which is valuable for several reasons. First, other research suggests that schools that are effective on one indicator of high school performance are not necessarily effective on others and that school effects may differ across outcomes (Jennings et al. 2015; Rumberger and Palardy 2005b). Second, two of the outcomes I examine – high school graduation and college enrollment – likely have tangible effects on students' lives (Gerber and Cheung 2008). In contrast, while tested math achievement may not directly affect students' lives, math achievement is particularly sensitive to what happens within schools (Balfanz and Byrnes 2012; Elliott 1998; Murnane 1975), and it offers a strong policy-directed argument given that inequalities in math achievement are more directly remediable. Finally, the outcomes I examine – the math achievement gap, graduation gap, and college enrollment gap – are measures about which educators and policymakers care deeply.

Another of the ELS' advantages is the large number of sampled schools and nationally representative sample, which permit an examination of school resources and demographic inequalities across the range of U.S. high schools. Also, the ELS contains rich school resource measures, including measures of students' school-based interpersonal experiences (described in detail below); such interpersonal measures are rarely available in educational datasets, making the ability to analyze interpersonal resources alongside more traditional instructional resources an important strength of the ELS.

The ELS' major disadvantage is its small within-school sample sizes. The relatively small number of sampled students per school limits the precision with which within-school differences between subgroups can be estimated. However, other researchers also have examined school effects using relatively small within-school sample sizes (cf. Condron 2009; Lee, Croninger and Smith 1997; Lee and Smith 1996; Legewie and DiPrete 2014; Lucas and Berends 2002). For example, Hill's (2008) analysis of high schools' effects on college enrollment had about seven students per school, with within-school clusters ranging from two to 23 students. Similarly, Fryer and Levitt (2004) documented within-school Black-White disparities using a dataset with fewer students per school, on average, than the ELS has. I discuss ways to compensate for the small sample sizes below.

The ELS' other disadvantage is that the data are now older, and patterns of educational inequality may have changed in the intervening years, especially given the 2002 implementation of No Child Left Behind, which had a strong focus on reducing achievement differences by race/ethnicity and economic status (Lee and Reeves 2012; Stiefel, Schwartz and Chellman 2007). However, the older data do permit an examination of longer-term outcomes, including students' postsecondary enrollment nearly a decade after high school completion.

ELS Sample

The ELS used a two-stage sampling process to collect data from students and schools. First, 752 regular public, charter, and private schools were selected with probability proportional to size.[1] Then, based on sophomore enrollment lists, an average of 26 students were randomly

[1] One of these schools had no eligible selected tenth-graders, so I exclude this school from all analyses.

selected from each school (Ingels et al. 2007). As Table 1 shows, considerable variation exists in the number of students sampled across schools: 97 percent of schools have ten or more sampled students, 86 percent have 15 or more sampled students, and 61 percent have 20 or more sampled students.

< Table 1 >

Data come from surveys administered to students in spring 2002 (students' sophomore year), spring 2004, spring 2006, and 2012, as well as from surveys administered to math and English teachers in 2002, parents in 2002, and school administrators in 2002 and 2004. In the base year, most students completed self-administered questionnaires during in-school sessions led by survey staff; four percent of students were surveyed outside of school via computer-assisted telephone interviews (CATI). About 15,360 students participated; the response rate was 88 percent. Teacher surveys were distributed via mail; at least one teacher report was received for 92 percent of all participating students. Of the school administrator questionnaires, 88 percent were completed via mail, and 11 percent by telephone. Parents received questionnaires in English and Spanish in the mail, then CATI was used to contact parents who had not returned the questionnaires; in total, parents of 88 percent of students responded (Ingels et al. 2004).[2]

[2] In 2002, the majority of students did not receive an incentive for participation. Students were offered an incentive (a $20 gift certificate) if they attended a school that only allowed survey administration during off-school hours or a school where parental consent materials were distributed by the school rather than the survey team; in schools that required active (rather than passive or implied) consent, a drawing was held for two $20 gift certificates. Incentives for teachers ranged from $10 to $40 depending on the number of students for whom the teacher completed surveys. School administrators and parents were not offered incentives. In 2004, more than 90 percent of students received $20 in cash or gift certificates for participation. In 2006, the "base" incentive was $20, with $40 offered to some participants who were expected to be less likely to respond, with other small incentives offered for participating early, participating after multiple contact attempts, etc. In 2012, incentives ranged from $25 to $55 depending on students' propensity to respond.

The 2004 follow-up response rate was 92 percent. Students at the base-year schools again completed surveys during in-school group sessions. Sample members who were no longer enrolled in base-year schools, who attended base-year schools that did not grant permission to conduct in-school survey sessions, or who did not participate in the survey sessions at their school were contacted by telephone or in-person. Seventy-four percent of surveys were completed in school sessions, 20 percent via telephone interviews, and 5 percent via field interviews. School administrator questionnaires again were mailed; surveys from school administrators were available for 95 percent of students (Ingels et al. 2005).

For the 2006 and 2012 surveys, the ELS used online questionnaires, computer-assisted telephone interviews, and computer-assisted personal interviews (CAPI). Eighty-nine percent of eligible students participated in the 2006 survey, and 84 percent in the 2012 survey. In 2006 and 2012, the majority of surveys were completed online (47 percent in 2006, 61 percent in 2012). Also, in both years, female, White, and higher SES students responded at higher rates, with response rates varying from 79 to 93 percent depending on the subgroup (Ingels et al. 2014; Ingels et al. 2007).

Student-Level Variables

I use the ELS base-year composite variables to measure students’ gender, race/ethnicity, and SES. The ELS gender composite was obtained from students’ self-reported gender if possible; if this was not available, information from the school roster or logical imputation based on first name was used instead. Likewise, the ELS race/ethnicity composite was obtained from the student survey when available; if missing, it was obtained from the following sources in order of preference: sampling roster, parent questionnaire, or logical imputation from other questionnaire items such as native language or surname. Fifty percent of sampled students are female, 14 percent are Black, 15 percent are Hispanic, 60 percent are non-Hispanic Whites, and the remaining 11 percent are from other racial/ethnic backgrounds or are multiracial (these students are grouped together in my analyses due to small sample sizes).

The SES composite is based on five equally weighted, standardized components: father's and mother's education, father's and mother's occupation, and family income. The SES composite was constructed from parent questionnaire data when available and student substitutions otherwise. When one or more of the components was missing, ELS staff imputed the missing value(s).[3] I use the SES composite measure, instead of the individual components, both because SES composites are widely used in the education literature (particularly in the literature that uses data from national education longitudinal surveys) and because looking separately at inequality by parental education, parental occupation, and family income in the chapter on socioeconomic inequality was not feasible given the limited within-school sample sizes that constrained the number of school-level slopes I could estimate.

I also control for whether the student was in a special education or English as a Second Language program during high school. Both variables come from students' tenth-grade survey responses.

School Resource Variables

School resources have been defined and measured in many different ways. Cohen, Raudenbush, and Ball write that "[e]ducational resources, conventionally conceived, refer to money or the things that money buys, including books, buildings, libraries, teachers' formal qualifications, and more" (2003: 120). Researchers often distinguish between resources that are

[3] Missing data on parents'/guardians' education and occupation were imputed even if there were indications elsewhere in the parent or student surveys that the student was from a single parent/guardian family.

wholly or partly outside of schools' control (sometimes called "school context"; for example, the population of students who attend the school) and factors that are at least partially under schools' control (sometimes called "school practices"), although there is little agreement about which factors are or are not exogenous to school staff's efforts and decisions (Ma 2008; Palardy 2013; Raudenbush and Willms 1995; Shen et al. 2012).

Beyond this common distinction, other resource groupings abound (cf. Bidwell and Kasarda 1980; Grubb 2008; Klugman 2012), but the focus is ordinarily on structural (e.g., sector) and organizational (e.g., course offerings) characteristics of schools (Carbonaro 2005). However, as Hallinan observed, "learning is a social psychological as well as cognitive process" (2008: 271), and relationships are crucial for student learning. Interpersonal relationships (e.g., between students and staff, staff and administrators, and students and peers) are resources that schools at least partially control because whom individuals know, how well they know them, and how they feel about them depends, in part, on the institutions and situations in which relationships develop (Crosnoe, Johnson and Elder 2004; Stanton-Salazar 2001). Thus, in addition to more traditionally conceived measures of resources that schools can purchase, my dissertation incorporates measures of student-staff and student-peer relationships.

In this section, I briefly describe the resource measures I use, as well as the literature supporting their selection and construction.[4] Table 2 shows the survey items used, respondent, wave when measured, and response categories; Table 3 shows the descriptive statistics for these indicators prior to standardization; and Table 4 provides detailed information about how these indicators were recoded (e.g., combining categories, taking the school mean).

< Table 2, Table 3, Table 4 >

[4] Though I selected variables primarily based on the prior literature, I excluded some variables that had little variation in the ELS sample.

Instruction. I measure instruction using the following student survey items: how frequently students use the school library or media center for course assignments and research papers; whether students took an Advanced Placement course or participated in International Baccalaureate by the end of tenth grade; whether students ever enrolled in remedial English or math; students' perceived track location (i.e., general, college-preparatory, or vocational/technical/business); the number of years of advanced math and advanced science students took by spring 2004; and whether students participated in work-based learning experiences (i.e., cooperative education, internships, job shadowing, or mentoring) by the end of tenth grade.

I include measures of both perceived track location and actual course-taking because prior research has shown that structural measures of tracking (based on the courses students take) and social-psychological measures of tracking (based on students' self-reported track location) have independent effects on achievement and tap into different dimensions of students' schooling experience (Lucas 1999; Lucas and Gamoran 2002). Also, describing students' track location in discrete categories like "college-preparatory" may not capture students' course-taking patterns very well (Kelly 2009; Kelly and Price 2011). Additionally, I include other measures of the instruction to which students have access (e.g., assignments that require the use of a school library or media center, experiential-based learning opportunities) in order to obtain a fuller picture of students' instructional context (Engberg and Wolniak 2010b).

Teachers. I measure teacher resources using students' tenth grade math and English teachers' responses to the following items: years of experience teaching at the secondary level, certification, major or second major/minor of their bachelor's degree and graduate degree (if applicable), the number of days they missed in the previous semester, and how likely they were to become a teacher again if starting over.

The Coleman Report (1966) found that teacher characteristics explained more variation in student achievement than any other school resource, and more recent research confirms that teachers substantially affect student achievement growth (Nye, Konstantopoulos and Hedges 2004; Rowan, Correnti and Miller 2002). However, there is little consensus on which aspects of teachers' formal qualifications (e.g., years of experience, education, certification) matter most or at all (cf. Dee and Cohodes 2008; Desimone and Long 2010; Goldhaber and Brewer 2000; Grubb 2008; Ingersoll 1999; Palardy and Rumberger 2008). In addition, less frequently quantified teacher characteristics, such as teachers' commitment to, and enthusiasm for, teaching; expectations and emotional support for students; and attendance rate have been associated with student achievement in some studies (Hallinan 2008; Miller, Murnane and Willett 2008; Park 2005). Because how to define teacher quality remains an open and highly controversial question, and because some methods of measuring teacher quality are not possible given the ELS data, I include a variety of measures of teacher characteristics but rely on a method of combining these measures (discussed below) that is not negatively affected by the high correlations among many measures of teacher characteristics. Initial descriptive analyses indicated that patterns were fairly similar for math and English teachers, so I generally combine their responses.[5]

Physical resources. I measure physical resources using school administrators' base-year reports regarding the extent to which student learning at their school was hindered by the following problems: poor condition of buildings; poor heating, cooling, or lighting; inadequate

[5] The one exception is for the degree variables. Researchers have argued that an in-field degree is particularly important for math and science teachers (Dee and Cohodes 2008; Hill and Dalton 2013), so I separate math and English teachers when identifying whether or not a student's teacher has an in-field degree.

science laboratory equipment; inadequate facilities for fine arts; lack of instructional space; lack of instructional materials in the library; lack of textbooks and basic supplies; not enough computers for instruction; lack of multimedia resources for instruction; or inadequate or outdated vocational-technical equipment.

Researchers have repeatedly emphasized the potential importance of physical resources, such as building conditions, laboratory equipment, instructional materials, and computers, to student learning (Ladson-Billings and Tate 1995), and there is ample evidence of racial/ethnic and socioeconomic disparities in schools' physical resources (Condron 2009; Elliott and Agiesta 2013; Massey 2006). Physical resources differ from some of the other school resources I measure in that they are often more visible to the public (compared to resources like teacher qualifications or student-staff relationships); additionally, in many cases, physical resources can be funded by different funding streams than non-physical resources, which may make acquiring physical resources easier or harder in specific instances (Odden and Picus 2008; Romer and Rosenthal 1979; Romer and Rosenthal 1982). Although research generally shows few observable effects of physical resources on student achievement (Bowers and Urick 2011), given that physical resources remain a visible – and inequitably distributed – aspect of students' schooling experiences, I test them here alongside other measures.

Student-staff relationships. I use students', teachers', and administrators' survey responses to measure student-staff relationships. Students reported the extent to which they agreed with the following statements: "students get along well with teachers"; "teachers are interested in students"; "when I work hard on schoolwork, teachers praise my efforts"; and "in class, I often feel 'put down' by teachers." Students also reported what their counselor, favorite teacher, and coach thought they should do after high school.[6] Teachers stated whether or not a particular student talked with them outside of class about school work, plans for after high school, or personal matters. School administrators reported how often verbal abuse of teachers and student disrespect for teachers occurred at their school, as well as how true the following statements were for their school: “student morale is high,” “teachers press students to achieve,” and “teacher morale is high.”

Prior research suggests that stronger student-teacher relationships are associated with higher achievement and greater achievement growth, as is a positive school climate more generally (Crosnoe, Johnson and Elder 2004; Gregory and Weinstein 2004; Grubb 2008). Students’ access to high school staff who encourage high school completion and college enrollment is associated with attainment (Roderick, Coca and Nagaoka 2011) and may be essential for the educational advancement of low-SES and minority students who rely more on school-based adults to guide them in making educational plans (Erickson, McDonald and Elder 2009; Martinez and Cervera 2012; Stanton-Salazar and Dornbusch 1995). Students are very attuned to teachers’ behavior toward, and perceptions of, them, and teachers affect the extent to which students enjoy attending school (Hallinan 2008; Muller, Katz and Dance 1999). Thus, I include measures of student-teacher relationships specifically, as well as broader measures of student and teacher morale.

Student-peer relationships. To measure student-peer relationships, I again use a combination of student, teacher, and administrator reports. On the base-year survey, students reported how important getting good grades and continuing education past high school were

[6] Response options were “go to college,” “get a full-time job,” “enter a trade school or apprenticeship,” “enter military service,” “get married, “they think I should do what I want,” or “they don’t care.” I use these items to measure students’ perceptions of whether or not at least one school-based adult aspires for the student to attend college.

among their close friends, as well as how much they agreed with the following statement: "In class, I often feel 'put down' by other students." On the first follow-up survey, students reported how many of their friends planned to have a full-time job and how many planned to attend a four-year college after high school. In 2002, teachers stated whether or not they agreed that the student relates well to peers, and administrators reported how often physical conflicts among students and student bullying occur at their school.

Peer relationships are particularly important in adolescence (Cherng, Calarco and Kao 2013; Patacchini, Rainone and Zenou 2011), and students are affected not only by their friends but by their school peers more broadly (Perna and Titus 2005). In some cases, students may become increasingly like their peers, both because students feed off their peers' contributions to the school climate and because peer groups foster particular reactions from school-based adults (Palardy 2013; Sokatch 2006). In other cases, students may benefit when they are able to stand out from peers and are protected from negative inter-student comparisons (Attewell 2001; Crosnoe 2009; Goldsmith 2011). Peer effects likely vary across subgroups and outcomes; for example, peers may have especially strong effects on the college enrollment decisions of students whose parents are not college-educated because such students more often rely on their friends to provide college information (Person and Rosenbaum 2006; Roderick, Coca and Nagaoka 2011).

Outcome Variables

I examine four outcomes: twelfth grade math achievement, high school graduation, immediate enrollment in a four-year college or university, and any postsecondary enrollment within eight years of students' expected high school graduation. To measure math achievement, I use the ELS standardized score, which is a norm-referenced measure with a mean of 50 and a standard deviation of 10. In the base year, a two-stage design was used to maximize measurement accuracy while minimizing floor and ceiling effects. In the first stage, all students received a short routing test; based on the results, survey administrators assigned students to a low, medium, or high difficulty second stage form.[7] Then, in the first follow-up, students were assigned a test form based on their 2002 math ability estimate. The twelfth grade math measure is only available for students who remained in their base-year school in 2004; the measure is not available for dropouts, early graduates, homeschoolers, or students who transferred schools.

I define high school graduation as graduating early or on-time with a regular diploma. I do not include GED recipients as "high school graduates" because GED credentials generally are not worth as much in the labor market (Heckman, Humphries and Mader 2010). Information on high school graduation comes from students' questionnaires supplemented by high school transcripts when necessary. About 88 percent of students graduated early or on-time with a regular diploma.

I look at two types of college enrollment. First, I examine a relatively privileged type of enrollment, on-time attendance at a four-year college or university. I define "on-time" as within one semester of students' expected high school graduation date. Students who delay entering college for one semester or more are less likely to earn a college credential (Bozick and DeLuca 2005; Goldrick-Rab and Han 2011), and students who begin at four-year institutions are more

[7] A possible concern is that the math achievement results may not be reliable because students are not motivated to do their best on low-stakes tests. Some evidence partially alleviates this concern. First, students were given a cash incentive for participation, which may have motivated them to take the test seriously. Second, in scoring the tests, the assessment contractor examined missing responses and "pattern marking" (e.g., when students complete tests by marking "ABCABC") and did not find high levels of either problem. In the base year, only 10 tests were discarded for pattern marking or incomplete items, while only 17 were discarded in the first follow-up. Third, 95 percent of participants in the base year, and 87 percent of participants in the first follow-up, completed the test. Since some participants could not complete the tests due to language or disability reasons, these response rates indicate that the vast majority of test-eligible students completed the assessments.

likely to earn bachelor's degrees than are equally prepared students who aspire to earn bachelor's degrees but who begin at two-year institutions (Doyle 2009; Long and Kurlaender 2009). Around 48 percent of the sample enrolled on-time in a four-year institution. Second, I examine any postsecondary enrollment within eight years of students' expected high school graduation (i.e., by the time of the third follow-up in 2012). This is a broader measure of postsecondary enrollment: about 88 percent of students enrolled in at least one postsecondary institution within eight years of their expected high school graduation date. Both college enrollment measures are based on students' self-reported enrollment[8]; information on the level of students' first-attended institution comes from the Integrated Postsecondary Education Data System data when available and from student reports otherwise. For the first postsecondary measure, I use responses from the second follow-up survey, which provides the most proximal measure of on-time enrollment, when available and the third follow-up survey otherwise. For the measure of any postsecondary enrollment, I use responses from the third follow-up when available; if the student did not respond to the third follow-up but did report in the second follow-up that s/he was enrolled in a postsecondary institution, I use that information.

Other School Variables

I include three commonly considered school characteristics as covariates: school sector, locale, and the percentage of free or reduced-price lunch (FRL)-eligible students they enroll. In the ELS, 77 percent of schools are public, 33 percent are located in urban areas, 19 percent in rural areas, and 48 percent in suburbs. I use FRL-eligibility, rather than a composite SES measure, because this measure captures the economic composition of the whole school, rather than just sampled students. Other researchers also have used the percentage of FRL-eligible

[8] Both self-reported survey and transcript data present advantages as well as limitations; I elected to use the composite variables provided by ELS to measure postsecondary enrollment.

students as a proxy for school SES in the ELS (cf. McGrady and Reynolds 2013). Low-FRL schools are those in which ten percent or less of students are FRL-eligible; medium-FRL schools have FRL eligibility rates from 11 to 50 percent; and high-FRL schools have more than 50 percent of students eligible for free or reduced-price lunch. Twenty schools are missing data on the percent of FRL-eligible students.[9] In the SES chapter, because of concerns about bias in group mean-centered models when average SES is omitted, I also include the average SES of sampled students to measure schools' socioeconomic composition (discussed in more detail in Chapter 4). The correlation between schools' percent FRL and mean student SES is -.7.

METHODS

The overall approach is to first estimate the degree of within-school inequality (by gender in Chapter 3, by SES in Chapter 4, and by race/ethnicity in Chapter 5) and then use measures of school resources to predict variation in inequality across schools.

Estimating the Degree of Within-School Inequality

The true subgroup-level differences in achievement and attainment at a school are unobserved both because the ELS did not collect data for all students at a school and because each outcome variable is measured with error. Therefore, the simplest approach to calculating within-school inequality (i.e., subtracting the average score for different subgroups on each outcome, then using this difference as the measure of school-level inequality) is biased. Instead, I use multilevel models to estimate the unobserved group-level differences. The key feature of these models is the inclusion of random slopes that allow the effect of the characteristic being examined (i.e., gender, race/ethnicity, or SES) to vary across schools.

---

[9] Some additional schools were missing FRL data on the base-year administrator survey; for these schools, I substituted data from the first follow-up survey when available. I divide schools into low-, medium-, and high-FRL groups because the ELS' percent FRL measure is not continuous and includes some categories with small sizes.

In the equation below, the γ terms represent coefficients, with the first subscript indexing level-one variables and the second subscript indexing level-two variables.[10]

$$Y_{ij} = \gamma_{00} + \gamma_{10}Gender_{ij} + \gamma_{20}X_{ij} + \gamma_{01}W_j + u_{0j} + u_{1j}Gender_{ij} + r_{ij}$$

The key parameter is the school-level slope, u_{1j}, for each demographic variable of interest (gender in the equation shown here, but SES or race/ethnicity depending on the chapter). The other parameters are the average student-level effect, γ_{10}, of the demographic characteristic of interest; school-level random intercepts, u_{0j}; student-level covariates (i.e., English-as-a-Second-Language, special education status, and the demographic covariates that are not of central interest), X_{ij}; and school-level covariates (i.e., sector, locale, and school SES), W_j.

The school-level slopes represent the extent to which the demographic (gender, racial/ethnic, or socioeconomic) difference at a *particular* school differs from the demographic difference at the *average* school.[11] Because the sample is nationally representative, the standard deviation of u_{1j} measures variation in gender, racial/ethnic, and socioeconomic inequalities across U.S. high schools. To avoid spurious findings and adjust for the small within-school sample sizes, I use the best linear unbiased predictions of the random effects, otherwise known as the empirical Bayes estimates, for each school (Gelman and Hill 2007). Compared to maximum likelihood estimates of random effects, empirical Bayes estimates shrink the random

[10] The equation depicts the model for the continuous outcome (twelfth grade math achievement); models for high school graduation and college enrollment require a transformation of the linear prediction to the logistic scale. Across chapters, all models for binomial outcomes are on the logistic (or log odds) scale.

[11] There is debate about how or if to center level-one variables when estimating slope heterogeneity. Raudenbush and Bryk (2002) recommend group mean-centering, and Borman and Dowling (2010), as well as others, follow this approach. Because some form of centering is necessary for the SES chapter, I follow Raudenbush and Bryk's recommendation, group mean-centering SES and including school mean SES as a predictor (discussed in more detail in chapter 4). However, for the gender and race/ethnicity chapters, I follow Legewie and DiPrete's (2014) approach in which they standardized continuous variables but did not further center variables. I do so because my analysis closely mirrors theirs and uses the same R package as theirs did.

effects toward the sample mean when within-school sample sizes are small, which somewhat attenuates problems related to measurement error. I follow the recommendations of Chung et al. (2012) who propose a maximum penalized likelihood approach that is appropriate for producing stable estimates of group-level variance parameters with small sample sizes using weakly informative priors.[12]

For each outcome, I estimate three models: an unconditional model (representing the average difference between students in the subgroups of interest without controlling for differences in other student or school characteristics), a model that conditions on student covariates, and a model that conditions on both student and school covariates. I impute the student-level covariates that are not of central interest; the demographic characteristic of central interest in a given chapter (i.e., gender in Chapter 3, SES in Chapter 4, and race/ethnicity in Chapter 5) and the outcome variables are not imputed.[13] Unconditional multilevel models for each outcome indicate that, depending on the sample (e.g., gender sample versus SES sample), 16 to 23 percent of the variation in math achievement, 12 to 18 percent of the variation in high school graduation, 23 to 27 percent of the variation in immediate four-year enrollment, and 13 to 19 percent of the variation in any postsecondary enrollment is between, rather than within, schools.

< Table 5 >

For the gender and race/ethnicity chapters, I restrict the sample to schools with at least three sampled students in the subgroups under consideration (e.g., three Black and three White students when comparing Black-White differences); for the SES chapter, I restrict the sample to

[12] This procedure relies on R's blme package, which extends the lme4 multilevel modeling package.

[13] I use the Amelia software in R to produce 20 complete versions of the dataset using a bootstrapped expectation-maximization algorithm. The parameters from these 20 datasets are then averaged together.

schools with at least five sampled students with SES data. At least one student per subgroup is required to estimate these models, but I chose to require three to five students per school as a compromise between sample representativeness and precision of estimates. Requiring fewer students per school would increase the representativeness of the school-level sample but decrease the precision of the estimates, while requiring more students per school would decrease the school-level sample's representativeness but increase the estimates' precision. I discuss the limitations of this choice in each chapter as well as the conclusion. Table 6 displays the number of sampled students per school in each subgroup with math achievement, high school graduation, and college enrollment data.

< Table 6 >

Obtaining Measures of School Resources

The ELS contains many items assessing different facets of schools' resources, which means multiple approaches for constructing resource measures are possible. The simplest approach would be to include the individual survey items directly in the models. However, there are limited degrees of freedom to test the items individually and, additionally, the individual resource items are both measured with error and correlated with one another in sometimes complex ways. A second approach would be to create clusters or scales of resources based on theory alone. While this would reduce the resources to a manageable number for estimation, the coding scheme would need to be driven by strong theory, which is lacking. Therefore, the approach I use to combine these items into parsimonious representations of school resources and types is latent class analysis (LCA), a dimension-reduction strategy useful for taking a rich but noisy set of measures and identifying the underlying classes or types that drive the observed measures.

LCA is useful for "empirically characterizing a multidimensional typology" (Hill 2008) and is an appropriate technique when researchers conceptualize particular phenomena as having "distinct subgroups, types, or categories" rather than being on a continuous gradient (Collins and Lanza 2010). In LCA, the unobserved, error-free latent variable *explains* observed indicators that are measured with error. By characterizing school types based on response patterns for multiple indicators, LCA offers an empirical (rather than ad hoc) method of clustering schools, as well as a way to explore measures of school resources in combination rather than isolation (Vermunt and Magidson 2005). A good latent class model has a high degree of homogeneity in individuals' responses within classes (i.e., one response pattern is highly characteristic of each class), as well as highly-differentiated, well-separated classes (i.e., a response pattern that is highly characteristic of one class has small probabilities of occurrence in the other latent classes).

The following equation represents the posterior probability of latent class membership conditional on the observed values of the indicator variables. The probability that observation i belongs to class r conditional on the observed Y_i is calculated by $\hat{p}_r$, the unconditional probability of membership in latent class r (i.e., the probability of membership in latent class r before taking into account the responses provided on the observed variables), multiplied by the latent class probability model $f(Y_i; \hat{\pi}_r)$ (i.e., the probability that individual i in class r produces a particular set of observed outcomes), divided by the sum of the products of the prior probabilities of membership in each latent class and the corresponding probability models for each class.

$$\hat{P}(r_i|Y_i) = \frac{\hat{p}_r f(Y_i; \hat{\pi}_r)}{\sum_{q=1}^{R} \hat{p}_q f\left(Y_i; \hat{\pi}_q\right)}$$

The equation is applied to each observation R times to calculate a vector of R probabilities that represent the probability of observation i's membership in each of the R latent classes. The latent classes are mutually exclusive and exhaustive, but the classifications are probabilistic.

I aggregate all of the resource indicators to the school level and standardize them to have equivalent scales.[14] Because LCA uses full information maximum likelihood, cases with missing data still contribute to the model estimation. I first use LCA to measure schools' levels of five different types of resources: instructional, teacher, school physical resources, student-staff relationships, and student-peer relationships. Then, I use the predicted latent class membership probabilities from each of the five resource models to create a multidimensional measure of school type that integrates the individual resource measures. This unordered set of latent classes (or "school types") permits an exploration of how certain types of common, joint resource allocations are related to variation in the degree of gender, racial/ethnic, and socioeconomic inequalities in outcomes.[15] Figure 1 illustrates this approach.

< Figure 1 >

Given that researchers rarely have specific hypotheses about the number of latent classes, the primary modeling decision in LCA is usually the number of classes to specify. I first fit models with increasing numbers of classes until the models became poorly identified. For each model, I collected fit statistics, which I used to decide on two to three plausible models that I

[14] This approach raises concerns about bias both because of aggregating students' responses to the school level and because of including students' own responses in the aggregate measures. Any bias from including students' own responses in the school-level measures should be small given that LCA already incorporates uncertainty in the membership probabilities and that schools with limited numbers of students are shrunk toward the sample mean by the empirical Bayes estimate. The disadvantage of potential bias from aggregating student responses to the school level may be countered by the advantage of using reports that reflect the resources experienced by the students for whom I am calculating achievement and attainment disparities.

[15] An alternative approach to creating an integrated measure of school type would be to categorize schools based on their modal class for each resource and then interact those modal classes. This approach could result in up to 72 cells (3 classes for instructional resources x 2 classes for teacher resources x 3 classes for physical resources x 2 classes for student-staff resources x 2 classes for student-peer resources). The number of cells would be unwieldy, and, in addition, by using the modal class rather than the class probabilities, this approach would obscure the uncertainty inherent in classification.

should investigate more closely. Then, I evaluated these plausible models in terms of classification measures, parsimony, and interpretability.[16] I also used both fit statistics and interpretability to decide whether to treat the classes as ordered or unordered and whether to relax assumptions of local independence for some items.[17]

Table 7 shows classification statistics, as well as latent class prevalences, for each latent class model. The models for instructional and physical resources have three classes, while the models for teacher, student-staff, and student-peer resources have two classes; the size of the classes ranges from a low of six percent of the sample for one of the physical resource classes to a high of 87 percent of the sample for one of the student-staff relationship classes. The proportion of cases that are estimated to be misclassified when classification is based on modal assignment ranges from two to eight percent depending on the model, with the lowest estimated proportion of errors for the teacher model and the highest estimated proportion for the student-peer model. The R^2 measures indicating how well the models predict class membership range from a low of 0.66 to a high of 0.95 with the lowest R^2 for the student-peer model and the highest for the combined model.

< Table 7 >

[16] There is no agreed-upon best method for comparing models with different numbers of classes (Collins and Lanza 2010). Information critia are the most commonly used method for selecting the number of latent classes but "are likely to be more useful in ruling out models and narrowing down the set of plausible options than in pointing unambiguously to a single best model" (Collins and Lanza 2010: 88). Since most classification diagnostics are based on the estimated posterior class probabilities, these measures should not be used for selecting models given that posterior classification uncertainty can increase simply by chance for models with more latent classes (Masyn 2013).

[17] One of LCA's assumptions is local independence, meaning that the observed indicators are related to each other only through the latent variables and not through the items' errors. However, some of the items I use are likely related to each other in part because of how they were asked in the ELS surveys (e.g., items asked in the same battery). Therefore, I examined the bivariate residuals for each set of items to decide when to relax the local independence assumption and allow various items to directly affect each other. Bivariate residuals substantially larger than one indicate that the initial model fails to account for all of the pairwise associations between items (Vermunt and Magidson 2005).

Table 8 shows the means for the indicators, and proportions for the school background characteristics, by class for the individual resource models. Based on the indicator means, I label the latent classes as follows: “general orientation to instructional resources,” “most vocationally oriented instructional resources,” “most academically oriented instructional resources,” “more experienced but less satisfied teachers,” “less experienced but more satisfied teachers,” “fewest physical resource problems,” “moderate physical resource problems,” “most physical resource problems,” “less positive student-staff relationships,” “more positive student-staff relationships,” “less academically oriented peers,” and “more academically oriented peers.”

< Table 8 >

Table 9 displays the means for the indicators and proportions for the background characteristics in the combined model. I label the combined model’s classes, in declining order of prevalence, as “middle-of-the-road schools”; “well-maintained, middle-of-the-road schools”; “most academically advantaged schools”; “poorly maintained schools”; “middle-of-the-road schools with less experienced teachers”; “most vocationally oriented schools”; “schools with the most positive student-staff relationships”; and “less well-maintained but academically advantaged schools.” The most common type of schools, “middle-of-the-road schools,” have a very high probability of being in the first class of instructional resources (i.e., general orientation to instructional resources), the first class of teacher resources (i.e., more experienced but less satisfied teachers), the second class of physical resources (i.e., moderate physical resource problems), the first class of student-staff resources (i.e., less positive student-staff relationships), and the first class of student-peer resources (i.e., less academically-oriented peers). Schools in this class also are most likely to be public, suburban, and medium FRL.

< Table 9 >

Table 10 shows the average math achievement score, high school graduation rate, rate of immediate enrollment in a four-year institution, and rate of any postsecondary enrollment for each class of the individual resource and combined models using modal classification for the class assignments. Schools in the most academically advantaged, less well-maintained but academically advantaged, and most positive student-staff relationships classes have higher than average math achievement, graduation, and college enrollment rates.

< Table 10 >

Predicting Variation in Inequalities across Schools

Finally, I use these measures of school resources to explain variability in gender, racial/ethnic, and socioeconomic inequalities across schools. I use two-level hierarchical models with a slopes-as-outcomes approach to model the relation between schools' levels of resources and variability in outcomes for students from different subgroups across schools (Borman and Dowling 2010). The equation is the same as the one shown above except that it includes two additional parameters: γ_{02}, the average effect of school type or resources, and the cross-level interaction, γ_{11}, between the demographic characteristic of interest and school type/resources:

$$\begin{aligned} Y_{ij} = \ & \gamma_{00} + \gamma_{10}Gender_{ij} + \gamma_{20}X_{ij} + \gamma_{01}W_j + \gamma_{02}School\ type_j \\ & + \gamma_{11}School\ type_j\left(Gender_{ij}\right) + u_{0j} + u_{1j}Gender_{ij} + r_{ij} \end{aligned}$$

Simply assigning individuals to latent classes based on posterior probabilities, then using the assigned classes to predict subsequent outcomes, is problematic because this approach does not account for the uncertainty in classification present in every LCA (Bray, Lanza and Tan 2015; Collins and Lanza 2010; Lanza, Tan and Bray 2013). Therefore, I use the class membership probabilities, rather than modal classes, for both the main effects and cross-level interactions between students' demographic characteristics and the probability of each school belonging to a particular class.[18] Figure 2 illustrates this approach.

< Figure 2 >

[18] Because of the limited number of schools in the sample, I use $p < .1$ instead of $p < .05$ as the threshold for statistically significant interactions, and I try to focus on substantive significance more than statistical significance. Aguinis et al. argue that "the power to detect cross-level interactions is severely limited in many circumstances" and that "it may be reasonable to adopt more liberal alpha levels for early investigations [of cross-level interactions] in a nascent topic area" (2013: 962).

Figure 1. Conceptual Model for Latent Class Analysis

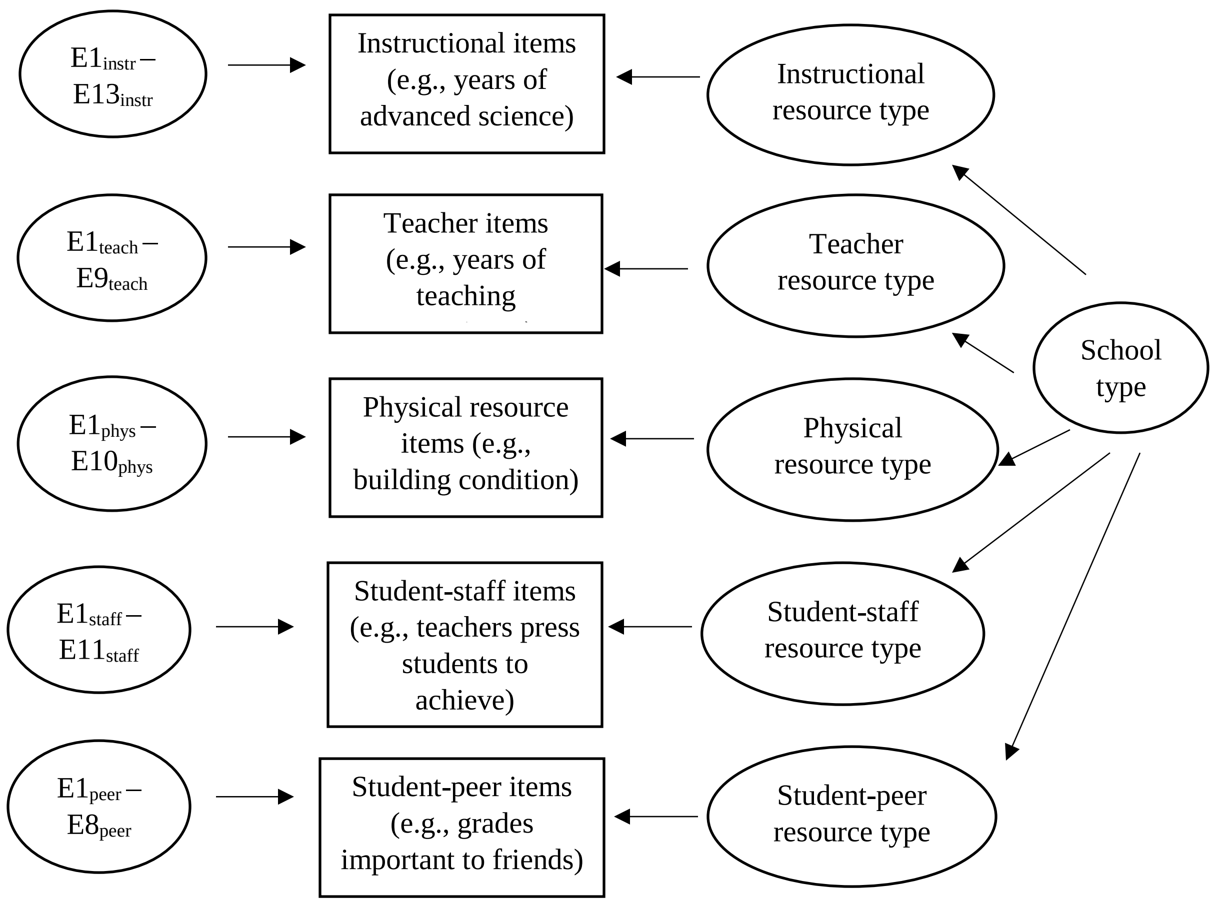


Figure 2. Conceptual Model for Slopes-as-Outcomes Analysis

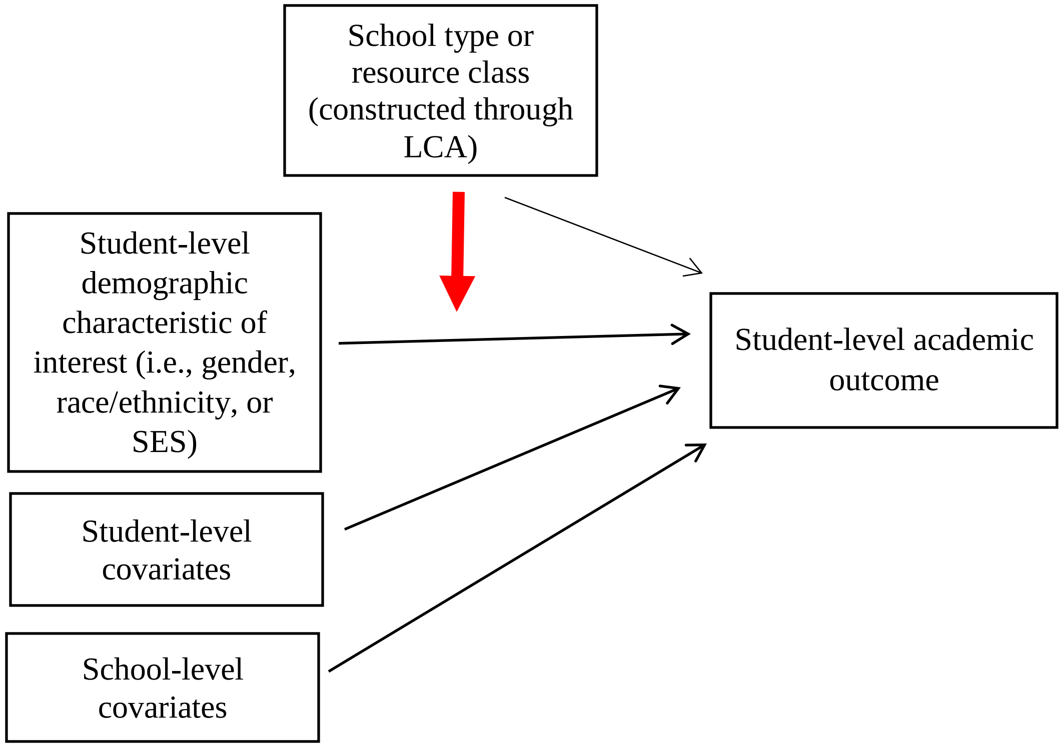


Table 1. Number of Sampled Students per School

Number of Sampled Students	Number of Schools	Percent of Schools
5 or fewer	9	1%
6 to 9	16	2%
10 to 14	82	11%
15 to 19	187	25%
20 to 24	220	29%
25 to 29	164	22%
30 to 34	66	9%
35 or more	7	1%
	751	100%

Table 2. Indicators Used to Measure School Resources

Type of Resource	Indicator	Respondent	Wave Measured	Response Categories
Instructional	Use of school media center for assignments	Student	Base year	Never, rarely, sometimes, often
	Use of school media center for research papers	Student	Base year	Never, rarely, sometimes, often
	Ever in Advanced Placement course or International Baccalaureate program	Student	Base year	Yes, no
	Ever in remedial English or math course	Student	Base year	Yes, no
	High school program	Student	Base year	General, college preparatory/academic, vocational including technical/business
	Years of advanced science (i.e., chemistry, physics) coursework completed	Student	First follow-up	0 - 3 years in half-year increments
	Years of advanced math (i.e., trigonometry, pre-calculus, calculus) coursework completed	Student	First follow-up	0 - 4 years in half-year increments
	Participation in cooperative education	Student	Base year	Yes, no
	Participation in school-organized internships	Student	Base year	Yes, no
	Participation in job shadowing or work visits	Student	Base year	Yes, no
	Participation in school-organized mentoring	Student	Base year	Yes, no
Teacher	Years of experience teaching at secondary level	Teacher	Base year	2 or fewer, 3 to 4, 5 or more
	Regular/standard certification	Teacher	Base year	Yes, no
	Bachelor's degree major (or minor/second major) in subject taught (i.e., English or math, respectively)	Teacher	Base year	Yes, no
	Graduate degree major (or minor/second major) in subject taught (i.e., English or math, respectively)	Teacher	Base year	Yes, no
	Number of days absent during first semester	Teacher	Base year	0 - 40
	If starting over, likelihood of becoming a teacher again	Teacher	Base year	Certainly would, probably would, chances for and against are even, probably or certainly would not
Physical	Learning hindered by…			
	Poor condition of buildings	Administrator	Base year	Not at all, very little, to some extent, a lot

	Poor heating, cooling, lighting	Administrator	Base year	Not at all, very little, to some extent, a lot
	Inadequate science laboratory equipment	Administrator	Base year	Not at all, very little, to some extent, a lot
	Inadequate facilities for fine arts	Administrator	Base year	Not at all, very little, to some extent, a lot
	Lack of instructional space	Administrator	Base year	Not at all, very little, to some extent, a lot
	Lack of instructional materials in the library	Administrator	Base year	Not at all, very little, to some extent, a lot
	Lack of textbooks and basic supplies	Administrator	Base year	Not at all, very little, to some extent, a lot
	Not enough computers for instruction	Administrator	Base year	Not at all, very little, to some extent, a lot
	Lack of multimedia resources for instruction	Administrator	Base year	Not at all, very little, to some extent, a lot
	Inadequate vocational equipment/facilities	Administrator	Base year	Not at all, very little, to some extent, a lot
Student-Staff	Students get along well with teachers	Student	Base year	Strongly disagree, disagree, agree, strongly agree
	Teachers are interested in students	Student	Base year	Strongly disagree, disagree, agree, strongly agree
	Teachers praise effort	Student	Base year	Strongly disagree, disagree, agree, strongly agree
	In class often feels put down by teachers	Student	Base year	Strongly disagree, disagree, agree, strongly agree
	Student talks with at least one teacher outside of class	Teacher	Base year	Yes, no
	At least one school-based adult (school counselor, favorite teacher, coach) wants student to attend college	Student	Base year	Yes, no
	Student morale is high	Administrator	Base year	Between not at all and somewhat accurate, somewhat accurate, between somewhat and very accurate, very accurate
	Teachers press students to achieve	Administrator	Base year	Not accurate at all, between not at all and somewhat accurate, somewhat accurate, between somewhat and very accurate, very accurate
	Teacher morale is high	Administrator	Base year	Not accurate at all, between not at all and somewhat accurate, somewhat accurate, between somewhat and very accurate, very accurate

	How often verbal abuse of teachers a problem at school	Administrator	Base year	Never happens, happens on occasion, happens at least once a month, happens at least once a week, happens daily
	How often student disrespect for teachers a problem at school	Administrator	Base year	Never happens, happens on occasion, happens at least once a month, happens at least once a week, happens daily
Student-Peer	Important to friends to get good grades	Student	Base year	Not important, somewhat important, very important
	Important to friends to continue education past high school	Student	Base year	Not important, somewhat important, very important
	How many friends plan to have full-time job after high school	Student	First follow-up	None, a few, some, most, all
	How many friends plan to attend four-year college/university	Student	First follow-up	None, a few, some, most, all
	In class often feels put down by other students	Student	Base year	Strongly agree, agree, disagree, strongly disagree
	Student relates well to others	Teacher	Base year	Yes, no
	How often physical conflicts a problem at school	Administrator	Base year	Never happens, happens on occasion, happens at least once a month, happens at least once a week, happens daily
	How often student bullying a problem at school	Administrator	Base year	Never happens, happens on occasion, happens at least once a month, happens at least once a week, happens daily

Table 3. Descriptive Statistics for School Resource Indicators at Student- and School-Level Prior to Standardization

		Student-Level			School-Level		
Type of Resource	Indicator	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Instructional	Use of school media center for assignments	2.17	0.95	13,881	2.16	0.44	748
	Use of school media center for research papers	2.45	1.03	13,838	2.43	0.50	748
	Ever in Advanced Placement course or International Baccalaureate program	0.19	-	14,413	0.19	-	748
	Ever in remedial English or math course	0.11	-	14,152	0.12	-	748
	General program	0.35	-	14,260	0.35	-	748
	College preparatory/academic program	0.55	-	14,260	0.55	-	748
	Vocational (including technical/business) program	0.10	-	14,260	0.10	-	748
	Years of advanced science coursework completed	1.08	0.86	14,385	1.07	0.45	751
	Years of advanced math coursework completed	0.68	0.90	14,269	0.66	0.43	751
	Participation in cooperative education	0.14	-	13,005	0.14	-	748
	Participation in school-organized internships	0.05	-	13,005	0.05	-	748
	Participation in job shadowing or work visits	0.13	-	13,005	0.14	-	748
	Participation in school-organized mentoring	0.05	-	13,005	0.05	-	748
Teacher	2 of fewer years of teaching experience	0.20	-	13,965	0.20	-	732
	3 to 4 years of teaching experience	0.17	-	13,965	0.17	-	732
	Regular/standard certification	0.73	-	14,084	0.72	-	732
	English teacher has bachelor's degree in English	0.83	-	11,596	0.81	-	716
	Math teacher has bachelor's degree in math	0.81	-	12,465	0.80	-	606
	English teacher has graduate degree in English	0.23	-	11,704	0.23	-	562
	Math teacher has graduate degree in math	0.21	-	12,226	0.21	-	583
	Number of days absent during first semester	2.95	3.11	14,114	2.94	1.79	733
	If starting over, likelihood of becoming a teacher again	2.97	0.85	14,126	2.97	0.55	733
Physical	Learning hindered by…						
	Poor condition of buildings		NA		1.54	0.79	616
	Poor heating, cooling, lighting				1.70	0.82	614
	Inadequate science laboratory equipment				1.76	0.87	616
	Inadequate facilities for fine arts				1.94	0.96	612

	Lack of instructional space				1.83	0.91	612
	Lack of instructional materials in the library				1.69	0.81	609
	Lack of textbooks and basic supplies				1.49	0.69	615
	Not enough computers for instruction				1.89	0.88	615
	Lack of multimedia resources for instruction				1.86	0.82	614
	Inadequate vocational equipment/facilities				1.79	0.89	605
Student-Staff	Students get along well with teachers	2.80	0.59	14,550	2.81	0.23	748
	Teachers are interested in students	2.88	0.70	14,295	2.90	0.26	748
	Teachers praise effort	2.76	0.75	14,440	2.78	0.24	748
	In class often feels put down by teachers	3.13	0.70	14,482	3.14	0.21	748
	Student talks with at least one teacher	0.53	0.50	14,005	0.53	0.19	733
	At least one school-based adult wants student to attend college	0.75	0.43	12,087	0.74	0.14	748
	Student morale is high		NA		3.98	0.76	617
	Teachers press students to achieve				4.09	0.81	616
	Teacher morale is high				3.82	0.84	618
	How often verbal abuse of teachers a problem				3.81	0.77	617
	How often disrespect for teachers a problem				3.59	0.89	618
Student-Peer	Important to friends to get good grades	2.45	0.60	10,624	2.45	0.21	748
	Important to friends to continue education	2.52	0.61	10,546	2.52	0.23	748
	How many friends plan to have full-time job	2.50	1.15	14,452	2.54	0.47	751
	How many friends plan to attend four-year college	3.37	1.08	14,458	3.34	0.53	751
	In class often feels put down by other students	3.08	0.71	14,457	3.08	0.21	748
	Student relates well to others	0.82	0.38	13,928	0.82	0.12	733
	How often physical conflicts a problem at school		NA		3.60	0.81	618
	How often student bullying a problem at school				3.58	0.81	614

Notes: 15,362 students from 751 schools participated in the base-year student questionnaire. Variables without standard deviations are proportions of respondents in a category.

Table 4. Coding Scheme for ELS School Resource Indicators

Type of Resource	Indicator	Transformation
Instructional	Use of school media center for assignments	Code students in schools without a school library or media center as "never"; take school mean
	Use of school media center for research papers	
	Ever in Advanced Placement course or International Baccalaureate program	Combine variables for AP and IB program participation; take school mean
	Ever in remedial English or math course	Combine variables for remedial English and math; take school mean
	General program	Take school mean
	College preparatory/academic program	
	Vocational (including technical/business) program	
	Years of advanced science coursework completed	Recode "less than half a year" as "0" and "more than one year" as "2"; add students' reported years of chemistry and physics; trim total years of advanced science to no more than 3; take school mean
	Years of advanced math coursework completed	Recode "less than half a year" as "0" and "more than one year" as "2"; add students' reported years of trigonometry, pre-calculus, and calculus; trim total years of advanced math to no more than 4; take school mean
	Participation in cooperative education	Take school mean
	Participation in school-organized internships	
	Participation in job shadowing or work visits	
	Participation in school-organized mentoring	
Teacher	2 or fewer years of teaching experience	Count percentage of sampled students at a school who have a math or English teacher with 2 or fewer years of experience at the secondary level
	3 to 4 years of teaching experience	Count percentage of sampled students at a school who have a math or English teacher with 3-4 years of experience at the secondary level and who do not have a math or English teacher with 2 or fewer years of experience

	Regular/standard certification	Count percentage of sampled students at a school whose sampled teachers have regular/standard certification (i.e., if both math and English teachers respond, both have regular certification; if only one teacher responds, that teacher has regular certification)
	English teacher has at least a bachelor's degree in English	Count percentage of sampled students at a school whose English teacher has at least a bachelor's degree major, second major, or minor in English
	Math teacher has at least a bachelor's degree in math	Count percentage of sampled students whose math teacher has at least a bachelor's degree major, second major, or minor in math
	English teacher has graduate degree in English	Count percentage of sampled students whose English teacher has a graduate degree major, second major, or minor in English
	Math teacher has graduate degree in math	Count percentage of sampled students whose math teacher has a graduate degree major, second major, or minor in math
	Number of days absent during first semester	Take mean number of days absent of student's English and math teachers; then take school mean
	If starting over, likelihood of becoming a teacher again	Combine "certainly would not" and "probably would not"; take mean of student's English and math teachers; then take school mean
Physical	Learning hindered by… Poor condition of buildings Poor heating, cooling, lighting Inadequate science laboratory equipment Inadequate facilities for fine arts Lack of instructional space Lack of instructional materials in the library Lack of textbooks and basic supplies Not enough computers for instruction Lack of multimedia resources for instruction Inadequate vocational equipment/facilities	No transformation except to combine missing categories
Student-Staff	Students get along well with teachers Teachers are interested in students Teachers praise effort	Reverse code and take school mean

	In class often feels put down by teachers	Take school mean
	Student talks with at least one teacher	Count percentage of sampled students at a school who talk with either their math or English teacher outside of class
	At least one school-based adult wants student to attend college	Recode all responses that are not "go to college" as "0"; count if student's favorite teacher, school counselor, or coach wants the student to attend college; take school mean
	Student morale is high	No transformation except to combine missing categories
	Teachers press students to achieve	
	Teacher morale is high	
	How often verbal abuse of teachers a problem	
	How often disrespect for teachers a problem	
Student-Peer	Important to friends to get good grades	Take school mean
	Important to friends to continue education	
	How many friends plan to have full-time job	
	How many friends plan to attend four-year college	
	In class often feels put down by other students	
	Student relates well to others	Count percentage of sampled students at a school whose sampled teachers say the student relates well to others (i.e., if both math and English teachers respond, both say student relates well; if only one teacher responds, that teacher says student relates well)
	How often physical conflicts a problem at school	No transformation except to combine missing categories
	How often student bullying a problem at school	

Note: After performing the transformations described here, all variables measured at the student- or teacher-level are then standardized to have a mean of 0 and standard deviation of 1.

Table 5. Intraclass Correlations

	Math achievement	High school graduation	Immediate four-year enrollment	Any postsecondary enrollment
Gender sample	0.22	0.16	0.24	0.18
SES sample	0.23	0.18	0.26	0.19
Black-White sample	0.20	0.12	0.23	0.13
Hispanic-White sample	0.16	0.14	0.27	0.17

Note: Because the sample restrictions (and, thus, sample sizes) differ across models, the ICCs also differ.

Table 6. Number of Sampled Students per School by Demographic Characteristics and Availability of Outcome Data

	No. of Schools w/ N Sampled Students w/ Math Achievement Data					No. of Schools w/ N Sampled Students w/ High School Graduation Data					No. of Schools w/ N Sampled Students w/ Data for Any Postsecondary Enrollment					No. of Schools w/ N Sampled Students w/ Data for Immediate Enrollment in a Four-Year Institution				
No. of Students	0	1-2	3-4	5-9	10+	0	1-2	3-4	5-9	10+	0	1-2	3-4	5-9	10+	0	1-2	3-4	5-9	10+
Overall	2	8	6	60	675	0	3	4	21	723	0	3	5	35	708	0	2	5	34	710
Male	25	26	75	354	271	21	17	38	306	369	22	23	62	332	312	22	21	56	344	308
Female	29	16	68	353	285	25	15	39	267	405	25	18	44	297	367	25	15	51	298	362
White	79	70	53	158	391	68	69	42	142	430	72	73	44	151	411	73	69	50	156	403
Black	319	233	78	89	32	297	237	80	84	53	312	238	70	85	46	308	233	81	86	43
Hispanic	281	272	73	87	38	235	296	76	83	61	253	292	77	80	49	252	290	80	82	47
SES	2	8	6	61	674	0	3	7	27	714	0	3	8	47	693	0	2	9	41	699

Table 7. Fit Statistics for Latent Class Models

	Instructional Resources	Teacher Resources	Physical Resources	Student-Staff Relationships	Student-Peer Relationships	Combined Model
Model type	Unordered model with 3 classes	Ordered model with 2 classes	Ordered model with 3 classes	Ordered model with 2 classes	Ordered model with 2 classes	Unordered model with 8 classes
Number of cases	751	733	618	751	751	751
Classification errors	0.06	0.02	0.06	0.04	0.08	0.04
Reduction of errors (lambda)	0.85	0.89	0.87	0.68	0.70	0.95
Entropy R-squared	0.84	0.89	0.83	0.73	0.66	0.95
Standard R-squared	0.84	0.90	0.87	0.73	0.70	0.94
Number of indicators	13	9	10	11	8	7
Class 1 size	0.61	0.80	0.43	0.87	0.73	0.18
Class 2 size	0.22	0.20	0.51	0.13	0.27	0.16
Class 3 size	0.17	-	0.06	-	-	0.16
Class 4 size	-	-	-	-	-	0.11
Class 5 size	-	-	-	-	-	0.10
Class 6 size	-	-	-	-	-	0.10
Class 7 size	-	-	-	-	-	0.10
Class 8 size	-	-	-	-	-	0.09

Notes: The fit statistics shown here include the estimated proportion of classification errors and three different R^2-type measures: the proportional reduction of classification errors, a measure based on entropy, and a measure based on variance (Vermunt and Magidson 2005; Vermunt and Magidson 2013). The class sizes indicate what proportion of the sample is in each class.

Table 8. School Resource Indicators and Background Characteristics by Resource Class

		General Orientation	Most Vocationally Oriented	Most Academically Oriented
Instructional Resource Indicators	Use of school media center for assignments	-0.10	-0.08	0.46
	Use of school media center for research papers	-0.03	-0.12	0.26
	Ever in Advanced Placement course or International Baccalaureate program	-0.11	0.15	0.23
	Ever in remedial English or math course	-0.06	0.19	-0.01
	General program	0.25	0.05	-0.98
	College preparatory program	-0.22	-0.33	1.19
	Vocational (including technical/business) program	-0.01	0.53	-0.64
	Years of advanced science coursework completed	-0.33	-0.02	1.18
	Years of advanced math coursework completed	-0.30	-0.17	1.26
	Participation in cooperative education	-0.02	0.35	-0.39
	Participation in school-organized internships	-0.21	0.81	-0.29
	Participation in job shadowing or work visits	-0.23	1.05	-0.50
	Participation in school-organized mentoring	-0.24	0.82	-0.19
School Background Characteristics	Private	0.12	0.16	0.69
	Urban	0.28	0.33	0.52
	Rural	0.22	0.19	0.06
	Suburban	0.49	0.49	0.42
	Low-FRL	0.34	0.28	0.82
	Medium-FRL	0.50	0.49	0.12
	High-FRL	0.16	0.23	0.05
		More Experienced but Less Satisfied Teachers	Less Experienced but More Satisfied Teachers	

Teacher Resource Indicators	2 or fewer years of teaching experience	-0.12	0.47	
	3 to 4 years of teaching experience	-0.08	0.32	
	Regular/standard certification	0.42	-1.71	
	English teacher has bachelor's degree in English	0.03	-0.15	
	Math teacher has bachelor's degree in math	0.13	-0.54	
	English teacher has graduate degree in English	0.02	-0.06	
	Math teacher has graduate degree in math	0.03	-0.13	
	Number of days absent during first semester	0.09	-0.37	
	If starting over, likelihood of being a teacher again	-0.07	0.30	
School Background Characteristics	Private	0.13	0.63	
	Urban	0.30	0.46	
	Rural	0.20	0.13	
	Suburban	0.50	0.41	
	Low-FRL	0.35	0.65	
	Medium-FRL	0.49	0.20	
	High-FRL	0.15	0.15	
		Fewest Physical Resource Problems	Moderate Physical Resource Problems	Most Physical Resource Problems
Physical Resource Indicators	Poor condition of buildings	1.08	1.73	3.15
	Poor heating, cooling, lighting	1.19	1.94	3.24
	Inadequate science laboratory equipment	1.17	2.06	3.35
	Inadequate facilities for fine arts	1.34	2.27	3.42
	Lack of instructional space	1.22	2.17	3.43
	Lack of instructional materials in the library	1.14	1.98	3.23
	Lack of textbooks and basic supplies	1.08	1.66	2.88
	Not enough computers for instruction	1.38	2.16	3.18
	Lack of multimedia resources for instruction	1.31	2.16	3.20
	Inadequate vocational equipment/facilities	1.23	2.04	3.29

School Background Characteristics	Private	0.27	0.21	0.06
	Urban	0.25	0.33	0.49
	Rural	0.22	0.18	0.17
	Suburban	0.53	0.48	0.34
	Low-FRL	0.48	0.40	0.18
	Medium-FRL	0.43	0.44	0.41
	High-FRL	0.08	0.16	0.41

		Less Positive Student-Staff Relationships	More Positive Student-Staff Relationships
Student-Staff Resource Indicators	Students get along well with teachers	-0.16	1.10
	Teachers are interested in students	-0.20	1.42
	Teachers praise effort	-0.15	1.03
	In class (do not) often feel put down by teachers	-0.12	0.81
	Student talks with at least one teacher	-0.10	0.69
	At least one school-based adult wants student to attend college	-0.05	0.37
	Student morale is high	3.90	4.50
	Teachers press students to achieve	3.97	4.82
	Teacher morale is high	3.71	4.44
	How often verbal abuse of teachers a problem[a]	3.67	4.67
	How often disrespect for teachers a problem[a]	3.48	4.27
School Background Characteristics	Private	0.15	0.86
	Urban	0.31	0.51
	Rural	0.20	0.10
	Suburban	0.49	0.40
	Low-FRL	0.35	0.85
	Medium-FRL	0.48	0.07
	High-FRL	0.17	0.07

		Less Academically Oriented Peers	More Academically Oriented Peers
Student-Peer Resource Indicators	Important to friends to get good grades	-0.15	0.42
	Important to friends to continue education	-0.29	0.81
	How many friends plan to have full-time job	0.34	-0.95
	How many friends plan to attend four-year college	-0.40	1.12
	In class (do not) often feel put down by other students	-0.16	0.45
	Student relates well to others	-0.09	0.26
	How often physical conflicts a problem at school[a]	3.44	4.02
	How often student bullying a problem at school[a]	3.51	3.76
School Background Characteristics	Private	0.10	0.60
	Urban	0.30	0.44
	Rural	0.22	0.11
	Suburban	0.49	0.46
	Low-FRL	0.26	0.85
	Medium-FRL	0.54	0.13
	High-FRL	0.20	0.02

Notes: Resource classes based on modal classification. Numbers shown for school resource indicators are means, while numbers shown for school background characteristics are proportions. [a] denotes that, for these outcomes, higher numbers indicate more positive outcomes.

Table 9. Individual Resource Classes and School Background Characteristics by Latent Classes of Combined Model

	Latent Classes							
	Middle-of-the-Road Schools	Well-Maintained Middle-of-the-Road Schools	Most Academically Advantaged Schools	Poorly Maintained Schools	Middle-of-the-Road Schools w/ Less Experienced Teachers	Most Vocationally Oriented Schools	Schools with Most Positive Student-Staff Relationships	Less Well-Maintained Academically Advantaged Schools
Class 1 of Instructional Resources (General Orientation)	0.98	0.99	0.32	0.53	0.57	0.01	0.37	0.37
Class 2 of Instructional Resources (Most Vocationally Oriented)	0.01	0.01	0.20	0.47	0.02	0.99	0.27	0.01
Class 1 of Teacher Resources (More Experienced but Less Satisfied)	0.99	0.99	0.64	0.98	0.57	0.83	0.49	0.70
Class 1 of Physical Resources (Fewest Physical Problems)	0.01	0.95	0.99	0.01	0.41	0.41	0.15	0.21
Class 2 of Physical Resources (Moderate Physical Problems)	0.99	0.05	0.01	0.58	0.59	0.59	0.84	0.71
Class 1 of Student-Staff Resources (Less Positive Relationships)	0.99	0.99	0.63	0.99	0.97	0.98	0.39	0.98
Class 1 of Student-Peer Resources (Less Academically Oriented)	0.94	0.88	0.30	0.81	0.98	0.96	0.50	0.45
Private	0.04	0.03	0.58	0.05	0.08	0.07	0.64	0.47
Urban	0.27	0.24	0.38	0.39	0.22	0.28	0.51	0.46
Rural	0.24	0.27	0.13	0.18	0.22	0.21	0.08	0.12
Suburban	0.49	0.49	0.50	0.44	0.56	0.51	0.40	0.43

Low-FRL	0.24	0.26	0.79	0.30	0.19	0.14	0.69	0.72
Medium-FRL	0.60	0.62	0.16	0.40	0.62	0.58	0.18	0.19
High-FRL	0.16	0.12	0.04	0.31	0.19	0.28	0.13	0.09

Notes: Latent classes for combined model are based on modal classification. Membership probabilities from individual resource models are used as indicators in the combined model. Numbers shown here are proportions.

Table 10. Outcomes for Each Latent Class

Type of Resource		Mean Math Achievement	Proportion High School Graduates	Proportion Any Postsecondary Enrollment	Proportion On-Time Enrollment in 4-Year Institution
Instructional	General Orientation	49.55	0.87	0.86	0.38
		(9.79)	-	-	-
	Most Vocationally Oriented	49.19	0.87	0.86	0.39
		(10.32)	-	-	-
	Most Academically Oriented	56.02	0.97	0.97	0.74
		(9.20)	-	-	-
Teacher	More Experienced but Less Satisfied	50.34	0.88	0.87	0.43
		(10.04)	-	-	-
	Less Experienced but More Satisfied	52.61	0.92	0.93	0.56
		(10.10)	-	-	-
Physical	Fewest Problems	51.98	0.91	0.89	0.50
		(9.84)	-	-	-
	Moderate Problems	50.28	0.89	0.88	0.44
		(10.14)	-	-	-
	Most Problems	49.53	0.84	0.86	0.37
		(10.69)	-	-	-
Student-Staff	Less Positive Relationships	50.13	0.88	0.87	0.42
		(10.04)	-	-	-
	More Positive Relationships	55.57	0.96	0.97	0.72
		(9.33)	-	-	-
Student-Peer	Less Academically Oriented Peers	48.75	0.86	0.85	0.35
		(9.83)	-	-	-
	More Academically Oriented Peers	55.99	0.97	0.97	0.73
		(8.90)	-	-	-
Combined Model	Middle-of-the-Road Schools	48.54	0.86	0.84	0.32
		(9.77)	-	-	-

Well-Maintained Middle-of-the-Road Schools	49.29	0.87	0.84	0.36
	(9.37)	-	-	-
Most Academically Advantaged Schools	55.31	0.96	0.96	0.69
	(9.19)	-	-	-
Poorly Maintained Schools	49.20	0.86	0.86	0.39
	(10.23)	-	-	-
Middle-of-the-Road Schools w/ Less Experienced Teachers	48.11	0.85	0.84	0.32
	(9.64)	-	-	-
Most Vocationally Oriented Schools	47.69	0.84	0.82	0.31
	(10.22)	-	-	-
Schools with the Most Positive Student-Staff Relationships	52.94	0.92	0.95	0.57
	(10.09)	-	-	-
Less Well-Maintained Academically Advantaged	54.56	0.94	0.95	0.66
	(9.51)	-	-	-

Note: Resource classes based on modal classification.

Chapter 3. Gender Disparities

In recent years, women's academic successes – or men's struggles – have sparked public debates, policy conversations, and academic research on the "rise of women" and the "trouble with boys" (Bertrand and Pan 2013; Lopez 2003; Rosin 2012). Books like *The Rise of Women: The Growing Gender Gap in Education and What It Means for American Schools* (DiPrete and Buchmann 2013), *The Trouble with Boys: A Surprising Report Card on Our Sons, Their Problems at School, and What Parents and Educators Must Do* (Tyre 2008), and *Boys Adrift: The Five Factors Driving the Growing Epidemic of Unmotivated Boys and Underachieving Young Men* (Sax 2009) share a consistent perspective that gender inequality is growing and that it is partly schools' fault that boys are struggling.

To deepen understandings of the extent to which women are "rising" in relation to men in different educational contexts in the U.S., this chapter examines three questions: (1) Do gender inequalities in achievement and attainment vary across high schools? (2) What types of schools, and school-based resources, are related to greater or lesser gender inequality? (3) Are the same types of schools associated with the greatest gender inequality across different outcomes?

EDUCATIONAL ACHIEVEMENT AND ATTAINMENT PATTERNS BY GENDER

Overall patterns of gender inequality in educational outcomes in the U.S. are well known. Although differences in math achievement by gender are generally small (Robinson and Lubienski 2011), on average, male students score slightly higher on math tests than female students (Downey and Vogt Yuan 2005; Halpern 2013; Marks 2008). Gender differences in math achievement vary by grade, point in the distribution (e.g., 10^{th} vs. 90^{th} percentile), and students' background characteristics (Robinson and Lubienski 2011); for example, "…the higher the parental education, the further the male advantage extends over the distribution" (Penner and

Paret 2008: 249). In contrast, women attain more education, on average, than men in every income group (Bailey and Dynarski 2011), and, across all racial groups, women are more likely than men to enroll in college (Ross et al. 2012). Women have completed high school at higher rates than men since at least the 1940s (Bailey and Dynarski 2011; DiPrete and Buchmann 2013). There is disagreement, however, about whether females' advantage in college completion is largest for families from the lowest (Buchmann and DiPrete 2006) or highest (Bailey and Dynarski 2011) income families.

SCHOOL EFFECTS ON GENDER DIFFERENCES IN OUTCOMES

There is not yet a consensus among researchers that schools affect gender differences in educational achievement and attainment, or that gender inequalities in achievement and attainment vary across schools. Using nationally representative data, Downey, von Hippel, and Broh found that elementary schools "have little if any effect on gender inequality" in learning (2004: 614). By comparing how much students learn during the school year versus the summer, Downey et al. showed that, on average, boys and girls learn at fairly equal rates when school is in session (even if they start at different points), so schools have little if any effect on gender inequality in reading and math. More broadly (as discussed in the introduction), a significant body of research suggests that what primarily – or exclusively – matters for student achievement and attainment are students' background characteristics (Coleman et al. 1966; Hanushek 1996; Hanushek 1997; Harris 2007; Ludwig and Bassi 1999). In addition (and also discussed in the introduction), much of the literature on school effects implicitly assumes that schools – and school quality – affect students from different subgroups equally, that is, that schools are uniformly "good" or "bad" for all students (Jennings et al. 2015).

However, there are many reasons to think that schools *might* matter for gender inequality in educational outcomes. In the U.S., individuals are almost always immediately and implicitly categorized based on three background identities: gender, race, and age (Ridgeway 2009). In schools, boys' and girls' academic abilities, classroom behaviors, and peer interactions – as well as teachers' perceptions of all of these – are shaped by cultural beliefs about gender (Jones and Dindia 2004; Pascoe 2011; Ridgeway and Correll 2004; Sadker and Zittleman 2009). For example, using the ELS, Riegle-Crumb and Humphries (2012) documented a consistent – but small – bias in teachers' perceptions of different students' math abilities; specifically, controlling for students' test scores and grades, teachers perceived White female students as having lower math ability than White male students. Riegle-Crumb and Humphries did not find similar patterns for Black or Hispanic students, and, in general, the ways in which – and the extent to which – boys and girls are perceived and treated differently depends on their racial background and SES (Entwisle, Alexander and Olson 2007; Ferguson 2001).

Variation in Gender Inequalities across Schools

Gender may be more or less salient in particular classrooms and schools (Johns, Schmader and Martens 2005; Steele 1997), and a small body of research has begun to explore how school resources and characteristics are associated with the extent of gender inequality in each school. One prominent study in this vein is Legewie and DiPrete's (2012) analysis of class-to-class variation in reading achievement among fifth-graders in Berlin. Legewie and DiPrete found that boys learn more in classrooms with higher average SES; based on these findings, as well as their theory, Legewie and DiPrete argued that classroom SES is a proxy for "peer culture," and, therefore, asserted that boys are more sensitive to school resources like "peer culture" than are girls. Legewie and DiPrete (2011) also documented a similar pattern using math and reading achievement data from fourth-grade students in Chicago Public Schools, although the size of the effect was smaller in that sample. In another study, Legewie and DiPrete (2014) used data from the National Education Longitudinal Study of 1988 (NELS) and the High School Effectiveness Study to show that high schools' math and science curricula matter more for female students' interest in STEM careers than for males'. Net of students' academic and demographic characteristics prior to high school, high schools with stronger math and science curricula have smaller gender differences in students' interest in STEM careers.

Additionally, using Program for International Student Assessment (PISA) data, Ma (2008) documented large variation across U.S. schools in the degree of within-school gender inequalities in reading, math, and science achievement, controlling for individual and family characteristics. U.S. schools with greater teacher absenteeism and more principal-reported teacher shortages had larger gender differences in math and science achievement favoring males. Overall, prior research provides some evidence that gender inequalities in educational achievement vary across schools, but we do not know much about the range of school characteristics associated with that variation or about how gender inequalities in attainment vary.

DATA

As discussed above, I restrict the sample to schools with at least three male and three female students with outcome data. Compared to the overall sample, schools in this sample are six percentage points less likely to be private, four percentage points more likely to have a general orientation to instructional resources, and three to four percentage points more likely to be in the "more experienced but less satisfied teachers" class. On other school characteristics, schools in this sample differ from the overall sample by less than three percentage points.

< Table 1 >

Consistent with broader trends, in this sample, female students have significantly lower average math scores than male students, but a higher proportion of female students graduate high school, enroll immediately in a four-year institution, and enroll in any postsecondary institution. To gain a more comprehensive sense of the school environment and school resources, I average all students' reports of the school environment. However, Table 2 does provide information about differences in male and female students' reports of school resources. These reports are often significantly different by gender and are in expected directions but are generally are not large (e.g., the differences are all less than one-quarter of a standard deviation or seven percentage points on the measure); in the "future work" section, I discuss potential ways to exploit these differences.

< Table 2 >

Table 3 compares model fit statistics for null models with a random intercept only, random intercept plus gender fixed effect, and random intercept plus random slope; including a random slope for gender only improves model fit for math achievement, not for any of the binomial outcomes.

< Table 3 >

RESULTS

I first examined the extent of variation in the relation between gender and each outcome across high schools. Table 4 shows that, in terms of math achievement, the standard deviation of the gender slope is relatively consistent across the unconditional and conditional models. The .39 correlation between the random intercepts and slopes in the unconditional model indicates that, in schools with higher average math scores (i.e., better achievement overall), males' advantage in math is larger (Gelman and Hill 2007). In contrast, for graduation and college enrollment, the correlations between the random intercepts and slopes are negative, indicating that, in schools with higher average graduation and college enrollment rates, male students' *disadvantage* relative to female students in graduation and college enrollment is larger.[1]

< Table 4 >

Figures 1 – 4 help illustrate the extent of variation in the gender slopes by depicting the predicted outcomes by gender for schools at different percentiles of the gender slope in the unconditional model and the model that conditions on both student and school covariates. The predicted gender difference in math achievement varies from an average male advantage of less than one point at the fifth percentile of the gender slope to a male advantage of a little over two points at the 95th percentile of the slope. The pattern is consistent for both the unconditional and conditional models.

< Figure 1 >

In the unconditional model, the difference in male and female students' predicted probability of high school graduation varies from four percentage points at a school at the fifth percentile of the gender slope to two percentage points at a school at the 95th percentile of the slope. In contrast to the pattern for math achievement, here conditioning on student and school covariates does shrink the size of the gender difference across the distribution. Additional analyses (not shown) indicate that this reduction occurs primarily due to conditioning on student, rather than school, covariates; the omitted category in terms of student covariates is White, high-SES, non-special education students, and male students in this group have high overall graduation rates.

[1] Controlling for covariates somewhat attenuates the relation between the school intercepts and gender slopes for math achievement but increases the correlations between the intercepts and slopes for both graduation and college enrollment.

< Figure 2 >

Regarding the predicted probability of immediate enrollment in a four-year institution, female students have about an eight percentage point advantage at the fifth percentile of the distribution in the unconditional model and a ten percentage point advantage in the conditional model. Across the distribution, this advantage narrows a bit more in the conditional model than in the unconditional model; at the 95^{th} percentile, female students have a seven percentage point advantage in the conditional model and a six percentage point advantage in the unconditional model.

< Figure 3 >

For any postsecondary enrollment, female students' advantage is about six percentage points at the fifth percentile of the slope distribution and four percentage points at the 95^{th} percentile, regardless of whether or not the models condition on student and school covariates.

< Figure 4 >

Overall, Table 4 and Figures 1 – 4 show that there is variation across high schools in the relation between gender, math achievement, high school graduation, and college enrollment. For math achievement, these results can be compared to Ma's (2008) study using PISA data from 15-year-olds. Ma found that the standard deviation across U.S. schools of within-school gender gaps in math was about 18 to 25 percent of the PISA math test's standard deviation (depending on whether or not student and school controls were included in the model). In contrast, in my study, the standard deviation of within-school gender gaps in math achievement is about 10 to 12 percent of the test's standard deviation. Unfortunately, I am not aware of any comparable studies on the degree of variation across schools in the relation between gender and high school graduation or college enrollment.

Predicting Variation in Gender Inequalities in Math Achievement across Schools

Using the latent class measures of school type, I next examined how the relation between gender and math achievement in different types of schools compares to the relation between gender and math in the most common type of schools, “middle-of-the-road schools.” As Table 5 shows, compared to middle-of-the-road schools, both male and female students have higher predicted math scores in schools with the most positive student-staff relationships; however, male students’ scores are even higher, relative to female students’ scores, than they are in the modal school. None of the other gender-by-school-type interactions are statistically significant, though the magnitude and direction of the coefficient for the gender-by-“most vocationally oriented schools” interaction suggests that the average male advantage in these schools may be lower than in middle-of-the-road schools.

< Table 5 >

Figure 5 illustrates these results, showing how the degree of male advantage in math achievement varies by school type. While male students have higher average math scores than female students across all eight school types, two school types – schools with the most positive student-staff relationships and schools that are less well-maintained but academically advantaged – are associated with a 0.5 to 1.5 additional advantage for male students above the reference male advantage (i.e., the average male advantage in “middle-of-the-road” schools).

< Figure 5 >

As discussed in the data and methods chapter, I classified schools into types based on the combined resources they provide. For example, schools in the “most vocationally oriented” school type are distinguished not only by their high levels of vocational course-taking but by their levels of other resources (e.g., physical resources). To unpack which aspects of school type might be most responsible for the patterns observed above, I next explored which individual resources are associated with the extent of gender inequality in math achievement. Table 6a depicts results from models with (a) instructional resource classes, (b) teacher resource classes, and (c) physical resources classes as predictors, while Table 6b depicts results from models with (d) student-staff resource classes and (e) student-peer resource classes as predictors.

Male students' average advantage relative to female students in math achievement is significantly smaller in schools in the most vocationally-oriented instructional resource class compared to the most academically-oriented instructional resource class. Across the unconditional and conditional models, male students' average advantage in math is also lower in schools with less positive student-staff relationships and in schools with less academically-oriented peers. The relation between gender and math achievement does not vary significantly across the teacher or physical resource classes.

Figure 6 illustrates these results. For example, male students' advantage in math achievement is about 1.5 points (15 percent of the math test's standard deviation) greater in schools with more positive, compared to less positive, student-staff relationships; one point greater in schools with the most academically-oriented instructional resources compared to schools with the most vocationally oriented instructional resources; and 0.5 points greater in schools with more, compared to less, academically-oriented peers.

< Table 6a, Table 6b, Figure 6 >

Predicting Variation in Gender Inequalities in High School Graduation across Schools

I next examined how the relation between gender and high school graduation in different types of schools compares to the relation between gender and graduation in middle-of-the-road schools. Table 7 shows that male students' average disadvantage in graduation relative to female students is significantly *larger* in less well-maintained but academically advantaged schools. However, compared to middle-of-the-road schools, overall graduation rates are higher in less well-maintained but academically advantaged schools. Thus, despite the larger than average male *disadvantage* in graduation in less well-maintained but academically advantaged schools, given that these schools have higher *overall* graduation rates than middle-of-the-road schools, male students' graduation rates are still more favorable in these schools, on average, than in middle-of-the-road schools. Figure 7 illustrates how the predicted male disadvantage in high school graduation varies by school type. Of note, the figure shows that there is no male disadvantage in graduation, on average, in schools with the most positive student-staff relationships.

< Table 7, Figure 7 >

Digging into the individual resource classes, Table 8a shows that the relation between gender and high school graduation does not vary significantly across instructional or teacher resource classes but does vary significantly across physical resource classes; male students' average disadvantage is smaller in schools with few to moderate physical resource problems than in schools with the most physical resource problems. As a reminder, these findings are robust to at least some student and school covariates.

< Table 8a >

The relation between gender and graduation varies significantly across classes of student-staff, but not student-peer, resources, as Table 8b shows. Specifically, male students' average disadvantage in high school graduation is larger in schools with less positive student-staff relationships; in fact, there is no male disadvantage in graduation, on average, in schools with more positive student-staff relationships. Figure 8 illustrates these results, depicting relatively large differences in the degree of male disadvantage in graduation across the physical resource and student-staff resource classes.

< Table 8b, Figure 8 >

Predicting Variation in Gender Inequalities in Immediate Enrollment in a Four-Year Institution across Schools

Returning to measures of school type but focusing on immediate enrollment in a four-year institution as the outcome, Table 9 shows that male students' disadvantage relative to female students is *larger* in less well-maintained but academically advantaged schools than in middle-of-the-road schools; however, less well-maintained but academically advantaged schools have higher *overall* on-time four-year enrollment rates than middle-of-the-road schools. As a result, male students' predicted on-time four-year enrollment rate is still higher in these schools than in middle-of-the-road schools. Additionally, male students' average disadvantage in on-time four-year enrollment relative to female students may be larger in schools with the most positive student-staff relationships, as well as in middle-of-the-road schools with less experienced teachers (although the differences are not consistently significant). However, on average, male students still have better outcomes in schools with the most positive student-staff relationships than in middle-of-the-road schools because, despite larger than average gender differences, these schools have higher rates of immediate enrollment in a four-year institution. Figure 9 depicts the results.

< Table 9, Figure 9 >

Table 10a shows that the relation between gender and on-time four-year enrollment does not vary significantly across classes of instructional, teacher, or physical resources. Similarly, Table 10b shows that the relation between gender and on-time four-year enrollment does not vary significantly across classes of student-staff or student-peer resources. Figure 10 illustrates these results, showing that there are no statistically distinguishable differences in the relation between gender and rates of immediate enrollment in a four-year institution across school resource classes, perhaps because the coefficients for the resource classes are not estimated with precision.

< Table 10a, Table 10b, Figure 10 >

Predicting Variation in Gender Inequalities in Any Postsecondary Enrollment across Schools

Male students' average disadvantage relative to female students in any postsecondary enrollment might be smaller in the most academically advantaged schools compared to middle-of-the-road schools, although the difference is not statistically significant.

< Table 11, Figure 11 >

Male students' average disadvantage relative to female students in any postsecondary enrollment might also be smaller in schools with the most academically oriented instructional resources, more positive student-staff relationships, and *less* academically oriented peers, though none of these differences are statistically significant.

< Table 12a, Table 12b, Figure 12 >

LIMITATIONS

Because I lack data on students' characteristics prior to high school, I cannot measure the extent to which male and female students follow different patterns when selecting into the same school. Although I control for some student covariates, unobserved differences across students are a concern if these differences vary by gender; are related to math achievement, high school graduation, and/or college enrollment; and are related to school types or school-based resources. If male and female students *differentially* select into particular high schools for reasons that go beyond the student covariates for which I control (e.g., race/ethnicity, SES), and, if these unobserved differences are related to both school types and the outcome measures I study, then observed differences in the relation between gender, each outcome, and each measure of school type or resources may be the result of differences in the characteristics of students who attend these schools rather than in the characteristics of schools themselves. Therefore, while the included student covariates eliminate some sources of bias due to student selection, without more information on students' characteristics prior to high school (e.g., academic ability, motivation), I cannot control for all sources of potential bias.

As mentioned in the data section above, a second limitation is that the relatively small number of sampled students per school limits the accuracy with which within-school gender differences can be estimated. The small within-group sample sizes might be particularly problematic for the high school graduation models, which involve an unbalanced binary outcome (Moineddin, Matheson and Glazier 2007).[2] Other limitations also are related to data issues. For example, the math achievement measure may not be as accurate as possible given that students are not always motivated when taking low-stakes tests; in addition, the measure is not available for all students. Also, I can only categorize students as male or female, and this binary definition of gender may limit my ability to capture the full variation in gender differences across schools, given that prior research has shown that individuals experience schooling differently depending on how they express their gender and gender identity (Pascoe 2011).

DISCUSSION

The national conversation about the "problem" or "trouble" with boys has rarely included a discussion of how homogenous or heterogeneous the problem is. Therefore, in this chapter, I

---

[2] Despite this, several of the resource measures are predictive of the gender slopes for high school graduation, which might indicate that graduation rates are particularly dependent on school resources.

first sought to investigate the *variability* of within-school gender inequalities across a range of educational outcomes. I found that, both before and after controlling for student and school characteristics, there are observable differences across schools in the extent of gender inequalities in math achievement, high school graduation, and college enrollment. Null models, as well as models that include student and school covariates, showed that correlations between the random intercepts and slopes for math achievement are positive, indicating that, on average, schools with higher math achievement have *larger* inequalities favoring males. In contrast, correlation coefficients indicated that schools with higher average graduation and college enrollment rates have *smaller* gender inequalities in graduation and enrollment. Given that gender inequalities in these outcomes tend to favor female students, the negative correlations indicate that male students' disadvantage relative to female students is smaller in schools with higher graduation and college enrollment rates.

I next examined what types of schools and school-based resources are related to greater or lesser within-school gender inequality. I found that male students have higher average math achievement scores than female students across all eight types of schools, but male students' advantage is larger, on average, in schools that are the most academically-oriented in their instructional resources, have the most positive student-staff relationships, and have more academically-oriented peers. Thus, it appears that male students' advantage in math is larger in well-functioning schools. In terms of high school graduation, I found that, although male students graduate at lower rates than female students on average, this is not true in schools with the most positive student-staff relationships. In contrast, male students' relative disadvantage in graduation is larger in less well-maintained but academically advantaged schools,[3] in schools

[3] Less well-maintained but academically advantaged schools have higher overall graduation rates than middle-of-the-road schools, but girls' graduation rate relative to boys' is higher in these schools.

with more experienced but less satisfied teachers, in schools with the most physical resource problems, and in schools with less positive student-staff relationships. In sum, male students' graduation rates are particularly low in schools that are struggling in terms of their physical resources, teacher engagement, or student-staff relationships.

The findings differ, however, for on-time enrollment in a four-year institution. For this outcome, male students' relative disadvantage is larger in less well-maintained but academically advantaged schools, middle-of-the-road schools with less experienced but more satisfied teachers, and schools with the most positive student-staff relationships. While average rates of immediate enrollment in a four-year institution are about the same in middle-of-the-road schools with less experienced teachers as in the reference category of schools, schools with the most positive student-staff relationships and schools that are less well-maintained but academically advantaged have significantly higher average rates of on-time four-year enrollment. Thus, given the findings above, it is surprising that boys do not seem to benefit from these schools to the same extent as girls. Perhaps this is an indication that, for a more differentiating outcome (i.e., on-time four-year enrollment versus high school graduation), while students of both genders benefit from attending better functioning schools, girls have more access to, or are able to take greater advantage of, the schools' resources. Only particular school types – not individual school resources – were associated with gender-specific effects for on-time four-year enrollment. This may affirm the benefits of the typology approach, which is able to capture some of the additive or joint associations of multiple resources in models with limited degrees of freedom.

I was not able to say much about what types of schools, or school-based resources, are associated with smaller or larger gender inequalities in any postsecondary enrollment within eight years of high school graduation.

Regarding the third research question about whether the same types of schools are consistently associated with the greatest gender equality or inequality across different outcomes, I found some evidence that schools with the most positive student-staff relationships consistently differed from middle-of-the-road schools in their levels of gender equality. In these schools, boys' performance relative to girls' is higher for both math achievement and high school graduation. In contrast, in schools with the most positive student-staff relationships, girls' performance relative to boys' is higher than average for on-time enrollment in a four-year institution. For math achievement and high school graduation, the results held in both the school type and school resource models, while, for on-time enrollment in a four-year institution, the results only appeared in the school type analyses; when looking at student-staff relationships as a separate resource, the interaction was near zero. Thus, this research suggests that a focus on improving student-staff relationships might benefit all students but the gendered effects might differ across outcomes. This finding is important because student-staff relationships can be enhanced through focused school improvement efforts, yet many school reform efforts focus on instructional resources at the expense of relational resources (Spillane, Parise and Sherer 2011). Future research should investigate whether the associations found here are observed when relational resources are manipulated experimentally.

Notably, some types of schools (e.g., "poorly maintained schools," the "most vocationally oriented schools") never exhibited statistically distinguishable differences in the degree of gender inequality when compared to "middle-of-the-road schools." This might suggest that levels of particular resources, rather than combinations of resources – or school types – are more helpful in explaining variation in gender inequalities across schools. Alternatively, it may indicate that there is not much meaningful variation between these types of schools and middle-of-the-road schools.

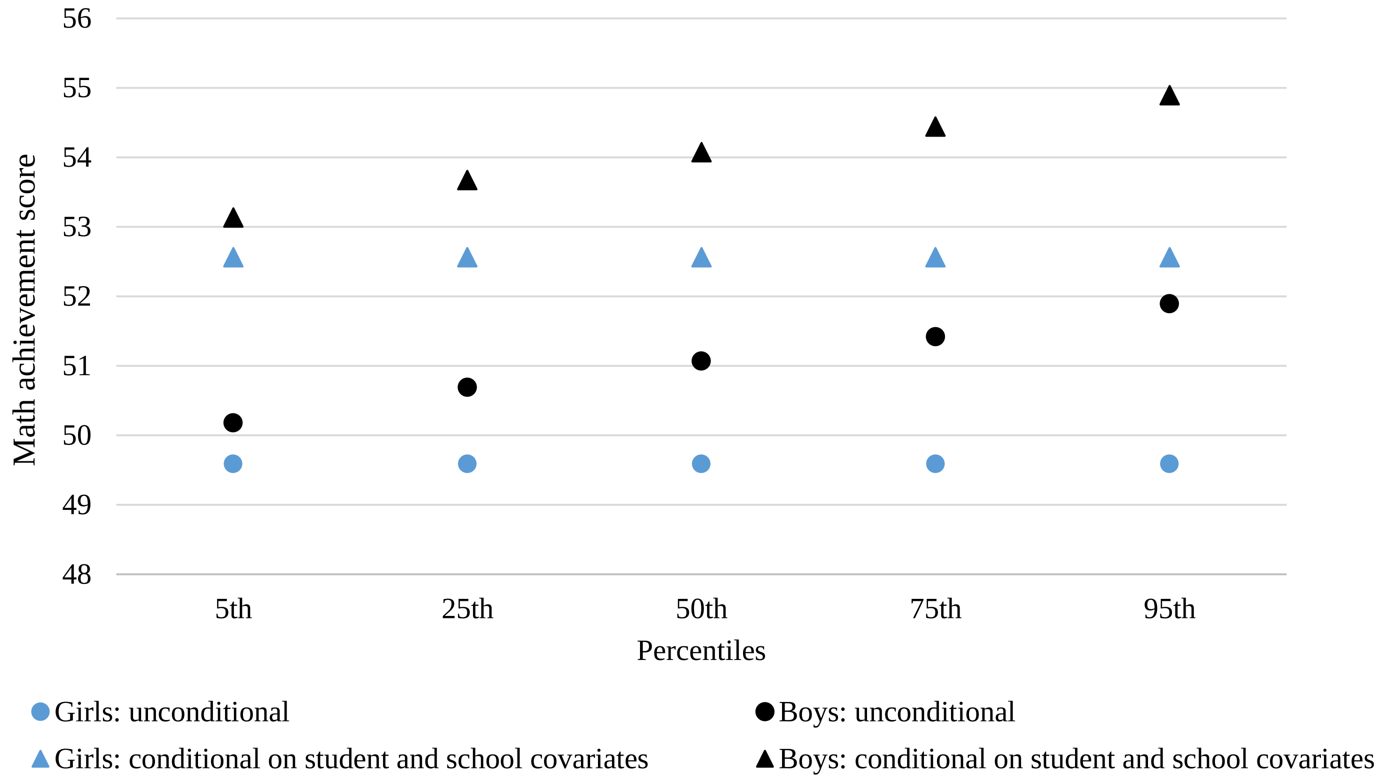
CONCLUSION

A common argument among the books cited in the introduction is that schools are organized to advantage girls (Sax 2009; Sommers 2001; Tyre 2008). However, this chapter's findings suggest that, in some ways, the opposite is true: male students do particularly well in well-functioning schools and particularly poorly in unpleasant or dysfunctional school conditions (less satisfied teachers, poor physical conditions). For educational outcomes like math, where male students have an average advantage, male students' advantage is *larger* in well-functioning schools. In contrast, for outcomes like high school graduation, where female students have an average advantage, male students' disadvantage is *smaller* in schools with more positive student-staff relationships, less experienced but more satisfied teachers, and fewer physical resource problems.

Thus, consistent with Legewie and DiPrete's (2012) and DiPrete and Buchmann's (2013) findings, I conclude that, in general, boys' outcomes are disproportionately better in "good" schools. However, DiPrete and colleagues' research focused on educational outcomes (e.g., reading achievement, attainment) where female students are doing better, on average, than male students, thus leading to the conclusion that increasing school quality will decrease the gender gap. Yet, my findings suggest that increasing school quality potentially could *exacerbate* gender gaps for outcomes where male students are doing better (e.g., math achievement). Given concerns about female students' participation in mathematics-intensive fields, this may preclude a simple policy prescription of assuming that improving schools across the board will decrease gender inequality.

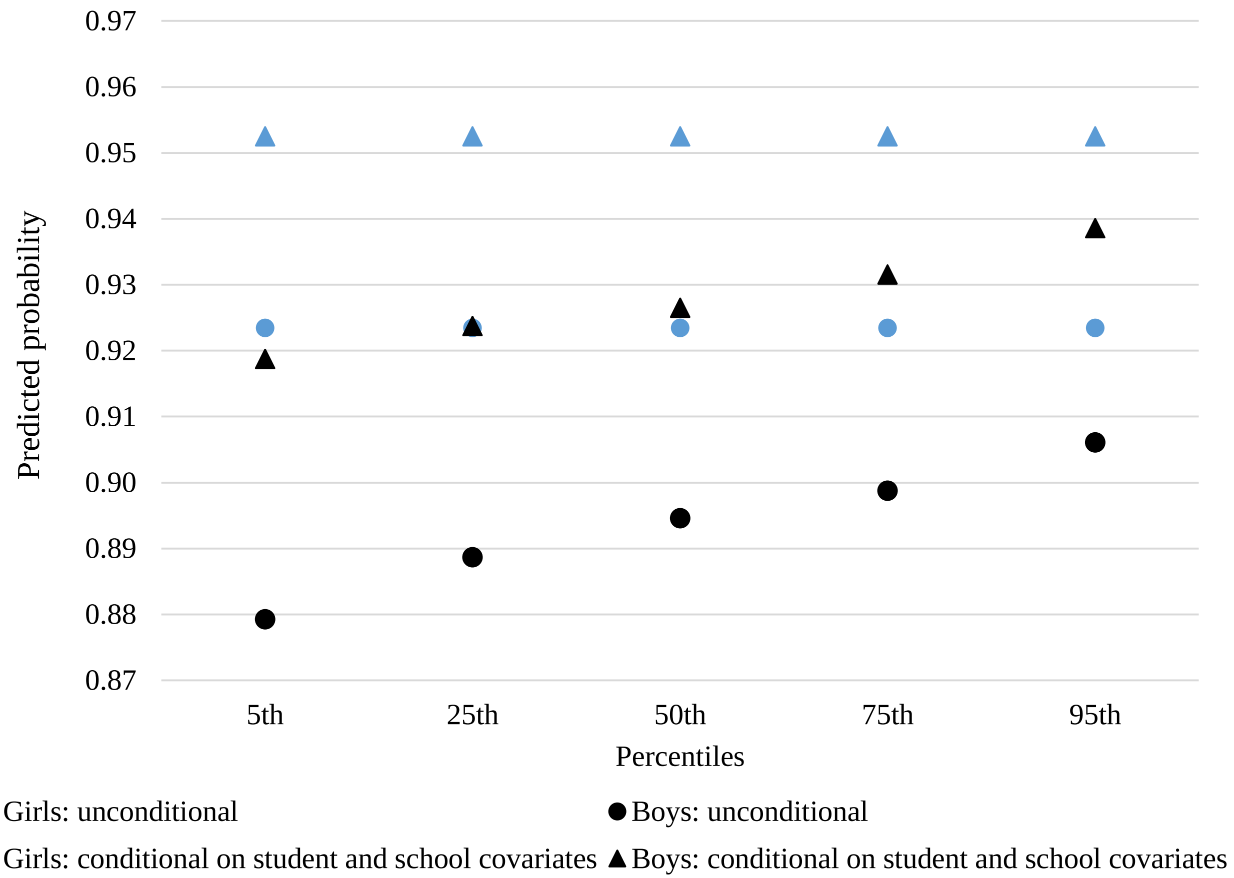
By identifying and explaining variation in gender inequalities across contexts, I aim to take a first step toward understanding how social institutions can mitigate or exacerbate particular inequalities. While most students from advantaged backgrounds will do well academically regardless of the school they attend or the resources their school provides, schools may have a greater role to play in improving the educational achievement and attainment of students from disadvantaged subgroups – which, in this case, may be men or women depending on the outcome. This chapter suggests that the extent to which "[e]ducational institutions still work as engines of gender inequality" (Barone 2011: 157) may vary across high schools and be partially explained by the allocation of schools' resources. Therefore, future research should continue to investigate whether schools can improve gender equality across educational outcomes by changing the types and levels of resources they provide.

Figure 1. Predicted Math Scores by Gender at Different Percentiles of the Gender Slope



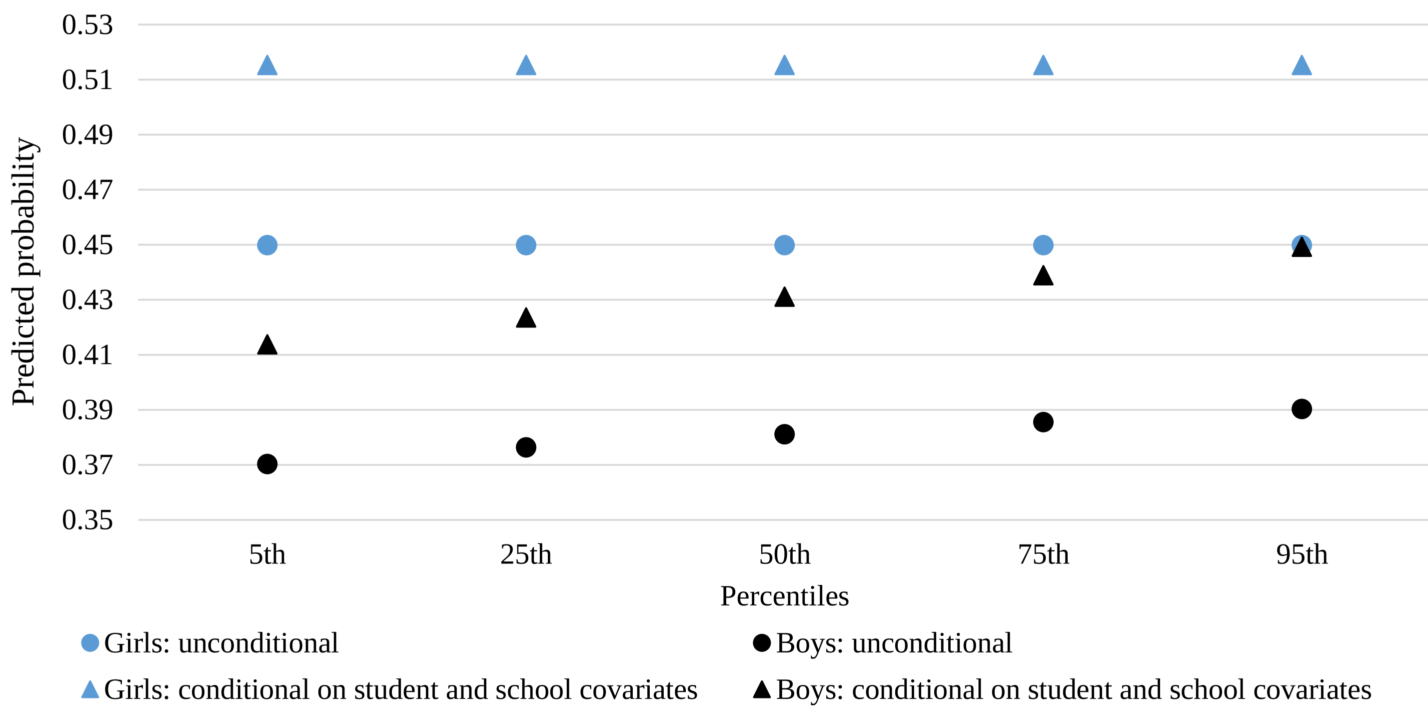
Note: "Unconditional" and "conditional on student and school covariates" refer to results from two separate models.

Figure 2. Predicted Probability of High School Graduation by Gender at Different Percentiles of the Gender Slope



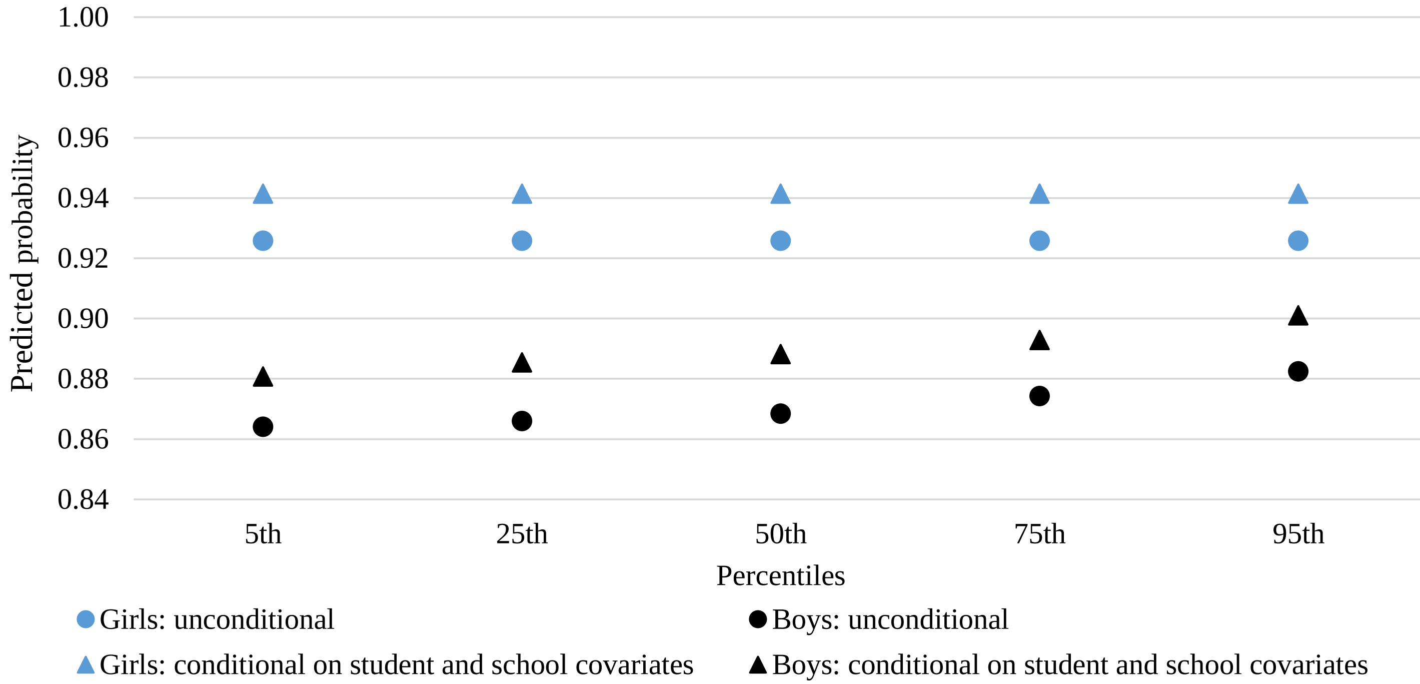
Note: "Unconditional" and "conditional on student and school covariates" refer to results from two separate models.

Figure 3. Predicted Probability of Immediate Enrollment in a Four-Year Institution by Gender at Different Percentiles of the Gender Slope



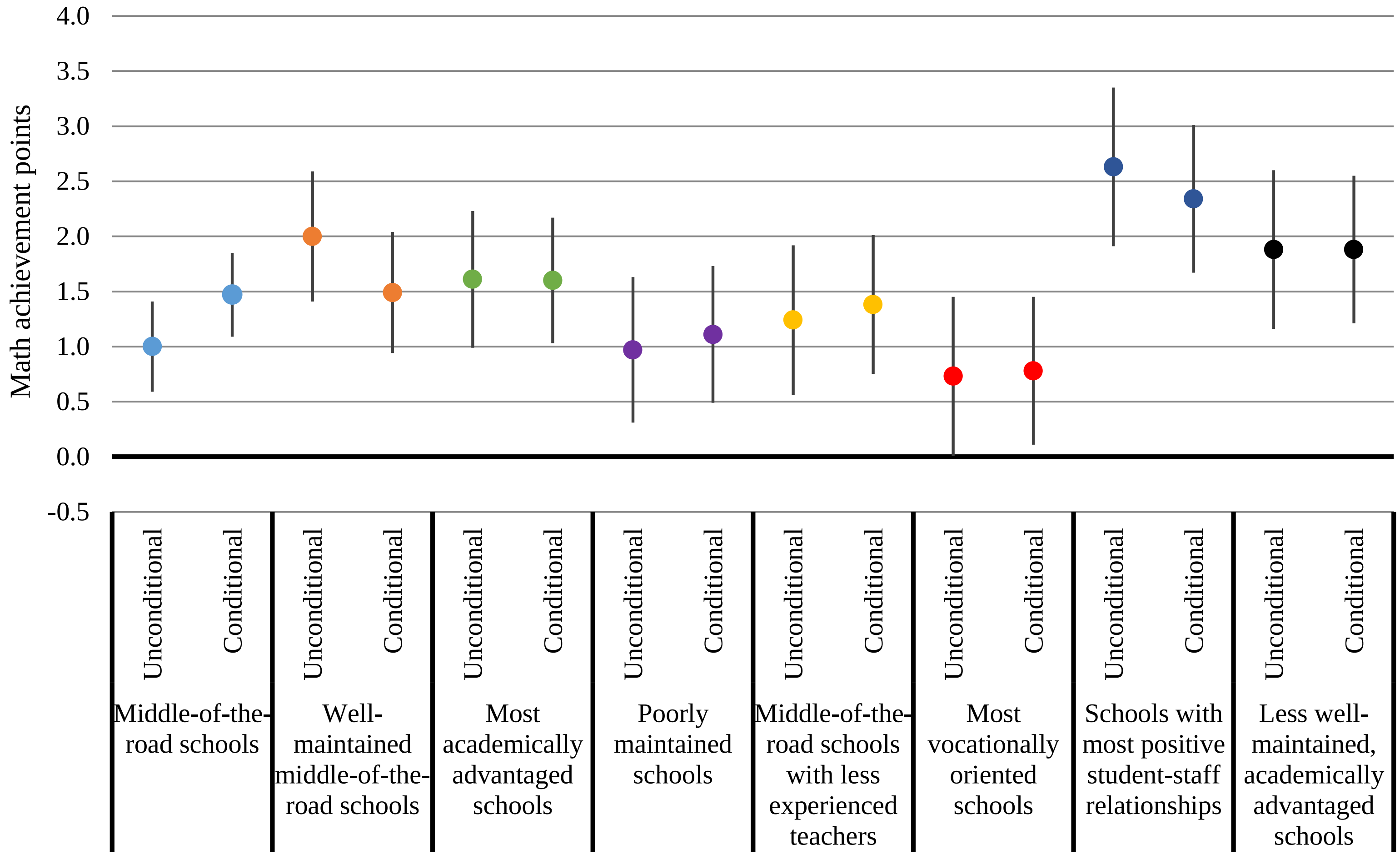
Note: "Unconditional" and "conditional on student and school covariates" refer to results from two separate models.

Figure 4. Predicted Probability of Any Postsecondary Enrollment by Gender at Different Percentiles of the Gender Slope



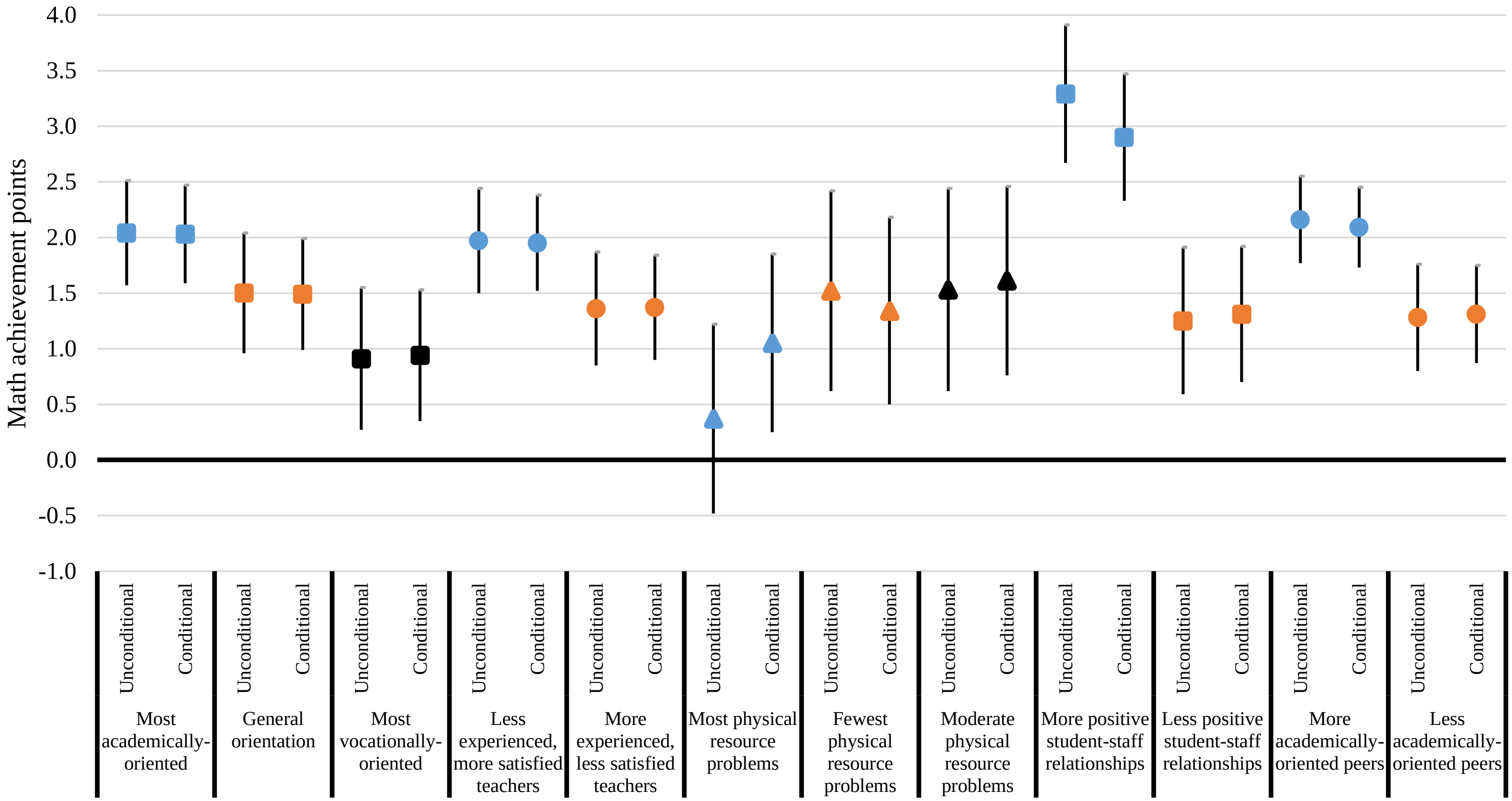
Note: "Unconditional" and "conditional on student and school covariates" refer to results from two separate models.

Figure 5. Predicted Male Advantage in Math Achievement by School Type



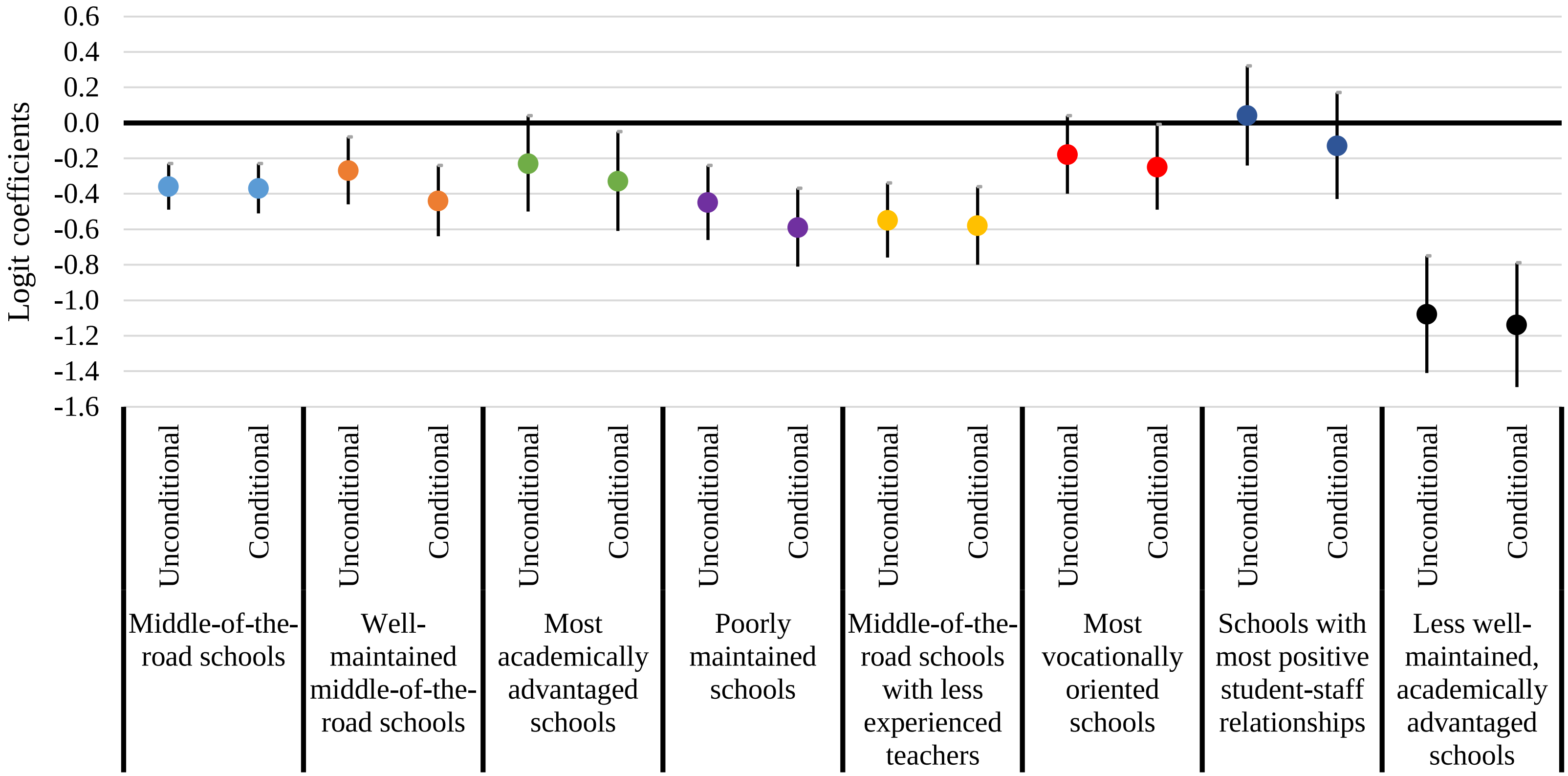
Notes: Male advantage as predicted by the student-level gender parameter plus cross-level interactions between gender and the measures of school type shown here. Results shown for both the unconditional model and the model that conditions on student and school covariates. Error bars represent plus or minus one standard error of the estimated effect.

Figure 6. Predicted Male Advantage in Math Achievement by Individual Resource Classes



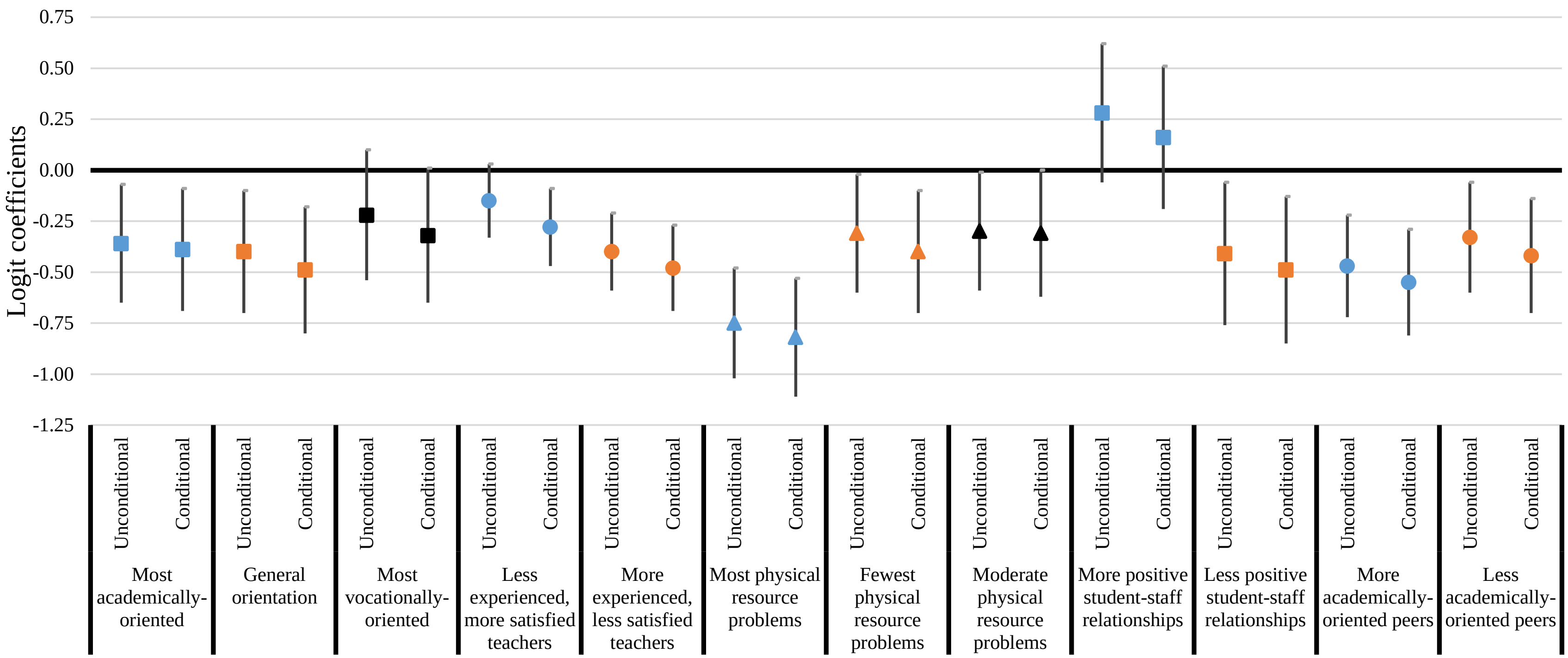
Notes: Male advantage as predicted by the student-level gender parameter plus cross-level interactions between gender and the measures of school resources shown here. Results shown for both the unconditional model and the model that conditions on student and school covariates. Error bars represent plus or minus one standard error of the estimated effect.

Figure 7. Predicted Male Disadvantage in High School Graduation by School Type



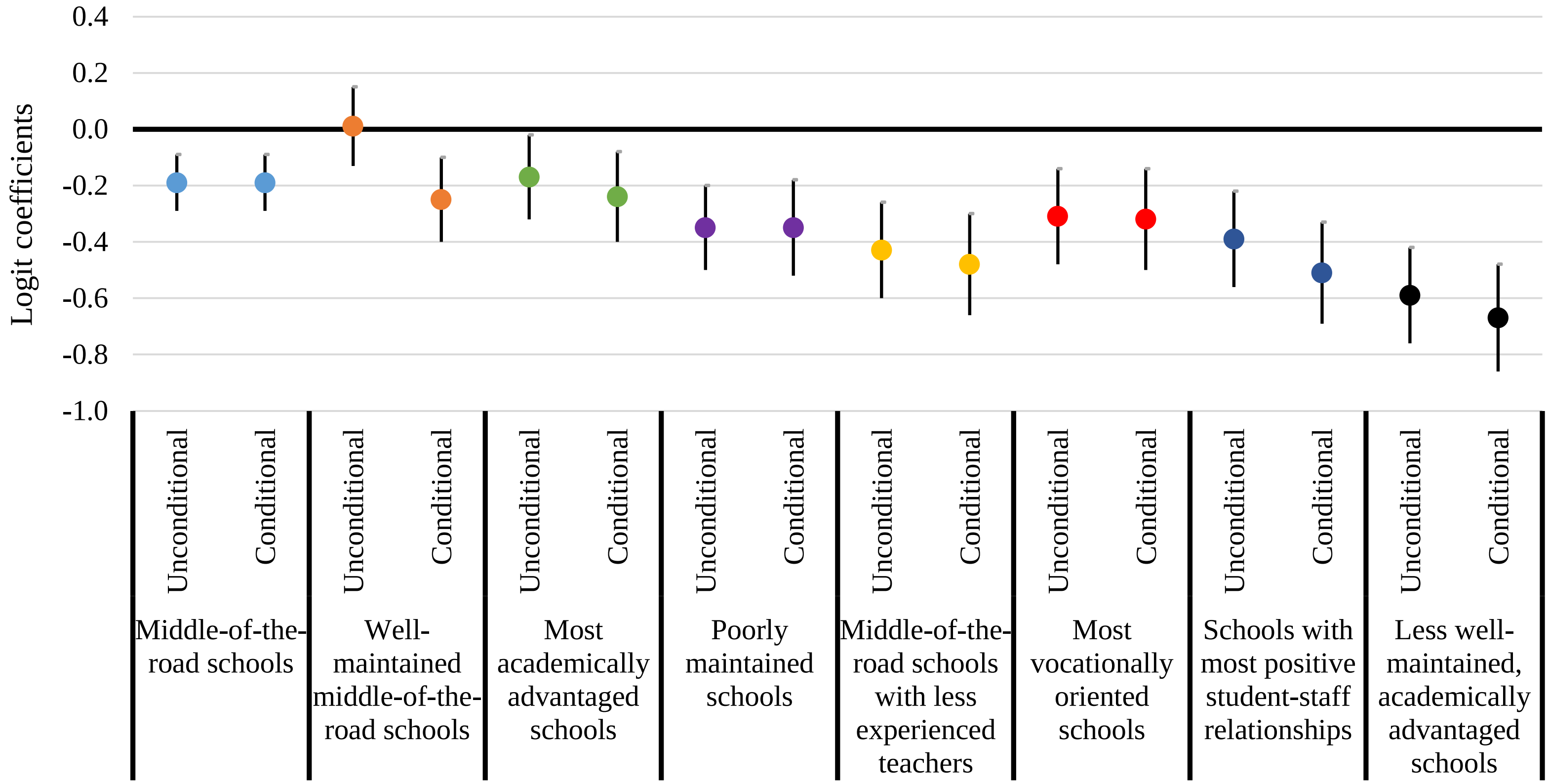
Notes: Male disadvantage as predicted by the student-level gender parameter plus cross-level interactions between gender and the measures of school type shown here. Results shown for both the unconditional model and the model that conditions on student and school covariates. Error bars represent plus or minus one standard error of the estimated effect.

Figure 8. Predicted Male Disadvantage in High School Graduation by Individual Resource Classes



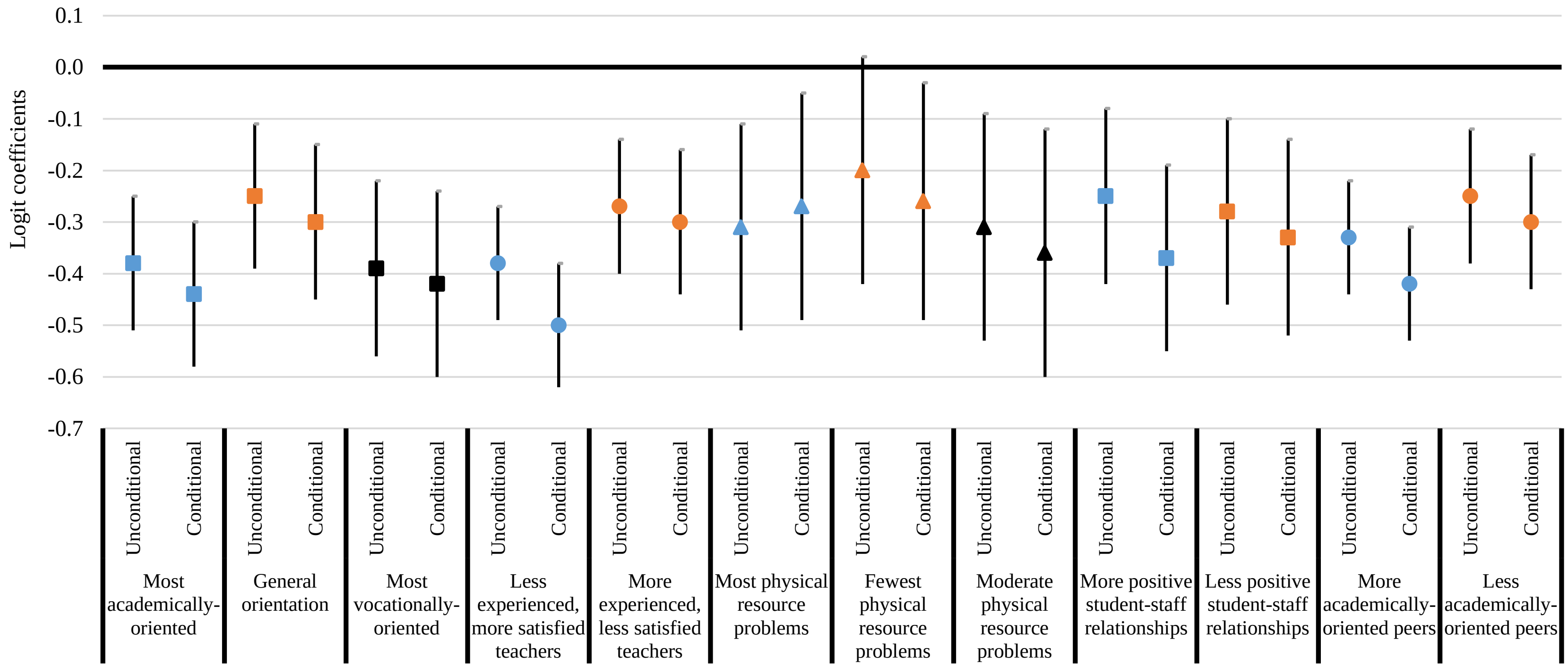
Notes: Male disadvantage as predicted by the student-level gender parameter plus cross-level interactions between gender and the measures of school resources shown here. Results shown for both the unconditional model and the model that conditions on student and school covariates. Error bars represent plus or minus one standard error of the estimated effect.

Figure 9. Predicted Male Disadvantage in Immediate Enrollment in a Four-Year Institution by School Type



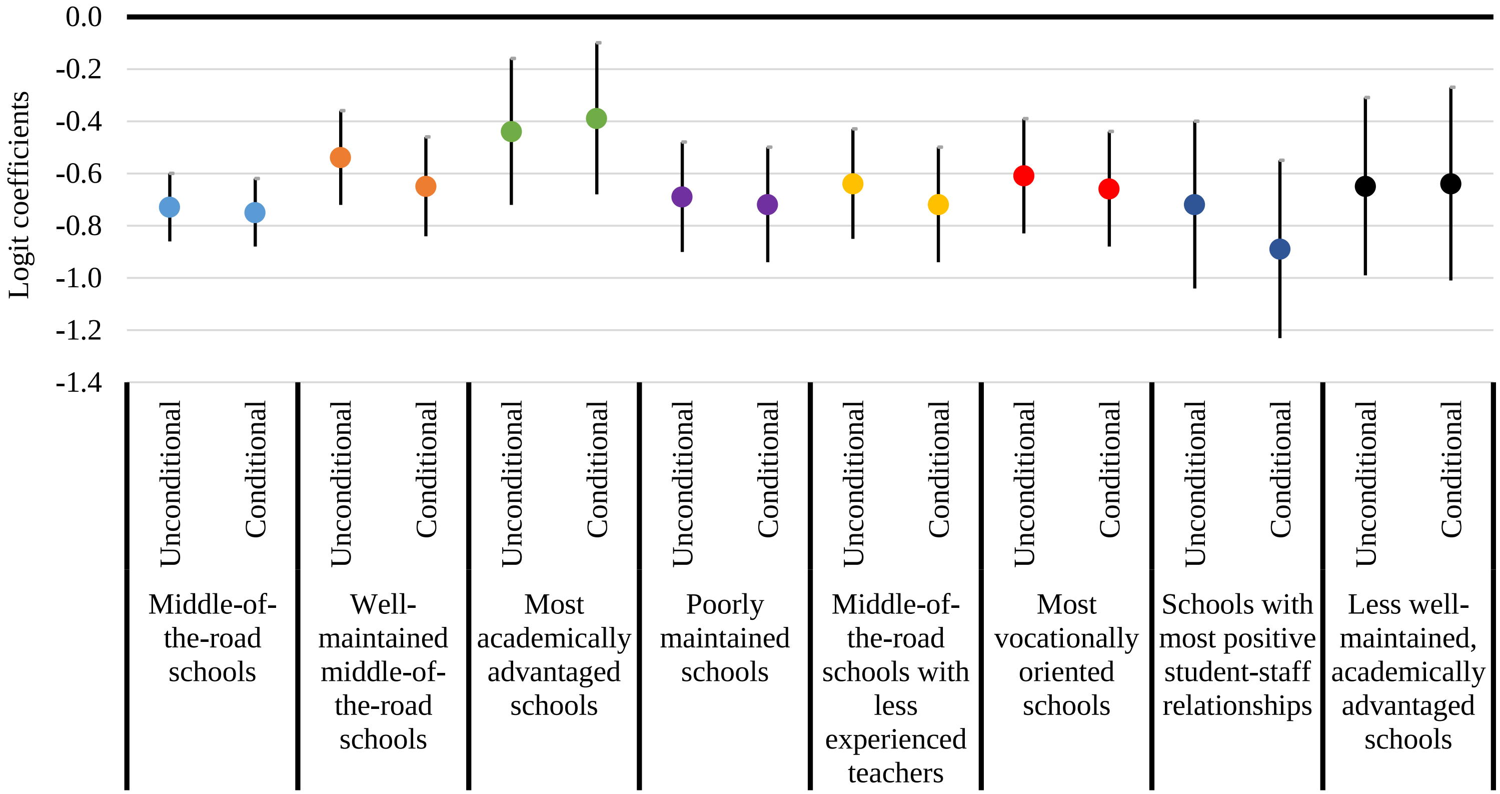
Notes: Male disadvantage as predicted by the student-level gender parameter plus cross-level interactions between gender and the measures of school type shown here. Results shown for both the unconditional model and the model that conditions on student and school covariates. Error bars represent plus or minus one standard error of the estimated effect.

Figure 10. Predicted Male Disadvantage in Immediate Enrollment in a Four-Year Institution by Individual Resource Classes



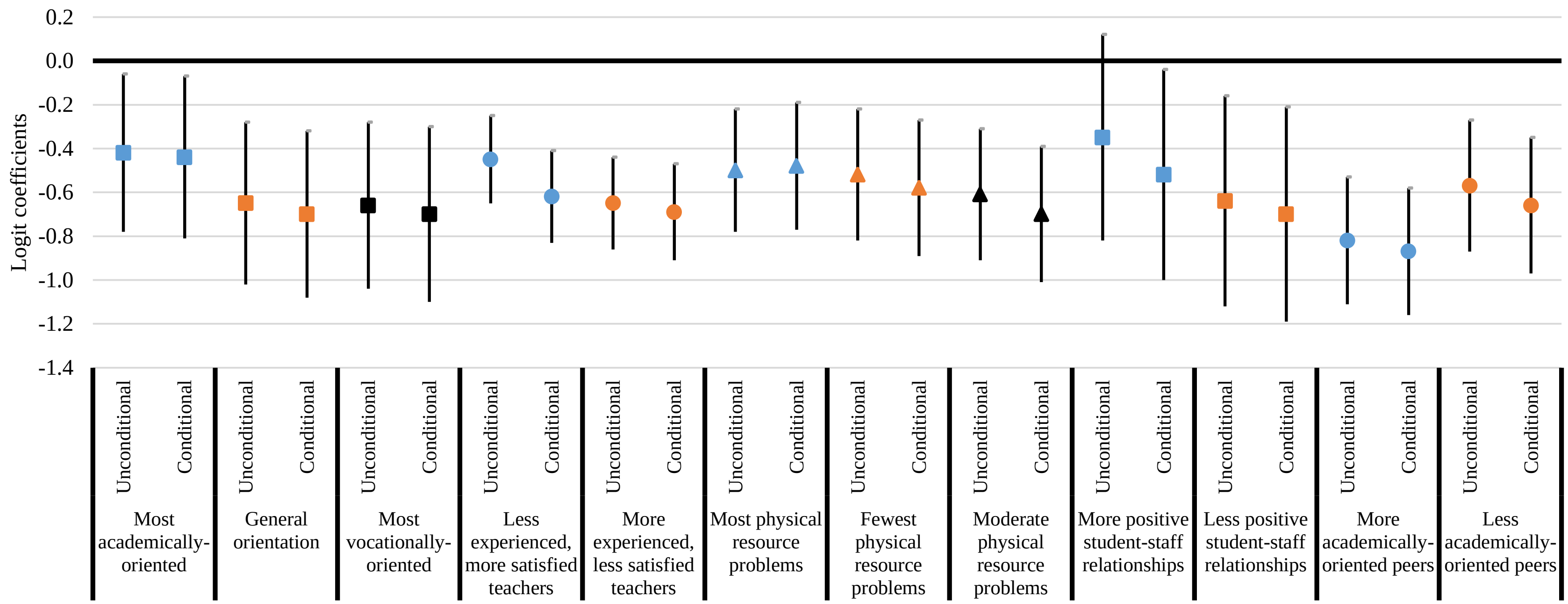
Notes: Male disadvantage as predicted by the student-level gender parameter plus cross-level interactions between gender and the measures of school resources shown here. Results shown for both the unconditional model and the model that conditions on student and school covariates. Error bars represent plus or minus one standard error of the estimated effect.

Figure 11. Predicted Male Disadvantage in Any Postsecondary Enrollment by School Type



Notes: Male disadvantage as predicted by the student-level gender parameter plus cross-level interactions between gender and the measures of school type shown here. Results shown for both the unconditional model and the model that conditions on student and school covariates. Error bars represent plus or minus one standard error of the estimated effect.

Figure 12. Predicted Male Disadvantage in Any Postsecondary Enrollment by Individual Resource Classes



Notes: Male disadvantage as predicted by the student-level gender parameter plus cross-level interactions between gender and the measures of school resources shown here. Results shown for both the unconditional model and the model that conditions on student and school covariates. Error bars represent plus or minus one standard error of the estimated effect.

Table 1. Comparison of School Types and Resource Classes in All Schools vs. Schools with Adequate Numbers of Sampled Male and Female Students

		Total Sample	Gender Sample
School Background Characteristics	Private	23%	17%
	Urban	33%	31%
	Rural	19%	19-20%
	Suburban	48%	49-50%
	Low-FRL	41%	38%
	Medium-FRL	43%	46%
	High-FRL	15%	16%
School Types	Middle-of-the-Road Schools	18%	20%
	Well-Maintained Middle-of-the-Road Schools	15%	17%
	Most Academically Advantaged Schools	16%	14%
	Poorly Maintained Schools	11%	12%
	Middle-of-the-Road Schools w/ Less Experienced Teachers	10%	11%
	Most Vocationally Oriented Schools	10%	10%
	Schools with Most Positive Student-Staff Relationships	10%	8-9%
	Less Well-Maintained, Academically Advantaged Schools	9%	8%
	N	*751*	*668-680*
Instructional Resource Classes	General Orientation	62%	66%
	Most Vocationally Oriented	21%	19-20%
	Most Academically Oriented	17%	15%
	N	*751*	*668-680*
Teacher Resource Classes	Less Experienced but More Satisfied Teachers	80%	83-84%
	More Experienced but Less Satisfied Teachers	20%	16-17%
	N	*733*	*651-663*
Physical Resource Classes	Fewest Problems	43%	42%
	Moderate Problems	51%	52%
	Most Problems	6%	6%
	N	*618*	*552-560*
Student-Staff Resource Classes	Less Positive Relationships	89%	91%
	More Positive Relationships	11%	9%
	N	*751*	*668-680*
Student-Peer Resource Classes	Less Academically Oriented Peers	75%	77-78%
	More Academically Oriented Peers	25%	22-23%
	N	*751*	*668-680*
Average Outcomes	Math Achievement Score	50.74	50.53
	High School Graduation	0.89	0.89
	Immediate Enrollment in a Four-Year Institution	0.45	0.43
	Any Postsecondary Enrollment	0.88	0.88

Notes: "Total sample" includes all schools; "gender sample" includes only schools with at least three male and three female students with data for a given outcome. For each sample, percentages and N's vary depending on the outcome variable.

Table 2. Outcome and Resource Measures by Gender

		Female	Male
Outcome Measures	Math score	50.00*	51.47*
		(9.71)	(10.45)
	Proportion high school graduates	0.91*	0.88*
	Proportion immediate enrollment in four-year institution	0.48*	0.42*
	Proportion any postsecondary enrollment	0.91*	0.85*
Instructional Resources	Use of school media center for assignments	2.27*	2.07*
		(0.94)	(0.95)
	Use of school media center for research papers	2.58*	2.32*
		(1.01)	(1.03)
	Proportion ever in Advanced Placement course or International Baccalaureate program	0.20	0.19
	Proportion ever in remedial English or math course	0.10*	0.13*
	Proportion in general program	0.35	0.35
	Proportion in college preparatory/academic program	0.58*	0.53*
	Proportion in vocational (including technical/business) program	0.08*	0.12*
	Years of advanced science coursework completed	1.07*	1.10*
		(0.82)	(0.90)
	Years of advanced math coursework completed	0.68	0.68
		(0.88)	(0.91)
	Proportion participated in cooperative education	0.13*	0.14*
	Proportion participated in school-organized internships	0.04*	0.06*
	Proportion participated in job shadowing or work visits	0.14	0.13
	Proportion participated in school-organized mentoring	0.05	0.05
Teacher Resources	Proportion w/ teacher w/ 2 or fewer years of teaching experience	0.19*	0.20*
	Proportion w/ teacher w/ 3 to 4 years of teaching experience	0.17	0.17
	Proportion w/ teacher w/ regular/standard certification	0.74*	0.72*
	Proportion w/ English teacher w/ bachelor's degree in English	0.84*	0.82*
	Proportion w/ math teacher w/ bachelor's degree in math	0.83*	0.79*
	Proportion w/ English teacher w/ graduate degree in English	0.24*	0.22*
	Proportion w/ math teacher w/ graduate degree in math	0.21	0.21
	Number of days teacher was absent during first semester	2.96	2.94
		(3.12)	(3.09)
	If starting over, likelihood of becoming a teacher again	2.97	2.96
		(0.85)	(0.85)

Physical Resources	Learning hindered by…		
	Poor condition of buildings	1.53 (0.78)	1.55 (0.79)
	Poor heating, cooling, lighting	1.69 (0.83)	1.70 (0.81)
	Inadequate science laboratory equipment	1.74 (0.87)	1.74 (0.85)
	Inadequate facilities for fine arts	1.90 (0.95)	1.92 (0.94)
	Lack of instructional space	1.84 (0.92)	1.82 (0.91)
	Lack of instructional materials in the library	1.69 (0.82)	1.68 (0.81)
	Lack of textbooks and basic supplies	1.48 (0.69)	1.48 (0.68)
	Not enough computers for instruction	1.87 (0.88)	1.87 (0.88)
	Lack of multimedia resources for instruction	1.85 (0.82)	1.83 (0.81)
	Inadequate vocational equipment/facilities	1.78 (0.89)	1.77 (0.88)
Student-Staff Resources	Students get along well with teachers	2.79 (0.58)	2.80 (0.60)
	Teachers are interested in students	2.90* (0.67)	2.86* (0.72)
	Teachers praise effort	2.79* (0.73)	2.74* (0.77)
	In class often feels put down by teachers	3.17* (0.67)	3.09* (0.72)
	Proportion talk with at least one teacher	0.56*	0.50*
	Proportion at least one school-based adult wants student to attend college	0.78*	0.71*
	Student morale is high	3.98 (0.76)	3.98 (0.75)
	Teachers press students to achieve	4.08 (0.82)	4.08 (0.81)
	Teacher morale is high	3.80 (0.83)	3.79 (0.83)
	How often verbal abuse of teachers a problem	3.82 (0.76)	3.82 (0.76)

	How often disrespect for teachers a problem	3.61 (0.88)	3.59 (0.86)
Student-Peer Resources	Important to friends to get good grades	2.52* (0.58)	2.38* (0.61)
	Important to friends to continue education	2.60* (0.58)	2.44* (0.63)
	How many friends plan to have full-time job	2.40* (1.13)	2.60* (1.15)
	How many friends plan to attend four-year college	3.48* (1.06)	3.26* (1.10)
	In class often feels put down by other students	3.09* (0.70)	3.06* (0.72)
	Proportion student relates well to others	0.85*	0.79*
	How often physical conflicts a problem at school	3.61 (0.83)	3.59 (0.80)
	How often student bullying a problem at school	3.59 (0.80)	3.59 (0.76)

Notes: Standard deviations are not included for proportions. * p < .05

Table 3. Model Fit Statistics for Random Intercept and Random Slope Null Models

	Math Achievement			High School Graduation			Immediate Enrollment in a Four-Year Institution			Any Postsecondary Enrollment		
Random Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Random Slope			Yes			Yes			Yes			Yes
AIC	87,455.7	87,347.5	87,340.8	9,895.3	9,424.3	9,428.1	16,498.1	15,922.7	15,927.9	9,623.1	9,162.3	9,167.2
Log-Likelihood	-43,724.9	-43,669.7	-43,664.4	-4,945.7	-4,709.1	-4,709.0	-8,247.1	-7,958.4	-7,959.0	-4,809.5	-4,578.2	-4,578.6
R-Squared	0.26	0.27	0.27	0.11	0.11	0.12	0.22	0.22	0.23	0.11	0.12	0.13

Table 4. Variation in the Relation between Gender and Each Outcome across High Schools

		Math Achievement			High School Graduation			Immediate Enrollment in Four-Year Institution			Any Postsecondary Enrollment		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Fixed Effects	Male	1.47*	1.46*	1.49*	-0.36*	-0.41*	-0.45*	-0.29*	-0.34*	-0.34*	-0.62*	-0.69*	-0.70*
		(0.17)	(0.16)	(0.16)	(0.08)	(0.07)	(0.07)	(0.04)	(0.04)	(0.04)	(0.08)	(0.07)	(0.07)
	Intercept	49.59*	51.24*	52.56*	2.49*	2.80*	3.00*	-0.20*	-0.09†	0.06	2.52*	2.63*	2.78*
		(0.21)	(0.16)	(0.28)	(0.07)	(0.07)	(0.11)	(0.05)	(0.05)	(0.08)	(0.07)	(0.07)	(0.10)
Random Effects	SD Gender Slope	1.09	1.22	1.25	0.37	0.44	0.39	0.14	0.18	0.20	0.26	0.24	0.28
	SD Intercept	4.52	2.35	2.09	0.83	0.64	0.66	1.04	0.76	0.66	0.90	0.58	0.51
	Corr. Interc. - Slope	0.39	0.40	0.22	-0.20	-0.32	-0.48	-0.24	-0.31	-0.35	-0.34	-0.41	-0.61
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes			Yes
N	Students	11,936	11,936	11,715	13,835	13,835	13,440	12,676	12,676	12,329	12,729	12,729	12,376
	Schools	668	668	659	680	680	671	675	675	666	671	671	662
Model Fit	AIC	87,341	84,549	82,859	9,428	8,865	8,303	15,928	14,374	13,812	9,167	8,337	7,855
	Log-likelihood	-43,664	-42,262	-41,411	-4,709	-4,421	-4,135	-7,959	-7,175	-6,889	-4,579	-4,156	-3,910
	R-squared	0.27	0.39	0.39	0.12	0.14	0.14	0.23	0.30	0.30	0.13	0.15	0.15

*p < .05

Table 5. Variation by School Type in the Relation between Gender and Math Achievement

		Model 1	Model 2	Model 3
Student-Level Variables	Male	1.00*	1.42*	1.47*
		(0.41)	(0.37)	(0.38)
	Intercept	48.08*	50.08*	51.34*
		(0.44)	(0.32)	(0.40)
School Types	Well-Maintained Middle-of-the-Road Schools	-0.03	0.53	0.50
		(0.65)	(0.46)	(0.45)
	Most Academically Advantaged Schools	6.08*	3.53*	2.62*
		(0.67)	(0.47)	(0.50)
	Poorly Maintained Schools	0.47	1.05*	1.05*
		(0.71)	(0.50)	(0.51)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.72	-0.10	0.04
		(0.72)	(0.51)	(0.51)
	Most Vocationally Oriented Schools	-0.91	-0.11	0.25
		(0.76)	(0.54)	(0.54)
	Schools with Most Positive Student-Staff Relationships	3.41*	1.82*	1.16*
		(0.79)	(0.56)	(0.59)
	Less Well-Maintained, Academically Advantaged Schools	5.92*	3.74*	3.09*
		(0.79)	(0.55)	(0.57)
Cross-Level Interactions	Male*Well-Maintained Middle-of-the-Road Schools	1.00†	0.03	0.02
		(0.59)	(0.55)	(0.55)
	Male*Most Academically Advantaged Schools	0.61	0.18	0.13
		(0.62)	(0.57)	(0.57)
	Male*Poorly Maintained Schools	-0.03	-0.44	-0.36
		(0.66)	(0.61)	(0.62)
	Male*Middle-of-the-Road Schools with Less Experienced Teachers	0.24	0.03	-0.09
		(0.68)	(0.62)	(0.63)
	Male*Most Vocationally Oriented Schools	-0.27	-0.62	-0.69
		(0.72)	(0.66)	(0.67)
	Male*Schools with Most Positive Student-Staff Relationships	1.63†	0.94	0.87
		(0.72)	(0.66)	(0.67)
	Male*Less Well-Maintained, Academically Advantaged Schools	0.88	0.45	0.41
		(0.72)	(0.66)	(0.67)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Slope	0.98	1.15	1.20
	Std. Dev. of Intercept	3.68	1.96	1.88
	Correlation between Intercept and Slope	0.31	0.38	0.28
N	Students	11,936	11,936	11,715
	Schools	668	668	659

Model Fit Statistics	AIC	87,144.4	84,421.0	82,814.0
	Log-likelihood	-43,552.2	-42,183.5	-41,375.0
	R-squared	0.27	0.39	0.39

School types based on class membership probabilities. *p < .05, †p < .10

Table 6a. Variation by Resource Classes in the Relation between Gender and Math Achievement

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Male	2.04*	2.05*	2.03*	1.97*	1.97*	1.95*	0.37	1.05	1.05
		(0.47)	(0.43)	(0.44)	(0.47)	(0.42)	(0.43)	(0.85)	(0.78)	(0.80)
	Intercept	56.42*	54.91*	55.53*	50.81*	51.44*	51.65*	49.12*	51.62*	53.58*
		(0.52)	(0.38)	(0.48)	(0.56)	(0.39)	(0.49)	(0.99)	(0.68)	(0.72)
School Resource Classes	General Orientation	-8.03*	-4.40*	-3.60*						
		(0.59)	(0.42)	(0.47)						
	Most Vocationally Oriented Instruction	-7.99*	-3.95*	-2.93*						
		(0.69)	(0.49)	(0.54)						
	More Experienced but Less Satisfied Teachers				-1.42*	-0.24	0.97*			
					(0.61)	(0.41)	(0.43)			
	Fewest Physical Resource Problems							1.81*	0.35	-0.59
								(1.05)	(0.71)	(0.71)
	Moderate Physical Resource Problems							0.03	-0.87	-1.58*
								(1.06)	(0.72)	(0.71)
Cross-Level Interactions	Male*General Orientation	-0.54	-0.58	-0.54						
		(0.54)	(0.49)	(0.50)						
	Male*Most Vocationally Oriented	-1.13†	-1.14†	-1.09†						
		(0.64)	(0.59)	(0.59)						
	Male*More Experienced but Less Satisfied Teachers				-0.61	-0.64	-0.58			
					(0.51)	(0.47)	(0.47)			
	Male*Fewest Physical Resource Problems							1.15	0.27	0.29
								(0.90)	(0.82)	(0.84)
	Male*Moderate Physical Resource Problems							1.16	0.52	0.56
								(0.91)	(0.83)	(0.85)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes

	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of Slope	1.03	1.15	1.20	1.10	1.16	1.20	1.13	1.21	1.22
	Std. Dev. of Intercept	3.70	1.96	1.84	4.47	2.35	2.07	4.33	2.32	2.07
	Correlation	0.35	0.39	0.28	0.35	0.40	0.21	0.43	0.48	0.26
N	Students	11,936	11,936	11,715	11,596	11,596	11,394	10,060	10,060	9,883
	Schools	668	668	659	651	651	643	552	552	544
Model Fit Statistics	AIC	87142.4	84407.8	82787.3	84824.8	82095.8	80537.5	73562.6	71208.9	69867.1
	Log-likelihood	-43561.2	-42186.9	-41371.7	-42404.4	-41032.9	-40248.8	-36771.3	-35587.5	-34911.6
	R-squared	0.27	0.39	0.39	0.27	0.39	0.39	0.27	0.39	0.39

Classes based on membership probabilities. *p < .05, †p < .10

Table 6b. Variation by Resource Classes in the Relation between Gender and Math Achievement

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Male	3.29*	2.88*	2.90*	2.16*	2.09*	2.09*
		(0.62)	(0.57)	(0.57)	(0.39)	(0.36)	(0.36)
	Intercept	54.88*	53.74*	53.70*	56.52*	54.83*	55.33*
		(0.74)	(0.51)	(0.64)	(0.39)	(0.31)	(0.40)
School Resource Classes	Less Positive Student-Staff Relationships	-5.90*	-2.80*	-1.17†			
		(0.80)	(0.55)	(0.62)			
	Less Academically Oriented Peers				-9.16*	-4.78*	-4.17*
					(0.47)	(0.36)	(0.44)
Cross-Level Interactions	Male*Less Positive Student-Staff Relationships	-2.04*	-1.59*	-1.59*			
		(0.66)	(0.61)	(0.61)			
	Male*Less Academically Oriented Peers				-0.88*	-0.79†	-0.78†
					(0.48)	(0.44)	(0.44)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Slope	0.97	1.14	1.18	1.01	1.15	1.20
	Std. Dev. of Intercept	4.27	2.27	2.08	3.13	1.77	1.74
	Correlation	0.24	0.33	0.20	0.28	0.38	0.30
N	Students	11,936	11,936	11,715	11,936	11,936	11,715
	Schools	668	668	659	668	668	659
Model Fit Statistics	AIC	87,260.2	84,499.0	82,845.4	86,977.5	84,328.9	82,744.1
	Log-likelihood	-43,622.1	-42,234.5	-41,402.7	-43,480.7	-42,149.5	-41,352.1
	R-squared	0.27	0.39	0.39	0.26	0.39	0.39

Classes based on membership probabilities. *p < .05, †p < .10

Table 7. Variation by School Type in the Relation between Gender and High School Graduation

		Model 1	Model 2	Model 3
Student-Level Variables	Male	-0.36*	-0.34*	-0.37*
		(0.13)	(0.14)	(0.14)
	Intercept	2.23*	2.61*	2.85*
		(0.12)	(0.12)	(0.15)
School Types	Well-Maintained Middle-of-the-Road Schools	0.01	0.06	0.04
		(0.17)	(0.16)	(0.17)
	Most Academically Advantaged Schools	1.10*	0.67*	0.33
		(0.22)	(0.22)	(0.23)
	Poorly Maintained Schools	0.02	0.07	0.14
		(0.19)	(0.18)	(0.19)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.06	0.05	-0.02
		(0.19)	(0.18)	(0.19)
	Most Vocationally Oriented Schools	-0.23	-0.17	-0.09
		(0.19)	(0.19)	(0.20)
	Schools with Most Positive Student-Staff Relationships	0.47*	0.24	-0.07
		(0.23)	(0.22)	(0.25)
	Less Well-Maintained, Academically Advantaged Schools	1.48*	1.14*	0.91*
		(0.30)	(0.29)	(0.31)
Cross-Level Interactions	Male*Well-Maintained Middle-of-the-Road Schools	0.09	-0.02	-0.07
		(0.19)	(0.20)	(0.20)
	Male*Most Academically Advantaged Schools	0.13	0.08	0.04
		(0.27)	(0.27)	(0.28)
	Male*Poorly Maintained Schools	-0.09	-0.14	-0.22
		(0.21)	(0.22)	(0.22)
	Male*Middle-of-the-Road Schools with Less Experienced Teachers	-0.19	-0.25	-0.21
		(0.21)	(0.22)	(0.22)
	Male*Most Vocationally Oriented Schools	0.18	0.14	0.12
		(0.22)	(0.23)	(0.24)
	Male*Schools with Most Positive Student-Staff Relationships	0.40	0.30	0.24
		(0.28)	(0.29)	(0.30)
	Male*Less Well-Maintained, Academically Advantaged Schools	-0.72*	-0.80*	-0.77*
		(0.33)	(0.34)	(0.35)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Slope	0.36	0.42	0.37
	Std. Dev. of Intercept	0.72	0.61	0.64
	Correlation between Intercept and Slope	-0.22	-0.30	-0.46

N	Students	13,835	13,835	13,440
	Schools	680	680	671
Model Fit Statistics	AIC	9,328.2	8,835.0	8,310.6
	Log-likelihood	-4,645.1	-4,391.5	-4,124.3
	R-squared	0.11	0.14	0.14

School types based on class membership probabilities. *p < .05, †p < .10

Table 8a. Variation by Resource Classes in the Relation between Gender and High School Graduation

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Male	-0.36	-0.40	-0.39	-0.15	-0.21	-0.28	-0.75*	-0.73*	-0.82*
		(0.29)	(0.29)	(0.30)	(0.18)	(0.19)	(0.19)	(0.27)	(0.27)	(0.29)
	Intercept	4.04*	3.83*	3.60*	2.64*	2.83*	2.72*	2.31*	2.73*	3.02*
		(0.24)	(0.24)	(0.26)	(0.16)	(0.15)	(0.20)	(0.25)	(0.24)	(0.27)
School Resource Classes	General Orientation	-1.76*	-1.15*	-0.69*						
		(0.25)	(0.24)	(0.26)						
	Most Vocationally Oriented Instruction	-1.84*	-1.21*	-0.64*						
		(0.26)	(0.26)	(0.28)						
	More Experienced but Less Satisfied Teachers				-0.18	-0.03	0.32†			
					(0.17)	(0.16)	(0.18)			
	Fewest Physical Resource Problems							0.40	0.17	-0.03
								(0.27)	(0.25)	(0.27)
	Moderate Physical Resource Problems							0.14	0.04	-0.14
								(0.27)	(0.25)	(0.27)
Cross-Level Interactions	Male*General Orientation	-0.04	-0.05	-0.10						
		(0.30)	(0.30)	(0.31)						
	Male*Most Vocationally Oriented	0.14	0.15	0.07						
		(0.32)	(0.32)	(0.33)						
	Male*More Experienced but Less Satisfied Teachers				-0.25	-0.23	-0.20			
					(0.19)	(0.20)	(0.21)			
	Male*Fewest Physical Resource Problems							0.44	0.38	0.42
								(0.29)	(0.29)	(0.30)
	Male*Moderate Physical Resource Problems							0.45	0.41	0.51†
								(0.29)	(0.29)	(0.31)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes

	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of Slope	0.37	0.43	0.38	0.39	0.45	0.40	0.33	0.35	0.32
	Std. Dev. of Intercept	0.72	0.61	0.65	0.84	0.66	0.67	0.81	0.62	0.61
	Correlation	-0.24	-0.33	-0.49	-0.26	-0.39	-0.50	-0.35	-0.29	-0.40
N	Students	13,835	13,835	13,440	13,439	13,439	13,081	11,565	11,565	11,267
	Schools	680	680	671	663	663	655	560	560	552
Model Fit Statistics	AIC	9,312.4	8,816.4	8,294.3	9,160.2	8,613.2	8,099.2	7,546.4	7,096.4	6,705.2
	Log-likelihood	-4,647.2	-4,392.2	-4,126.1	-4,573.1	-4,292.6	-4,030.6	-3,764.2	-3,532.2	-3,331.6
	R-squared	0.12	0.14	0.14	0.12	0.14	0.14	0.11	0.13	0.13

Classes based on membership probabilities. *$p < .05$, †$p < .10$

Table 8b. Variation by Resource Classes in the Relation between Gender and High School Graduation

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Male	0.28	0.19	0.16	-0.47†	-0.49†	-0.55*
		(0.34)	(0.33)	(0.35)	(0.25)	(0.25)	(0.26)
	Intercept	3.53*	3.32*	2.79*	4.22*	3.95*	3.83*
		(0.26)	(0.24)	(0.30)	(0.20)	(0.20)	(0.23)
School Resource Classes	Less Positive Student-Staff Relationships	-1.15*	-0.58*	0.22			
		(0.27)	(0.25)	(0.30)			
	Less Academically Oriented Peers				-2.19*	-1.45*	-1.14*
					(0.21)	(0.21)	(0.24)
Cross-Level Interactions	Male*Less Positive Student-Staff Relationships	-0.69*	-0.63†	-0.65†			
		(0.35)	(0.34)	(0.36)			
	Male*Less Academically Oriented Peers				0.14	0.11	0.13
					(0.27)	(0.27)	(0.28)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Slope	0.37	0.43	0.38	0.38	0.44	0.38
	Std. Dev. of Intercept	0.79	0.63	0.66	0.62	0.57	0.62
	Correlation	-0.29	-0.34	-0.48	-0.24	-0.33	-0.46
N	Students	13,835	13,835	13,440	13,835	13,835	13,440
	Schools	680	680	671	680	680	671
Model Fit Statistics	AIC	9,372.5	8,843.8	8,303.8	9,203.9	8,771.5	8,269.6
	Log-likelihood	-4,679.2	-4,407.9	-4,132.9	-4,595.0	-4,371.8	-4,115.8
	R-squared	0.12	0.14	0.14	0.11	0.14	0.14

Classes based on membership probabilities. *p < .05, †p < .10

Table 9. Variation by School Type in the Relation between Gender and Immediate Enrollment in a Four-Year Institution

		Model 1	Model 2	Model 3
Student-Level Variables	Male	-0.19*	-0.20†	-0.19†
		(0.10)	(0.10)	(0.10)
	Intercept	-0.73*	-0.50*	-0.33*
		(0.10)	(0.09)	(0.11)
School Types	Well-Maintained Middle-of-the-Road Schools	0.12	0.15	0.14
		(0.14)	(0.13)	(0.13)
	Most Academically Advantaged Schools	1.58*	1.09*	0.75*
		(0.15)	(0.14)	(0.15)
	Poorly Maintained Schools	0.40*	0.36*	0.36*
		(0.15)	(0.14)	(0.15)
	Middle-of-the-Road Schools with Less Experienced Teachers	0.01	0.10	0.12
		(0.16)	(0.15)	(0.15)
	Most Vocationally Oriented Schools	0.02	0.06	0.11
		(0.17)	(0.16)	(0.16)
	Schools with Most Positive Student-Staff Relationships	1.23*	0.91*	0.52*
		(0.18)	(0.16)	(0.17)
	Less Well-Maintained, Academically Advantaged Schools	1.72*	1.31*	1.05*
		(0.18)	(0.16)	(0.17)
Cross-Level Interactions	Male*Well-Maintained Middle-of-the-Road Schools	0.02	-0.07	-0.06
		(0.14)	(0.15)	(0.15)
	Male*Most Academically Advantaged Schools	0.02	-0.02	-0.05
		(0.15)	(0.16)	(0.16)
	Male*Poorly Maintained Schools	-0.16	-0.16	-0.16
		(0.15)	(0.16)	(0.17)
	Male*Middle-of-the-Road Schools with Less Experienced Teachers	-0.24	-0.31†	-0.29
		(0.17)	(0.17)	(0.18)
	Male*Most Vocationally Oriented Schools	-0.12	-0.15	-0.13
		(0.17)	(0.18)	(0.18)
	Male*Schools with Most Positive Student-Staff Relationships	-0.20	-0.30†	-0.32†
		(0.17)	(0.18)	(0.18)
	Male*Less Well-Maintained, Academically Advantaged Schools	-0.40*	-0.45*	-0.48*
		(0.17)	(0.18)	(0.19)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Slope	0.13	0.17	0.18
	Std. Dev. of Intercept	0.77	0.61	0.59
	Correlation between Intercept and Slope	-0.07	-0.18	-0.29
N	Students	12,676	12,676	12,329

	Schools	675	675	666
Model Fit Statistics	AIC	15,678.0	14,221.0	13,769.5
	Log-likelihood	-7,820.0	-7,084.5	-6,853.7
	R-squared	0.22	0.29	0.29

School types based on class membership probabilities. *$p < .05$, †$p < .10$

Table 10a. Variation by Resource Classes in the Relation between Gender and Immediate Enrollment in a Four-Year Institution

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Male	-0.38*	-0.41*	-0.44*	-0.38*	-0.47*	-0.50*	-0.31	-0.27	-0.27
		(0.13)	(0.13)	(0.14)	(0.11)	(0.12)	(0.12)	(0.20)	(0.22)	(0.22)
	Intercept	1.64*	1.19*	0.98*	0.33*	0.28*	-0.01	-0.50*	-0.30	0.06
		(0.13)	(0.12)	(0.15)	(0.13)	(0.12)	(0.14)	(0.24)	(0.21)	(0.22)
School Resource Classes	General Orientation	-2.18*	-1.51*	-1.10*						
		(0.14)	(0.13)	(0.15)						
	Most Vocationally Oriented Instruction	-2.00*	-1.34*	-0.89*						
		(0.16)	(0.15)	(0.16)						
	More Experienced but Less Satisfied Teachers				-0.63*	-0.44*	0.05			
					(0.14)	(0.12)	(0.13)			
	Fewest Physical Resource Problems							0.49†	0.30	0.06
								(0.25)	(0.22)	(0.21)
	Moderate Physical Resource Problems							0.25	0.19	0.01
								(0.26)	(0.23)	(0.22)
Cross-Level Interactions	Male*General Orientation	0.13	0.11	0.14						
		(0.14)	(0.15)	(0.15)						
	Male*Most Vocationally Oriented	-0.01	-0.01	0.02						
		(0.17)	(0.17)	(0.18)						
	Male*More Experienced but Less Satisfied Teachers				0.11	0.16	0.20			
					(0.13)	(0.13)	(0.14)			
	Male*Fewest Physical Resource Problems							0.11	0.00	0.01
								(0.22)	(0.23)	(0.23)
	Male*Moderate Physical Resource Problems							0.00	-0.09	-0.09
								(0.22)	(0.23)	(0.24)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes

	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of Slope	0.13	0.17	0.19	0.14	0.17	0.19	0.16	0.22	0.24
	Std. Dev. of Intercept	0.78	0.62	0.59	1.01	0.75	0.66	1.05	0.80	0.69
	Correlation	-0.16	-0.29	-0.35	-0.21	-0.28	-0.41	-0.54	-0.56	-0.60
N	Students	12,676	12,676	12,329	12,328	12,328	12,012	10,608	10,608	10,348
	Schools	675	675	666	659	659	651	556	556	548
Model Fit Statistics	AIC	15,665.2	14,204.5	13,750.1	15,479.4	13,967.6	13,452.1	13,369.2	12,041.3	11,599.2
	Log-likelihood	-7,823.6	-7,086.2	-6,854.1	-7,732.7	-6,969.8	-6,707.1	-6,675.6	-6,004.6	-5,778.6
	R-squared	0.22	0.29	0.29	0.23	0.30	0.30	0.23	0.30	0.30

Classes based on membership probabilities. *p < .05, †p < .10

Table 10b. Variation by Resource Classes in the Relation between Gender and Immediate Enrollment in a Four-Year Institution

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Male	-0.25	-0.38*	-0.37*	-0.33*	-0.40*	-0.42*
		(0.17)	(0.17)	(0.18)	(0.11)	(0.11)	(0.11)
	Intercept	1.57*	1.14*	0.67*	1.64*	1.20*	1.06*
		(0.18)	(0.16)	(0.20)	(0.09)	(0.09)	(0.12)
School Resource Classes	Less Positive Student-Staff Relationships	-1.96*	-1.37*	-0.64*			
		(0.19)	(0.17)	(0.19)			
	Less Academically Oriented Peers				-2.39*	-1.69*	-1.46*
					(0.11)	(0.11)	(0.13)
Cross-Level Interactions	Male*Less Positive Student-Staff Relationships	-0.03	0.04	0.04			
		(0.18)	(0.19)	(0.19)			
	Male*Less Academically Oriented Peers				0.08	0.10	0.12
					(0.13)	(0.13)	(0.13)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Slope	0.14	0.18	0.20	0.14	0.18	0.19
	Std. Dev. of Intercept	0.92	0.70	0.65	0.57	0.52	0.52
	Correlation	-0.33	-0.32	-0.37	-0.19	-0.27	-0.34
N	Students	12,676	12,676	12,329	12,676	12,676	12,329
	Schools	675	675	666	675	675	666
Model Fit Statistics	AIC	15,798.6	14,288.4	13,801.2	15,407.2	14,069.1	13,661.9
	Log-likelihood	-7,892.3	-7,130.2	-6,881.6	-7,696.6	-7,020.6	-6,811.9
	R-squared	0.22	0.29	0.30	0.21	0.29	0.29

Classes based on membership probabilities. *p < .05, †p < .10

Table 11. Variation by School Type in the Relation between Gender and Any Postsecondary Enrollment

		Model 1	Model 2	Model 3
Student-Level Variables	Male	-0.73*	-0.76*	-0.75*
		(0.13)	(0.13)	(0.13)
	Intercept	2.20*	2.45*	2.66*
		(0.12)	(0.11)	(0.14)
School Types	Well-Maintained Middle-of-the-Road Schools	-0.22	-0.17	-0.19
		(0.17)	(0.16)	(0.16)
	Most Academically Advantaged Schools	1.39*	0.79*	0.37
		(0.24)	(0.23)	(0.23)
	Poorly Maintained Schools	0.14	0.13	0.09
		(0.19)	(0.18)	(0.18)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.17	-0.10	-0.08
		(0.19)	(0.18)	(0.18)
	Most Vocationally Oriented Schools	-0.23	-0.24	-0.21
		(0.20)	(0.18)	(0.19)
	Schools with Most Positive Student-Staff Relationships	1.27*	0.89*	0.45
		(0.28)	(0.27)	(0.28)
	Less Well-Maintained, Academically Advantaged Schools	1.43*	0.93*	0.65*
		(0.29)	(0.28)	(0.30)
Cross-Level Interactions	Male*Well-Maintained Middle-of-the-Road Schools	0.19	0.09	0.10
		(0.18)	(0.19)	(0.19)
	Male*Most Academically Advantaged Schools	0.29	0.35	0.36
		(0.28)	(0.28)	(0.29)
	Male*Poorly Maintained Schools	0.04	0.03	0.03
		(0.21)	(0.22)	(0.22)
	Male*Middle-of-the-Road Schools with Less Experienced Teachers	0.09	0.05	0.03
		(0.21)	(0.21)	(0.22)
	Male*Most Vocationally Oriented Schools	0.12	0.12	0.09
		(0.22)	(0.22)	(0.22)
	Male*Schools with Most Positive Student-Staff Relationships	0.01	-0.04	-0.14
		(0.32)	(0.32)	(0.34)
	Male*Less Well-Maintained, Academically Advantaged Schools	0.08	0.07	0.11
		(0.34)	(0.34)	(0.37)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Slope	0.27	0.25	0.27
	Std. Dev. of Intercept	0.71	0.51	0.48
	Correlation between Intercept and Slope	-0.50	-0.50	-0.62

N	Students	12,729	12,729	12,376
	Schools	671	671	662
Model Fit Statistics	AIC	8,962.4	8,236.9	7,840.2
	Log-likelihood	-4,462.2	-4,092.5	-3,889.1
	R-squared	0.11	0.15	0.15

School types based on class membership probabilities. *p < .05, ✝p < .10

Table 12a. Variation by Resource Classes in the Relation between Gender and Any Postsecondary Enrollment

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Male	-0.42	-0.42	-0.44	-0.45*	-0.51*	-0.62*	-0.50†	-0.46	-0.48
		(0.36)	(0.36)	(0.37)	(0.20)	(0.20)	(0.21)	(0.28)	(0.29)	(0.29)
	Intercept	4.64*	4.06*	3.66*	3.03*	2.91*	2.71*	2.28*	2.49*	2.72*
		(0.29)	(0.28)	(0.31)	(0.18)	(0.17)	(0.20)	(0.27)	(0.24)	(0.26)
School Resource Classes	General Orientation	-2.42*	-1.60*	-1.00*						
		(0.30)	(0.29)	(0.31)						
	Most Vocationally Oriented Instruction	-2.37*	-1.60*	-0.99*						
		(0.31)	(0.30)	(0.32)						
	More Experienced but Less Satisfied Teachers				-0.60*	-0.33†	0.08			
					(0.19)	(0.17)	(0.18)			
	Fewest Physical Resource Problems							0.30	0.09	-0.05
								(0.28)	(0.25)	(0.25)
	Moderate Physical Resource Problems							0.23	0.17	0.07
								(0.29)	(0.25)	(0.25)
Cross-Level Interactions	Male*General Orientation	-0.23	-0.29	-0.26						
		(0.37)	(0.37)	(0.38)						
	Male*Most Vocationally Oriented	-0.24	-0.27	-0.26						
		(0.38)	(0.38)	(0.40)						
	Male*More Experienced but Less Satisfied Teachers				-0.20	-0.20	-0.07			
					(0.21)	(0.21)	(0.22)			
	Male*Fewest Physical Resource Problems							-0.02	-0.12	-0.10
								(0.30)	(0.30)	(0.31)
	Male*Moderate Physical Resource Problems							-0.11	-0.22	-0.22
								(0.30)	(0.31)	(0.31)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes

Variance Parameters	Std. Dev. of Slope	0.26	0.25	0.28	0.27	0.25	0.27	0.24	0.23	0.24
	Std. Dev. of Intercept	0.73	0.52	0.48	0.90	0.58	0.52	0.91	0.54	0.46
	Correlation	-0.51	-0.52	-0.62	-0.41	-0.47	-0.57	-0.24	-0.09	-0.29
N	Students	12,729	12,729	12,376	12,370	12,370	12,048	10,677	10,677	10,404
	Schools	671	671	662	655	655	647	554	554	546
Model Fit Statistics	AIC	8,963.0	8,230.9	7,827.2	8,870.2	8,083.5	7,651.2	7,625.9	6,883.0	6,522.5
	Log-likelihood	-4,472.5	-4,099.4	-3,892.6	-4,428.1	-4,027.8	-3,806.6	-3,803.9	-3,425.5	-3,240.2
	R-squared	0.12	0.15	0.15	0.13	0.15	0.15	0.13	0.16	0.15

Classes based on membership probabilities. *$p < .05$, †$p < .10$

Table 12b. Variation by Resource Classes in the Relation between Gender and Any Postsecondary Enrollment

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Male	-0.35	-0.44	-0.52	-0.82*	-0.84*	-0.87*
		(0.47)	(0.46)	(0.48)	(0.29)	(0.29)	(0.29)
	Intercept	4.82*	4.23*	3.57*	4.77*	4.19*	3.81*
		(0.38)	(0.36)	(0.40)	(0.24)	(0.23)	(0.25)
School Resource Classes	Less Positive Student-Staff Relationships	-2.51*	-1.75*	-0.84*			
		(0.39)	(0.37)	(0.41)			
	Less Academically Oriented Peers				-2.83*	-1.94*	-1.41*
					(0.25)	(0.25)	(0.26)
Cross-Level Interactions	Male*Less Positive Student-Staff Relationships	-0.29	-0.26	-0.18			
		(0.48)	(0.47)	(0.49)			
	Male*Less Academically Oriented Peers				0.25	0.19	0.21
					(0.30)	(0.30)	(0.31)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Slope	0.26	0.24	0.28	0.26	0.24	0.27
	Std. Dev. of Intercept	0.79	0.53	0.50	0.56	0.44	0.43
	Correlation	-0.41	-0.43	-0.61	-0.36	-0.41	-0.56
N	Students	12,729	12,729	12,376	12,729	12,729	12,376
	Schools	671	671	662	671	671	662
Model Fit Statistics	AIC	9,038.2	8,262.7	7,845.6	8,827.8	8,176.9	7,802.4
	Log-likelihood	-4,512.1	-4,117.4	-3,903.8	-4,406.9	-4,074.4	-3,882.2
	R-squared	0.12	0.15	0.15	0.11	0.15	0.14

Classes based on membership probabilities. *p < .05, †p < .10

Chapter 4: Socioeconomic Disparities

Reducing the relation between students' initial socioeconomic status and their educational achievement and attainment has long been a central goal of federal education policy (Harris and Herrington 2006; Manna 2006; Raudenbush and Eschmann 2015). Despite decades of effort by educational institutions, socioeconomic inequalities in educational achievement and attainment are not shrinking and may, in fact, be widening due to growing levels of inequality in American society more broadly (Duncan and Murnane 2011). Achievement differences between children from high-income families (those in the 90^{th} percentile of the family income distribution) and low-income families (those in the 10^{th} percentile) are now more than twice as large as average differences in achievement between Black and White students (Reardon 2011). Low-SES students are much less likely than high-SES students to enroll in college (Bozick, Lauff and Wirt 2007; Kane 2004) and, over the past two decades, inequality in college entry and completion by SES has increased, even among students with the same measured cognitive skills as teenagers (Bailey and Dynarski 2011).

Differences in educational achievement and attainment by SES are produced primarily through non-school mechanisms (Condron 2009; Downey, von Hippel and Broh 2004; Raudenbush and Eschmann 2015; Reardon 2011). Home environments, families, and neighborhoods are extremely unequal, and schools, "although far from equal in their instructional resources, are much less variable than homes are" (Raudenbush and Eschmann 2015: 453). By comparing kindergartners' and first-graders' rates of learning in math and reading when school was in session to their learning rates when school was out-of-session, Downey, von Hippel, and Broh showed that, "although schooling does not equalize high- and low-socioeconomic status children in the absolute sense, and although schooling does not necessarily ensure that they learn at the same rate when school is in session, schooling does reduce the rate at which inequality grows, compared to when school is out of session" (2004: 632). Other research echoes this finding. For example, using data from the NELS, Rumberger and Palardy found that "school characteristics account for more of the differences in student learning during high school than student background characteristics" (2005a: 2018).

If SES effects on achievement depended only on families, then these effects should be constant across schools. However, there is evidence that SES effects on achievement vary across schools (Jennings et al. 2015; Raudenbush and Eschmann 2015), and there is reason to think that SES effects on *attainment* might also vary across schools, perhaps even more so given that students from disadvantaged backgrounds often depend on the schools they attend to provide opportunities to increase their educational attainment prospects (cf. Erickson, McDonald and Elder 2009; Martinez and Cervera 2012; Stanton-Salazar and Dornbusch 1995). This chapter examines whether and why SES effects differ across schools. Specifically, I ask: (1) To what extent do SES inequalities in educational achievement and attainment vary across high schools? (2) What types of schools and school-based resources are associated with greater or lesser SES inequality? (3) Are the same types of schools and school resources associated with the greatest socioeconomic inequality across different outcomes?

DIFFERENCES IN SCHOOL-BASED RESOURCES BY STUDENT SES

Socioeconomic disparities in schooling arise in part because U.S. neighborhoods and schools are segregated by SES, meaning that low- and high-SES students tend to attend different schools, and in part because students within the same school experience schooling differently depending on their SES (Jennings et al. 2015; Kalogrides and Loeb 2013; Quillian 2014; Reardon and Owens 2014; Wenglinsky 2004). I focus on this second form of socioeconomic disparities in this chapter. In this section, I briefly review the literature on average differences in instructional, teacher, school physical, student-staff, and student-peer resources by student SES. As I discuss below, lower SES students usually are disadvantaged in the five types of resources I consider. Federal, state, and local programs – most notably Title I – have long attempted to compensate for these inequalities by providing compensatory resources to low-SES students and schools (Borman and D'Agostino 1996; Gordon 2004; Jennings 2000). Unfortunately, these programs often face barriers in redistributing resources, partly as a result of higher-SES parents' advocacy on behalf of their children and partly as a result of schools' choices about how to allocate resources (Gordon and Reber 2015; McGrath and Kuriloff 1999; Posey-Maddox 2012).

When it comes to students' access to **instructional resources**, a large body of literature has shown that low-SES students are disproportionately placed in lower tracks, lower ability groups, and less academically demanding courses (cf. Attewell and Domina 2008; Gamoran 2010; Lucas and Berends 2002; Oakes 2005; Tach and Farkas 2006), though debate continues regarding whether the extent of tracking by SES is higher in schools with more socioeconomic diversity (Kelly and Price 2011; Lucas 1999; Lucas and Berends 2002). In addition, most research suggests that, both within and across schools, poor students are more likely to have novice **teachers,** less likely to have teachers with an in-field degree, and less likely to have teachers with graduate degrees (cf. Akiba, LeTendre and Scribner 2007; Clotfelter, Ladd and Vigdor 2010; Dee and Cohodes 2008; Kain and Singleton 1996; Kalogrides and Loeb 2013; Klugman 2012).[1] Based on data from the 2003 Trends in International Mathematics and Science Study, Akiba, LeTendre, and Scribner (2007) concluded that, although the national level of teacher quality in the U.S. is similar to the international average, the opportunity gap between

[1] For exceptions see Borman and Rachuba 1999; Condron 2009; Desimone and Long 2010.

low- and high-SES students in access to qualified teachers is among the largest in the countries studied.

In terms of **schools' physical characteristics**, on average, low-SES students attend schools that are in worse physical condition and are more often overcrowded than the schools attended by middle- and high-SES students (Condron 2009; Wolniak and Engberg 2010). Though most research does not examine how *within-school* access to physical resources varies by student SES, based on distribution patterns for other resources, it is certainly plausible that schools' physical resources (e.g., textbooks, classroom condition, laboratory equipment) sometimes are distributed within schools in ways that disadvantage low-SES students.

As discussed above, **student-staff relationships** may be particularly important for socioeconomically disadvantaged students (cf. Engberg and Wolniak 2010a; Hill 2008; Martinez and Cervera 2012; McDonough 1997; Roderick, Coca and Nagaoka 2011; Stanton-Salazar 2001). Yet, on average, low-SES students perceive teacher-student relationships and school climate more negatively (Fan, Williams and Corkin 2011); teachers' expectations about low-SES students' ability to learn are lower (Rumberger and Palardy 2005a); and, even after controlling for students' academic performance, teachers have lower college expectations for students from low-SES backgrounds (Crosnoe 2009; Muller, Katz and Dance 1999).

Perhaps most importantly, students tend to be concentrated in schools full of **peers** with similar socioeconomic resources. Many studies suggest that the effect of schools' socioeconomic composition on achievement is as large as, or larger than, the effect of students' individual SES (cf. Borman and Dowling 2010; Gamoran 1996; Gamoran and An 2016; Lee, Smith and Croninger 1997; Rumberger and Palardy 2005a; Sui-Chu and Willms 1996). Importantly, peers' socioeconomic composition may matter more for low-SES students than for high-SES students

(Bryk and Driscoll 1988; Legewie and DiPrete 2012). While students tend to attend schools with peers who are socioeconomically "like them," this, of course, is not universally the case (Kalogrides and Loeb 2013), and, within schools, students may differ in their exposure to students of disparate SES. Also, importantly, schools and their staff may be able to shape at least some characteristics of students' peers, including their morale, educational expectations, and interest in school (Engberg and Wolniak 2010a; Palardy 2013).

DIFFERENCES ACROSS SCHOOLS IN THE EFFECT OF SES

Prior literature repeatedly has found that, on average, low-SES students tend to experience schools in less positive ways than their higher-SES within-school counterparts. However, the degree to which low-SES students suffer in terms of access to challenging instruction, qualified teachers, caring staff, or motivated peers may vary across schools and, therefore, the ways in which – or the extent to which – schools differentiate achievement by SES also may vary across schools.

Much of the initial research on the extent to which the relation between SES and achievement varies across schools compared public schools to Catholic schools (or private schools more generally) and found that the relation between students' SES and their academic achievement was weaker in Catholic than in public schools (Coleman, Hoffer and Kilgore 1982; Hoffer, Greeley and Coleman 1985; Lee and Bryk 1989). The relation between students' SES and their risk of dropping out also seemed to be weaker in Catholic schools (Bryk and Schneider 2002; Bryk and Thum 1989). However, more recent research either has not found that Catholic schools are more equitable than public schools with respect to the relation between SES and achievement or has concluded that whether Catholic schools are more equitable is subject- and grade-specific (Carbonaro and Covay 2010; Hallinan and Kubitschek 2012).

Other studies suggest that schools with more advantaged socioeconomic compositions differentiate achievement by SES to a greater extent. Using NELS data, Rumberger and Palardy (2005a) found that students' SES is an important predictor of achievement growth in all subjects over the course of high school in middle- and high-, but not low-, SES schools. Rumberger and Palardy conclude that low-SES schools "have more uniform (and some might say, equitable) effects on students no matter what their background" (2005a: 2017). These results are consistent with Crosnoe's hypothesis that, "[b]ecause SES is an evaluative marker in diverse settings, poverty is more likely to be a social liability in a school where it is rare than one in which it is well-represented" (2009: 711). Using data from the National Longitudinal Study of Adolescent to Adult Health, Crosnoe (2009) found that low-income students progress less far in math and science and experience more psychosocial problems in middle- and high-SES schools than in low-SES ones. These findings seem to contradict past research on the advantages of attending higher SES schools for academic achievement, but Crosnoe suggests that higher SES schools may offer both benefits and drawbacks. In particular, if access to high grades or seats in courses is limited, low-SES students may be at a greater competitive disadvantage in high-SES than low-SES schools. In contrast, two studies using the ELS found little evidence that the relation between students' SES and their likelihood of enrolling in college is moderated by the socioeconomic composition of their high school (Engberg and Wolniak 2010a; Palardy 2013).

Bryk, Lee, and colleagues conducted much of the initial research on school characteristics associated with the degree of SES-based differentiation in achievement. Consistent with the broader literature on the effects of tracking and curriculum differentiation in schools (cf. Gamoran 2010; Lucas 1999), Bryk, Lee, and colleagues found that SES-based inequality in achievement is positively associated with greater differentiation or variability in math course taking, academic course taking more broadly, programs of study, and the percent of students in academic programs (Bryk and Schneider 2002; Lee and Bryk 1989; Lee, Croninger and Smith 1997; Lee and Smith 1995). Likewise, SES-based differentiation in dropout rates is smaller in schools in which a high proportion of students are in an academic program (Bryk and Thum 1989). These findings led Lee and Bryk to conclude that “the academic organization of high schools has a significant impact on the social distribution of achievement within them” (1989: 188).

Bryk, Lee, and colleagues also found that SES-based inequality in achievement gains is smaller in high schools with higher proportions of teachers reporting collective responsibility for students’ learning, rather than attributing students’ difficulties to their family background (Lee and Smith 1996; Lee, Smith and Croninger 1997), and that SES-based differentiation in high school dropout is larger in schools with a greater frequency of discipline problems (Bryk and Thum 1989). These findings, which were largely based on analyses of NELS and High School and Beyond (HSB), were echoed by Borman and Dowling’s (2010) reanalysis of the Coleman Report’s data. Borman and Dowling found that, on average, social class inequalities were larger in schools with greater curricular differentiation (as measured by the number of alternative curricular tracks available at the school). Social class differentiation was also larger in schools in which teachers reported greater “preferences for middle-class students” (measured by three variables: the type of high school teachers said they preferred to work in, teachers’ preferred choice of school setting, and teachers’ preferred student ability level to teach or counsel). Findings of less differentiation by SES in schools with less curriculum differentiation are also consistent with a review of the comparative literature conducted by Van de Werfhorst and Mijs

(2010) who found that, cross-nationally, standardization of schools reduces the association between social origin and student achievement.

Overall, prior literature indicates that variation in the relation between students' SES and their outcomes across schools may be partly attributable to school resources, particularly peer composition, academically-oriented instruction, and teachers' perceptions of responsibility for student learning. However, this research has been ad hoc, with researchers examining the effect of individual resources on different samples for different student outcomes. Therefore, I aim to provide a more comprehensive look at the way resources are associated with SES disadvantages in American high schools. Using a nationally representative dataset, examining a number of different outcomes, and measuring school resources both independently and as a package or typology, I explore whether particular school resources are associated with the relation between SES and student outcomes across schools.

DATA AND METHODS

In this chapter, I estimate group mean-centered models in which each student's SES is evaluated relative to his or her school's mean in the sample (Raudenbush and Bryk 2002). Group mean-centered models are consistent with the theory that, within schools, resources usually are distributed in ways that favor the most advantaged students, regardless of the overall level of advantage or disadvantage at the school. For instance, as Crosnoe writes, "students evaluate themselves relative to those in their specific contexts, often regardless of how that context 'ranks' in the larger world" (2009: 711). I include the school's mean SES, based on the average SES of sampled students, in all models because of literature suggesting both that the effect of schools' SES on achievement remains even after controlling for a wide variety of other school characteristics and that the effect of students' SES may vary for schools of different SES (Borman and Dowling 2010; Raudenbush and Bryk 2002; Rumberger and Palardy 2005a).

I restrict the sample to high schools with at least five sampled students with data on both SES and a given outcome. Table 1 compares schools in this sample to the overall sample; all differences are one percentage point or less.

< Table 1 >

Although there are many ways to measure SES, as discussed in the previous chapter, I use the most common approach in the education literature: a standardized, continuous measure that combines parents' education, income, and occupation (Bryk and Thum 1989; Lee and Bryk 1989; Lee, Croninger and Smith 1997; Lee and Smith 1995; Lee and Smith 1996; Lee, Smith and Croninger 1997). Table 2 compares model fit statistics for null models with a random intercept only, random intercept plus SES fixed effects (at both the student- and school-level), and random intercept plus random slope; including a random slope for student-level SES improves model fit for all outcomes.

< Table 2 >

RESULTS

To what extent does the relation between SES and each outcome vary across schools? The standard deviation of the SES slope for math achievement ranges from 1.49 to 1.85; thus, the SES slope's standard deviation is equivalent to 15 to 19 percent of the math test's standard deviation, depending on the model. The standard deviations of the SES slopes for the binary outcomes are similar to each other, ranging from 0.36 for immediate enrollment in a four-year institution to 0.52 for any postsecondary enrollment. Group mean-centering student SES removes most of the relation between schools' intercepts and their SES slopes: the correlations are near zero (ranging from -.18 to .15) for math achievement, high school graduation, and any postsecondary enrollment. For immediate enrollment in a four-year institution, a moderate correlation between the school intercept and SES slopes remains, decreasing from -.40 in the model that does not include student or school covariates (except for mean SES) to -.18 in the model that includes both student and school covariates. The remaining negative correlation indicates that, conditional on schools' average SES, schools with higher average rates of on-time four-year enrollment have a *weaker* relation between students' relative within-school SES and their probability of on-time four-year enrollment.

< Table 3 >

Figures 1 – 4 illustrate the range of variation in the relation between (group mean-centered) SES and each outcome across schools. In these figures, each gray line represents the relation between student SES and the outcome in a single school, while the red line depicts the average relation between SES and the outcome across the sample. All results are from models that condition on both student and school covariates. Each figure also includes a *horizontal* line marking the sample average for the reference category (White, female, non-English language learner, non-special education students in suburban public schools with average SES and a low percentage of FRL-eligible students).

In Figure 1, some variation in the relation between student SES and math achievement is visible via differences in the lines' slopes, but, in general, the relation between SES and math achievement appears fairly consistent across schools. More variation is evident in the relation between SES and graduation across schools (Figure 2); in some schools, all or nearly all students graduate regardless of SES, whereas SES is more strongly related to graduation in other schools. Not surprisingly, this variation is concentrated at the low to very low end of the SES scale;

regardless of school, students with above average SES have a very high probability of graduating high school, whereas lower-SES students' probability varies more across schools.

< Figure 1, Figure 2 >

At a few schools in the sample, students one standard deviation *below* their school's mean SES have a better than 50 percent chance of enrolling in a four-year institution immediately after high school. At other schools, students must be one standard deviation *above* their school's mean SES to have a 50 percent chance of enrolling immediately in a four-year institution (Figure 3). The figure for students' probability of any postsecondary enrollment is similar to the figure for high school graduation in that the vast majority of the variation across schools is for students at the low end of the SES distribution. In some high schools, all or almost all students, regardless of their relative within-school SES, enroll in a postsecondary institution; in other schools, students' SES is strongly related to their probability of postsecondary enrollment (Figure 4).

< Figure 3, Figure 4 >

Overall, Figures 1 – 4 illustrate variability in the relation between SES and various educational outcomes across schools. Can particular school types (i.e., clusters of resources) or individual school resources explain some of this variability?

Predicting Variation in SES Inequalities in Math Achievement across Schools

Students' SES is not as strongly related to their math achievement in schools with the most positive student-staff relationships as it is in the most common type of schools, "middle-of-the-road schools." Schools with the most positive student-staff relationships have significantly higher average math achievement than middle-of-the-road schools, but it is not the case for all types of schools that the relation between SES and math achievement is weaker in schools with higher average achievement. Both the most academically advantaged schools and less well-maintained but academically advantaged schools have significantly higher average achievement than middle-of-the-road schools but do not have a relation between SES and achievement that differs from that found in middle-of-the-road schools.

< Table 4 >

Figure 5 illustrates the average relation between SES and math achievement in each type of school. Each line in the figure is based on the main effect of SES, the main effect of a particular school type, and the school type's interaction with SES; results are from the model that conditions on both student and school covariates. The less steep slope for schools with the most positive student-staff relationships is clearly visible in the figure. Students of lower SES have the highest math achievement in schools with the most positive student-staff relationships, while higher SES students have higher math achievement, particularly in the most academically advantaged schools and less well-maintained but academically advantaged schools, than in schools with the most positive student-staff relationships.

< Figure 5 >

How are specific types of school resources associated with the degree of SES differentiation in math achievement across schools? In terms of instructional resources, the relation between SES and math achievement may be weaker in schools that have the most academically-oriented instructional resources than in schools with a general orientation to instructional resources, though the interaction coefficient is not statistically significant after conditioning on both student and school covariates. Schools with the most academically-oriented instruction have math achievement that is two to three points higher, on average, than schools with a general orientation, and lower SES students' math achievement may be an additional half-point higher in these schools. The relation between student SES and math achievement is significantly stronger in schools with more experienced but less satisfied teachers; in these schools, average math achievement is three-quarters of a point higher, and each unit of SES is associated with an additional one point advantage in math achievement compared to schools with less experienced but more satisfied teachers. In terms of schools' physical resources, the pattern of coefficients suggests that the relation between SES and math achievement may be weaker in schools with the most physical resource problems compared to schools with few or moderate physical resource problems, though only one of the physical resource interactions is statistically significant.

< Table 5a >

Schools with less positive student-staff relationships have lower average math achievement than schools with more positive student-staff relationships, but the relation between SES and math achievement is significantly stronger in schools with less positive student-staff relationships. Perhaps higher-SES students' math achievement is not hurt as much as lower-SES students' by attending schools with less positive student-staff relationships or, perhaps, lower SES students' math achievement is *helped* relatively more than higher SES students' by attending schools with more positive student-staff relationships. Figure 6 illustrates the pattern; students at the lowest SES levels have higher scores in schools with more positive versus less positive student-staff relationships, but the difference in achievement between schools with more versus less positive student-staff relationships narrows across the SES distribution. For student-peer resources, the interaction coefficients are very small, suggesting that the relation between student SES and math achievement does not vary much across classes of student-peer resources

< Table 5b, Figure 6 >

Predicting Variation in SES Inequalities in High School Graduation across Schools

The relation between students' SES and their log odds of graduating high school generally does not appear to vary significantly by school type with the possible exception that there may be less SES-based differentiation in well-maintained middle-of-the-road schools (Table 6). As Figure 7 suggests, while average- to high-SES students' probability of graduation is very similar across schools, low-SES students' graduation probability varies more by school type. Specifically, lower-SES students appear to have a lower probability of graduating high school in middle-of-the-road schools, the most vocationally oriented schools, or middle-of-the-road schools with less experienced teachers than do lower SES students in the most academically advantaged schools or less well-maintained but academically advantaged schools (though again the differences are not statistically significant).

< Table 6, Figure 7 >

Schools with higher average SES, the most academic orientation to instructional resources, and more academically oriented peers have significantly higher log odds of high school graduation, but the relation between SES and graduation does not vary much across classes of instructional, teacher, physical, student-staff, or student-peer resources.

< Table 7a, Table 7b >

Predicting Variation in SES Inequalities in Immediate Enrollment in a Four-Year Institution across Schools

Differences across high school types in the relation between student SES and immediate enrollment in a four-year institution appear small (Table 8). The relation between SES and on-time four-year enrollment seems to be stronger in well-maintained middle-of-the-road schools and weaker in schools with the most positive student-staff relationships, though these differences are rarely statistically significant. Figure 8 illustrates what these small differences may mean for students at different locations in the SES distribution. In well-maintained middle-of-the-road schools, lower-SES students have particularly low probabilities of on-time four-year enrollment but higher-SES students have the third highest probability of four-year enrollment. Again, the differences across school types are small, however.

< Table 8, Figure 8 >

The relation between students' SES and their probability of enrolling in a four-year institution immediately after high school does not vary significantly across classes of physical or student-peer resources. The relation between SES and on-time four-year enrollment may be stronger in schools with a general orientation to instructional resources than in schools with the most academically oriented instruction; though the interaction coefficients have similar magnitudes across models, only the coefficient in the first model is statistically significant. The relation between SES and immediate four-year enrollment is significantly stronger in schools with more experienced but less satisfied teachers (Table 9a). Lower-SES students' odds of on-time four-year enrollment are higher in schools with less experienced but more satisfied teachers than in schools with more experienced but less satisfied teachers; the pattern is reversed, however, for higher-SES students (Figure 9).

< Table 9a, Figure 9 >

The relation between SES and on-time four-year enrollment also is significantly stronger in schools with less positive, compared to more positive, student-staff relationships; these schools also have significantly lower average rates of on-time four-year enrollment (Table 9b). Thus, while attending schools with less positive relationships is associated with lower rates of on-time four-year enrollment for all students, lower SES students' odds of on-time four-year enrollment are particularly low in these schools.

< Table 9b >

Predicting Variation in SES Inequalities in Any Postsecondary Enrollment across Schools

The relation between SES and the odds of any postsecondary enrollment is weaker in well-maintained middle-of-the-road schools, poorly maintained schools, and middle-of-the-road schools with less experienced but more satisfied teachers than in the reference category of schools.[2] Figure 10 illustrates this relation. Students with average or above average SES have very high probabilities of postsecondary enrollment regardless of the school they attend. The lowest SES students have the lowest probability of any college enrollment if they attend middle-of-the-road schools and relatively high probabilities of any college enrollment if they attend poorly maintained schools or schools with the most positive student-staff relationships.

< Table 10, Figure 10 >

The relation between SES and the odds of any postsecondary enrollment does not appear to vary much across classes of instructional, teacher, or physical resources (Table 11a), though one possible exception is that the relation between SES and any postsecondary enrollment may be weaker in schools with a general orientation to instructional resources than in schools with the most academically oriented approach. Conditional on schools' average SES, the relation between students' SES and their odds of any postsecondary enrollment is significantly *weaker* in schools with less academically-oriented peers compared to schools with more academically-oriented peers (Table 11b). Figure 11 illustrates this result. In schools with more academically-oriented

[2] Average odds of any postsecondary enrollment are lower in well-maintained middle-of-the-road schools than in middle-of-the-road schools but are fairly similar in the other two types of schools compared to middle-of-the-road schools.

peers, the probability of any postsecondary enrollment grows more quickly for each additional unit of SES at the lower end of the SES scale; at average or above average levels of SES, additional units of SES are associated with relatively little change in the odds of any postsecondary enrollment in schools with more academically-oriented peers but more change in schools with less academically-oriented peers.

< Table 11a, Table 11b, Figure 11 >

LIMITATIONS

In addition to the limitations discussed in the previous chapters, which include limitations of the ELS data as well as my analytic strategy, a few additional limitations apply specifically to this chapter. First, there are many ways to measure the social and economic resources students' families may be able to contribute to their education. SES indices like the one employed in this chapter have been widely used in the literature and are preferable to other measures of economic status (e.g., eligibility for free or reduced-price lunch). However, Condron (2009) warns that, if different social classes use distinctly different educational strategies in raising children, then these differences are not well measured by an SES index. In addition, SES indices do not capture family wealth, and different components of SES (e.g., income, wealth, parental education) may affect schooling and inequality in different ways or be differentially important for particular educational outcomes (Ensminger and Fothergill 2003; Hauser and Sewell 1986).

Second, while this chapter focuses on overall resources available at the school (as reported by students, teachers, and administrators), a great deal of literature has documented differential access to resources *within* schools by SES (cf. Camburn and Han 2011; Clotfelter, Ladd and Vigdor 2010; Gamoran 2010; Klugman 2012; Palardy 2013). Though I discussed, based on prior literature, how resource inequalities within schools *might* relate to the degree of

SES-based differentiation in achievement or attainment, an explicit investigation of how within-school differences in resource access, not just overall levels of resources, are associated with variation in the SES-achievement relation is warranted.

Finally, as discussed above, American schools are extremely segregated by SES (cf. Quillian 2014; Reardon and Owens 2014), which limits the true variability in SES within schools and shrinks the variation in school effects on individuals of different class backgrounds that is detectable with the ELS. For example, presumably very few students of high absolute SES attend the most vocationally oriented schools; as a result, this analysis cannot shed light on the degree of SES inequality that might occur if particular schools (e.g., vocationally oriented schools) educated students from a greater diversity of socioeconomic backgrounds.

DISCUSSION

The relation between SES and educational outcomes is so consistent across a range of outcomes – and across genders, race/ethnicities, and ages – that it often seems to be a "sociological necessity rather than…the product of a set of social conditions, policy choices, and educational practices" (Reardon 2011: 92). Yet, some research – much of it conducted by Bryk, Lee, and colleagues in the 1980s and 90s – has documented a small number of factors that partly explain variation in the relation between students' SES and their outcomes across schools. Aiming to extend and update this literature, I examined the extent to which SES-based inequalities in achievement and attainment vary across a nationally representative sample of high schools, as well as the extent to which particular school types and resources are consistently associated with smaller or larger SES-based inequalities. By presenting results from models that control to varying extents for student and school characteristics associated with these school resources and types, the chapter also provided insight into how controlling for other differences across schools changes, or does not change, conclusions about the relation between school resources and the degree of SES advantage in particular types of schools.

I found that the relation between SES and each outcome does vary across the high schools in the ELS. For example, being in a school one standard deviation higher on the SES slope distribution is associated with a 1.5 to 1.9 point increase in the returns to a given value of student SES; this is equivalent to 15 to 19 percent of the math test's standard deviation.

With regard to the question of whether variation in the relation between students' SES and their outcomes is associated with school resources, I found mixed evidence, partly as a result of the limited power at the school level in the ELS data. The presence of detectable differences, though, suggests that some of the heterogeneity in the link between SES and outcomes is associated with differences in resources. For example, the relation between SES and math achievement is not as strong in schools with the most positive student-staff relationships as it is in middle-of-the-road schools; in other words, there is less SES-based differentiation in math achievement in these schools. Importantly, lower SES students attending these schools may be doubly advantaged given that schools with the most positive student-staff relationships have both higher average achievement and less variation by SES compared to middle-of-the-road schools.

Well-maintained middle-of-the-road schools have significantly less SES-based differentiation in two important attainment outcomes – high school graduation and any postsecondary enrollment – than do the reference category of schools. Perhaps well-maintained middle-of-the-road schools are less resource-strapped (given that they are "well-maintained") and have more resources to devote to promoting attainment of lower SES students. Compared to the reference category of schools, the relation between SES and the odds of any postsecondary enrollment is also weaker in middle-of-the-road schools with less experienced but more satisfied teachers and, strangely, in poorly maintained schools.

Why some school types, particularly “poorly maintained schools,” are associated with particular patterns in terms of the relation between students’ SES and their outcomes is difficult to know. To attain a clearer understanding, I examined individual resource types independently, and these results provided some clues as to what may be driving differences between school types. For example, the relation between students’ SES and their math achievement may be weaker in schools that take the most academic orientation to instructional resources compared to a more general orientation. This suggests that a more academically oriented curriculum benefits all students (at least in terms of tested math achievement), not just the most socioeconomically advantaged students, and also supports the prior literature’s finding that schools with a higher proportion of students in the academic track have less class differentiation in achievement (Lee and Bryk 1989). The pattern of coefficients also suggested that the relation between students’ SES and their odds of immediate enrollment in a four-year institution might be weaker in schools with the most academic orientation to instructional resources compared to those with a more general orientation but only one interaction coefficient was statistically significant.

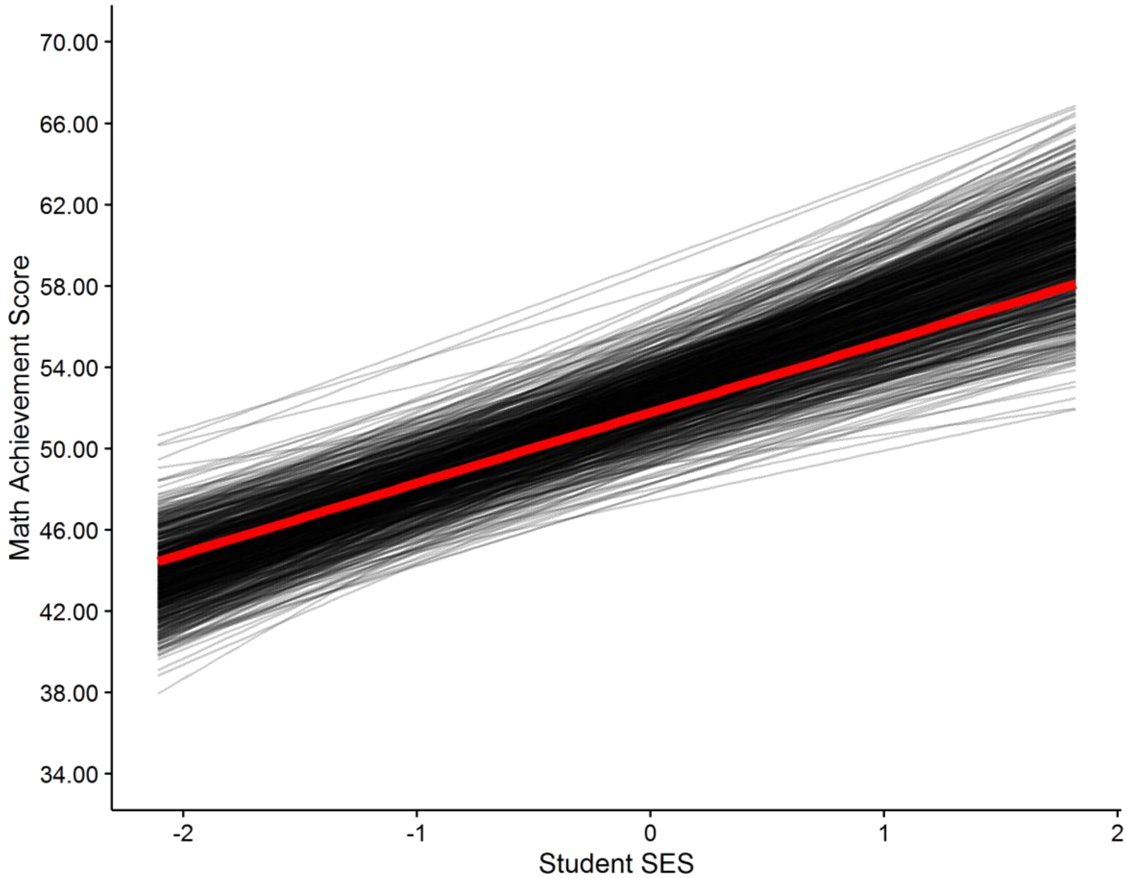
The relation between SES and both math achievement and immediate enrollment in a four-year institution is significantly stronger in schools with more experienced but less satisfied teachers than in schools with less experienced but more satisfied teachers. This finding of greater SES-based differentiation in schools with less satisfied teachers broadly fits with Lee and colleagues’ conclusion that SES-based inequality in achievement is greater in schools with smaller proportions of teachers reporting collective responsibility for students’ learning (Lee and Smith 1996; Lee, Smith and Croninger 1997). Though Lee and colleagues did not look directly at teacher satisfaction, it seems reasonable to assume that more satisfied teachers might be more willing to accept collective responsibility for their students' learning.

The relation between SES and both math achievement and immediate enrollment in a four-year institution also is significantly stronger in schools with less positive student-staff relationships. Perhaps in schools with better student-staff relationships, staff spend more time and effort assisting and building relationships with lower SES students, which has positive effects for their math achievement and odds of immediate postsecondary enrollment. Additionally, perhaps being higher SES shields students from the negative effects of poor student-staff relationships, resulting in greater SES-based inequality in schools with less positive relationships.

The relation between students' SES and their math achievement, odds of high school graduation, and odds of immediate enrollment in a four-year institution does not appear to vary across classes of student-peer resources (the coefficients are very small as well as nonsignificant). However, the relation between students' SES and their odds of enrollment in any postsecondary institution is significantly weaker in schools with less academically oriented peers. Figure 11 shows that variation in the strength of the relation between students' SES and their odds of any postsecondary enrollment is driven mainly by students with below average SES. In schools with more academically oriented peers, the odds of any postsecondary enrollment rise rapidly with each additional unit of SES; in contrast, in schools with less academically oriented peers, the odds of any postsecondary enrollment grow more slowly across the SES distribution. Thus, students with below average SES have higher than expected odds of postsecondary enrollment in schools with more academically oriented peers.

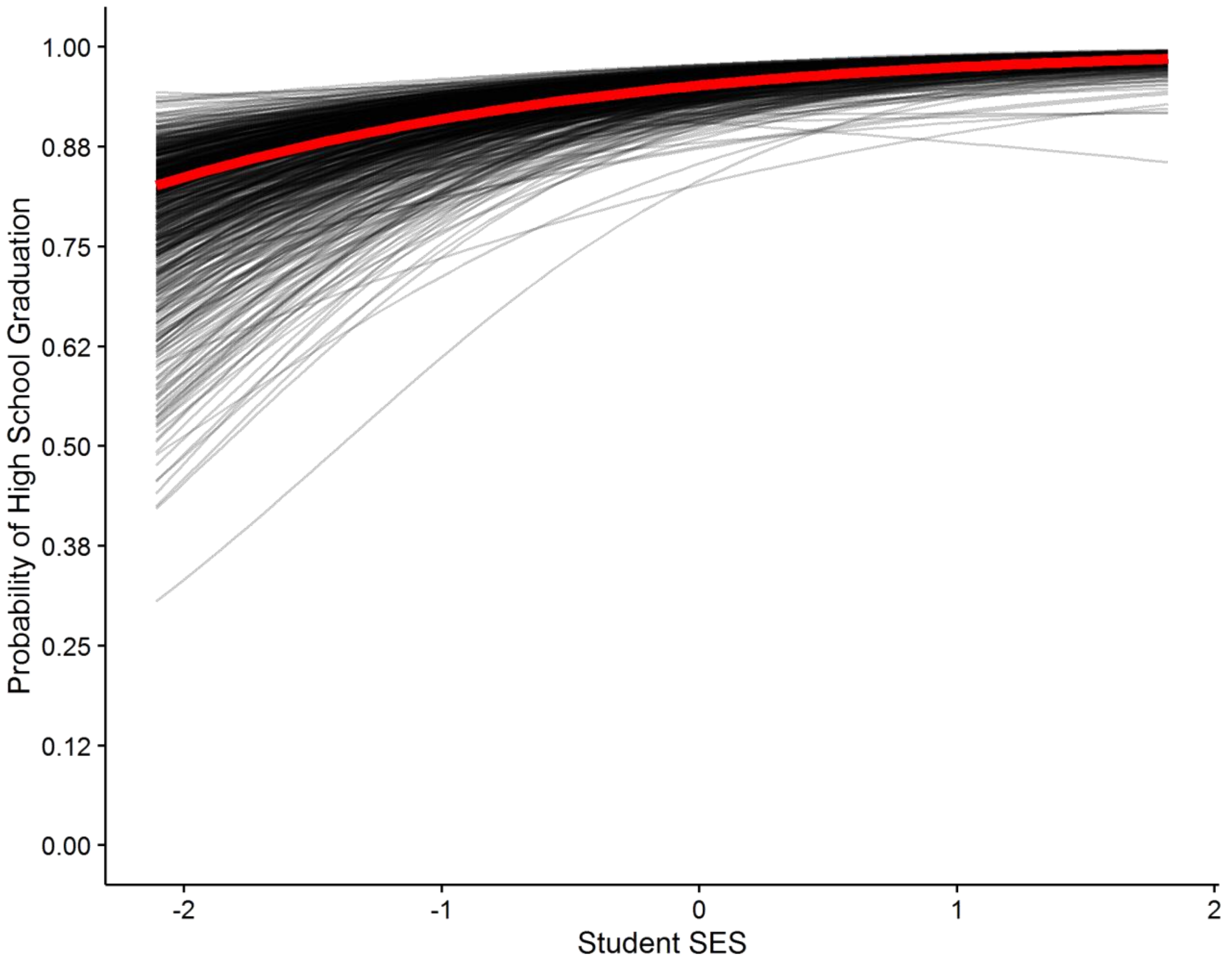
Overall, one of the main conclusions of this chapter is that patterns of SES-based inequality differ across educational outcomes that are more differentiating versus less differentiating. For the more differentiating outcomes of math achievement and immediate enrollment in a four-year postsecondary institution, schools with the most academic orientation to instructional resources and more positive student-staff relationships seem to have both higher average achievement or attainment and smaller SES-based inequalities. Results for the less differentiating outcomes of high school graduation and enrollment in any postsecondary institution do not follow this pattern of higher average values of the outcome associated with less SES-based differentiation. This suggests that for more differentiating outcomes – that is, those where there is a wider range of results – specific school resources, like academically-focused instruction and positive student-staff relationships, may both promote positive outcomes for all students and reduce SES-based inequality.

Figure 1. Relation between Student SES and Math Achievement in Different Schools



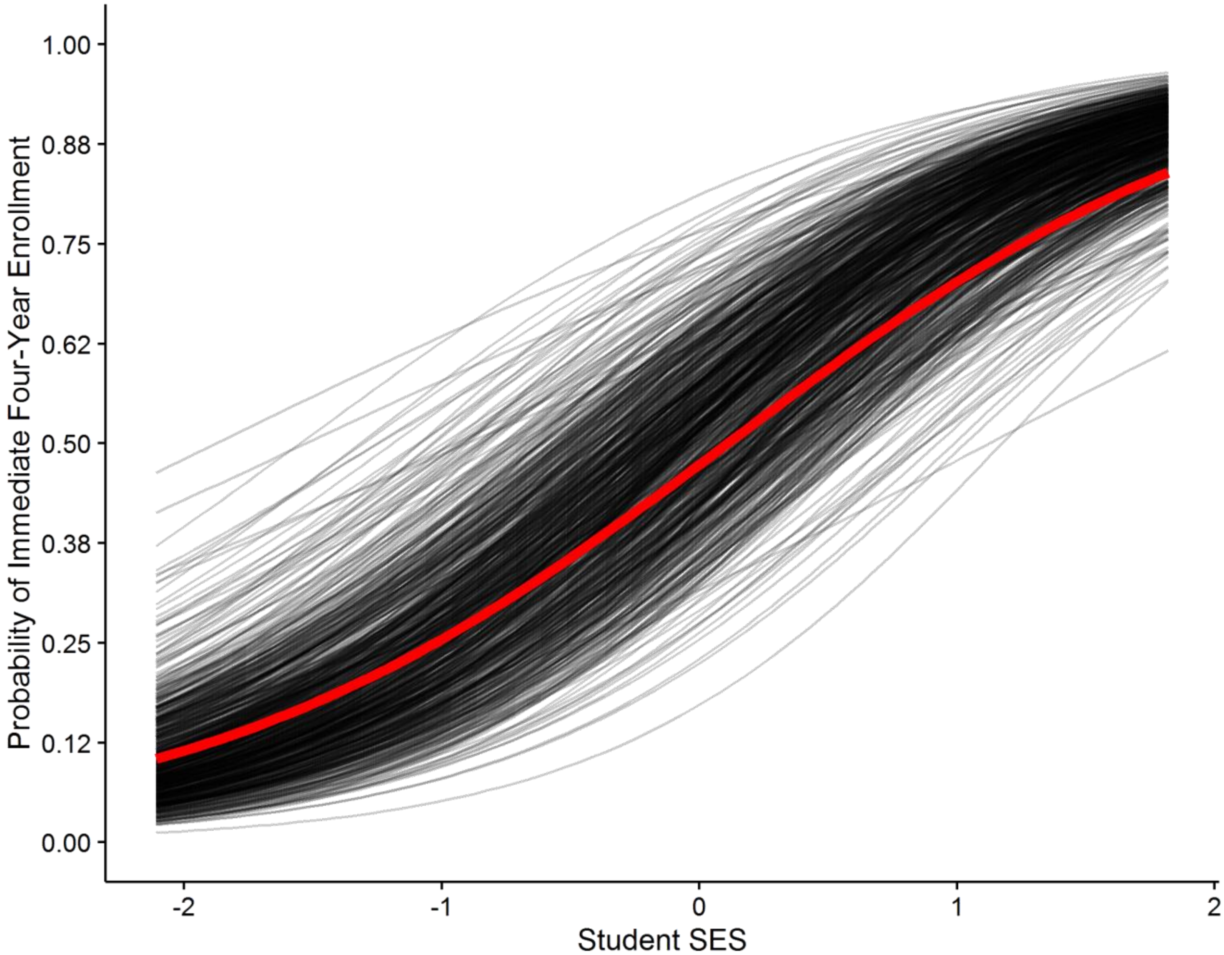
Note: Each line represents the relation between student SES and math achievement in a single school; the red line depicts the average relation between student SES and math achievement across the sample. Results are from the model that conditions on both student and school covariates. The math test has a mean of 50, standard deviation of 10.

Figure 2. Relation between Student SES and the Probability of High School Graduation in Different Schools



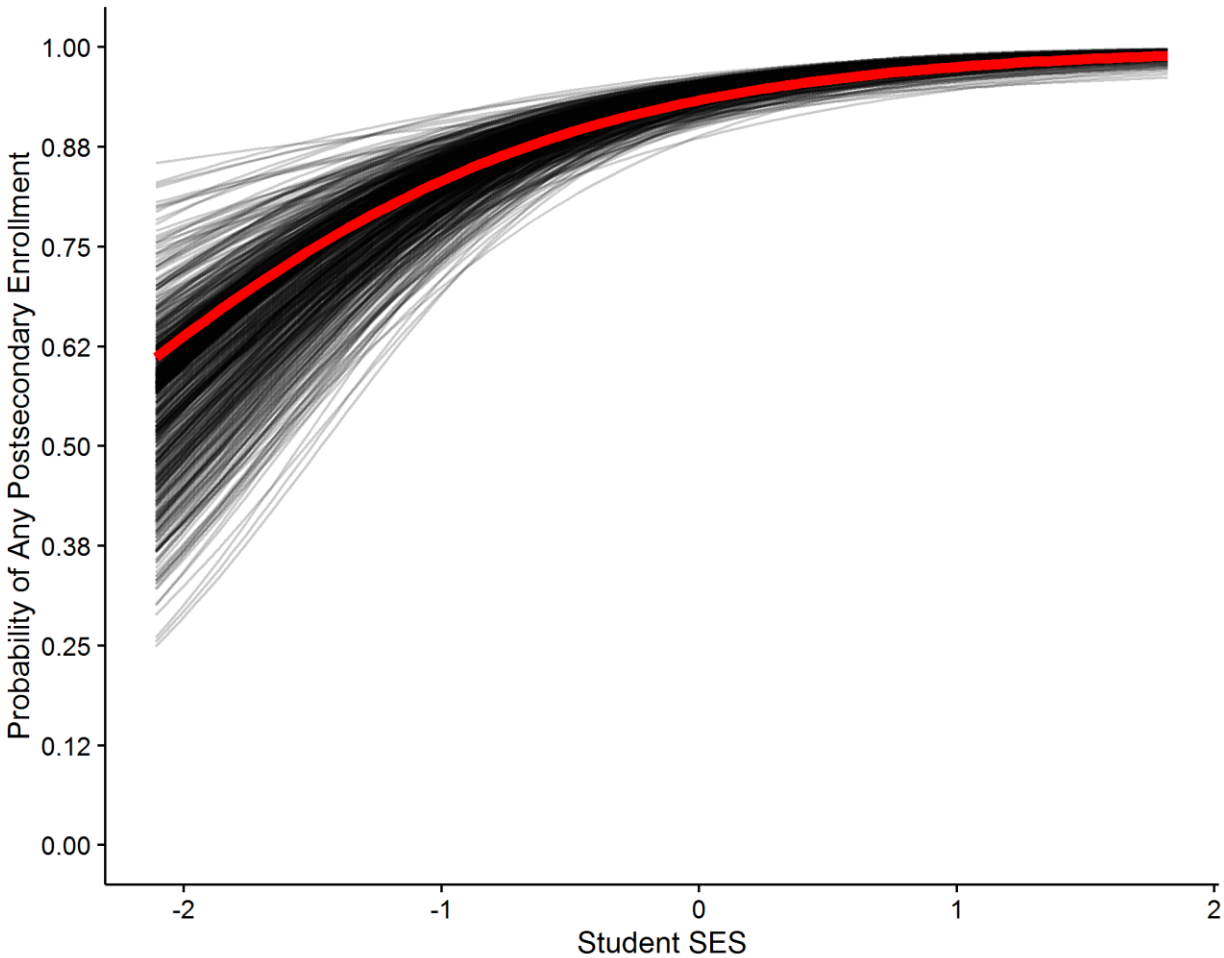
Note: Each line represents the relation between student SES and the probability of high school graduation in a single school; the red line depicts the average relation between student SES and the probability of high school graduation across the sample. Results are from the model that conditions on both student and school covariates.

Figure 3. Relation between Student SES and the Probability of Immediate Four-Year Enrollment in Different Schools



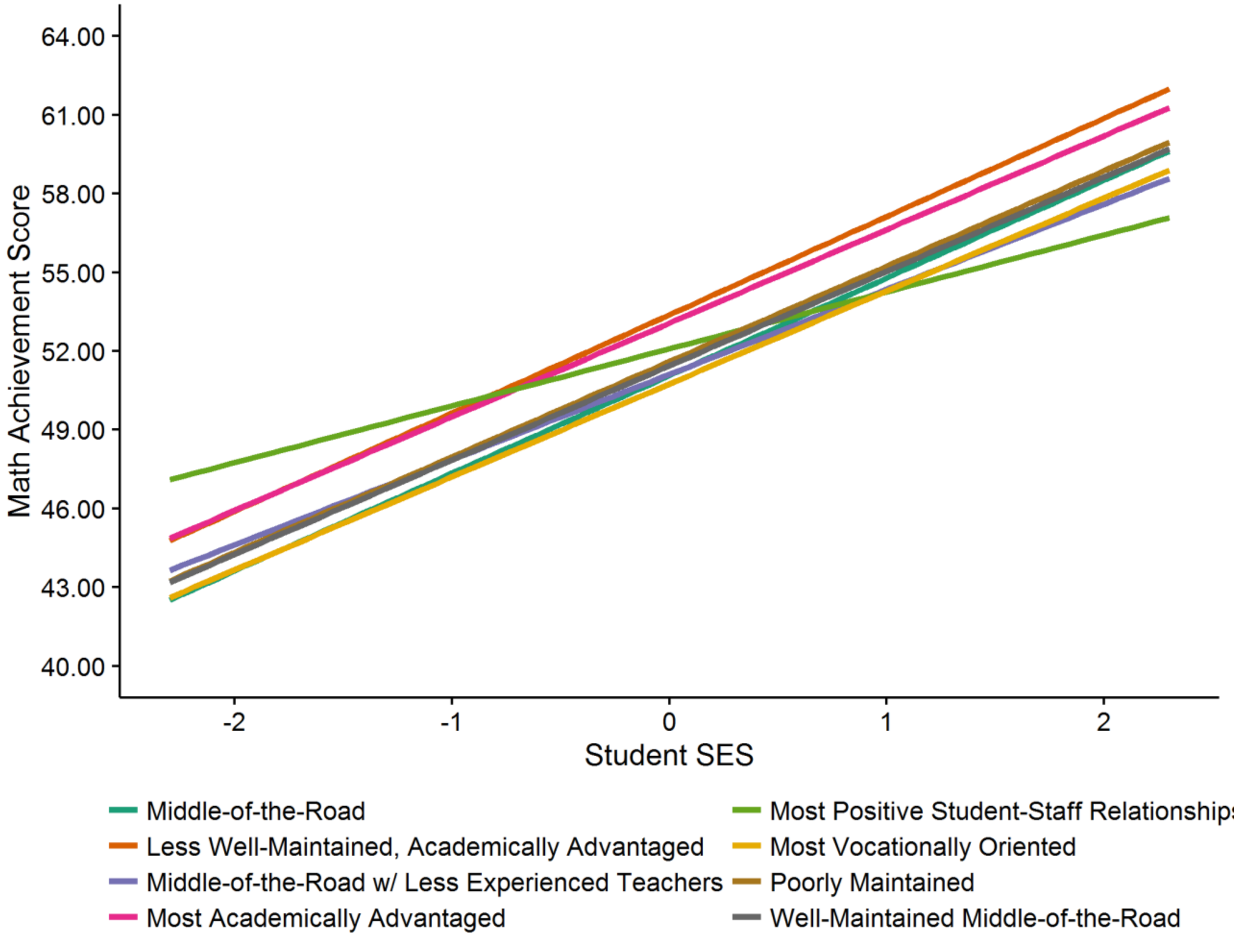
Note: Each line represents the relation between student SES and the probability of immediate four-year enrollment in a single school; the red line depicts the average relation between student SES and the probability of immediate four-year enrollment across the sample. Results are from the model that conditions on both student and school covariates.

Figure 4. Relation between Student SES and the Probability of Any Postsecondary Enrollment in Different Schools



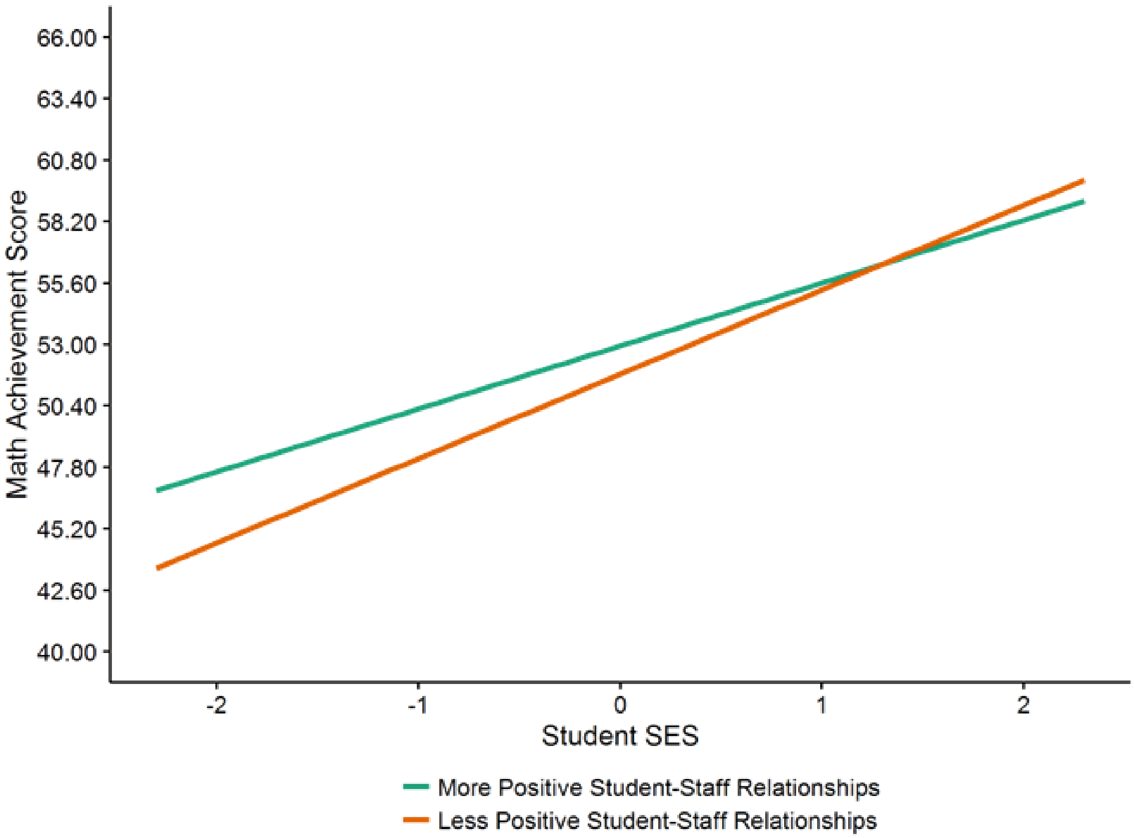
Note: Each line represents the relation between student SES and the probability of any postsecondary enrollment in a single school; the red line depicts the average relation between student SES and the probability of any postsecondary enrollment across the sample. Results are from the model that conditions on both student and school covariates.

Figure 5. Average Relation between Student SES and Math Achievement in Different School Types



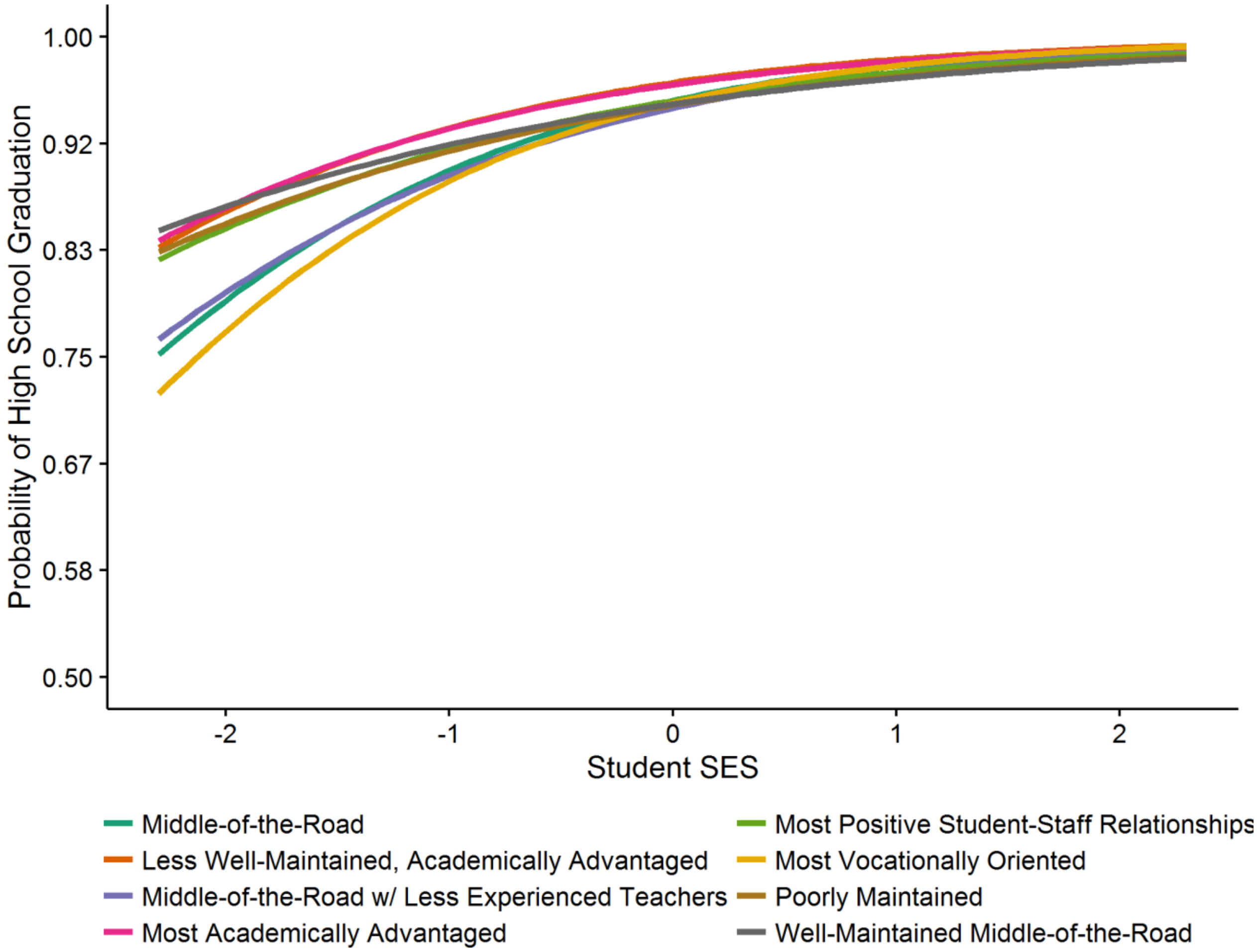
Note: Each line represents the average relation between student SES and math achievement in a particular type of school; the lines are based on the main effect of SES, main effect of school type, and the interaction between school type and SES. Results are from the model that conditions on both student and school covariates. The math test has a mean of 50, standard deviation of 10.

Figure 6. Average Relation between Student SES and Math Achievement in Schools with Different Classes of Student-Staff Resources



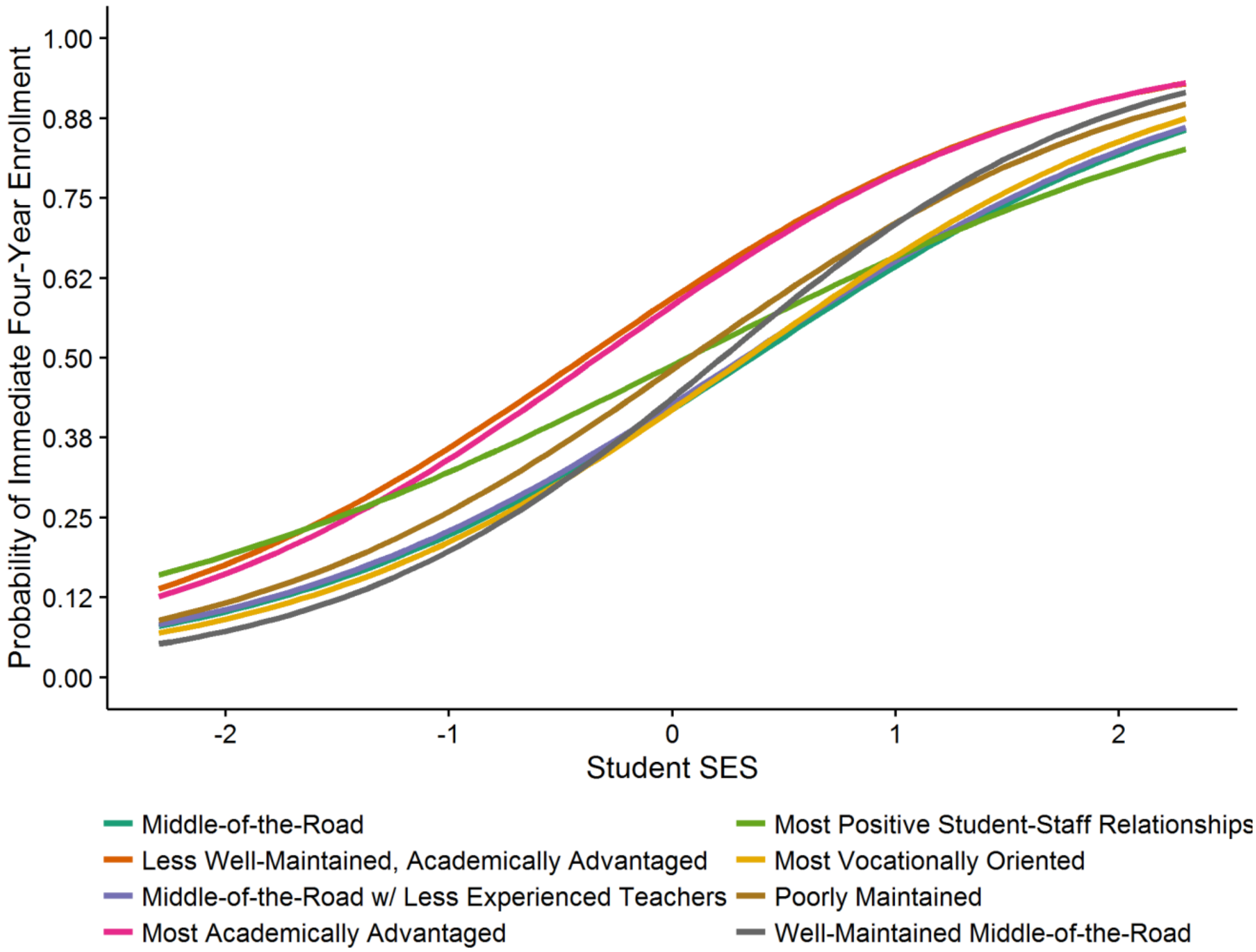
Note: The lines represent the average relation between student SES and math achievement in schools with a particular resource class. Results are from the model that conditions on both student and school covariates. The math test has a mean of 50, standard deviation of 10.

Figure 7. Average Relation between Student SES and the Probability of High School Graduation in Different School Types



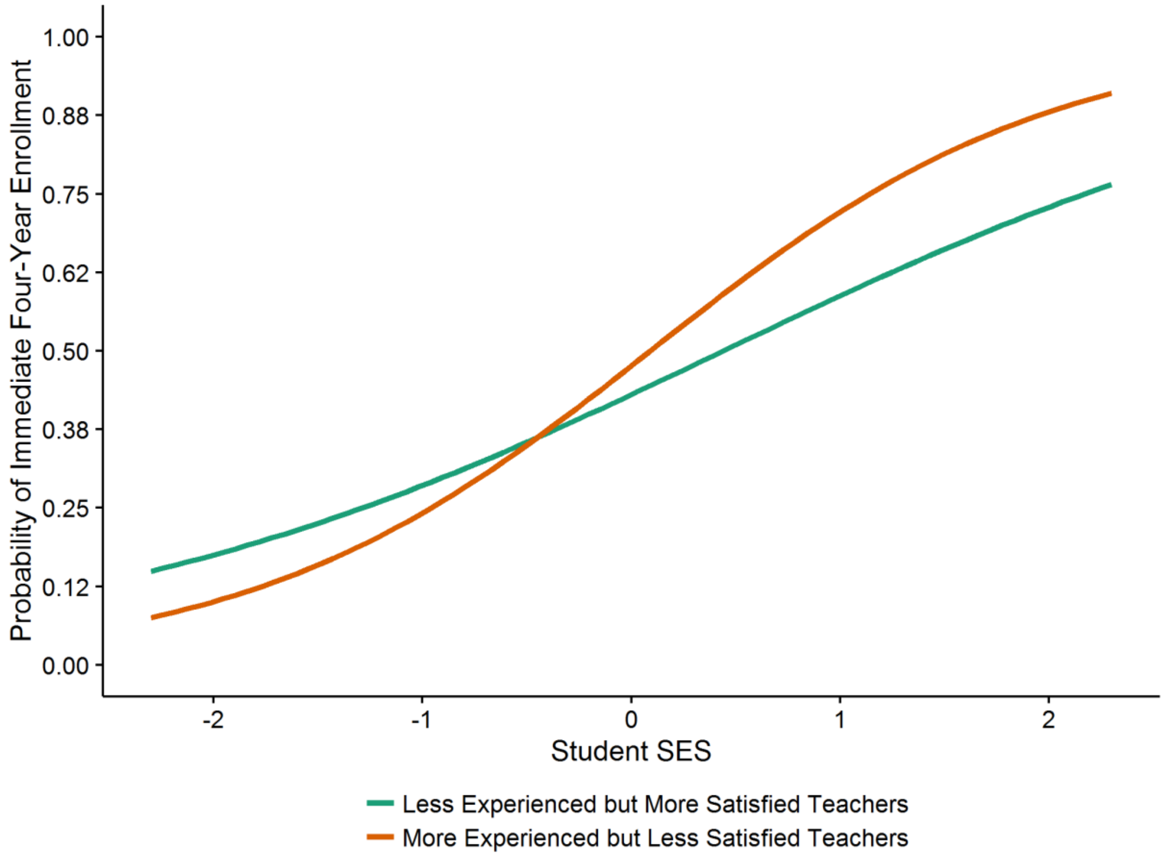
Note: Each line represents the average relation between student SES and the probability of high school graduation in a particular type of school; the lines are based on the main effect of SES, main effect of school type, and the interaction between school type and SES. Results are from the model that conditions on both student and school covariates.

Figure 8. Average Relation between Student SES and the Probability of Immediate Four-Year Enrollment in Different School Types



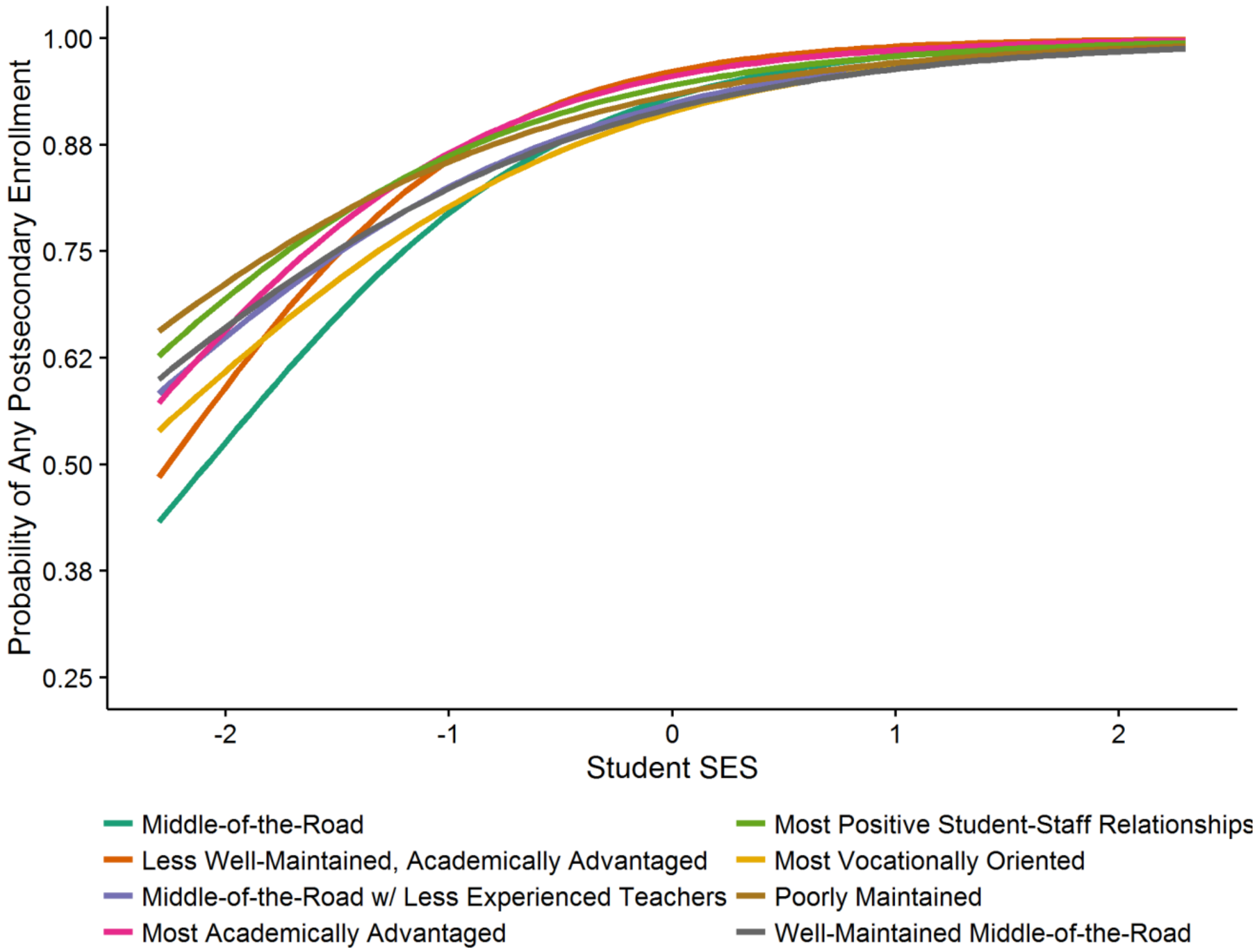
Note: Each line represents the average relation between student SES and the probability of immediate four-year enrollment in a particular type of school; the lines are based on the main effect of SES, main effect of school type, and the interaction between school type and SES. Results are from the model that conditions on both student and school covariates.

Figure 9. Average Relation between Student SES and the Probability of Immediate Four-Year Enrollment in Schools with Different Classes of Teacher Resources



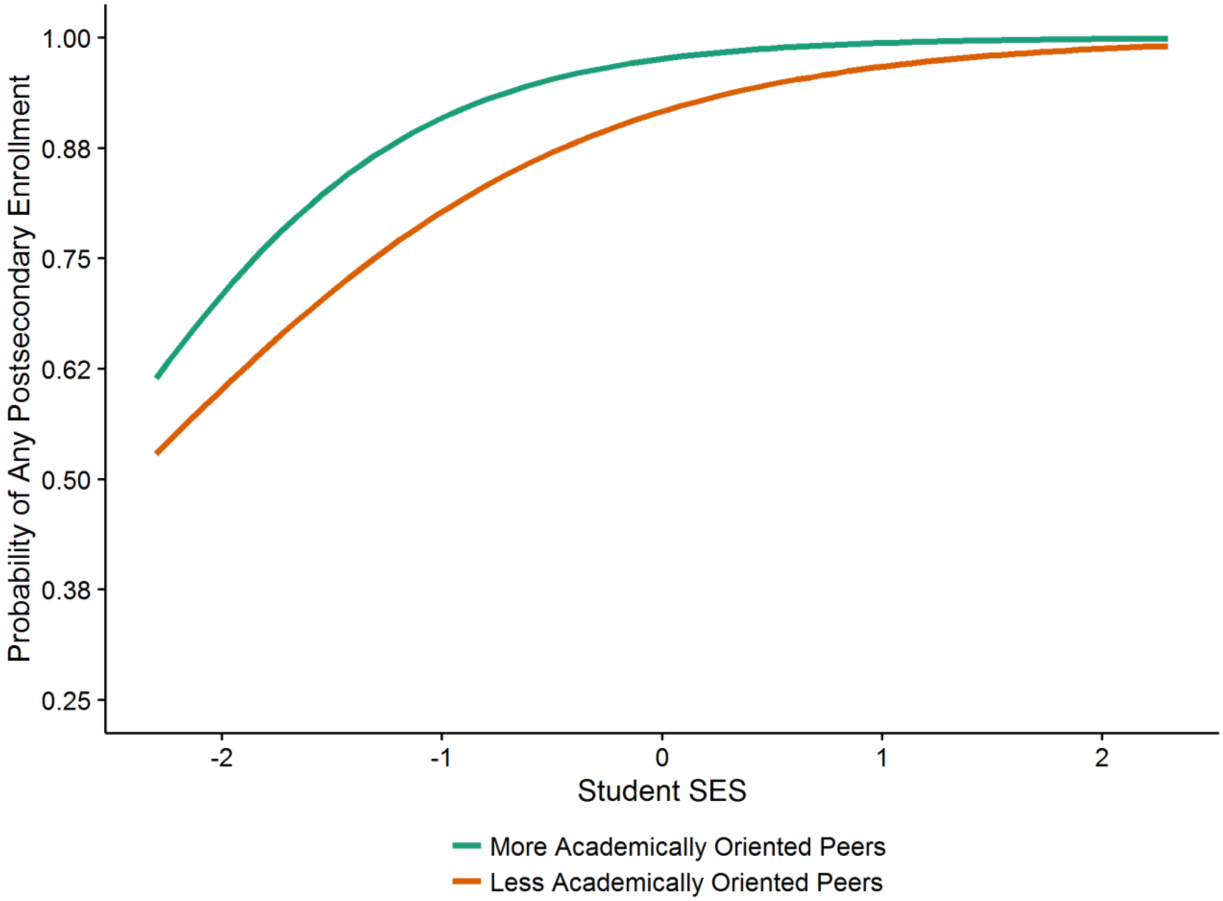
Note: The lines represent the average relation between student SES and the probability of immediate four-year enrollment in schools with a particular resource class. Results are from the model that conditions on both student and school covariates.

Figure 10. Average Relation between Student SES and the Probability of Any Postsecondary Enrollment in Different School Types



Note: Each line represents the average relation between student SES and the probability of any postsecondary enrollment in a particular type of school; the lines are based on the main effect of SES, main effect of school type, and the interaction between school type and SES. Results are from the model that conditions on both student and school covariates.

Figure 11. Average Relation between Student SES and the Probability of Any Postsecondary Enrollment in Schools with Different Classes of Student-Peer Resources



Note: The lines represent the average relation between student SES and the probability of any postsecondary enrollment in schools with a particular resource class. Results are from the model that conditions on both student and school covariates.

Table 1. Comparison of School Types and Resource Classes in All Schools vs. Schools with at Least Five Sampled Students with SES Data

		Total Sample	SES Sample
School Background Characteristics	Private	23%	22%
	Urban	33%	33%
	Rural	19%	19%
	Suburban	48%	48%
	Low-FRL	41%	41%
	Medium-FRL	43%	44%
	High-FRL	15%	15%
School Types	Middle-of-the-Road Schools	18%	19%
	Well-Maintained Middle-of-the-Road Schools	15%	16%
	Most Academically Advantaged Schools	16%	16%
	Poorly Maintained Schools	11%	11%
	Middle-of-the-Road Schools w/ Less Experienced Teachers	10%	10%
	Most Vocationally Oriented Schools	10%	10%
	Schools with Most Positive Student-Staff Relationships	10%	9%
	Less Well-Maintained, Academically Advantaged Schools	9%	9%
	N	*751*	*735-741*
Instructional Resource Classes	General Orientation	62%	62-63%
	Most Vocationally Oriented	21%	20%
	Most Academically Oriented	17%	18%
	N	*751*	*735-741*
Teacher Resource Classes	Less Experienced but More Satisfied Teachers	80%	81%
	More Experienced but Less Satisfied Teachers	20%	19%
	N	*733*	*717-723*
Physical Resource Classes	Fewest Problems	43%	43%
	Moderate Problems	51%	51%
	Most Problems	6%	5-6%
	N	*618*	*604-609*
Student-Staff Resource Classes	Less Positive Relationships	89%	89-90%
	More Positive Relationships	11%	10-11%
	N	*751*	*735-741*
Student-Peer Resource Classes	Less Academically Oriented Peers	75%	75%
	More Academically Oriented Peers	25%	25%
	N	*751*	*735-741*
Average Outcomes	Math Achievement Score	50.74	50.74
	High School Graduation	0.89	0.89
	Immediate Enrollment in a Four-Year Institution	0.45	0.45
	Any Postsecondary Enrollment	0.88	0.88

Notes: "Total sample" includes all schools; "SES sample" includes only schools with at least five students with SES data and data for a given outcome. For each sample, percentages and N's vary depending on the outcome variable.

Table 2. Model Fit Statistics for Random Intercept and Random Slope Null Models

		Math Achievement			High School Graduation			Immediate Enrollment in a Four-Year Institution			Any Postsecondary Enrollment		
Parameters	Random Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	SES Fixed Effects		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
	Random Slope			Yes			Yes			Yes			Yes
Model Fit Statistics	AIC	93,473.9	91,722.5	91,691.6	9,558.0	9,071.3	9,065.8	16,980.0	15,518.5	15,504.8	9,478.0	8,684.3	8,675.1
	Log-likelihood	-46,734.0	-45856.3	-45,838.8	-4,777.0	-4,531.6	-4,526.9	-8,488.0	-7,755.2	-7,746.4	-4,737.0	-4,338.2	-4,331.5
	R-squared	0.27	0.32	0.35	0.11	0.12	0.14	0.24	0.28	0.29	0.12	0.13	0.15

Table 3. Variation in the Relation between SES and Each Outcome across High Schools

		Math Achievement			High School Graduation			Immediate Enrollment in a Four-Year Institution			Any Postsecondary Enrollment		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Fixed Effects	Student SES	4.19*	3.48*	3.47*	0.73*	0.70*	0.67*	1.00*	0.97*	0.97*	0.92*	1.02*	1.04*
		(0.15)	(0.14)	(0.14)	(0.06)	(0.07)	(0.07)	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)	(0.07)
	School Mean SES	9.58*	7.99*	7.30*	1.64*	1.49*	0.93*	2.22*	2.18*	1.74*	2.11*	2.25*	1.69*
		(0.29)	(0.26)	(0.37)	(0.10)	(0.11)	(0.14)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.14)
	Intercept	49.97*	50.97*	51.78*	2.47*	2.85*	2.99*	-0.38*	-0.11*	-0.11	2.38*	2.65*	2.65*
		(0.13)	(0.15)	(0.29)	(0.05)	(0.07)	(0.11)	(0.03)	(0.04)	(0.08)	(0.05)	(0.06)	(0.10)
Random Effects	SD of SES Slope	1.85	1.55	1.49	0.51	0.49	0.49	0.38	0.37	0.36	0.52	0.51	0.49
	SD of Intercept	2.64	2.18	2.14	0.64	0.63	0.61	0.66	0.66	0.61	0.55	0.48	0.43
	Corr. Interc.-Slope	0.04	0.10	0.14	0.09	0.10	0.07	-0.40	-0.38	-0.18	-0.18	-0.07	0.15
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes			Yes
N	Students	12,809	12,809	12,585	14,674	14,674	14,276	13,526	13,526	13,174	13,637	13,637	13,273
	Schools	735	735	726	741	741	732	740	740	731	740	740	731
Model Fit	AIC	91,692	90,266	88,671	9,066	8,902	8,370	15,505	15,126	14,663	8,675	8,382	7,977
	Log-likelihood	-45,839	-45,119	-44,317	-4,527	-4,438	-4,167	-7,746	-7,550	-7,313	-4,332	-4,178	-3,970
	R-squared	0.35	0.40	0.40	0.14	0.15	0.15	0.29	0.31	0.32	0.15	0.17	0.16

*p < .05

Table 4. Variation by School Type in the Relation between Student SES and Math Achievement

		Model 1	Model 2	Model 3
	Student SES	4.31*	3.80*	3.72*
		(0.34)	(0.31)	(0.31)
	School Mean SES	8.62*	6.89*	6.62*
		(0.35)	(0.31)	(0.38)
	Intercept	49.65*	50.34*	51.07*
		(0.30)	(0.28)	(0.37)
School Types	Well-Maintained Middle-of-the-Road Schools	0.24	0.40	0.38
		(0.44)	(0.38)	(0.38)
	Most Academically Advantaged Schools	1.48*	2.00*	2.00*
		(0.48)	(0.42)	(0.44)
	Poorly Maintained Schools	0.01	0.61	0.53
		(0.48)	(0.42)	(0.42)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.31	-0.01	0.04
		(0.49)	(0.42)	(0.43)
	Most Vocationally Oriented Schools	-0.99*	-0.44	-0.32
		(0.51)	(0.44)	(0.44)
	Schools with Most Positive Student-Staff Relationships	0.28	0.85†	1.02*
		(0.54)	(0.46)	(0.49)
	Less Well-Maintained, Academically Advantaged Schools	2.07*	2.28*	2.32*
		(0.53)	(0.46)	(0.47)
Cross-Level Interactions	SES*Well-Maintained Middle-of-the-Road Schools	0.28	-0.21	-0.13
		(0.50)	(0.46)	(0.46)
	SES*Most Academically Advantaged Schools	-0.25	-0.38	-0.15
		(0.51)	(0.47)	(0.47)
	SES*Poorly Maintained Schools	0.12	-0.20	-0.09
		(0.55)	(0.51)	(0.51)
	SES*Middle-of-the-Road Schools with Less Experienced Teachers	0.09	-0.51	-0.47
		(0.58)	(0.53)	(0.53)
	SES*Most Vocationally Oriented Schools	-0.17	-0.21	-0.18
		(0.60)	(0.56)	(0.55)
	SES*Schools with Most Positive Student-Staff Relationships	-1.51*	-1.58*	-1.55*
		(0.61)	(0.57)	(0.57)
	SES*Less Well-Maintained, Academically Advantaged Schools	-0.07	0.03	0.03
		(0.59)	(0.54)	(0.54)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of SES Slope	1.79	1.50	1.43
	Std. Dev. of Intercept	2.54	2.06	2.04
	Corr. between Intercept & Slope	0.08	0.16	0.16

N	Students	12,809	12,809	12,585
	Schools	735	735	726
Model Fit Statistics	AIC	91,674.1	90,236.9	88,649.5
	Log-likelihood	-45,816.1	-45,090.4	-44,291.7
	R-squared	0.34	0.40	0.40

School types based on class membership probabilities. *p < .05, ǂp < .10

Table 5a. Variation by Resource Classes in the Relation between Student SES and Math Achievement

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Student SES	3.44*	2.97*	3.02*	3.27*	2.65*	2.64*	3.15*	2.69*	2.75*
		(0.38)	(0.36)	(0.35)	(0.37)	(0.35)	(0.35)	(0.71)	(0.65)	(0.67)
	School Mean SES	8.44*	6.80*	6.46*	9.76*	8.09*	7.22*	9.32*	7.93*	7.17*
		(0.34)	(0.30)	(0.38)	(0.30)	(0.27)	(0.37)	(0.32)	(0.29)	(0.41)
	Intercept	52.07*	53.14*	54.32*	49.20*	50.47*	51.09*	50.31*	51.64*	52.43*
		(0.37)	(0.35)	(0.46)	(0.32)	(0.30)	(0.43)	(0.62)	(0.56)	(0.64)
School Resource Classes	General Orientation	-2.36*	-2.54*	-2.81*						
		(0.43)	(0.37)	(0.41)						
	Most Vocationally Oriented	-2.90*	-2.52*	-2.69*						
		(0.48)	(0.42)	(0.45)						
	More Experienced but Less Satisfied Teachers				0.91*	0.59†	0.74*			
					(0.35)	(0.31)	(0.34)			
	Fewest Physical Resource Problems							0.12	-0.30	-0.32
								(0.66)	(0.58)	(0.60)
	Moderate Physical Resource Problems							-0.58	-0.99†	-1.03†
								(0.66)	(0.59)	(0.60)
Cross-Level Interactions	SES*General Orientation	1.04*	0.68†	0.59						
		(0.44)	(0.41)	(0.41)						
	SES*Most Vocationally Oriented	0.46	0.39	0.38						
		(0.52)	(0.48)	(0.48)						
	SES*More Experienced but Less Satisfied Teachers				1.17*	1.06*	1.06*			
					(0.41)	(0.38)	(0.38)			
	SES*Fewest Physical Resource Problems							1.28†	0.90	0.89
								(0.75)	(0.69)	(0.71)
	SES*Moderate Physical Resource Problems							1.03	0.84	0.70
								(0.76)	(0.70)	(0.72)

Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of SES Slope	1.81	1.53	1.47	1.79	1.49	1.42	1.94	1.66	1.61
	Std. Dev. of Intercept	2.54	2.07	2.02	2.60	2.16	2.11	2.63	2.20	2.14
	Corr. between Intercept & Slope	0.11	0.21	0.19	0.03	0.09	0.15	0.05	0.10	0.16
N	Students	12,809	12,809	12,585	12,453	12,453	12,246	10,778	10,778	10,596
	Schools	735	735	726	717	717	709	604	604	596
Model Fit Statistics	AIC	91,654.6	90,222.7	88,628.5	89,082.3	87,717.5	86,238.0	77,117.6	75,911.5	74,625.7
	Log-likelihood	-45,816.3	-45,093.3	-44,291.2	-44,532.2	-43,842.7	-43,098.0	-38,547.8	-37,937.7	-37,289.8
	R-squared	0.34	0.40	0.40	0.35	0.40	0.40	0.34	0.40	0.40

Classes based on membership probabilities. *p < .05, †p < .10

Table 5b. Variation in the Relation between SES and Math Achievement by Student-Staff and Student-Peer Resource Classes

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Student SES	3.20*	2.68*	2.66*	3.95*	3.48*	3.54*
		(0.51)	(0.48)	(0.48)	(0.33)	(0.31)	(0.31)
	School Mean SES	9.41*	7.69*	7.10*	7.72*	5.95*	5.63*
		(0.32)	(0.29)	(0.38)	(0.40)	(0.36)	(0.42)
	Intercept	50.47*	51.87*	52.94*	52.22*	53.42*	54.42*
		(0.47)	(0.42)	(0.55)	(0.37)	(0.34)	(0.44)
School Resource Classes	Less Positive Student-Staff Relationships	-0.56	-1.00*	-1.19*			
		(0.50)	(0.44)	(0.48)			
	Less Academically Oriented Peers				-2.96*	-3.21*	-3.36*
					(0.47)	(0.40)	(0.44)
Cross-Level Interactions	SES*Less Positive Student-Staff Relationships	1.11*	0.91†	0.91†			
		(0.55)	(0.51)	(0.51)			
	SES*Less Academically Oriented Peers				0.32	-0.01	-0.09
					(0.40)	(0.37)	(0.37)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of SES Slope	1.84	1.54	1.48	1.85	1.56	1.50
	Std. Dev. of Intercept	2.64	2.17	2.12	2.53	2.02	1.99
	Corr. between Intercept & Slope	0.05	0.13	0.15	0.12	0.19	0.16
N	Students	12,809	12,809	12,585	12,809	12,809	12,585
	Schools	735	735	726	735	735	726
Model Fit Statistics	AIC	91,690.2	90,261.2	88,665.8	91,656.0	90,209.3	88,618.4
	Log-likelihood	-45,836.1	-45,114.6	-44,311.9	-45,819.0	-45,088.6	-44,288.2
	R-squared	0.35	0.40	0.40	0.35	0.40	0.40

Classes based on membership probabilities. *p < .05, †p < .10

Table 6. Variation by School Type in the Relation between Student SES and High School Graduation

		Model 1	Model 2	Model 3
	Student SES	0.84*	0.81*	0.80*
		(0.12)	(0.12)	(0.13)
	School Mean SES	1.36*	1.20*	0.82*
		(0.11)	(0.12)	(0.15)
	Intercept	2.38*	2.75*	2.95*
		(0.09)	(0.10)	(0.14)
School Types	Well-Maintained Middle-of-the-Road Schools	-0.02	-0.01	-0.06
		(0.13)	(0.13)	(0.13)
	Most Academically Advantaged Schools	0.55*	0.57*	0.30
		(0.17)	(0.17)	(0.18)
	Poorly Maintained Schools	-0.14	-0.10	-0.07
		(0.14)	(0.14)	(0.15)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.11	-0.07	-0.12
		(0.14)	(0.14)	(0.15)
	Most Vocationally Oriented Schools	-0.12	-0.09	-0.04
		(0.15)	(0.15)	(0.15)
	Schools with Most Positive Student-Staff Relationships	0.25	0.30†	-0.01
		(0.18)	(0.18)	(0.20)
	Less Well-Maintained, Academically Advantaged Schools	0.50*	0.49*	0.34†
		(0.19)	(0.19)	(0.20)
Cross-Level Interactions	SES*Well-Maintained Middle-of-the-Road Schools	-0.28	-0.30†	-0.29
		(0.17)	(0.18)	(0.18)
	SES*Most Academically Advantaged Schools	-0.12	-0.14	-0.11
		(0.23)	(0.23)	(0.23)
	SES*Poorly Maintained Schools	-0.19	-0.21	-0.25
		(0.18)	(0.19)	(0.19)
	SES*Middle-of-the-Road Schools with Less Experienced Teachers	-0.04	-0.09	-0.08
		(0.19)	(0.19)	(0.20)
	SES*Most Vocationally Oriented Schools	0.13	0.10	0.05
		(0.20)	(0.20)	(0.21)
	SES*Schools with Most Positive Student-Staff Relationships	-0.08	-0.10	-0.20
		(0.25)	(0.25)	(0.26)
	SES*Less Well-Maintained, Academically Advantaged Schools	-0.07	-0.06	-0.08
		(0.25)	(0.25)	(0.26)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of SES Slope	0.50	0.48	0.48
	Std. Dev. of Intercept	0.62	0.61	0.60

	Corr. between Intercept & Slope	0.15	0.15	0.08
N	Students	14,674	14,674	14,276
	Schools	741	741	732
Model Fit Statistics	AIC	9,059.9	8,897.9	8,384.2
	Log-likelihood	-4,510.0	-4,422.0	-4,160.1
	R-squared	0.14	0.15	0.15

School types based on class membership probabilities. *p < .05, †p < .10

Table 7a. Variation by Resource Classes in the Relation between Student SES and High School Graduation

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Student SES	0.77*	0.74*	0.72*	0.74*	0.71*	0.63*	0.60*	0.60*	0.64*
		(0.23)	(0.23)	(0.23)	(0.16)	(0.16)	(0.17)	(0.24)	(0.24)	(0.25)
	School Mean SES	1.33*	1.16*	0.77*	1.65*	1.48*	0.93*	1.54*	1.40*	0.79*
		(0.11)	(0.12)	(0.15)	(0.10)	(0.11)	(0.15)	(0.12)	(0.12)	(0.16)
	Intercept	3.34*	3.75*	3.65*	2.50*	2.95*	2.78*	2.20*	2.58*	2.76*
		(0.17)	(0.18)	(0.22)	(0.11)	(0.12)	(0.17)	(0.18)	(0.19)	(0.23)
School Resource Classes	General Orientation	-1.01*	-1.03*	-0.74*						
		(0.18)	(0.18)	(0.20)						
	Most Vocationally Oriented	-1.01*	-0.99*	-0.63*						
		(0.20)	(0.20)	(0.21)						
	More Experienced but Less Satisfied Teachers				-0.05	-0.12	0.24†			
					(0.12)	(0.12)	(0.14)			
	Fewest Physical Resource Problems							0.38†	0.35†	0.25
								(0.20)	(0.20)	(0.20)
	Moderate Physical Resource Problems							0.31	0.30	0.22
								(0.20)	(0.20)	(0.20)
Cross-Level Interactions	SES*General Orientation	-0.06	-0.08	-0.08						
		(0.24)	(0.24)	(0.24)						
	SES*Most Vocationally Oriented	0.07	0.05	0.03						
		(0.25)	(0.25)	(0.26)						
	SES*More Experienced but Less Satisfied Teachers				-0.01	-0.02	0.05			
					(0.17)	(0.17)	(0.18)			
	SES*Fewest Physical Resource Problems							0.13	0.07	0.03
								(0.26)	(0.26)	(0.27)

	SES*Moderate Physical Resource Problems							0.26 (0.26)	0.21 (0.26)	0.13 (0.27)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of SES Slope	0.50	0.48	0.48	0.52	0.50	0.50	0.54	0.52	0.53
	Std. Dev. of Intercept	0.61	0.60	0.59	0.63	0.62	0.60	0.63	0.62	0.58
	Corr. between Intercept & Slope	0.16	0.14	0.06	0.07	0.06	0.04	0.12	0.13	0.13
N	Students	14,674	14,674	14,276	14,262	14,262	13,898	12,273	12,273	11,973
	Schools	741	741	732	723	723	715	609	609	601
Model Fit Statistics	AIC	9,035.8	8,871.9	8,362.2	8,811.4	8,655.9	8,166.2	7,269.6	7,151.9	6,771.0
	Log-likelihood	-4,507.9	-4,418.9	-4,159.1	-4,397.7	-4,312.9	-4,063.1	-3,624.8	-3,559.0	-3,363.5
	R-squared	0.14	0.15	0.15	0.14	0.15	0.16	0.13	0.15	0.15

Classes based on membership probabilities. *$p < .05$, †$p < .10$

Table 7b. Variation in the Relation between SES and High School Graduation by Student-Staff and Student-Peer Resource Classes

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Student SES	0.76*	0.72*	0.69*	0.73*	0.69*	0.65*
		(0.28)	(0.28)	(0.28)	(0.20)	(0.20)	(0.20)
	School Mean SES	1.53*	1.36*	0.93*	0.95*	0.81*	0.49*
		(0.11)	(0.11)	(0.15)	(0.13)	(0.13)	(0.16)
	Intercept	2.98*	3.40*	2.97*	3.59*	3.95*	3.88*
		(0.20)	(0.20)	(0.25)	(0.16)	(0.17)	(0.20)
School Resource Classes	Less Positive Student-Staff Relationships	-0.57*	-0.61†	0.02			
		(0.21)	(0.21)	(0.24)			
	Less Academically Oriented Peers				-1.42*	-1.39*	-1.12*
					(0.18)	(0.18)	(0.20)
Cross-Level Interactions	SES*Less Positive Student-Staff Relationships	-0.03	-0.03	-0.01			
		(0.29)	(0.29)	(0.29)			
	SES*Less Academically Oriented Peers				0.03	0.02	0.04
					(0.21)	(0.21)	(0.22)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of SES Slope	0.50	0.48	0.49	0.50	0.48	0.49
	Std. Dev. of Intercept	0.63	0.62	0.61	0.59	0.58	0.58
	Corr. between Intercept & Slope	0.10	0.11	0.07	0.26	0.23	0.14
N	Students	14,674	14,674	14,276	14,674	14,674	14,276
	Schools	741	741	732	741	741	732
Model Fit Statistics	AIC	9,061.6	8,896.7	8,373.6	8,999.8	8,840.4	8,338.2
	Log-likelihood	-4,522.8	-4,433.3	-4,166.8	-4,491.9	-4,405.2	-4,149.1
	R-squared	0.14	0.15	0.15	0.14	0.15	0.15

Classes based on membership probabilities. *p < .05, †p < .10

Table 8. Variation by School Type in the Relation between Student SES and Immediate Enrollment in a Four-Year Institution

		Model 1	Model 2	Model 3
	Student SES	0.97*	0.94*	0.92*
		(0.09)	(0.09)	(0.09)
	School Mean SES	1.78*	1.72*	1.52*
		(0.09)	(0.09)	(0.11)
	Intercept	-0.62*	-0.37*	-0.33*
		(0.07)	(0.08)	(0.10)
School Types	Well-Maintained Middle-of-the-Road Schools	0.06	0.08	0.07
		(0.11)	(0.11)	(0.11)
	Most Academically Advantaged Schools	0.76*	0.81*	0.66*
		(0.12)	(0.12)	(0.12)
	Poorly Maintained Schools	0.22*	0.25*	0.25*
		(0.12)	(0.12)	(0.12)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.02	0.02	0.04
		(0.12)	(0.12)	(0.12)
	Most Vocationally Oriented Schools	-0.08	-0.04	0.00
		(0.13)	(0.13)	(0.13)
	Schools with Most Positive Student-Staff Relationships	0.45*	0.49*	0.28*
		(0.13)	(0.13)	(0.14)
	Less Well-Maintained, Academically Advantaged Schools	0.85*	0.83*	0.71*
		(0.13)	(0.13)	(0.14)
Cross-Level Interactions	SES*Well-Maintained Middle-of-the-Road Schools	0.21	0.21	0.23†
		(0.13)	(0.13)	(0.13)
	SES*Most Academically Advantaged Schools	-0.04	0.00	0.07
		(0.14)	(0.14)	(0.14)
	SES*Poorly Maintained Schools	0.04	0.02	0.06
		(0.14)	(0.14)	(0.15)
	SES*Middle-of-the-Road Schools with Less Experienced Teachers	0.01	-0.04	0.00
		(0.15)	(0.16)	(0.16)
	SES*Most Vocationally Oriented Schools	0.08	0.08	0.07
		(0.16)	(0.16)	(0.16)
	SES*Schools with Most Positive Student-Staff Relationships	-0.24	-0.25	-0.22
		(0.16)	(0.16)	(0.16)
	SES*Less Well-Maintained, Academically Advantaged Schools	0.03	0.06	0.04
		(0.15)	(0.15)	(0.16)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of SES Slope	0.37	0.35	0.34
	Std. Dev. of Intercept	0.59	0.59	0.57

	Corr. between Intercept & Slope	-0.38	-0.35	-0.26
N	Students	13,526	13,526	13,174
	Schools	740	740	731
Model Fit Statistics	AIC	15,442.8	15,064.6	14,633.9
	Log-likelihood	-7,701.4	-7,505.3	-7,285.0
	R-squared	0.29	0.31	0.31

School types based on class membership probabilities. *p < .05, †p < .10

Table 9a. Variation by Resource Classes in the Relation between Student SES and Immediate Enrollment in a Four-Year Institution

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Student SES	0.83*	0.83*	0.82*	0.65*	0.62*	0.64*	0.97*	0.98*	1.01*
		(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.10)	(0.19)	(0.19)	(0.19)
	School Mean SES	1.76*	1.71*	1.48*	2.20*	2.15*	1.73*	2.23*	2.18*	1.67*
		(0.09)	(0.09)	(0.11)	(0.08)	(0.09)	(0.11)	(0.09)	(0.09)	(0.12)
	Intercept	0.50*	0.79*	0.69*	-0.34*	-0.04	-0.28*	-0.44*	-0.21	-0.12
		(0.10)	(0.10)	(0.13)	(0.08)	(0.09)	(0.13)	(0.16)	(0.17)	(0.19)
School Resource Classes	General Orientation	-1.04*	-1.06*	-0.89*						
		(0.11)	(0.11)	(0.12)						
	Most Vocationally Oriented	-0.97*	-0.96*	-0.77*						
		(0.12)	(0.12)	(0.13)						
	More Experienced but Less Satisfied Teachers				-0.05	-0.10	0.18†			
					(0.09)	(0.09)	(0.10)			
	Fewest Physical Resource Problems							0.08	0.13	0.10
								(0.17)	(0.18)	(0.17)
	Moderate Physical Resource Problems							0.04	0.08	0.03
								(0.18)	(0.18)	(0.18)
Cross-Level Interactions	SES*General Orientation	0.22†	0.19	0.20						
		(0.12)	(0.12)	(0.12)						
	SES*Most Vocationally Oriented	0.09	0.06	0.07						
		(0.14)	(0.14)	(0.14)						
	SES*More Experienced but Less Satisfied Teachers				0.42*	0.43*	0.41*			
					(0.11)	(0.11)	(0.11)			
	SES*Fewest Physical Resource Problems							0.13	0.10	0.08
								(0.20)	(0.20)	(0.20)

	SES*Moderate Physical Resource Problems							0.00 (0.20)	-0.05 (0.20)	-0.11 (0.21)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of SES Slope	0.38	0.36	0.36	0.37	0.35	0.34	0.39	0.36	0.36
	Std. Dev. of Intercept	0.58	0.58	0.57	0.66	0.66	0.62	0.67	0.68	0.62
	Corr. between Intercept & Slope	-0.31	-0.26	-0.20	-0.40	-0.36	-0.21	-0.32	-0.29	-0.06
N	Students	13,526	13,526	13,174	13,153	13,153	12,830	11,318	11,318	11,052
	Schools	740	740	731	722	722	714	608	608	600
Model Fit Statistics	AIC	15,418.0	15,039.8	14,611.9	15,071.6	14,711.5	14,276.2	12,982.6	12,667.6	12,298.7
	Log-likelihood	-7,699.0	-7,502.9	-7,284.0	-7,527.8	-7,340.8	-7,118.1	-6,481.3	-6,316.8	-6,127.4
	R-squared	0.29	0.31	0.31	0.29	0.31	0.32	0.30	0.32	0.32

Classes based on membership probabilities. *p < .05, †p < .10

Table 9b. Variation in the Relation between SES and Immediate Enrollment in a Four-Year Institution by Student-Staff and Student-Peer Resource Classes

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Student SES	0.63*	0.64*	0.64*	0.97*	1.00*	0.99*
		(0.14)	(0.14)	(0.15)	(0.09)	(0.09)	(0.10)
	School Mean SES	2.03*	1.97*	1.68*	1.25*	1.21*	1.04*
		(0.08)	(0.09)	(0.11)	(0.09)	(0.10)	(0.12)
	Intercept	0.24*	0.55*	0.35*	0.80*	1.05*	0.99*
		(0.12)	(0.13)	(0.16)	(0.09)	(0.10)	(0.12)
School Resource Classes	Less Positive Student-Staff Relationships	-0.69*	-0.74*	-0.47*			
		(0.13)	(0.13)	(0.14)			
	Less Academically Oriented Peers				-1.52*	-1.49*	-1.37*
					(0.11)	(0.11)	(0.12)
Cross-Level Interactions	SES*Less Positive Student-Staff Relationships	0.41*	0.37*	0.37*			
		(0.15)	(0.16)	(0.16)			
	SES*Less Academically Oriented Peers				0.04	-0.04	-0.04
					(0.11)	(0.11)	(0.11)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of SES Slope	0.37	0.36	0.36	0.38	0.37	0.37
	Std. Dev. of Intercept	0.64	0.64	0.61	0.51	0.52	0.51
	Corr. between Intercept & Slope	-0.38	-0.33	-0.23	-0.31	-0.32	-0.28
N	Students	13,526	13,526	13,174	13,526	13,526	13,174
	Schools	740	740	731	740	740	731
Model Fit Statistics	AIC	15,474.8	15,093.4	14,650.6	15,332.0	14,963.8	14,543.1
	Log-likelihood	-7,729.4	-7,531.7	-7,305.3	-7,658.0	-7,466.9	-7,251.6
	R-squared	0.29	0.31	0.32	0.29	0.31	0.31

Classes based on membership probabilities. *p < .05, †p < .10

Table 10. Variation by School Type in the Relation between Student SES and Any Postsecondary Enrollment

		Model 1	Model 2	Model 3
	Student SES	1.16*	1.26*	1.25*
		(0.12)	(0.12)	(0.13)
	School Mean SES	1.70*	1.85*	1.53*
		(0.11)	(0.12)	(0.14)
	Intercept	2.23*	2.54*	2.61*
		(0.09)	(0.09)	(0.13)
School Types	Well-Maintaned Middle-of-the-Road Schools	-0.21†	-0.19†	-0.19†
		(0.12)	(0.11)	(0.11)
	Most Academically Advantaged Schools	0.77*	0.72*	0.46*
		(0.18)	(0.17)	(0.18)
	Poorly Maintained Schools	0.11	0.09	0.04
		(0.13)	(0.13)	(0.13)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.10	-0.11	-0.12
		(0.13)	(0.13)	(0.13)
	Most Vocationally Oriented Schools	-0.25†	-0.25†	-0.25†
		(0.13)	(0.13)	(0.13)
	Schools with Most Positive Student-Staff Relationships	0.67*	0.62*	0.24
		(0.19)	(0.19)	(0.20)
	Less Well-Maintained, Academically Advantaged Schools	0.87*	0.76*	0.61*
		(0.21)	(0.21)	(0.22)
Cross-Level Interactions	SES*Well-Maintaned Middle-of-the-Road Schools	-0.41*	-0.42*	-0.38*
		(0.17)	(0.17)	(0.17)
	SES*Most Academically Advantaged Schools	-0.11	-0.11	-0.04
		(0.24)	(0.25)	(0.25)
	SES*Poorly Maintained Schools	-0.36†	-0.40*	-0.38†
		(0.19)	(0.19)	(0.20)
	SES*Middle-of-the-Road Schools with Less Experienced Teachers	-0.33†	-0.40*	-0.32
		(0.20)	(0.20)	(0.20)
	SES*Most Vocationally Oriented Schools	-0.28	-0.32	-0.29
		(0.20)	(0.20)	(0.20)
	SES*Schools with Most Positive Student-Staff Relationships	-0.25	-0.24	-0.24
		(0.28)	(0.29)	(0.29)
	SES*Less Well-Maintained, Academically Advantaged Schools	0.09	0.16	0.17
		(0.28)	(0.29)	(0.30)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of SES Slope	0.49	0.46	0.45
	Std. Dev. of Intercept	0.48	0.42	0.39

	Corr. between Intercept & Slope	-0.16	-0.06	0.11
N	Students	13,637	13,637	13,273
	Schools	740	740	731
Model Fit Statistics	AIC	8,619.8	8,334.8	7,968.5
	Log-likelihood	-4,289.9	-4,140.4	-3,952.3
	R-squared	0.15	0.16	0.16

School types based on class membership probabilities. *p < .05, †p < .10

Table 11a. Variation by Resource Classes in the Relation between Student SES and Any Postsecondary Enrollment

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Student SES	1.15*	1.30*	1.25*	0.76*	0.86*	0.95*	0.92*	1.07*	1.05*
		(0.27)	(0.27)	(0.28)	(0.17)	(0.17)	(0.18)	(0.27)	(0.27)	(0.27)
	School Mean SES	1.71*	1.87*	1.54*	2.10*	2.22*	1.70*	2.24*	2.36*	1.73*
		(0.11)	(0.11)	(0.14)	(0.11)	(0.11)	(0.14)	(0.12)	(0.12)	(0.15)
	Intercept	3.70*	3.90*	3.55*	2.62*	2.88*	2.52*	2.62*	2.85*	2.77*
		(0.20)	(0.21)	(0.24)	(0.12)	(0.12)	(0.16)	(0.19)	(0.20)	(0.22)
School Resource Classes	General Orientation	-1.50*	-1.40*	-0.97*						
		(0.21)	(0.21)	(0.22)						
	Most Vocationally Oriented	-1.50*	-1.40*	-0.99*						
		(0.22)	(0.22)	(0.23)						
	More Experienced but Less Satisfied Teachers				-0.29*	-0.26*	0.13			
					(0.12)	(0.11)	(0.13)			
	Fewest Physical Resource Problems							-0.32	-0.25	-0.19
								(0.20)	(0.20)	(0.20)
	Moderate Physical Resource Problems							-0.21	-0.17	-0.13
								(0.20)	(0.20)	(0.20)
Cross-Level Interactions	SES*General Orientation	-0.24	-0.31	-0.24						
		(0.28)	(0.28)	(0.29)						
	SES*Most Vocationally Oriented	-0.18	-0.25	-0.20						
		(0.30)	(0.30)	(0.30)						
	SES*More Experienced but Less Satisfied Teachers				0.17	0.18	0.09			
					(0.18)	(0.18)	(0.19)			
	SES*Fewest Physical Resource Problems							0.02	-0.02	0.04
								(0.28)	(0.29)	(0.29)
								0.11	0.05	0.07

	SES*Moderate Physical Resource Problems							(0.29)	(0.29)	(0.29)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of SES Slope	0.50	0.49	0.48	0.53	0.52	0.50	0.50	0.49	0.46
	Std. Dev. of Intercept	0.48	0.43	0.40	0.54	0.47	0.43	0.54	0.49	0.43
	Corr. between Intercept & Slope	-0.12	-0.04	0.14	-0.20	-0.10	0.12	-0.11	0.06	0.27
N	Students	13,637	13,637	13,273	13,252	13,252	12,919	11,422	11,422	11,147
	Schools	740	740	731	722	722	714	608	608	600
Model Fit Statistics	AIC	8,614.8	8,330.6	7,961.2	8,412.1	8,138.1	7,772.5	7,146.2	6,903.2	6,619.2
	Log-likelihood	-4,297.4	-4,148.3	-3,958.6	-4,198.1	-4,054.1	-3,866.2	-3,563.1	-3,434.6	-3,287.6
	R-squared	0.15	0.16	0.16	0.15	0.17	0.17	0.15	0.17	0.16

Classes based on membership probabilities. *p < .05, †p < .10

Table 11b. Variation in the Relation between SES and Any Postsecondary Enrollment by Student-Staff and Student-Peer Resource Classes

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Student SES	0.93*	1.07*	1.03*	1.28*	1.41*	1.41*
		(0.37)	(0.37)	(0.37)	(0.23)	(0.23)	(0.23)
	School Mean SES	1.89*	2.02*	1.64*	1.31*	1.54*	1.27*
		(0.11)	(0.11)	(0.14)	(0.12)	(0.12)	(0.15)
	Intercept	3.63*	3.85*	3.29*	3.88*	4.00*	3.72*
		(0.25)	(0.25)	(0.28)	(0.18)	(0.18)	(0.20)
School Resource Classes	Less Positive Student-Staff Relationships	-1.36*	-1.31*	-0.68*			
		(0.26)	(0.26)	(0.27)			
	Less Academically Oriented Peers				-1.87*	-1.67*	-1.32*
					(0.20)	(0.20)	(0.21)
Cross-Level Interactions	SES*Less Positive Student-Staff Relationships	-0.01	-0.05	0.01			
		(0.38)	(0.38)	(0.39)			
	SES*Less Academically Oriented Peers				-0.38	-0.43†	-0.42†
					(0.24)	(0.25)	(0.25)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of SES Slope	0.51	0.50	0.49	0.50	0.48	0.47
	Std. Dev. of Intercept	0.51	0.45	0.42	0.44	0.39	0.38
	Corr. between Intercept & Slope	-0.14	-0.02	0.15	-0.01	0.08	0.24
N	Students	13,637	13,637	13,273	13,637	13,637	13,273
	Schools	740	740	731	740	740	731
Model Fit Statistics	AIC	8,641.1	8,350.1	7,973.3	8,573.1	8,300.6	7,935.9
	Log-likelihood	-4,312.6	-4,160.0	-3,966.7	-4,278.6	-4,135.3	-3,947.9
	R-squared	0.15	0.17	0.16	0.15	0.16	0.16

Classes based on membership probabilities. *p < .05, †p < .10

Chapter 5: Racial/Ethnic Disparities

Racial and ethnic inequality is a defining feature of American society and American schools. Across grades and subjects, on average, White students perform significantly better on assessments than do Black or Hispanic students (Hallinan 2001; Hemphill and Vanneman 2011; Jencks and Phillips 1998; Magnuson and Waldfogel 2008; Reardon and Galindo 2009). For example, in 2008, the average difference in math and reading achievement between Black and White 17-year-olds on the National Assessment of Educational Progress (NAEP) was 0.77 standard deviations (Hanushek 2010). Unconditional differences in high school graduation and college enrollment are also large; for example, 83 percent of White students, 71 percent of Hispanic students, and 66 percent of Black students graduate high school within four years (National Center for Education Statistics 2013). In 2010, 43 percent of White 18- to 24-year-olds enrolled in a degree-granting institution compared to 38 percent of Black and 32 percent of Hispanic young adults (Ross et al. 2012).

The most common explanation for racial/ethnic differences in educational outcomes is that they simply reflect SES differences across groups. Conditioning on SES explains all or nearly all of the Black-White difference in achievement at the start of kindergarten and a substantial, but smaller, portion of the Hispanic-White difference (Fryer and Levitt 2004; Quinn 2015; Reardon and Galindo 2009). While Hispanic-White differences in math and reading achievement narrow over the course of elementary school, Black-White differences widen, and family SES does not explain this widening (Downey, von Hippel and Broh 2004; Fryer and Levitt 2006; Quinn 2015; Reardon and Galindo 2009). Studies consistently show that, although Black and Hispanic students enter school with roughly equal socioeconomic backgrounds and with equally low achievement levels relative to White students, the achievement trajectories of

Black and Hispanic students diverge strikingly over the course of schooling. This has led many researchers to examine the extent to which differences in the quality of schools attended by Black, White, and Hispanic students explain the divergence in achievement over time, as well as what school factors explain this divergence (Condron 2009; Fryer and Levitt 2004; Hanushek and Rivkin 2006; Quinn 2015; Reardon 2008).

Condron was undoubtedly correct in writing that, "[r]egardless of what occurs at school, the broader structure of social stratification produces class and racial disparities in learning, and school reforms cannot eliminate achievement gaps as long as that stratification is left intact…" (2009: 683-4). Yet, while students and staff bring racial disparities into schools, schools also shape these disparities as students move through them. In schools, as in the larger society, race operates on multiple levels, influencing perceptions, interactions, access to resources, institutional processes and responses (Ferguson 2001; James 2008; Lewis and Diamond 2015). Through their practices, schools often translate "differential resources outside of schools into actual advantages in school" (Lewis-McCoy 2014: 168). However, the salience of students' racial identity is not constant across schools; rather, it depends on the school's context and social setting (Lewis-McCoy 2014; Lewis and Diamond 2015; Mullen 1983). For example, Kelly (2009) hypothesized that race may be a more salient aspect of Black students' identity if they attend racially integrated schools rather than schools with predominantly Black students.

Lewis and Diamond (2015) recently explored how racial inequality thrives in "good" schools. Studying a highly resourced, award-winning suburban high school with strong financial support in a liberal community that many families chose in part because of its diverse schools, Lewis and Diamond wrote that the school "presents a 'least likely case' in which to find deep racial divisions in educational outcomes. In many ways, the school is a picture of racial integration and high student achievement (e.g., all groups are outperforming their peers in the city next door)" (2015: xv). Yet, White students are extremely overrepresented in the school's "top" tracks, White families have more information about the school and more influence over school officials, and differential discipline by race/ethnicity creates barriers to minority students' sense of belonging at the school. Lewis and Diamond point out that race is always relational – "[f]or every privileged group there is another group that is penalized" (2015: 65) – and that many of the school practices that disadvantage Black and Hispanic students actually benefit White students. Like other researchers (cf. Lewis-McCoy 2014), Lewis and Diamond (2015) argue that schools should not be considered "good" or "great" schools, even if they have high average achievement, if they produce stark inequalities by race or ethnicity.

In this chapter, I examine the extent to which within-school differences in educational outcomes by race or ethnicity vary across high schools and what types of schools, and school-based resources, are associated with more equal educational outcomes by race and ethnicity. It is important to note from the start, though, that Black or Hispanic students mostly do not attend the same schools as White students. Despite decreasing school segregation from the mid-1950s through the 1980s, U.S. schools today remain very segregated by race and SES (Logan, Oakley and Stowell 2008; Orfield and Lee 2007; Reardon et al. 2012; Reardon and Owens 2014). Condron argues that, "[w]hen it comes to both housing and schools, race trumps class as the central axis upon which blacks and whites in the United States are segregated" (2009: 701). This study sets aside the most segregated schools to examine how, in relatively integrated schools, Black and Hispanic students' achievement and attainment varies from their within-school White peers.

SCHOOL SEGREGATION AND ACHIEVEMENT AND ATTAINMENT

Higher levels of school and neighborhood segregation usually are associated with negative academic outcomes for minority students (Massey 2006; Quillian 2014). The Coleman Report (1966) found that, controlling for students' background characteristics, Black students had moderately higher achievement in schools with a higher proportion of White students. In their reanalysis of the Report's data, after controlling for students' background characteristics as well as other school, teacher, and peer effects, G. Borman and Dowling (2010) reported an even larger effect of schools' racial composition on achievement: the school-level effect for proportion of Black students in the school was 1.75 times larger than the student-level effect of the Black coefficient. Other research has found that, even after controlling for a wide range of covariates, students attending minority-segregated schools have lower average reading and math achievement or achievement gains than students attending predominantly White or integrated schools (K. Borman et al. 2004; Condron 2009; Lee and Smith 1997; Lleras 2008).

The effect of schools' racial/ethnic composition on achievement may differ for students of different races/ethnicities. Several studies have found that a higher percentage of Black schoolmates reduces achievement for Black students to a much larger extent than for White students; the percentage of Hispanic students at the school seems to have a smaller effect than the percentage of Black students (Hanushek and Rivkin 2006; Hanushek, Kain and Rivkin 2009). Using the ELS, Riegle-Crumb and Grodsky (2010) reported that, net of students' social background, achievement levels were lower in schools with a higher percentage of minority students; the negative association was stronger for Black, but not Hispanic, students compared to White students.

However, racial/ethnic composition effects on achievement likely differ across contexts and may not always occur. Not all studies find a relation between schools' racial composition and achievement or achievement gains (cf. Lee, Croninger and Smith 1997; Lee and Smith 1996). For example, examining student achievement in Nashville before, during, and after the end of court-ordered desegregation, Gamoran and An (2016) found no evidence that increases in the proportion of Black students at a school decreased achievement growth; they did find, however, that increases in the proportion of students on free or reduced price lunch restricted achievement growth. Other studies also have found that schools' socioeconomic composition is a much stronger predictor of educational outcomes than schools' racial composition (cf. Coleman et al. 1966; Palardy 2013; Rumberger and Palardy 2005a).

In addition, the effects of racial/ethnic composition on attainment may differ from the effects on achievement. Using NELS, P. R. Goldsmith (2009) reported that students who attended predominantly Black or Latino high schools were less likely to earn a high school diploma and less likely to earn a bachelor's degree or higher by age 26 than were students from predominantly White schools, net of a wide variety of controls. However, earlier research based on HSB data found no evidence of a compositional effect for high concentrations of Black and/or Hispanic students on high school dropout (Bryk and Thum 1989). Conditional on SES, Black students are more likely than White students to attend a four-year institution (Engberg and Wolniak 2010b; Jennings et al. 2015). Many studies have found that Black and Hispanic students have more optimistic and more pro-school beliefs, and are more likely to expect to graduate from a four-year college, when they attend schools with a higher proportion of Black or Hispanic students (Frost 2007; P. A. Goldsmith 2004).

Overall, the magnitude – and existence – of racial/ethnic compositional effects varies across outcomes and contexts, and relatively little is known about the mechanisms by which composition affects achievement or attainment (Gamoran and An 2016; Hanushek, Kain and Rivkin 2009). In their reanalysis of the Coleman Report's data, Borman and Dowling (2010) found that, although part of the compositional effect was explained by differences in school facilities and curriculum, most of the effects of school composition could not be explained. Similarly, Condron (2009) found that school mechanisms explain only about 15 percent of the minority segregated school effect in the Early Childhood Longitudinal Study-Kindergarten Class of 1998-99.

Racial/Ethnic Inequality in School Resources

One widely theorized mechanism is that schools' racial composition is related to both measured – and unmeasured – resource differences across schools. The assumption that school segregation and unequal school resources were linked was one of the key motivations of the Coleman Report (1966). While the Report did not document as clear of a link between segregated schools and inadequate resources as had been expected, there are still "long-standing patterns in which more resources flow to schools and classrooms with the most advantaged populations" (Gamoran, Collares and Barfels 2016: 1156).

In terms of **instructional resources**, debate continues regarding whether minority students, conditional on SES, are differentially assigned to lower tracks (Attewell and Domina 2008; Gamoran and Mare 1989; Hallinan 1992; Mickelson 2001); the answer may depend in part on the measure of tracking used (Lucas and Gamoran 2002) and on schools' degree of racial diversity (Kelly 2009; Kelly and Price 2011; Lucas and Berends 2002). Using HSB data, Lucas and Berends (2002) found that racial diversity was positively associated with de facto tracking.

Based on NELS data, Kelly (2009) found that, in predominantly White public schools, Black students were assigned to lower math classes than White students, controlling for individual-level differences in prior preparation and family background, and that, as the racial composition of the school became less White, White students' relative advantage in math course taking decreased. However, based on a content analysis of curriculum guides from North Carolina high schools, Kelly and Price (2011) found little evidence that racial/ethnic heterogeneity was associated with tracking policies.

Findings for **teacher resource** patterns are more consistent: most studies suggest that, on average, Black and Hispanic students have newer, more often alternatively certified teachers than do White students (cf. Clotfelter, Ladd and Vigdor 2010; Condron 2009; Hanushek and Rivkin 2006; Kain and Singleton 1996; Kalogrides and Loeb 2013; Thompson 2012). Findings for **school physical resource** patterns also tend to be consistent across studies. Minority students who attend integrated high schools rate their schools' building condition, audiovisual equipment, library, and computers more favorably than do minority students who attend segregated schools (Massey 2006). Independent observers rate the physical conditions of elementary schools attended by middle- and working-class Black students as worse than those of schools attended by middle- and working-class White students (Condron 2009). Black and Hispanic students' parents are more likely than White students' parents to say that inadequate physical resources, such as a lack of computers, are a problem at their child's school (Elliott and Agiesta 2013).

Prior studies report contradictory findings in terms of whether Black and Hispanic students have more or less negative **relationships with school staff** than do White students. Using ELS data, Fan, Williams, and Corkin (2011) found that Black students perceive teacher-student relationships more negatively than White students. In contrast, using NELS data, Ma and

Willms (2004) found that Black and Hispanic students have more favorable teacher-student relationships than White students. Some studies suggest that teachers have lower expectations for minority students, particularly Black students, but this may vary depending on teachers' race/ethnicity, and research on this topic is far from conclusive (Ferguson 2003; McKown and Weinstein 2002; Muller, Katz and Dance 1999; Riegle-Crumb and Humphries 2012).

Finally, a key way in which school composition may affect students' outcomes is by shaping the composition of the peer group with which students attend school, as well as students' **peer relationships**. In some cases, students may become like their peers, benefiting from attending school with students who value paying attention in class, who expect to attend college, or whose parents are very invested in their education, or suffering from attending school with students who do not have such expectations or resources (Cherng, Calarco and Kao 2013; Coleman et al. 1966; Lauen and Gaddis 2013). In other cases, students may benefit when they can stand out positively from their peers in terms of their ability or effort (Espenshade, Hale and Chung 2005). Goldsmith (2011) calls these alternative types of peer effects "normative" versus "frog pond" models and finds evidence for both; while normative processes disadvantage students in minority-concentrated high schools, frog pond processes advantage them, in effect canceling each other out. Overall, extensive research finds racial/ethnic inequalities in school resources – particularly teacher, school physical, and peer relationship resources – both between and within schools and even in relatively well-resourced schools (Lewis-McCoy 2014).

VARIATION ACROSS SCHOOLS IN THE EXTENT OF DIFFERENCES BY RACE/ETHNICITY IN EDUCATIONAL OUTCOMES

Given that there is variation across schools in resources – and given that many students attend very segregated schools – within relatively racially and/or ethnically diverse schools, are particular school resources associated with greater or lesser achievement and attainment disparities? Several studies using NELS data examined how the relation between students' race/ethnicity and their educational outcomes varied across schools of different socioeconomic compositions. These studies found that, controlling for students' SES, Black students' achievement growth was lower than White students' in low-, and possibly middle-, but not high-SES schools (Palardy 2008; Rumberger and Palardy 2005a). However, in the ELS data, Palardy (2013) found that the relation between students' racial/ethnic background and their attainment did not vary by schools' socioeconomic composition.

Other studies have examined how the relation between students' race/ethnicity and their outcomes varies by school sector. Using HSB data, Lee and Bryk (1989) found that the difference between minority (defined as Black or Hispanic) and White students' achievement was smaller in Catholic schools than public schools. This echoed other findings that, controlling for student background and prior ability, Catholic schools had a moderate positive effect, relative to public schools, on Black and Hispanic students' achievement but not necessarily White students' achievement (Keith and Page 1985; Morgan 2001). In contrast, using ELS data, Carbonaro and Covay (2010) found that the relation between students' race/ethnicity and their math achievement gains from tenth through twelfth grade was the same in public and private schools; the coefficients suggested that, if anything, differences in achievement between Black and White students were larger, not smaller, in Catholic schools. And, using data from sixth and eighth grade students in Chicago schools, Hallinan and Kubitschek (2012) found that, compared to public schools, Catholic schools had a weaker relation between students' race/ethnicity and reading achievement but a stronger relation between race/ethnicity and math achievement. Thus, with more recent data, differences by school sector in the relation between students' race/ethnicity and their outcomes are less clear.

What school resources may explain sector differences, as well as differences by socioeconomic composition, if they exist? In the HSB data, Lee and Bryk (1989) found that schools' disciplinary climate explained the sector difference, and that the difference between minority and White students' achievement was larger in schools with a higher incidence of disciplinary problems. Using NELS data and controlling for students' demographic characteristics and schools' structural characteristics, Lee and Smith (1997) found that very large high schools had the greatest differences in students' math achievement growth; they concluded that school size is especially important for disadvantaged students. In their analysis of the Coleman Report data, Borman and Dowling (2010) found that, while curricular differentiation did not explain variation across schools in Black-White achievement inequalities in ninth-graders' verbal achievement, teachers' preferences did; specifically, schools in which teachers had stronger preferences for working with middle-class students had larger Black-White achievement inequalities. Thus, several studies point to some school characteristics that are associated with greater or lesser within-school inequality in achievement by race/ethnicity.

Might the school characteristics – and indeed schools themselves – associated with greater or lesser within-school inequality by race/ethnicity vary for attainment? Some recent research suggests so. Using data from public schools in Massachusetts and Texas, Jennings et al. (2015) found that, for math and reading achievement, differences in schools' value-added for White and nonwhite students who attended the same high school were rarely significant, but schools' value-added in terms of students' probability of enrolling in a four-year institution often differed for White and nonwhite students who attended the same school. Though Jennings et al.

(2015) did not examine the school characteristics associated with schools' value-added, the different patterns they documented for achievement versus college enrollment by race/ethnicity suggest that the schools and school characteristics associated with smaller or larger racial/ethnic inequalities in achievement might not be the same as those associated with smaller or larger racial/ethnic inequalities in attainment.

DATA AND METHODS

As mentioned above, this chapter examines variation in racial/ethnic inequalities within a particular subset of schools, those I define as relatively racially diverse. Consistent with my approach in the previous chapters, I restrict the analyses to schools with at least three sampled White and three Black or three Hispanic students with data on a given outcome[1]; I define these schools as "relatively racially diverse." Because of the limited number of schools in this sample, statistical significance is harder to obtain. Therefore, in the results section, I focus on interpreting the magnitude of the coefficients and note where statistical significance is found. In all models, the reference category is non-Hispanic Whites (hereafter, "Whites").

Table 1 compares the characteristics of all schools in the sample to those of schools with at least three Black and three White students and those with at least three Hispanic and three White students. Compared to the overall sample, schools in the Black-White sample are slightly less likely to be private or located in a rural area, slightly more likely to be located in an urban area, and much less likely to have a low percentage of FRL-eligible students. In terms of the percentage of schools in each school type category, most differences between the Black-White and overall sample are only two to three percentage points; exceptions are that schools in the

[1] As noted in previous chapters, at least one student from each subgroup is required to estimate these models. To balance adequate precision in predicting within-school racial/ethnic disparities with the goal of including a broad group of schools, I restrict the sample to schools with at least three students from each subgroup. Future work should explore how robust the results are to different sample restrictions.

Black-White sample are five to six percentage points more likely to be categorized as "middle-of-the-road schools" and five to six percentage points less likely to be categorized as "schools with the most positive student-staff relationships." Schools in the Black-White sample do not differ from the overall sample in terms of their distribution across categories of physical resources but are less likely to be categorized as having the most vocationally oriented instructional resources and more likely to be categorized as having a general orientation to instructional resources, more experienced but less satisfied teachers, less positive student-staff relationships, and less academically oriented peers; differences from the overall sample range from three to eight percentage points.

< Table 1 >

Compared to the overall sample, schools in the Hispanic-White sample are much less likely to be located in a rural area[2] and slightly less likely to have either a low or high percentage of FRL-eligible students. Differences between the Hispanic-White and overall sample in terms of the percentage of schools in each school type are generally only two to three percentage points; the exception is that schools in the Hispanic-White sample are four to six percentage points more likely to be categorized as "well-maintained middle-of-the-road schools." In terms of the individual resource categories, schools in the Hispanic-White sample are five to six percentage points more likely to have a general orientation to instructional resources, and five to seven percentage points less likely to be in the most vocationally oriented category of instructional resources, but are similar to the overall sample in terms of teacher resources, physical resources, student-staff relationships, and student-peer relationships.

[2] Because of the small number of rural schools in both the Black-White and Hispanic-White samples, I do not include a rural indicator in the models in this chapter; therefore, rural and suburban schools together comprise the reference category.

Consistent with the approach in the previous chapters, I average all students' reports of the school environment to use as resource measures. Table 2 shows, though, that White and Black or Hispanic students' reports of school resources are often significantly different, even in these relatively diverse schools. This is a limitation of the work because, as I discuss in the future research section, while sample sizes may be adequate to examine differences in resource reports by gender, they are not adequate to examine differences in resource reports by race/ethnicity.

< <u>Table 2</u> >

Tables 3a and 3b compare model fit statistics for null models with a random intercept only, random intercept plus race/ethnicity fixed effect, and random intercept plus random slope. In both the Black-White and Hispanic-White samples, including a random slope may improve model fit for math achievement. For the Black-White sample, including a random slope may also improve model fit for high school graduation, while, for the Hispanic-White sample, including a random slope may improve model fit for any postsecondary enrollment.

< <u>Table 3a</u>, <u>Table 3b</u> >

RESULTS

Black and Hispanic students have significantly lower math achievement than White students, but, conditional on other demographic characteristics, the average Black-White difference in math achievement is about twice as large as the average Hispanic-White difference. In these relatively integrated schools, Black and White students' odds of graduating are roughly equal even in the unconditional models, and, after controlling for other student background characteristics, Black students are more likely to graduate than White students. In contrast, Hispanic students' odds of graduating are lower than White students', though the difference declines across models. Similarly, conditioning on students' other demographic characteristics erases the difference between Black and White students' odds of immediate four-year enrollment, but the difference between Hispanic and White students' odds of immediate four-year enrollment remains significant and substantial. Finally, conditional on students' other background characteristics, both Black and Hispanic students' odds of enrolling in any postsecondary institution within eight years of completing high school are higher than White students', but the Hispanic-White difference is about half as large as the Black-White difference.

< Table 4a, Table 4b >

To what extent does the relation between students' race/ethnicity and their educational outcomes vary across these high schools? For math achievement, the estimated standard deviations of the Black and Hispanic slopes are fairly similar; in these relatively integrated schools, conditional on student and school covariates, the standard deviation of within-school Black-White and Hispanic-White differences in achievement is about 16 to 18 percent of the math test's standard deviation. Black students' average disadvantage relative to White students in math achievement is greater in schools with higher average levels of achievement; in contrast, schools' average level of math achievement is not strongly related to the magnitude of the difference between Hispanic and White students' achievement.

In terms of high school graduation, the standard deviation of the Black slope is about twice as large as that of the Hispanic slope, indicating that there is more variation across schools in the within-school difference between Black and White students' odds of graduating than between Hispanic and White students' odds of graduating. In the unconditional and student covariates only models, for both the Black-White and Hispanic-White samples, higher average graduation rates are associated with larger differences, favoring White students, between minority and White students' odds of graduating. However, in the Hispanic-White sample, conditional on both student and school covariates, there is no relation between a school's overall graduation rate and the average size of the Hispanic-White difference in graduation.

For students' odds of immediate enrollment in a four-year institution, the standard deviations of the Black and Hispanic slopes are similar, as they are for students' odds of any postsecondary enrollment. In the unconditional model and model conditioning on student covariates, higher average odds of immediate four-year enrollment are associated with a greater difference, favoring White students, between Black and White students' odds of enrollment. In contrast, across the three models, Hispanic students' disadvantage relative to White students in immediate four-year enrollment is smaller in schools with higher average odds of immediate four-year enrollment. The average difference between Hispanic and White students' odds of any postsecondary enrollment is larger, favoring White students, in schools with high overall odds of any postsecondary enrollment; in the Black-White sample, the pattern is the same but the magnitude of the correlation is less than half as large.

Figures 1 – 4 depict predicted math achievement scores, probability of high school graduation, probability of immediate enrollment in a four-year institution, and probability of any postsecondary enrollment for White, Black, and Hispanic students. At the 5^{th} percentile of the Black slope, the unconditional average difference between Black and White students' math achievement is about ten points, equivalent to one standard deviation of the ELS math test. After conditioning on both student and school covariates, the average difference between Black and White students' math achievement varies from about six points at the 5^{th} percentile of the Black slope to about four points at the 95^{th} percentile, while the average difference between Hispanic and White students' math achievement varies from about four points at the 5^{th} percentile of the Hispanic slope to about two points at the 95^{th} percentile.

< Figure 1 >

Conditional on student and school covariates, Black and Hispanic students have similar probabilities of graduating high school at the 5th percentile of the respective slopes (.84 compared to .87), but Black students' graduation probability improves to .97 at the 95th percentile of the slope, whereas Hispanic students' probability only improves to .92 at the 95th percentile. In terms of immediate enrollment in a four-year institution, conditional on student and school covariates, Black and White students' probabilities are similar at the 5th percentile, but Black students have a six percentage point advantage relate to White students at the 95th percentile. In contrast, after conditioning on student and school covariates, Hispanic and White students' probabilities of immediate four-year enrollment differ by nearly 20 percentage points at the 5th percentile of the school slope, and Hispanic students do not reach parity with White students on this outcome even at the 95th percentile of the slope. Finally, conditional on student and school covariates, Black and Hispanic students' predicted probabilities of any postsecondary enrollment surpass White students' by the 25th percentile of their respective slopes.

< Figure 2, Figure 3, Figure 4 >

Variation in Racial/Ethnic Inequalities in Math Achievement across Schools

The average difference between Black and White students' math achievement is about the same in the reference category of schools, "middle-of-the-road schools," as in the other seven types of schools examined here. The average difference between Hispanic and White students' math achievement is smaller in schools with the most positive student-staff relationships than in middle-of-the-road schools; the coefficient's magnitude in both the second and third models (i.e., conditional on student or student and school covariates) is large enough to erase Hispanic students' average disadvantage relative to White students in math achievement.

< Table 5a, Table 5b, Figure 5 >

Black students' average disadvantage relative to White students in math achievement does not vary significantly across classes of instructional or teacher resources, although the pattern of coefficients suggests that the difference between Black and White students' math achievement may be larger in schools with a more general or more vocational orientation to instructional resources than in schools with the most academically oriented instructional resources. White students' average achievement is significantly lower in the schools with moderate to the most physical resource problems than in schools with the fewest physical resource problems, but Black students' achievement does not differ by physical resource classes to the extent that White students' does.

< Table 6a >

Similar to the results for the Black-White sample, the pattern of coefficients suggests that the difference between Hispanic and White students' average math achievement is greater in schools with the most vocationally oriented instructional resources. Also, the average difference between Hispanic and White students' math achievement may be greater in schools with more experienced but less satisfied teachers, though the interaction is only significant in the unconditional model (as was the case for the instructional resource interaction).

< Table 6b >

Hispanic students' average disadvantage relative to White students in math achievement is significantly larger in schools with less positive student-staff relationships; in fact, the difference between Hispanic and White students' average achievement is less than one point and is not statistically significant in schools with more positive student-staff relationships. Likewise, the difference between Hispanic and White students' average math achievement is significantly greater in schools with less academically-oriented peers. Relations between classes of student-staff or student-peer resources and inequality in math achievement are in the same direction in the Black-White sample, but the coefficients are much smaller and not statistically significant.

< Table 6c, Table 6d >

Figure 6 depicts these results and also shows the large standard errors for the "most physical resource problems" interactions; these large standard errors likely result because of the small number of schools in this category.

< Figure 6 >

Variation in Racial/Ethnic Inequalities in High School Graduation across Schools

In middle-of-the-road schools, Black and White students' odds of graduating are very similar, conditional on other student and school characteristics. In contrast, Black students' odds of graduating are significantly higher than White students' in at least two types of schools. First, compared to middle-of-the-road schools, the most academically advantaged schools have significantly higher overall graduation rates (at least in the first two of three models), and Black students' odds of graduating are particularly high relative to White students' in these schools. Black students' odds of graduating also are significantly higher than White students' in poorly maintained schools, though these schools have lower overall graduation rates. The size of Hispanic-White disparities in graduation does not vary significantly across school types.

< Table 7a, Table 7b, Figure 7 >

Conditional on student and school covariates, Black students' odds of graduating are significantly higher than White students' in schools with the most academically oriented instructional resources; Black students' advantage relative to White students is smaller in schools with a general or vocational orientation to instructional resources. Similarly, conditional on student and school covariates, Black students' odds of graduating are significantly higher than White students' in schools with the fewest physical resource problems, but Black students' advantage is largely erased in schools with moderate physical resource problems. Perhaps these two findings suggest that, when resource deprivation in access to high-quality instruction or well-maintained and resourced classrooms exists in a school, then Black students are more likely to experience that deprivation than are their within-school White counterparts. The magnitude of the difference between Black and White students' graduation odds does not vary across classes of teacher resources, and the magnitude of Hispanic-White differences in graduation does not appear to be strongly related to classes of instructional, teacher, or school physical resources.

< Table 8a, Table 8b >

In schools with more positive student-staff relationships, Black students' graduation odds are higher than White students'; in contrast, in schools with less positive student-staff relationships, Black and White students' graduation odds are about equal. Similarly, Black students' odds of graduating are significantly higher than White students' in schools with more academically oriented peers, while Black and White students' graduation odds are about equal in schools with less academically oriented peers. This pattern is reversed in the Hispanic-White sample: Hispanic students' odds of graduating are significantly lower than White students' in schools with the most academically oriented peers but are more similar to White students' in schools with less academically oriented peers. Likewise, though the coefficients are smaller than in the Black-White sample and are not significant, the coefficients' direction suggests that the difference between Hispanic and White students' graduation odds may be larger in schools with more positive, versus less positive, student-staff relationships.

< Table 8c, Table 8d >

Figure 8 depicts these results, illustrating most strikingly the potentially large but imprecisely estimated coefficients for student-staff resources in the Black-White sample as well as the opposite direction of the coefficients for most academically oriented peers in the Black-White versus Hispanic-White samples.

< Figure 8 >

Variation in Racial/Ethnic Inequalities in Immediate Four-Year Enrollment across Schools

Although different school types are associated with higher or lower overall odds of immediate four-year enrollment, for the most part, these school types are not differentially associated with Black or White students' four-year enrollment odds. The exception is less well-maintained but academically advantaged schools; these schools have higher average rates of immediate four-year enrollment than do middle-of-the-road schools, but Black students' odds of immediate four-year enrollment are not as high relative to their odds in middle-of-the-road schools, as White students' are. In middle-of-the-road schools, Hispanic students are less likely than White students to enroll in a four-year institution immediately after high school, and the magnitude of the Hispanic-White difference seems to be relatively similar across the other school types with two exceptions: first, Hispanic students' disadvantage relative to White students is significantly larger in well-maintained middle-of-the-road schools, and, second, Hispanic students' odds of immediate four-year enrollment may be about equal to White students' in less well-maintained but academically advantaged schools.

< Table 9a, Table 9b, Figure 9 >

In the most academically oriented schools, schools with less experienced but more satisfied teachers, and schools with the fewest physical resource problems, Black and White students' odds of immediate four-year enrollment are similar, conditional on other student and school characteristics. In contrast, Black students' odds of immediate four-year enrollment may be higher than White students' in schools with the most vocationally oriented instructional resources and with the most physical resource problems. Similarly, while in schools with the fewest physical resource problems, Hispanic students are significantly less likely than White students to enroll in a four-year institution immediately after high school, Hispanic and White students attending schools with the most physical resource problems have comparable odds of immediate four-year enrollment. The difference between Hispanic and White students' odds of immediate four-year enrollment does not vary significantly across classes of instructional or teacher resources.

< Table 10a, Table 10b >

Conditional on other student and school characteristics, the difference between Black and White students' odds of immediate four-year enrollment is similar regardless of their school's level of student-staff or student-peer resources. Likewise, regardless of their school's level of student-peer resources, Hispanic students are less likely than White students to enroll immediately in a four-year institution. In contrast, conditional on other student and school covariates, Hispanic and White students' odds of immediate four-year enrollment are similar if they attend schools with more positive student-staff relationships but, in schools with less positive student-staff relationships, Hispanic students may be less likely to enroll in a four-year institution.

< Table 10c, Table 10d, Figure 10 >

Variation in Racial/Ethnic Inequalities in Any Postsecondary Enrollment across Schools

Black students' advantage relative to White students in any postsecondary enrollment may be larger in schools with the most positive student-staff relationships compared to middle-of-the-road schools, but the average Black-White difference in any postsecondary enrollment does not vary across the other school types examined here. Conditional on other student covariates, White and Hispanic students' odds of any postsecondary enrollment are very similar in middle-of-the-road schools. In contrast, Hispanic students' odds of any postsecondary enrollment are lower than White students' in less well-maintained but academically advantaged schools.

< Table 11a, Table 11b, Figure 11 >

Conditional on other student and school covariates, in schools with less experienced but more satisfied teachers, Black students are significantly more likely than White students to enroll in any postsecondary institution; Black students' advantage relative to White students may be smaller in schools with more experienced but less satisfied teachers. The pattern is similar for Hispanic-White differences in the odds of any postsecondary enrollment across classes of teacher resources, but the coefficients are smaller and not statistically significant. Black-White and Hispanic-White differences in the odds of any postsecondary enrollment do not seem to vary across classes of instructional or physical resources, conditional on student and school covariates.

< Table 12a, Table 12b >

In schools with more positive student-staff relationships, Black students' odds of any postsecondary enrollment are higher than White students', while, in schools with less positive student-staff relationships, Black and White students have similar odds of any postsecondary enrollment. In contrast, coefficients for the student-peer indicators suggest that, if anything, Black students' odds of any postsecondary enrollment relative to White students' may be more favorable in schools with less, rather than more, academically oriented peers. Similarly, in schools with more academically oriented peers, Hispanic students may be less likely than White students to enroll in any postsecondary institution; this Hispanic-White difference is erased in schools with less academically oriented peers. The difference between Hispanic and White students' conditional odds of any postsecondary enrollment does not vary by schools' level of student-staff resources.

< Table 12c, Table 12d, Figure 12 >

LIMITATIONS

This chapter has a number of limitations. First, the results certainly do not speak to the full range of U.S. high schools. Extensive research has shown that U.S. schools are very segregated and that students sort into different schools, particularly segregated versus integrated schools, in different ways depending on their race/ethnicity (Gamoran, Collares and Barfels 2016; Goldsmith 2009; Quillian 2014; Reardon et al. 2012). These results do not speak at all to students' experiences in fully segregated schools; the results only capture differences in schools that are relatively racially diverse in that the schools had at least three White and three Black or Hispanic students sampled by the ELS. Additionally, small within-school sample sizes limit the precision of these estimates, a problem that other studies using the ELS or NELS to estimate within-school Black-White differences have also faced (cf. Kelly 2009). Also, the segregation of students across schools greatly limits the number of schools in the sample, reducing power to detect school resource effects.

Second, because of the limited number of students in the ELS who identified as multiracial, I dropped these students. However, Ferguson (2001) found that students' racial identification was associated with their academic achievement: students who were viewed by the school as "troublemakers" were more likely to identify as African American or Black, whereas students who were especially committed to academic achievement chose to identify as multiracial. Therefore, it is possible that the most academically advantaged racial/ethnic minority students may be omitted from these analyses because of my decision to drop multiracial students. In addition, although I try to highlight what makes racial/ethnic inequality more or less likely in particular contexts, I am cognizant of James' critique that statistical analyses of race tend to treat race "as if it were a fixed characteristic" rather than as a social construction (2008: 32).

Third, because Black and Hispanic students are particularly disadvantaged relative to White students in terms of wealth, the SES measure I use (like SES measures used in other national surveys) probably does not equalize Black or Hispanic and White students on important aspects of SES. Research also is equivocal on whether Black students' achievement is affected in the same ways by their parents' SES as is White students' (cf. Lubienski 2002; Riegle-Crumb and Grodsky 2010), and Black students may not be able to gain as much from their middle-class status as do White students (Lewis-McCoy 2014). In addition, the White students who attend these relatively diverse schools may be very different from the average White student. For example, it could be that the White students who attend these schools have parents who are less engaged in their education and who, thus, have not "selected out" of schools with minority students. Thus, there are many reasons to think both that White and Black or Hispanic students of "equal SES" in this sample are not equal in a host of ways and that White and Black or Hispanic students may follow different patterns in selecting into the schools in this sample.

Finally, although I restrict the sample to schools that are presumably somewhat racially diverse in that they include at least three sampled White and three Black or Hispanic students, I do not explicitly control for the racial composition of the school. I control for schools' SES composition, which some research suggests is more consequential than racial/ethnic composition for achievement (Gamoran, Collares and Barfels 2016; Goldsmith 2009; Quillian 2014; Reardon et al. 2012). Schools' socioeconomic and racial/ethnic composition are likely highly correlated, and, given the school controls I presently include, the degrees of freedom at the school level are already quite limited. However, particularly given larger within-school sample sizes and a better measure of racial composition,[3] it would be valuable in future work to examine the extent to which racial/ethnic composition effects on the degree of racial/ethnic inequality in outcomes persist net of the school-based resources examined here.

DISCUSSION

This chapter examined how Black-White and Hispanic-White disparities in educational outcomes vary across a set of U.S. high schools with relatively diverse student populations. Correlations between the random intercepts and slopes indicate that the average within-school Black-White disparity, favoring White students, is larger in schools with higher average levels of achievement and attainment; the one exception is that, conditional on both student and school covariates, there does not appear to be a relation between schools' average rate of immediate enrollment in a four-year institution and the magnitude of Black-White disparities in immediate four-year enrollment. The pattern for the Hispanic-White sample is less clear. For high school graduation and any postsecondary enrollment, the average within-school Hispanic-White disparity, favoring White students, is larger in schools with higher average levels of achievement and attainment (though this does not hold for graduation after conditioning on both student and school covariates; the correlation then is near zero). Hispanic students' disadvantage relative to White students in immediate four-year enrollment is *smaller* in schools with higher average odds of four-year enrollment, and schools' average level of math achievement is not strongly related

[3] I also recently learned that the measure of schools' percent minority is only available in the restricted use file to which I do not have access.

to the magnitude of the Hispanic-White difference in achievement. Overall, the findings, especially those from the Black-White sample, seem to contradict Lee and Bryk's (1989) finding from the HSB data that a higher average level of achievement was associated with a smaller difference between Black or Hispanic students and White students; perhaps this is because of the increasing segregation of schools from the early 1980s to the early 2000s or because Lee and Bryk included a wider array of schools in their sample than I do.

In terms of differences among school types in Black-White and Hispanic-White disparities, the most consistent difference from middle-of-the-road schools is found in less well-maintained but academically advantaged schools. Compared to middle-of-the-road schools, less well-maintained but academically advantaged schools have higher average rates of immediate four-year enrollment in the Black-White sample, but the difference in terms of odds of immediate four-year enrollment between these two types of schools is greater for White students than Black students. Similarly, in the Hispanic-White sample, White students have higher odds of any postsecondary enrollment in less well-maintained but academically advantaged schools than in middle-of-the-road schools, Hispanic students do not. Perhaps less well-maintained but academically advantaged schools have limited resources (given that we know they have physical resource problems); if this is the case, prior literature suggests that White students generally are privileged over Black or Hispanic students in terms of access to existing resources. All other differences from middle-of-the-road schools were restricted to a particular outcome and sample.

Black-White inequalities favoring White students in math achievement and high school graduation seem to be larger in schools with a more general or vocational orientation to instructional resources than in schools with the most academically oriented resources, though the differences are not statistically significant. Similarly, Hispanic-White disparities favoring White students in math achievement may be larger in schools with a more vocational orientation compared to schools with the most academically orientated instructional resources. Overall, consistent with prior literature, the findings suggest that a highly academic orientation to instruction is associated with particularly positive outcomes for minority students.

In some cases, White students' outcomes differ more between schools with the most physical resource problems and other schools than do minority students' outcomes. White students' math achievement differs more between schools with the most physical resource problems and other schools than does Black students'; coefficients for Hispanic students are in the same direction but are smaller. Likewise, Hispanic students' odds of immediate enrollment in a four-year institution differ less between schools with the most physical resource problems and other schools than do White students'; again, coefficients for Black-White differences are in the same direction. Perhaps White students benefit more than Black or Hispanic students from attending schools with the fewest physical resource problems, possibly because these schools have more resources available and disproportionately devote them to White students. However, given the small number of schools in the "most physical resource problems" category in these samples and the possibility that the results may be driven by student selection into schools, any implications should be interpreted with caution.

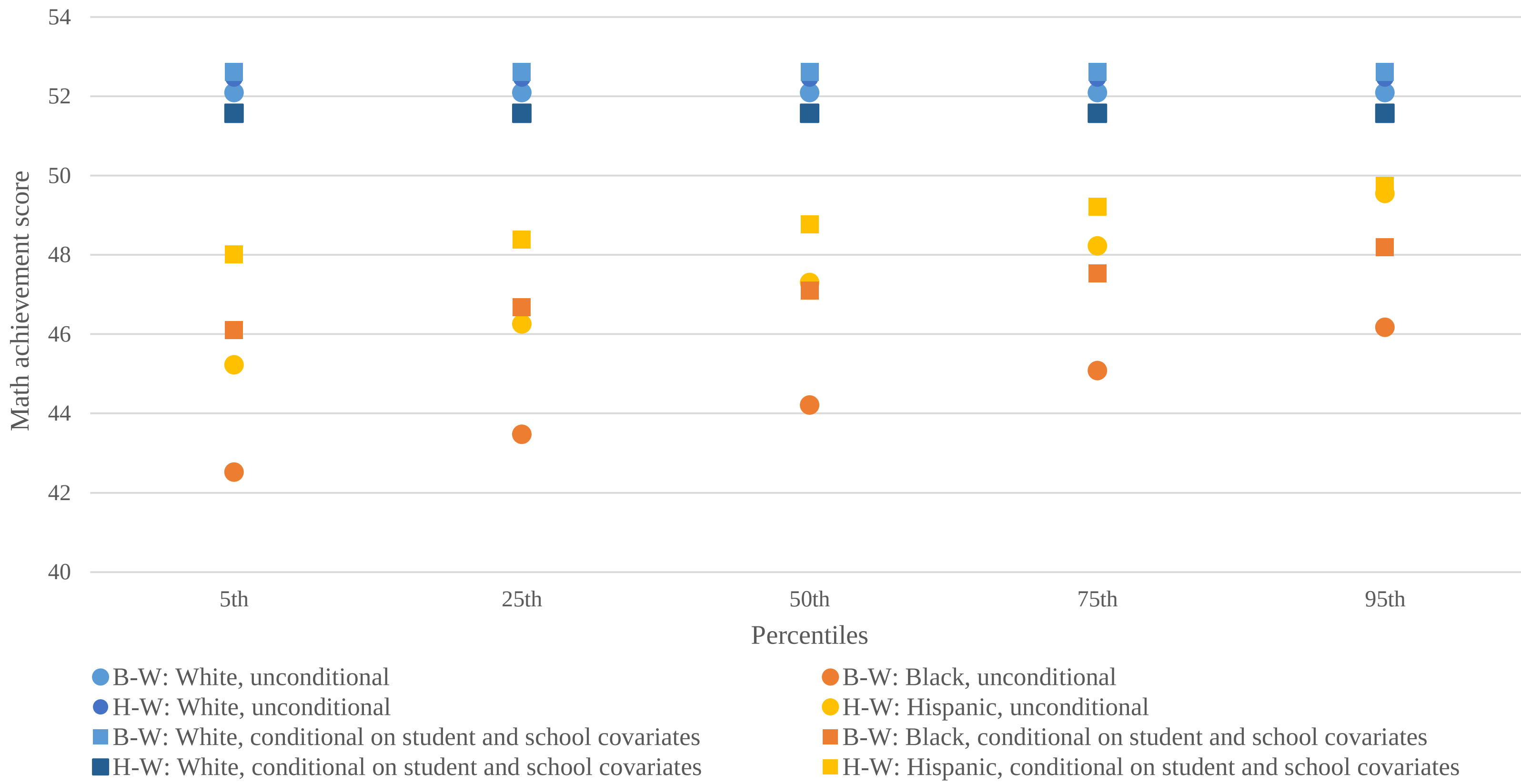
Schools with more positive student-staff relationships are associated with particularly positive outcomes for minority students in this sample. The Hispanic-White difference in math achievement is significantly more favorable for Hispanic students in schools with more positive student-staff relationships. Black students' odds of graduating high school, as well as their odds of any postsecondary enrollment, may be higher than White students' in schools with more positive student-staff relationships. Hispanic students' odds of immediate four-year enrollment are similar to White students' if they attend schools with more positive student-staff relationships but lower than White students' if they attend schools with less positive student-staff relationships. These findings are hopeful because improving student-staff relationships is one of the modifications over which schools have the most control; however, this hope should be tempered by continued uncertainty about whether and under what conditions teachers' relationships with minority students are less positive than their relationships with White students.

In some cases, schools with more academically oriented peers are associated with particularly positive outcomes for minority students: the average difference between Hispanic and White students' math achievement is significantly smaller in schools with more academically oriented peers, and Black students' odds of graduating are significantly higher than White students' in these schools. These findings support normative models of peer effects (i.e., the idea that traditionally disadvantaged groups benefit by becoming "more similar" to their academically oriented peers). In other cases, schools with less academically oriented peers are associated with particularly negative outcomes for *White* students: Hispanic and White students' graduation odds are more similar in schools with less academically oriented peers, and both Black and Hispanic students' odds of any postsecondary enrollment relative to White students' may be more favorable in schools with less academically oriented peers. These findings, all for attainment outcomes, support frog pond models of peer effects. Although frog pond models have been used to describe both cases when students benefit from being able to stand out from their peers and cases when students suffer from being compared negatively to their peers, the latter seems most plausible in this situation (i.e., Black and Hispanic students may not suffer as much from inter-student comparisons in schools with less academically-oriented peers).

CONCLUSION

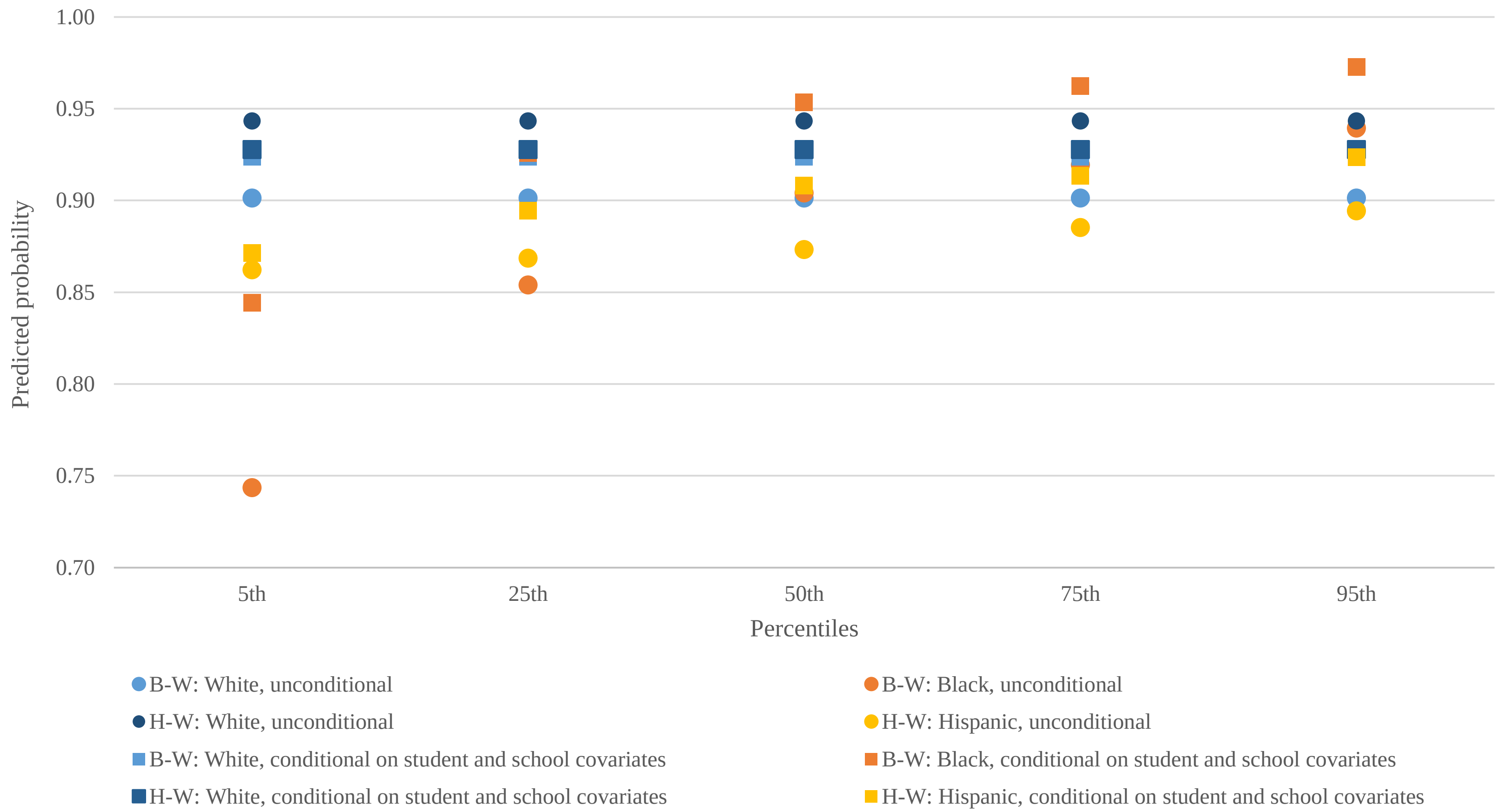
Despite the greatly reduced number of schools in these samples and the small within-school sample sizes, I found notable patterns in the relation between levels of racial/ethnic inequalities in outcomes and schools' instructional resources, physical resources, and student-staff and student-peer relationships. Additionally, I documented how, in schools with particular types of resources, Black or Hispanic and White students have fairly similar outcomes. These findings suggest that, despite the overwhelming presence of racial/ethnic inequalities in American society, under certain circumstances, racial/ethnic inequalities may not be so grim in some relatively diverse U.S. high schools.

Figure 1. Predicted Math Scores for White, Black, and Hispanic Students at Different Percentiles of the School Slopes



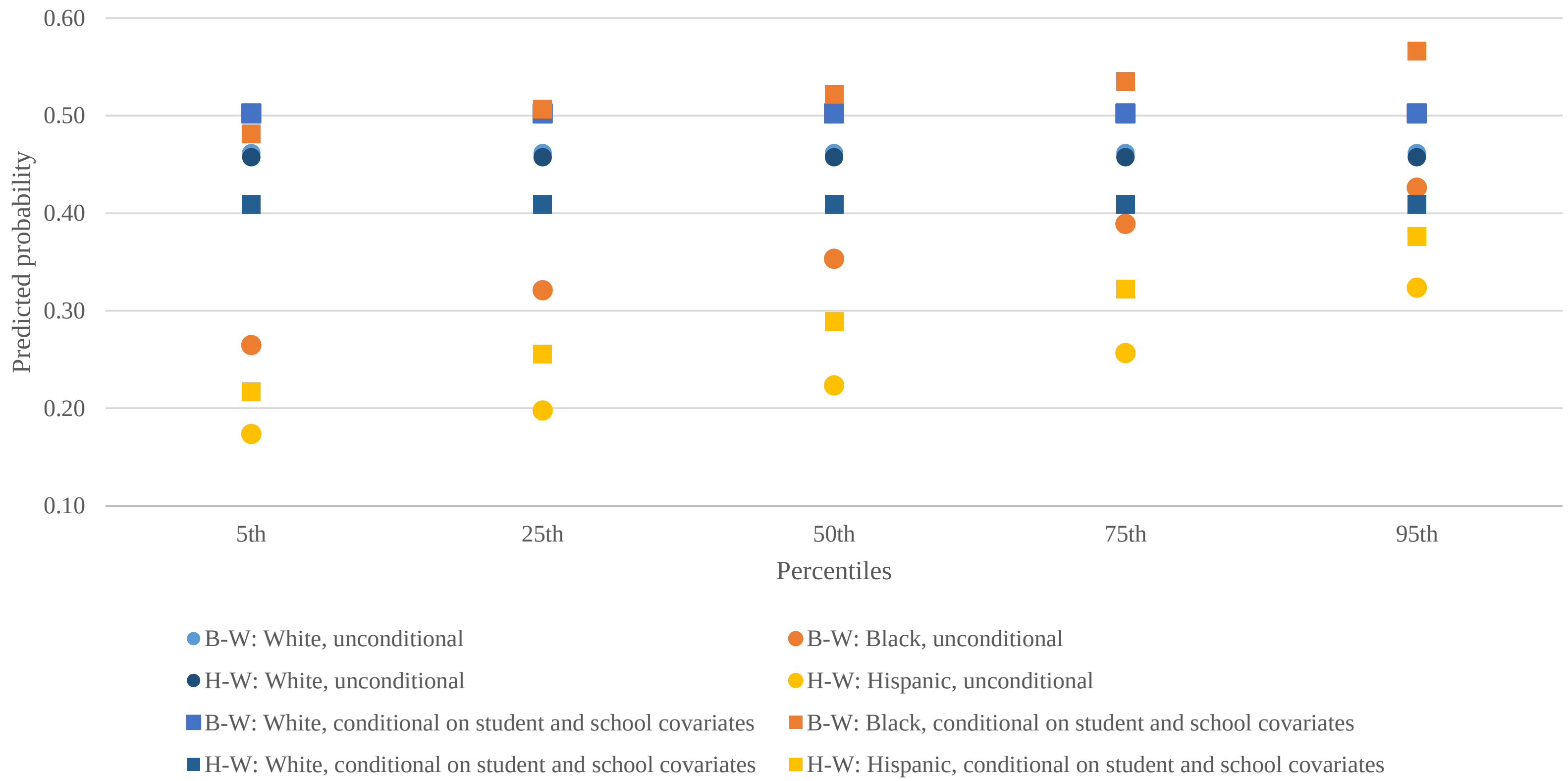
Note: "B-W" denotes predictions from the sample of schools with at least three Black and three White students, while "H-W" denotes predictions from the sample of schools with at least three Hispanic and three White students. "Unconditional" and "conditional on student and school covariates" refer to results from separate models.

Figure 2. Predicted Probability of High School Graduation for White, Black, and Hispanic Students at Different Percentiles of the School Slopes



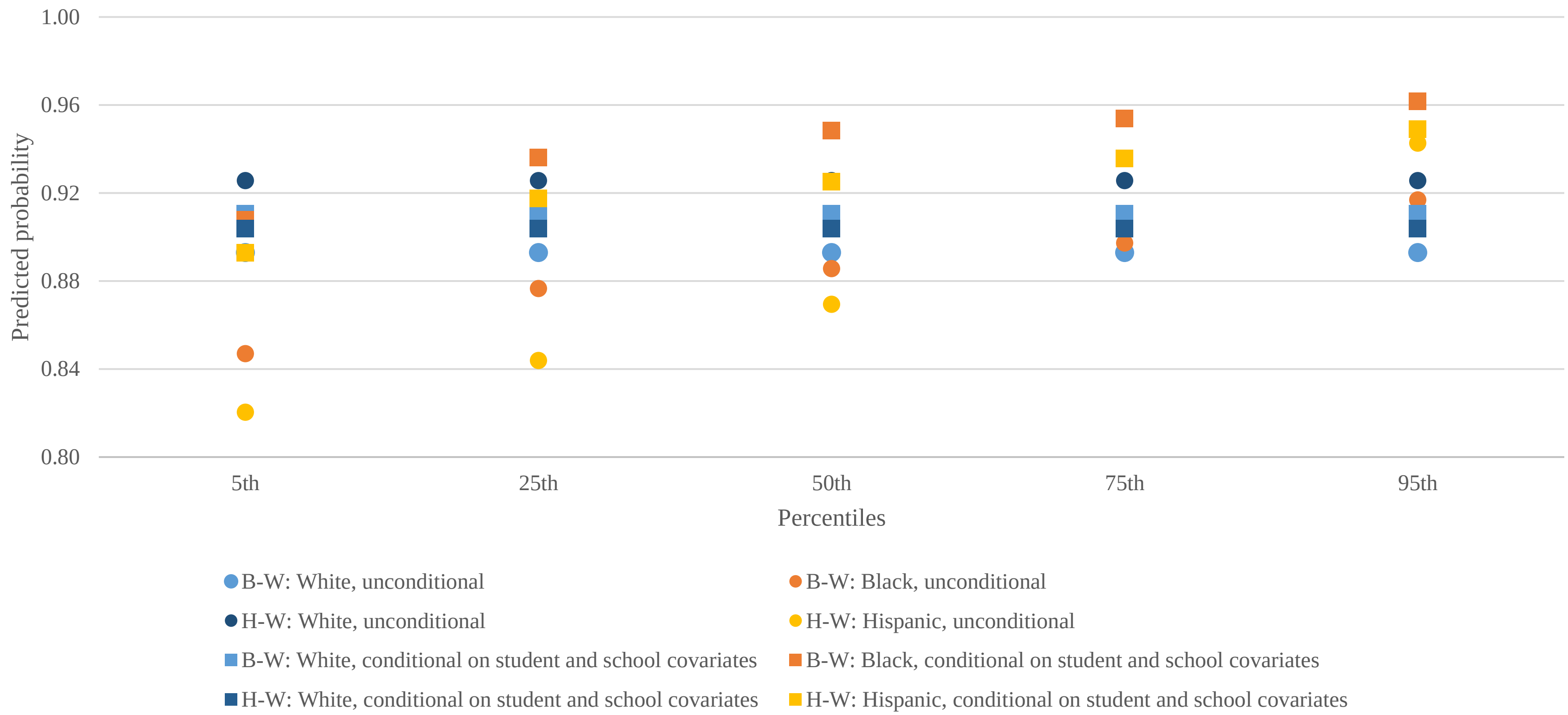
Note: "B-W" denotes predictions from the sample of schools with at least three Black and three White students, while "H-W" denotes predictions from the sample of schools with at least three Hispanic and three White students. "Unconditional" and "conditional on student and school covariates" refer to results from separate models.

Figure 3. Predicted Probability of Immediate Enrollment in a Four-Year Institution for White, Black, and Hispanic Students at Different Percentiles of the School Slopes



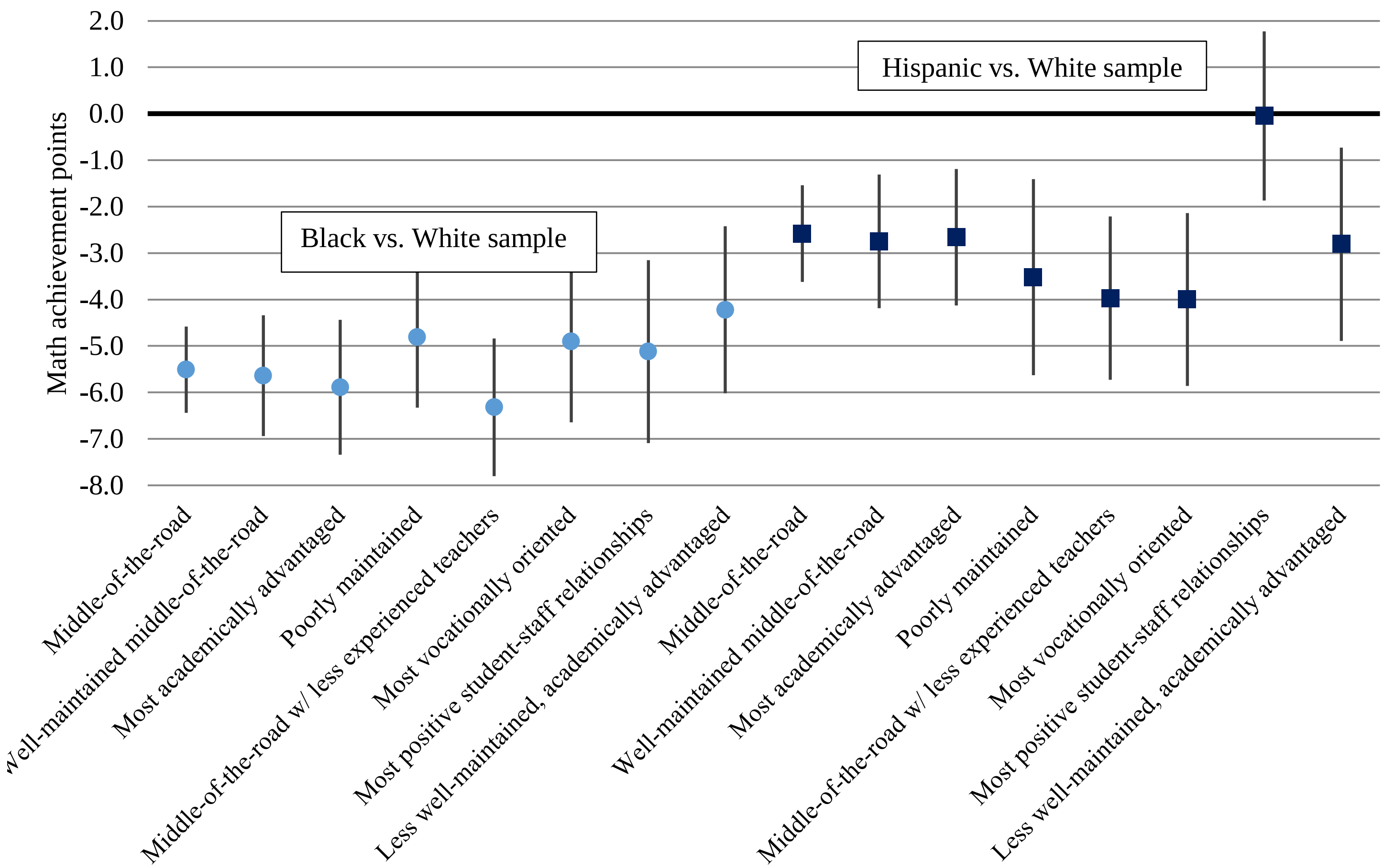
Note: "B-W" denotes predictions from the sample of schools with at least three Black and three White students, while "H-W" denotes predictions from the sample of schools with at least three Hispanic and three White students. "Unconditional" and "conditional on student and school covariates" refer to results from separate models.

Figure 4. Predicted Probability of Any Postsecondary Enrollment for White, Black, and Hispanic Students at Different Percentiles of the School Slopes



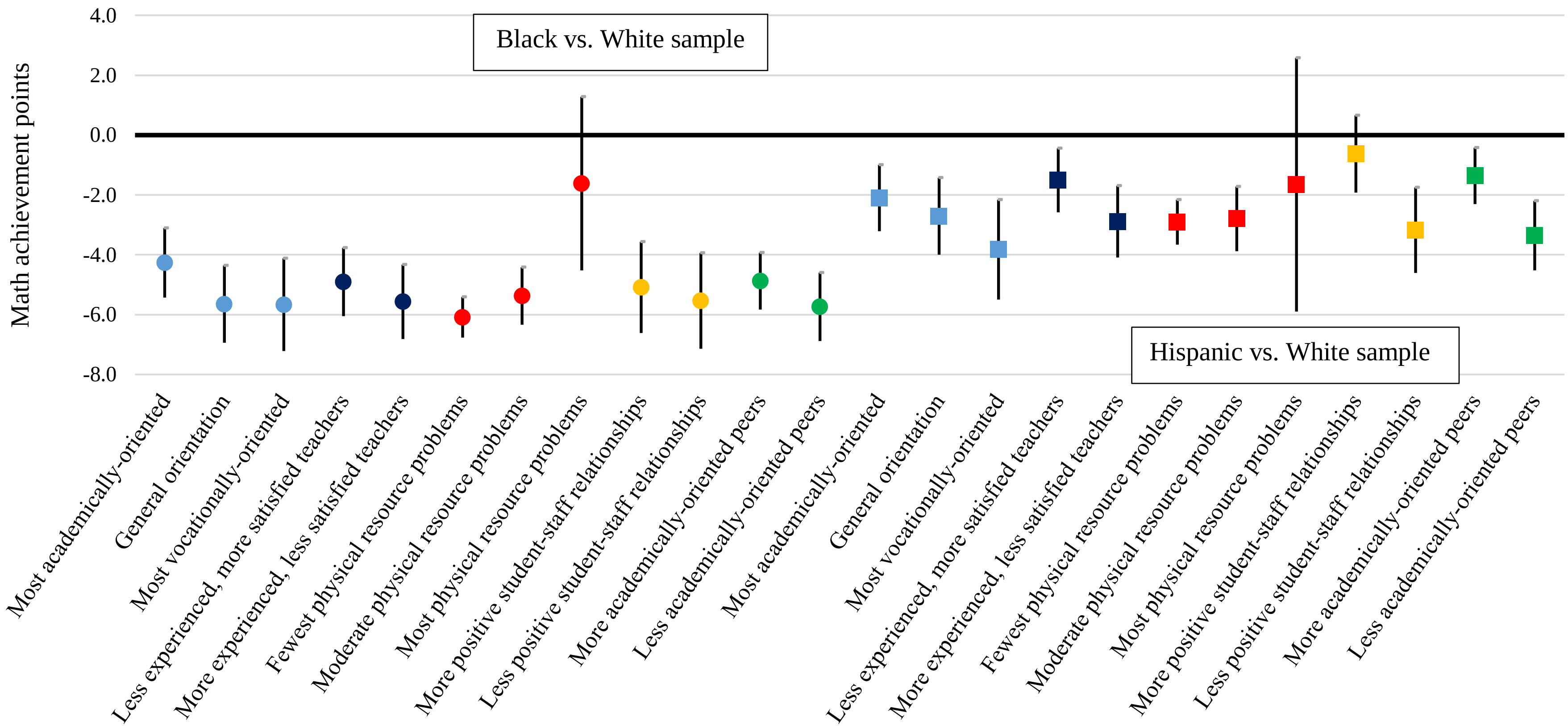
Note: “B-W” denotes predictions from the sample of schools with at least three Black and three White students, while “H-W” denotes predictions from the sample of schools with at least three Hispanic and three White students. “Unconditional” and “conditional on student and school covariates” refer to results from separate models.

Figure 5. Predicted Difference in Math Achievement for White versus Black or Hispanic Students by School Type



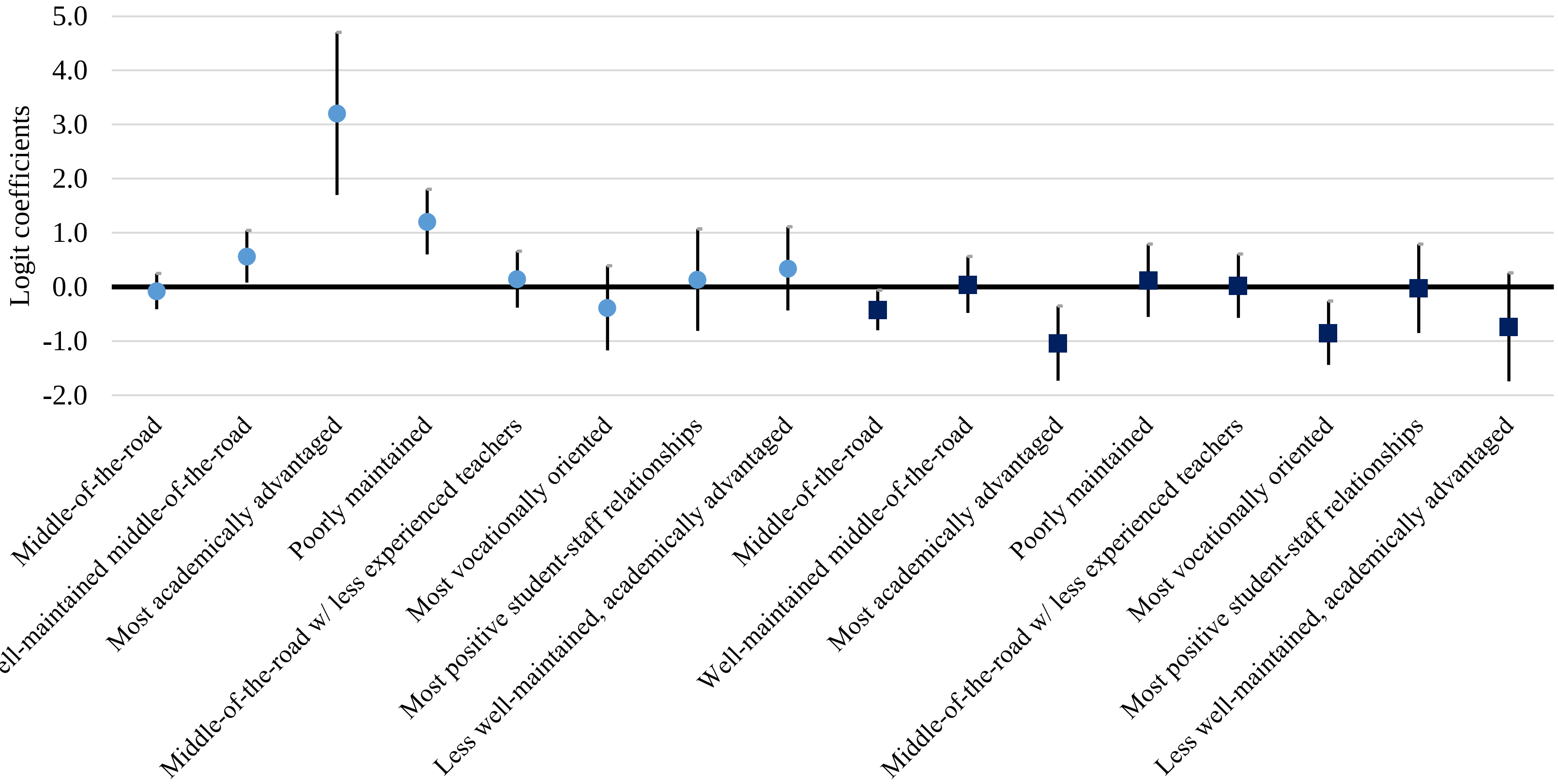
Note: Point estimates in light blue are from the sample of schools with at least three Black and three White students; point estimates in dark blue are from the sample of schools with at least three Hispanic and three White students. Point estimates represent the student-level race/ethnicity parameter plus the cross-level interaction between race/ethnicity and the measures of school type shown here. Error bars represent plus or minus one standard error of the estimated effect. Models condition on student and school covariates.

Figure 6. Predicted Difference in Math Achievement for White versus Black or Hispanic Students by Individual Resource Classes



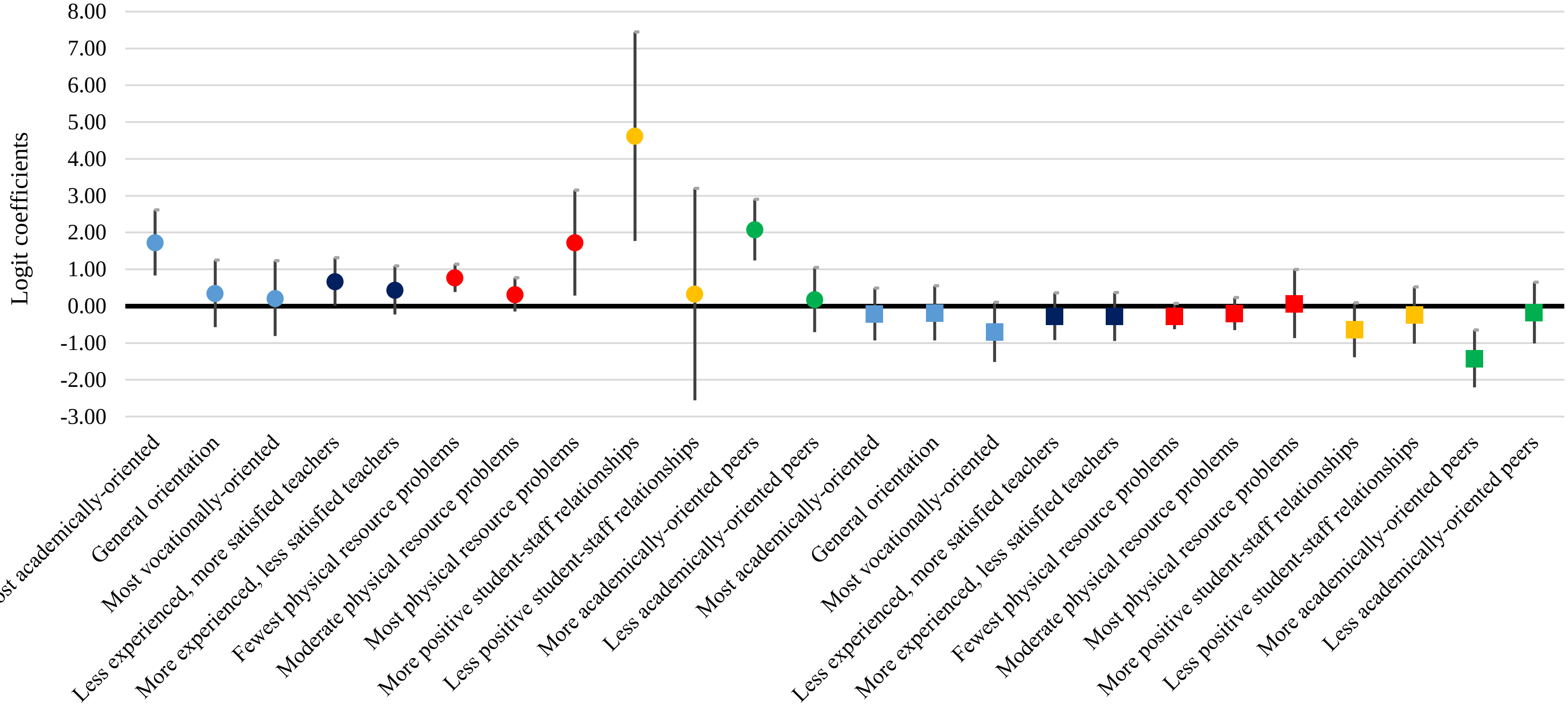
Note: The first set of point estimates are from the sample of schools with at least three Black and three White students; the second set are from the sample of schools with at least three Hispanic and three White students. Point estimates represent the student-level race/ethnicity parameter plus the cross-level interaction between race/ethnicity and the measures of school resources shown here. Error bars represent plus or minus one standard error of the estimated effect. Models condition on student and school covariates.

Figure 7. Predicted Difference in Log Odds of High School Graduation for White versus Black or Hispanic Students by School Type



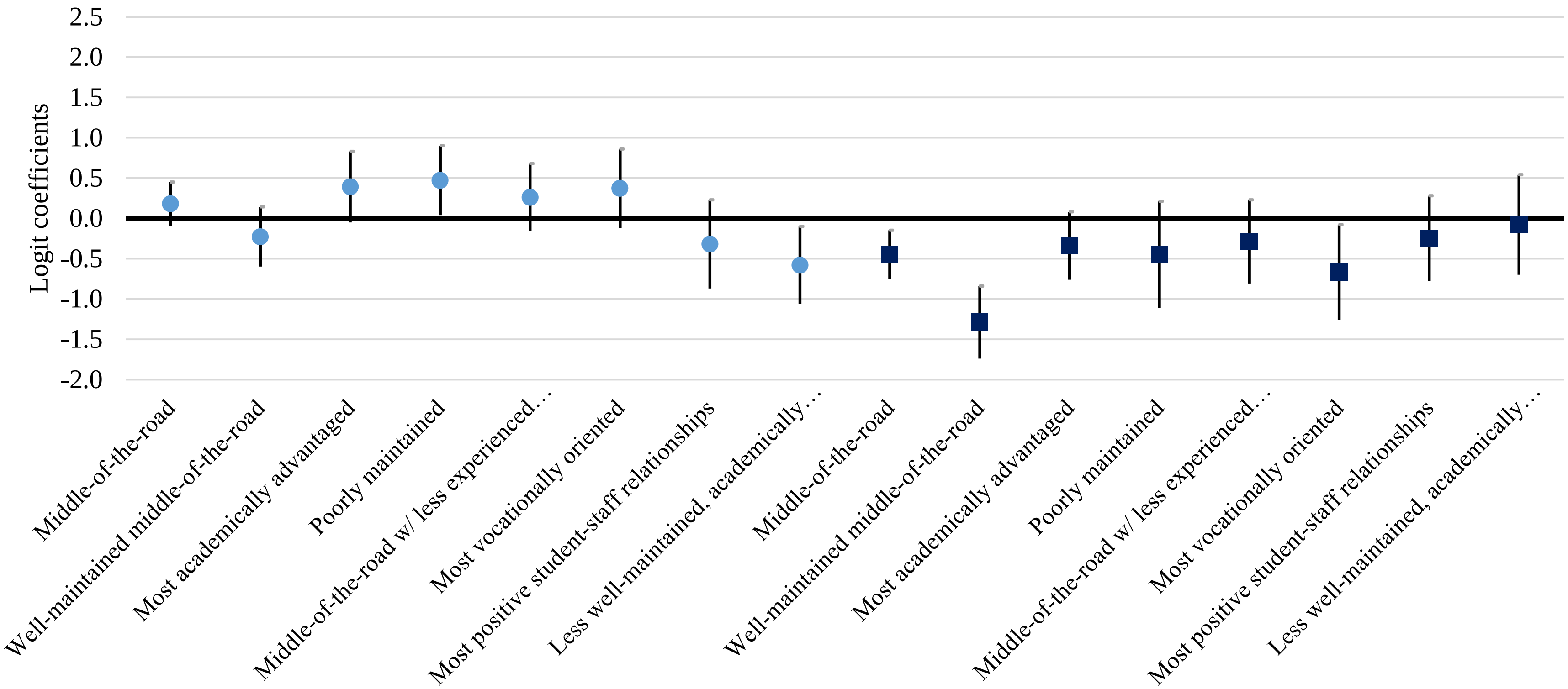
Note: Point estimates in light blue are from the sample of schools with at least three Black and three White students; point estimates in dark blue are from the sample of schools with at least three Hispanic and three White students. Point estimates represent the student-level race/ethnicity parameter plus the cross-level interaction between race/ethnicity and the measures of school type shown here. Error bars represent plus or minus one standard error of the estimated effect. Models condition on student and school covariates.

Figure 8. Predicted Difference in Log Odds of High School Graduation for White versus Black or Hispanic Students by Individual Resource Classes



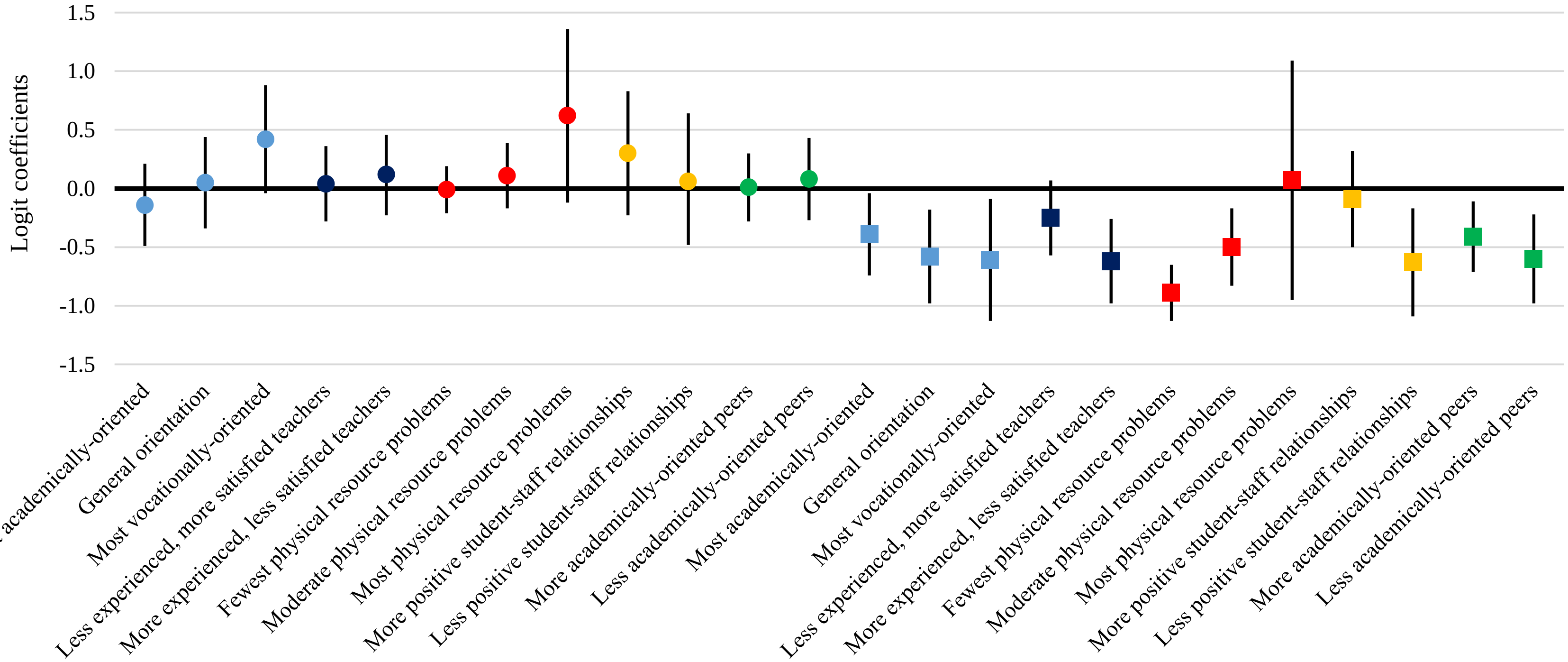
Note: The first set of point estimates are from the sample of schools with at least three Black and three White students; the second set are from the sample of schools with at least three Hispanic and three White students. Point estimates represent the student-level race/ethnicity parameter plus the cross-level interaction between race/ethnicity and the measures of school resources shown here. Error bars represent plus or minus one standard error of the estimated effect. Models condition on student and school covariates.

Figure 9. Predicted Difference in Log Odds of Immediate Enrollment in a Four-Year Institution for White versus Black or Hispanic Students by School Type



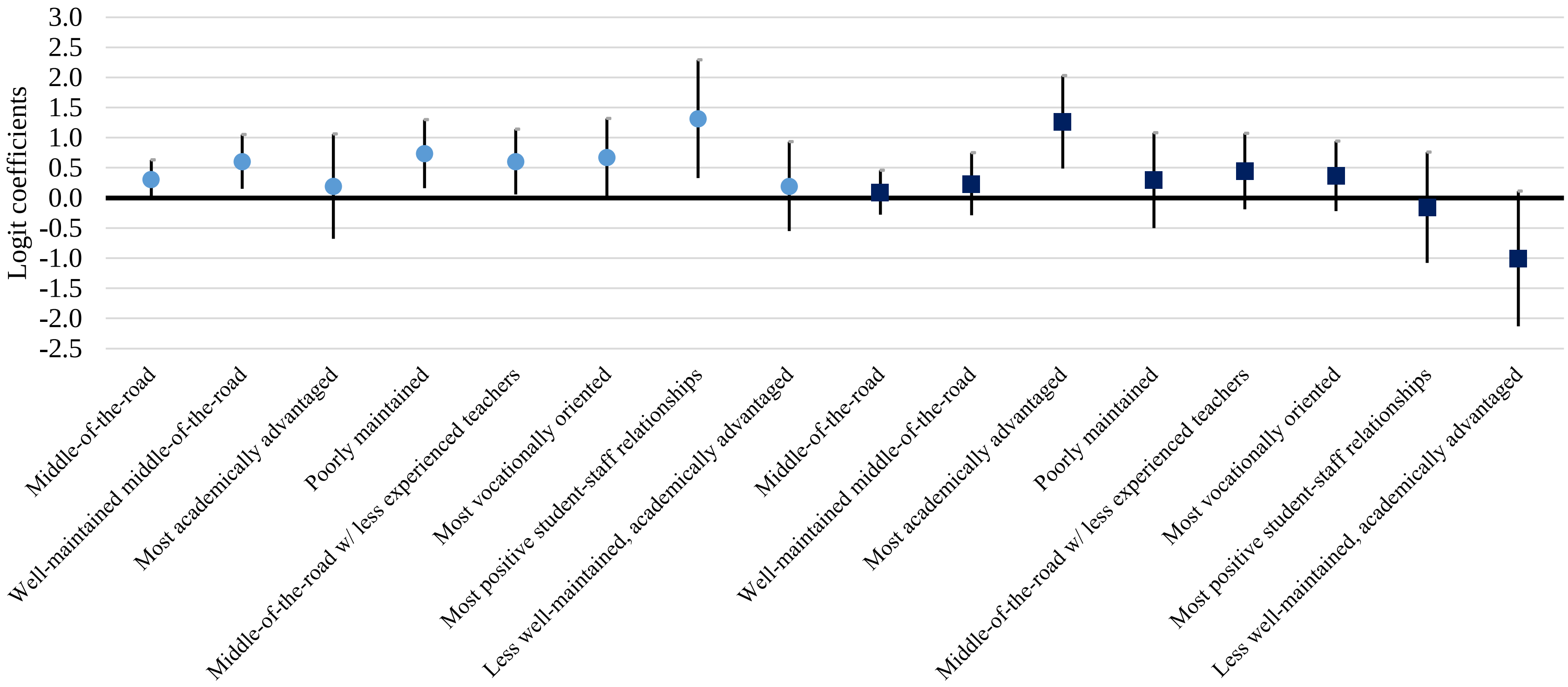
Note: Point estimates in light blue are from the sample of schools with at least three Black and three White students; point estimates in dark blue are from the sample of schools with at least three Hispanic and three White students. Point estimates represent the student-level race/ethnicity parameter plus the cross-level interaction between race/ethnicity and the measures of school type shown here. Error bars represent plus or minus one standard error of the estimated effect. Models condition on student and school covariates.

Figure 10. Predicted Difference in Log Odds of Immediate Enrollment in a Four-Year Institution for White versus Black or Hispanic Students by Individual Resource Classes



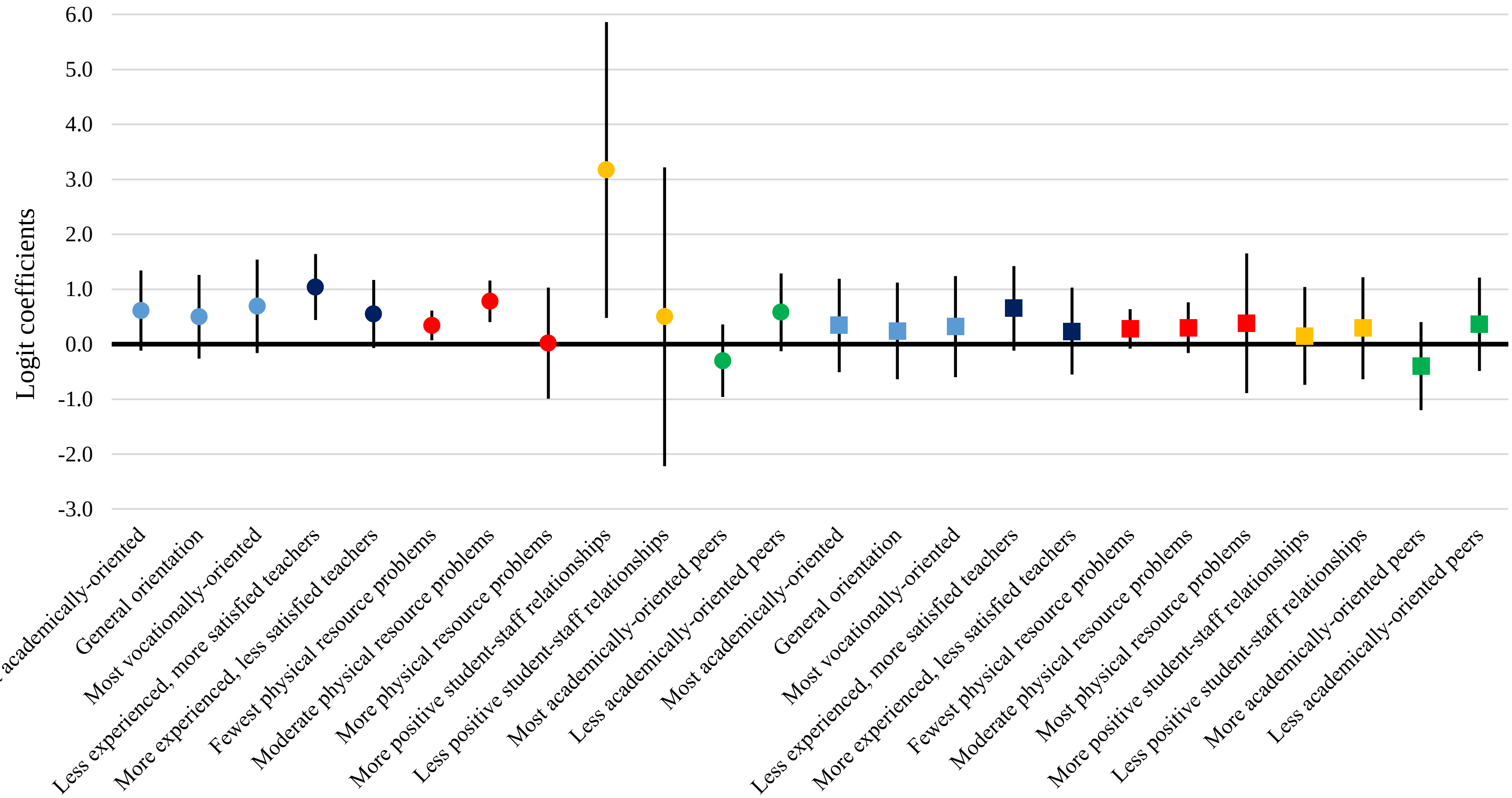
Note: The first set of point estimates are from the sample of schools with at least three Black and three White students; the second set are from the sample of schools with at least three Hispanic and three White students. Point estimates represent the student-level race/ethnicity parameter plus the cross-level interaction between race/ethnicity and the measures of school resources shown here. Error bars represent plus or minus one standard error of the estimated effect. Models condition on student and school covariates.

Figure 11. Predicted Difference in Log Odds of Any Postsecondary Enrollment for White versus Black or Hispanic Students by School Type



Note: Point estimates in light blue are from the sample of schools with at least three Black and three White students; point estimates in dark blue are from the sample of schools with at least three Hispanic and three White students. Point estimates represent the student-level race/ethnicity parameter plus the cross-level interaction between race/ethnicity and the measures of school type shown here. Error bars represent plus or minus one standard error of the estimated effect. Models condition on student and school covariates.

Figure 12. Predicted Difference in Log Odds of Any Postsecondary Enrollment for White versus Black or Hispanic Students by Individual Resource Classes



Note: The first set of point estimates are from the sample of schools with at least three Black and three White students; the second set are from the sample of schools with at least three Hispanic and three White students. Point estimates represent the student-level race/ethnicity parameter plus the cross-level interaction between race/ethnicity and the measures of school resources shown here. Error bars represent plus or minus one standard error of the estimated effect. Models condition on student and school covariates.

Table 1. Comparison of School Types and Resource Classes for All Schools versus Schools with Adequate Numbers of Sampled White, Black, and Hispanic Students

		Total Sample	Black-White Sample	Hispanic-White Sample
School Background Characteristics	Private	23%	15-17%	24-26%
	Urban	33%	35-36%	36-38%
	Rural	19%	15-17%	8-10%
	Suburban	48%	47-50%	52-54%
	Low-FRL	41%	25-28%	37-39%
	Medium-FRL	43%	53-56%	49-52%
	High-FRL	15%	18-20%	10-13%
School Types	Middle-of-the-Road Schools	18%	23-24%	21-22%
	Well-Maintained Middle-of-the-Road Schools	15%	18-19%	19-21%
	Most Academically Advantaged Schools	16%	13-14%	16-18%
	Poorly Maintained Schools	11%	10-11%	8%
	Middle-of-the-Road Schools w/ Less Experienced Teachers	10%	13-14%	11-12%
	Most Vocationally Oriented Schools	10%	6-8%	9-11%
	Schools with Most Positive Student-Staff Relationships	10%	4-5%	7-8%
	Less Well-Maintained, Academically Advantaged Schools	9%	7-8%	5-6%
	N	*751*	*135-156*	*117-136*
Instructional Resource Classes	General Orientation	62%	69-70%	67-68%
	Most Vocationally Oriented	21%	14-16%	14-16%
	Most Academically Oriented	17%	15-16%	17-18%
	N	*751*	*135-156*	*117-136*
Teacher Resource Classes	More Experienced but Less Satisfied Teachers	80%	85-86%	80-82%
	Less Experienced but More Satisfied Teachers	20%	14-15%	18-20%
	N	*733*	*133-154*	*116-134*

Physical Resource Classes	Fewest Problems	43%	43-46%	42-44%
	Moderate Problems	51%	50-53%	52-53%
	Most Problems	6%	4%	3-5%
	N	*618*	*112-130*	*97-112*
Student-Staff Resource Classes	Less Positive Relationships	89%	93-94%	88-90%
	More Positive Relationships	11%	6-7%	10-12%
	N	*751*	*135-156*	*117-136*
Student-Peer Resource Classes	Less Academically Oriented Peers	75%	78-80%	75-77%
	More Academically Oriented Peers	25%	20-22%	23-25%
	N	*751*	*135-156*	*117-136*
Average Outcomes	Math Achievement Score	50.74	49.38	50.44
	High School Graduation	0.89	0.87	0.90
	Immediate Enrollment in a Four-Year Institution	0.45	0.43	0.42
	Any Postsecondary Enrollment	0.88	0.87	0.89

Notes: "Total sample" includes all schools; "Black-White sample" includes only schools with at least three Black and three White students with data for a given outcome; "Hispanic-White sample" includes only schools with at least three Hispanic and three White students with data for a given outcome. For each sample, percentages and N's vary depending on the outcome variable.

Table 2. Outcome and Resource Measures by Race/Ethnicity

		Black-White Sample		Hispanic-White Sample	
		White	Black	White	Hispanic
Outcome Measures	Mean math achievement	52.56*	44.27*	52.48*	46.90*
		(9.54)	(0.29)	(9.34)	(9.71)
	Proportion high school graduates	0.89*	0.85*	0.93*	0.85*
	Proportion immediate enrollment in four-year institution	0.48*	0.36*	0.47*	0.27*
	Proportion any postsecondary enrollment	0.87	0.86	0.90*	0.85*
Instructional Resources	Use of school media center for assignments	2.15*	2.30*	2.08	2.04
		(0.93)	(0.98)	(0.93)	(0.93)
	Use of school media center for research papers	2.42*	2.58*	2.32	2.33
		(1.02)	(1.04)	(1.02)	(1.03)
	Proportion ever in Advanced Placement course or International Baccalaureate program	0.23*	0.15*	0.22*	0.17*
	Proportion ever in remedial English or math course	0.10	0.13	0.12	0.14
	Proportion in general program	0.31	0.30	0.33*	0.38*
	Proportion in college preparatory/academic program	0.60*	0.54*	0.58*	0.50*
	Proportion in vocational (including technical/business) program	0.09*	0.16*	0.09*	0.12*
	Years of advanced science coursework completed	1.06*	0.87*	1.14*	0.86*
		(0.87)	(0.79)	(0.84)	(0.80)
	Years of advanced math coursework completed	0.69*	0.41*	0.72*	0.42*
		(0.88)	(0.71)	(0.93)	(0.74)
	Proportion participated in cooperative education	0.13*	0.18*	0.14	0.14
	Proportion participated in school-organized internships	0.04*	0.10*	0.05	0.04
	Proportion participated in job shadowing or work visits	0.11*	0.18*	0.11*	0.08*
	Proportion participated in school-organized mentoring	0.05*	0.08*	0.05	0.06
Teacher Resources	Proportion w/ teacher w/ 2 or fewer years of teaching experience	0.20	0.22	0.21*	0.27*
	Proportion w/ teacher w/ 3 to 4 years of teaching experience	0.14	0.15	0.17	0.17

	Proportion w/ teacher w/ regular/standard certification	0.78	0.76	0.74*	0.69*
	Proportion w/ English teacher w/ bachelor's degree in English	0.90*	0.86*	0.82	0.80
	Proportion w/ math teacher w/ bachelor's degree in math	0.86*	0.80*	0.81	0.78
	Proportion w/ English teacher w/ graduate degree in English	0.27	0.24	0.20*	0.15*
	Proportion w/ math teacher w/ graduate degree in math	0.26	0.23	0.17	0.18
	Number of days teacher was absent during first semester	2.67*	2.98*	2.79	2.95
		(2.39)	(3.16)	(2.68)	(2.86)
	If starting over, likelihood of becoming a teacher again	2.93*	2.85*	3.02	3.04
		(0.85)	(0.90)	(0.83)	(0.86)
Physical Resources	Learning hindered by…				
	Poor condition of buildings	1.53	1.49	1.52*	1.60*
		(0.74)	(0.73)	(0.76)	(0.87)
	Poor heating, cooling, lighting	1.66	1.73	1.76*	1.67*
		(0.79)	(0.87)	(0.86)	(0.84)
	Inadequate science laboratory equipment	1.65	1.69	1.69*	1.82*
		(0.85)	(0.85)	(0.79)	(0.89)
	Inadequate facilities for fine arts	2.03*	1.89*	1.89*	1.77*
		(0.97)	(0.95)	(0.88)	(0.82)
	Lack of instructional space	1.76	1.72	1.81*	1.67*
		(0.95)	(0.85)	(0.88)	(0.84)
	Lack of instructional materials in the library	1.60	1.55	1.63	1.57
		(0.79)	(0.75)	(0.82)	(0.74)
	Lack of textbooks and basic supplies	1.38	1.40	1.40	1.42
		(0.64)	(0.61)	(0.62)	(0.64)
	Not enough computers for instruction	1.80	1.84	1.84*	1.72
		(0.88)	(0.85)	(0.81)	(0.73)
	Lack of multimedia resources for instruction	1.82*	1.93*	1.78*	1.69*
		(0.82)	(0.80)	(0.76)	(0.72)
	Inadequate vocational equipment/facilities	1.66	1.68	1.64	1.66
		(0.84)	(0.83)	(0.88)	(0.91)
Student-Staff Resources	Students get along well with teachers	2.78*	2.60*	2.81	2.77
		(0.59)	(0.67)	(0.57)	(0.63)
	Teachers are interested in students	2.88*	2.77*	2.88	2.89
		(0.68)	(0.76)	(0.67)	(0.71)
	Teachers praise effort	2.75	2.78	2.74	2.80
		(0.73)	(0.80)	(0.75)	(0.76)

	In class often feels put down by teachers	3.14 (0.67)	3.19 (0.73)	3.14 (0.67)	3.10 (0.74)
	Proportion talk with at least one teacher	0.53*	0.46*	0.57*	0.53*
	Proportion at least one school-based adult wants student to attend college	0.77*	0.82*	0.76	0.73
	Student morale is high	3.99 (0.76)	3.94 (0.75)	4.14* (0.75)	3.99* (0.81)
	Teachers press students to achieve	4.17* (0.81)	4.09* (0.80)	4.17* (0.77)	3.99* (0.86)
	Teacher morale is high	3.81 (0.80)	3.81 (0.80)	3.85* (0.74)	3.73* (0.79)
	How often verbal abuse of teachers a problem	3.73 (0.85)	3.68 (0.74)	3.86 (0.74)	3.85 (0.74)
	How often disrespect for teachers a problem	3.50* (0.97)	3.38* (1.00)	3.67 (0.90)	3.65 (0.94)
Student-Peer Resources	Important to friends to get good grades	2.45* (0.60)	2.59* (0.60)	2.45 (0.59)	2.43 (0.62)
	Important to friends to continue education	2.55 (0.60)	2.58 (0.61)	2.53 (0.61)	2.49 (0.65)
	How many friends plan to have full-time job	2.47* (1.16)	2.70* (1.19)	2.48* (1.17)	2.70* (1.10)
	How many friends plan to attend four-year college	3.42* (1.07)	3.23* (1.09)	3.42* (1.03)	3.10* (1.13)
	In class often feels put down by other students	3.08* (0.70)	3.18* (0.75)	3.08 (0.69)	3.08 (0.75)
	Proportion student relates well to others	0.82	0.81	0.82	0.82
	How often physical conflicts a problem at school	3.56* (0.82)	3.44* (0.82)	3.66* (0.69)	3.47* (0.76)
	How often student bullying a problem at school	3.64 (0.67)	3.67 (0.62)	3.64 (0.72)	3.66 (0.68)

*p < .05

Table 3a. Model Fit Statistics for Random Intercept and Random Slope Null Models

	Math Achievement			High School Graduation			Immediate Enrollment in a Four-Year Institution			Any Postsecondary Enrollment		
Random Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Black Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Random Slope			Yes			Yes			Yes			Yes
AIC	15,183.4	14,827.9	14,827.9	1,992.7	1,989.9	1,396.4	3,000.3	2,979.7	2,981.5	1,780.9	1,782.6	1,787.0
Log-Likelihood	-7,588.7	-7,409.9	-7,407.9	-993.3	-989.9	-693.2	-1,498.2	-1,486.8	-1,485.7	-888.4	-888.3	-888.5
R-Squared	0.26	0.37	0.39	0.10	0.15	0.12	0.23	0.24	0.25	0.11	0.11	0.13

Table 3b. Model Fit Statistics for Random Intercept and Random Slope Null Models

	Math Achievement			High School Graduation			Immediate Enrollment in a Four-Year Institution			Any Postsecondary Enrollment		
Random Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hisp. Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Random Slope			Yes			Yes			Yes			Yes
AIC	12,395.8	12,280.6	12,278.4	1,416.6	1,391.2	1,396.4	2,381.6	2,317.3	2,319.4	1,342.3	1,339.4	1,339.5
Log-Likelihood	-6,194.9	-6,136.3	-6,133.2	-706.3	-692.6	-693.2	-1,188.8	-1,155.6	-1,154.7	-669.2	-666.7	-664.8
R-Squared	0.22	0.26	0.29	0.10	0.11	0.12	0.26	0.28	0.29	0.12	0.12	0.15

Table 4a. Variation in the Difference between Black and White Students' Outcomes across High Schools

		Math Achievement			High School Graduation			Immediate Enrollment in a Four-Year Institution			Any Postsecondary Enrollment		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Fixed Effects	Black	-7.78*	-5.59*	-5.50*	-0.05	0.29	0.43*	-0.47*	0.02	0.08	-0.06	0.51*	0.55*
		(0.44)	(0.42)	(0.42)	(0.20)	(0.20)	(0.21)	(0.11)	(0.12)	(0.12)	(0.18)	(0.18)	(0.18)
	Intercept	52.09*	51.20*	52.62*	2.21*	2.32*	2.50*	-0.15	-0.12	0.01	2.12*	2.33*	2.32*
		(0.45)	(0.40)	(0.71)	(0.11)	(0.13)	(0.23)	(0.11)	(0.11)	(0.17)	(0.12)	(0.13)	(0.22)
Random Effects	SD of Black Slope	2.24	1.77	1.79	0.96	1.01	1.09	0.44	0.34	0.34	0.59	0.65	0.66
	SD of Intercept	4.37	3.06	2.58	0.65	0.55	0.43	1.10	0.82	0.52	0.78	0.44	0.29
	Corr. Interc. - Slope	-0.53	-0.48	-0.31	-0.24	-0.34	-0.36	-0.65	-0.44	0.06	-0.32	-0.18	-0.19
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes			Yes
N	Students	2,077	2,077	2,050	2,693	2,693	2,602	2,376	2,376	2,305	2,335	2,335	2,256
	Schools	135	135	134	156	156	153	146	146	144	142	142	139
Model Fit Statistics	AIC	14,827.9	14,498.0	14,294.1	1,989.9	1,924.8	1,801.5	2,981.5	2,695.8	2,566.0	1,787.0	1,644.9	1,553.6
	Log-likelihood	-7,407.93	-7,238.98	-7,133.05	-989.94	-953.42	-887.76	-1,485.73	-1,338.91	-1,269.01	-888.52	-813.47	-763.81
	R-squared	0.39	0.45	0.45	0.15	0.15	0.15	0.25	0.31	0.31	0.13	0.14	0.14

*p < .05

Table 4b. Variation in the Difference between Hispanic and Non-Hispanic White Students' Outcomes across High Schools

		Math Achievement			High School Graduation			Immediate Enrollment in a Four-Year Institution			Any Postsecondary Enrollment		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Fixed Effects	Hispanic	-5.10*	-2.76*	-2.78*	-0.85*	-0.37†	-0.29	-1.04*	-0.54*	-0.54*	-0.56*	0.18	0.29
		(0.52)	(0.48)	(0.48)	(0.20)	(0.20)	(0.21)	(0.14)	(0.14)	(0.14)	(0.21)	(0.21)	(0.20)
	Intercept	52.46*	51.19*	51.56*	2.81*	2.76*	2.56*	-0.17	-0.23†	-0.37*	2.52*	2.47*	2.24*
		(0.42)	(0.41)	(0.66)	(0.16)	(0.17)	(0.25)	(0.12)	(0.12)	(0.19)	(0.18)	(0.17)	(0.23)
Random Effects	SD of Hispanic Slope	2.60	1.69	1.58	0.44	0.46	0.54	0.46	0.41	0.48	0.80	0.78	0.73
	SD of Intercept	3.27	2.23	1.79	0.82	0.63	0.54	1.04	0.80	0.50	1.12	0.71	0.44
	Corr. Interc. - Slope	0.16	-0.01	-0.16	-0.47	-0.29	0.01	0.55	0.38	0.50	-0.81	-0.83	-0.74
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes			Yes
N	Students	1,695	1,695	1,669	2,239	2,239	2,189	1,946	1,946	1,910	1,913	1,913	1,870
	Schools	117	117	116	136	136	135	128	128	127	123	123	122
Model Fit Statistics	AIC	12,278.4	12,002.6	11,810.7	1,396.4	1,352.2	1,281.2	2,319.4	2,142.0	2,050.7	1,339.5	1,246.0	1,191.8
	Log-likelihood	-6,133.2	-5,991.3	-5,891.3	-693.2	-667.1	-627.6	-1,154.7	-1,062.0	-1,012.4	-664.8	-614.0	-582.9
	R-squared	0.29	0.35	0.34	0.12	0.12	0.13	0.29	0.34	0.33	0.15	0.13	0.13

*p < .05

Table 5a. Variation by School Type in the Difference between Black and White Students' Math Achievement

		Model 1	Model 2	Model 3
Student-Level Variables	Black	-7.63*	-5.66*	-5.51*
		(1.00)	(0.92)	(0.93)
	Intercept	50.96*	50.53*	52.15*
		(0.88)	(0.74)	(0.97)
School Types	Well-Maintained Middle-of-the-Road Schools	0.25	0.20	0.15
		(1.28)	(1.04)	(1.01)
	Most Academically Advantaged Schools	6.14*	3.88*	3.02*
		(1.34)	(1.09)	(1.30)
	Poorly Maintained Schools	-0.40	-0.52	-0.32
		(1.50)	(1.23)	(1.21)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.35	-0.35	-0.66
		(1.42)	(1.16)	(1.14)
	Most Vocationally Oriented Schools	-2.14	-1.59	-1.31
		(1.73)	(1.42)	(1.39)
	Schools with Most Positive Student-Staff Relationships	0.76	0.35	-0.23
		(1.93)	(1.54)	(1.66)
	Less Well-Maintained, Academically Advantaged Schools	5.51*	3.76*	3.02*
		(1.65)	(1.32)	(1.33)
Cross-Level Interactions	Black*Well-Maintained Middle-of-the-Road Schools	-0.08	0.05	-0.13
		(1.43)	(1.28)	(1.30)
	Black*Most Academically Advantaged Schools	-0.18	-0.28	-0.38
		(1.60)	(1.44)	(1.45)
	Black*Poorly Maintained Schools	0.69	1.25	0.70
		(1.66)	(1.50)	(1.52)
	Black*Middle-of-the-Road Schools with Less Experienced Teachers	-0.76	-0.78	-0.81
		(1.62)	(1.46)	(1.48)
	Black*Most Vocationally Oriented Schools	0.91	0.75	0.61
		(1.92)	(1.73)	(1.74)
	Black*Schools with Most Positive Student-Staff Relationships	0.18	0.51	0.39
		(2.18)	(1.96)	(1.97)
	Black*Less Well-Maintained, Academically Advantaged Schools	-0.11	0.72	1.29
		(1.95)	(1.76)	(1.80)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Black Slope	2.23	1.73	1.70
	Std. Dev. of Intercept	3.50	2.55	2.34

	Correlation between Intercept and Slope	-0.55	-0.51	-0.38
N	Students	2,077	2,077	2,050
	Schools	135	135	134
Model Fit Statistics	AIC	14,807.1	14,489.2	14,301.3
	Log-likelihood	-7,383.6	-7,220.6	-7,122.7
	R-squared	0.38	0.45	0.45

School types based on class membership probabilities. *p < .05, †p < .10

Table 5b. Variation by School Type in the Difference between Hispanic and Non-Hispanic White Students' Math Achievement

		Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-4.73*	-3.00*	-2.58*
		(1.13)	(1.02)	(1.04)
	Intercept	51.10*	50.41*	51.18*
		(0.78)	(0.73)	(0.90)
School Types	Well-Maintained Middle-of-the-Road Schools	-0.47	-0.07	0.34
		(1.14)	(1.03)	(1.03)
	Most Academically Advantaged Schools	4.54*	3.03*	1.96†
		(1.13)	(1.03)	(1.17)
	Poorly Maintained Schools	1.11	0.81	0.89
		(1.60)	(1.45)	(1.46)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.90	-0.60	-0.45
		(1.48)	(1.35)	(1.35)
	Most Vocationally Oriented Schools	-0.79	-0.24	0.48
		(1.41)	(1.27)	(1.28)
	Schools with Most Positive Student-Staff Relationships	3.70*	1.32	0.01
		(1.36)	(1.23)	(1.32)
	Less Well-Maintained, Academically Advantaged Schools	5.58*	3.27*	1.99
		(1.48)	(1.33)	(1.42)
Cross-Level Interactions	Hispanic*Well-Maintained Middle-of-the-Road Schools	-0.27	0.44	-0.17
		(1.60)	(1.42)	(1.44)
	Hispanic*Most Academically Advantaged Schools	1.03	0.39	-0.08
		(1.65)	(1.46)	(1.47)
	Hispanic*Poorly Maintained Schools	-2.91	-0.57	-0.94
		(2.30)	(2.05)	(2.11)
	Hispanic*Middle-of-the-Road Schools with Less Experienced Teachers	-1.49	-0.94	-1.39
		(1.96)	(1.74)	(1.76)
	Hispanic*Most Vocationally Oriented Schools	-1.45	-0.91	-1.42
		(2.08)	(1.84)	(1.86)
	Hispanic*Schools with Most Positive Student-Staff Relationships	2.07	3.10†	2.53
		(2.05)	(1.81)	(1.82)
	Hispanic*Less Well-Maintained, Academically Advantaged Schools	0.27	0.19	-0.23
		(2.33)	(2.07)	(2.08)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	2.24	1.44	1.36
	Std. Dev. of Intercept	2.16	1.81	1.67
	Correlation between Intercept and Slope	0.03	-0.11	-0.12
N	Students	1,695	1,695	1,669
	Schools	117	117	116

Model Fit Statistics	AIC	12,245.2	11,996.4	11,825.2
	Log-likelihood	-6,102.6	-5,974.2	-5,884.6
	R-squared	0.27	0.35	0.34

School types based on class membership probabilities. *$p < .05$, †$p < .10$

Table 6a. Variation by Resource Classes in the Difference between Black and White Students' Math Achievement

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Black	-6.60*	-4.54*	-4.27*	-6.85*	-5.14*	-4.91*	-8.32*	-6.15*	-6.09*
		(1.26)	(1.15)	(1.16)	(1.25)	(1.14)	(1.14)	(0.72)	(0.67)	(0.68)
	Intercept	57.99*	55.06*	55.34*	53.08*	51.69*	51.64*	53.41*	52.15*	53.64*
		(1.06)	(0.88)	(1.19)	(1.25)	(0.98)	(1.17)	(0.77)	(0.63)	(0.91)
School Resource Classes	General Orientation	-6.91*	-4.46*	-3.49*						
		(1.21)	(0.97)	(1.22)						
	Most Vocationally Oriented	-7.14*	-4.72*	-3.49*						
		(1.50)	(1.21)	(1.36)						
	More Experienced but Less Satisfied Teachers				-1.09	-0.57	1.05			
					(1.36)	(1.04)	(1.02)			
	Moderate Physical Resource Problems							-2.47*	-1.78*	-1.48†
								(1.09)	(0.85)	(0.78)
	Most Physical Resource Problems							-3.19	-2.19	-1.48
								(3.20)	(2.49)	(2.32)
Cross-Level Interactions	Black*General Orientation	-1.20	-1.13	-1.38						
		(1.41)	(1.28)	(1.29)						
	Black*Most Vocationally Oriented	-1.05	-1.05	-1.40						
		(1.71)	(1.55)	(1.55)						
	Black*More Experienced but Less Satisfied Teachers				-1.15	-0.48	-0.66			
					(1.36)	(1.24)	(1.24)			
	Black*Moderate Physical Resource Problems							0.63	0.62	0.71
								(1.03)	(0.95)	(0.96)
	Black*Most Physical Resource Problems							5.68†	4.53	4.47
								(3.11)	(2.88)	(2.90)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes
	Std. Dev. of Black Slope	2.28	1.82	1.75	2.23	1.85	1.86	2.01	1.76	1.85

Variance Parameters	Std. Dev. of Intercept	3.69	2.69	2.54	4.37	3.07	2.58	4.40	3.12	2.63
	Correlation	-0.62	-0.56	-0.45	-0.52	-0.47	-0.29	-0.55	-0.55	-0.40
N	Students	2,077	2,077	2,050	2,034	2,034	2,007	1,758	1,758	1,741
	Schools	135	135	134	133	133	132	112	112	111
Model Fit Statistics	AIC	14,790.7	14,473.8	14,289.0	14,513.1	14,191.8	13,988.5	12,506.8	12,227.8	12,101.9
	Log-likelihood	-7,385.4	-7,222.9	-7,126.5	-7,248.6	-7,083.9	-6,978.2	-6,243.4	-6,099.9	-6,033.0
	R-squared	0.38	0.45	0.45	0.39	0.46	0.46	0.40	0.47	0.47

Classes based on membership probabilities. *p < .05, †p < .10

Table 6b. Variation by Resource Classes in the Difference between Hispanic and White Students' Math Achievement

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-3.10*	-2.10†	-2.10†	-3.09*	-1.39	-1.51	-4.85*	-2.77*	-2.91*
		(1.26)	(1.12)	(1.11)	(1.24)	(1.09)	(1.07)	(0.85)	(0.76)	(0.75)
	Intercept	57.52*	54.38*	53.47*	53.58*	50.95*	49.53*	53.36*	52.01*	52.57*
		(0.85)	(0.80)	(1.07)	(1.00)	(0.86)	(0.98)	(0.72)	(0.64)	(0.98)
School Resource Classes	General Orientation	-6.37*	-3.96*	-2.35*						
		(1.00)	(0.89)	(1.03)						
	Most Vocationally Oriented	-5.80*	-3.34*	-1.43						
		(1.27)	(1.12)	(1.26)						
	More Experienced but Less Satisfied Teachers				-1.33	0.34	2.58*			
					(1.13)	(0.92)	(0.93)			
	Moderate Physical Resource Problems							-1.57	-1.36	-1.36†
								(1.04)	(0.83)	(0.82)
	Most Physical Resource Problems							-3.41	-3.51	-2.16
								(3.79)	(3.12)	(3.08)
Cross-Level Interactions	Hispanic*General Orientation	-2.03	-0.66	-0.61						
		(1.46)	(1.29)	(1.29)						
	Hispanic*Most Vocationally Oriented	-3.55†	-1.73	-1.73						
		(1.89)	(1.68)	(1.67)						
	Hispanic*More Experienced but Less Satisfied Teachers				-2.49†	-1.59	-1.38			
					(1.40)	(1.22)	(1.20)			
	Hispanic*Moderate Physical Resource Problems							-0.61	-0.23	0.11
								(1.24)	(1.09)	(1.08)
	Hispanic*Most Physical Resource Problems							-1.12	1.41	1.25
								(4.51)	(4.03)	(4.24)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes
	Std. Dev. of Hispanic Slope	2.35	1.58	1.49	2.50	1.61	1.48	2.60	1.83	1.66

Variance Parameters	Std. Dev. of Intercept	2.31	1.77	1.65	3.24	2.28	1.69	3.42	2.36	1.96
	Correlation	0.05	-0.02	-0.12	0.11	-0.02	-0.10	0.07	-0.02	-0.12
N	Students	1,695	1,695	1,669	1,678	1,678	1,652	1,453	1,453	1,432
	Schools	117	117	116	116	116	115	97	97	96
Model Fit Statistics	AIC	12,234.6	11,983.1	11,810.1	12,156.0	11,881.0	11,683.6	10,504.6	10,270.1	10,119.1
	Log-likelihood	-6,107.3	-5,977.6	-5,887.0	-6,070.0	-5,928.5	-5,825.8	-5,242.3	-5,121.1	-5,041.5
	R-squared	0.27	0.35	0.34	0.29	0.36	0.35	0.30	0.37	0.36

Classes based on membership probabilities. $*p < .05$, $\dagger p < .10$

Table 6c. Variation by Resource Classes in the Difference between Black and White Students' Math Achievement

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Black	-7.40*	-5.11*	-5.09*	-7.06*	-4.86*	-4.88*
		(1.67)	(1.52)	(1.52)	(1.05)	(0.96)	(0.95)
	Intercept	59.44*	55.67*	55.78*	58.15*	55.10*	56.39*
		(1.39)	(1.13)	(1.53)	(0.83)	(0.74)	(1.05)
School Resource Classes	Less Positive Student-Staff Relationships	-8.12*	-4.92*	-3.34*			
		(1.48)	(1.18)	(1.44)			
	Less Academically Oriented Peers				-8.08*	-5.17*	-5.46*
					(1.01)	(0.86)	(1.13)
Cross-Level Interactions	Black*Less Positive Student-Staff Relationships	-0.29	-0.48	-0.45			
		(1.76)	(1.60)	(1.60)			
	Black*Less Academically Oriented Peers				-0.70	-0.91	-0.86
					(1.26)	(1.14)	(1.14)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Black Slope	2.25	1.80	1.77	2.41	1.98	1.84
	Std. Dev. of Intercept	3.76	2.77	2.52	3.26	2.52	2.43
	Correlation	-0.53	-0.48	-0.32	-0.73	-0.67	-0.63
N	Students	2,077	2,077	2,050	2,077	2,077	2,050
	Schools	135	135	134	135	135	134
Model Fit Statistics	AIC	14,798.9	14,481.3	14,291.8	14,756.0	14,452.0	14,269.6
	Log-likelihood	-7,391.5	-7,228.7	-7,129.9	-7,370.0	-7,214.0	-7,118.8
	R-squared	0.38	0.45	0.45	0.38	0.45	0.45

Classes based on membership probabilities. *p < .05, †p < .10

Table 6d. Variation by Resource Classes in the Difference between Hispanic and White Students' Math Achievement

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-1.65	-0.51	-0.63	-2.08*	-1.34	-1.36
		(1.48)	(1.30)	(1.29)	(1.05)	(0.95)	(0.94)
	Intercept	56.57*	53.51*	51.87*	56.40*	53.47*	53.07*
		(1.16)	(0.99)	(1.18)	(0.75)	(0.72)	(1.09)
School Resource Classes	Less Positive Student-Staff Relationships	-4.77*	-2.64*	-0.30			
		(1.29)	(1.06)	(1.15)			
	Less Academically Oriented Peers				-5.39*	-3.07*	-1.56
					(0.93)	(0.84)	(1.05)
Cross-Level Interactions	Hispanic*Less Positive Student-Staff Relationships	-4.02*	-2.69†	-2.55†			
		(1.65)	(1.44)	(1.43)			
	Hispanic*Less Academically Oriented Peers				-3.86*	-2.03†	-2.00†
					(1.28)	(1.16)	(1.16)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	2.37	1.55	1.45	2.03	1.49	1.41
	Std. Dev. of Intercept	2.94	2.10	1.79	2.48	1.99	1.78
	Correlation	-0.08	-0.24	-0.23	-0.29	-0.30	-0.32
N	Students	1,695	1,695	1,669	1,695	1,695	1,669
	Schools	117	117	116	117	117	116
Model Fit Statistics	AIC	12,254.8	11,989.4	11,810.0	12,223.6	11,980.1	11,806.3
	Log-likelihood	-6,119.4	-5,982.7	-5,889.0	-6,103.8	-5,978.1	-5,887.1
	R-squared	0.28	0.35	0.34	0.27	0.35	0.34

Classes based on membership probabilities. *$p < .05$, †$p < .10$

Table 7a. Variation by School Type in the Difference between Black and White Students' Odds of High School Graduation

		Model 1	Model 2	Model 3
Student-Level Variables	Black	-0.46	-0.18	-0.08
		(0.31)	(0.32)	(0.33)
	Intercept	1.98*	2.16*	2.55*
		(0.19)	(0.20)	(0.28)
School Types	Well-Maintained Middle-of-the-Road Schools	-0.22	-0.18	-0.16
		(0.27)	(0.27)	(0.27)
	Most Academically Advantaged Schools	1.09*	0.65†	-0.20
		(0.37)	(0.37)	(0.42)
	Poorly Maintained Schools	-0.26	-0.33	-0.33
		(0.32)	(0.31)	(0.32)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.19	-0.17	-0.24
		(0.30)	(0.30)	(0.29)
	Most Vocationally Oriented Schools	1.14*	1.24*	1.17*
		(0.54)	(0.54)	(0.53)
	Schools with Most Positive Student-Staff Relationships	0.94†	0.85†	0.26
		(0.50)	(0.49)	(0.52)
	Less Well-Maintained, Academically Advantaged Schools	0.71†	0.51	0.21
		(0.41)	(0.41)	(0.41)
Cross-Level Interactions	Black*Well-Maintained Middle-of-the-Road Schools	0.71	0.73	0.64
		(0.45)	(0.46)	(0.48)
	Black*Most Academically Advantaged Schools	2.73*	2.93*	3.28*
		(1.37)	(1.40)	(1.50)
	Black*Poorly Maintained Schools	1.13*	1.24*	1.28*
		(0.54)	(0.55)	(0.60)
	Black*Middle-of-the-Road Schools with Less Experienced Teachers	0.22	0.11	0.22
		(0.49)	(0.49)	(0.52)
	Black*Most Vocationally Oriented Schools	-0.59	-0.63	-0.31
		(0.73)	(0.73)	(0.78)
	Black*Schools with Most Positive Student-Staff Relationships	0.25	0.29	0.21
		(0.88)	(0.89)	(0.94)
	Black*Less Well-Maintained, Academically Advantaged Schools	0.16	0.23	0.42
		(0.70)	(0.71)	(0.77)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Black Slope	0.84	0.87	0.96
	Std. Dev. of Intercept	0.46	0.42	0.35
	Correlation between Intercept and Slope	-0.24	-0.34	-0.29
N	Students	2,693	2,693	2,602

	Schools	156	156	153
Model Fit Statistics	AIC	1,963.4	1,908.8	1,804.6
	Log-likelihood	-962.7	-931.4	-875.3
	R-squared	0.12	0.13	0.14

School types based on class membership probabilities. *p < .05, †p < .10

Table 7b. Variation by School Type in the Difference between Hispanic and White Students' Odds of High School Graduation

		Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-0.77*	-0.38	-0.43
		(0.34)	(0.35)	(0.37)
	Intercept	2.43*	2.46*	2.45*
		(0.27)	(0.27)	(0.33)
School Types	Well-Maintained Middle-of-the-Road Schools	0.13	0.21	0.17
		(0.40)	(0.38)	(0.39)
	Most Academically Advantaged Schools	1.58*	1.33*	0.83
		(0.53)	(0.52)	(0.57)
	Poorly Maintained Schools	-0.40	-0.41	-0.25
		(0.46)	(0.44)	(0.46)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.17	-0.10	-0.14
		(0.47)	(0.46)	(0.46)
	Most Vocationally Oriented Schools	0.10	0.29	0.34
		(0.43)	(0.42)	(0.44)
	Schools with Most Positive Student-Staff Relationships	0.97†	0.59	0.12
		(0.58)	(0.57)	(0.60)
	Less Well-Maintained, Academically Advantaged Schools	1.05	0.73	0.65
		(0.64)	(0.63)	(0.73)
Cross-Level Interactions	Hispanic*Well-Maintained Middle-of-the-Road Schools	0.30	0.33	0.47
		(0.50)	(0.50)	(0.52)
	Hispanic*Most Academically Advantaged Schools	-0.62	-0.74	-0.61
		(0.66)	(0.67)	(0.69)
	Hispanic*Poorly Maintained Schools	0.35	0.50	0.55
		(0.62)	(0.63)	(0.67)
	Hispanic*Middle-of-the-Road Schools with Less Experienced Teachers	0.20	0.19	0.45
		(0.56)	(0.57)	(0.59)
	Hispanic*Most Vocationally Oriented Schools	-0.46	-0.49	-0.42
		(0.55)	(0.57)	(0.59)
	Hispanic*Schools with Most Positive Student-Staff Relationships	-0.01	0.24	0.40
		(0.79)	(0.81)	(0.82)
	Hispanic*Less Well-Maintained, Academically Advantaged Schools	-0.34	-0.38	-0.31
		(0.85)	(0.87)	(1.00)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	0.39	0.42	0.48
	Std. Dev. of Intercept	0.64	0.55	0.53
	Correlation between Intercept and Slope	-0.29	-0.15	0.02
N	Students	2,239	2,239	2,189

	Schools	136	136	135
Model Fit Statistics	AIC	1,395.2	1,361.5	1,300.3
	Log-likelihood	-678.6	-657.7	-623.2
	R-squared	0.11	0.12	0.13

School types based on class membership probabilities. *p < .05, †p < .10

Table 8a. Variation by Resource Classes in the Difference between Black and White Students' Odds of High School Graduation

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Black	0.67	1.08	1.72†	-0.13	0.15	0.66	0.30	0.63†	0.76*
		(0.74)	(0.77)	(0.89)	(0.59)	(0.59)	(0.65)	(0.35)	(0.36)	(0.38)
	Intercept	3.27*	3.06*	2.55*	3.04*	3.00*	2.62*	2.25*	2.39*	2.36*
		(0.32)	(0.33)	(0.42)	(0.35)	(0.35)	(0.41)	(0.17)	(0.19)	(0.29)
School Resource Classes	General Orientation	-1.42*	-1.03*	-0.14						
		(0.34)	(0.34)	(0.41)						
	Most Vocationally Oriented	-0.48	-0.10	0.81†						
		(0.43)	(0.44)	(0.49)						
	More Experienced but Less Satisfied Teachers				-0.95*	-0.78*	-0.13			
					(0.37)	(0.36)	(0.37)			
	Moderate Physical Resource Problems							-0.01	0.04	0.14
								(0.24)	(0.23)	(0.23)
	Most Physical Resource Problems							-0.48	-0.42	-0.47
								(0.57)	(0.56)	(0.56)
Cross-Level Interactions	Black*General Orientation	-0.69	-0.83	-1.38						
		(0.77)	(0.79)	(0.91)						
	Black*Most Vocationally Oriented	-0.99	-1.11	-1.51						
		(0.86)	(0.88)	(1.02)						
	Black*More Experienced but Less Satisfied Teachers				0.12	0.17	-0.23			
					(0.60)	(0.60)	(0.66)			
	Black*Moderate Physical Resource Problems							-0.42	-0.45	-0.45
								(0.43)	(0.43)	(0.46)
	Black*Most Physical Resource Problems							1.13	1.00	0.96
								(1.36)	(1.37)	(1.43)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes

	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of Black Slope	0.92	0.98	1.04	1.00	1.06	1.14	1.19	1.24	1.33
	Std. Dev. of Intercept	0.48	0.45	0.37	0.59	0.51	0.43	0.62	0.56	0.44
	Correlation	-0.28	-0.42	-0.39	-0.21	-0.35	-0.40	-0.29	-0.43	-0.49
N	Students	2,693	2,693	2,602	2,639	2,639	2,548	2,288	2,288	2,211
	Schools	156	156	153	154	154	151	130	130	127
Model Fit Statistics	AIC	1,961.1	1,906.1	1,793.4	1,938.6	1,877.2	1,760.0	1,656.8	1,602.0	1,504.1
	Log-likelihood	-971.6	-940.1	-879.7	-962.3	-927.6	-865.0	-819.4	-788.0	-735.1
	R-squared	0.13	0.14	0.14	0.15	0.15	0.15	0.15	0.16	0.16

Classes based on membership probabilities. *$p < .05$, †$p < .10$

Table 8b. Variation by Resource Classes in the Difference between Hispanic and White Students' Odds of High School Graduation

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-0.77	-0.36	-0.22	-1.09†	-0.63	-0.28	-0.85*	-0.36	-0.28
		(0.67)	(0.68)	(0.71)	(0.60)	(0.60)	(0.64)	(0.34)	(0.35)	(0.35)
	Intercept	4.05*	3.64*	2.91*	3.86*	3.58*	2.94*	3.24*	3.16*	3.09*
		(0.49)	(0.48)	(0.56)	(0.49)	(0.48)	(0.54)	(0.27)	(0.27)	(0.37)
School Resource Classes	General Orientation	-1.53*	-1.08*	-0.48						
		(0.52)	(0.50)	(0.56)						
	Most Vocationally Oriented	-1.32*	-0.79	-0.14						
		(0.57)	(0.55)	(0.61)						
	More Experienced but Less Satisfied Teachers				-1.21*	-0.92†	-0.36			
					(0.51)	(0.49)	(0.52)			
	Moderate Physical Resource Problems							-0.60†	-0.54†	-0.47
								(0.33)	(0.32)	(0.32)
	Most Physical Resource Problems							-1.89*	-1.75*	-1.35*
								(0.63)	(0.59)	(0.58)
Cross-Level Interactions	Hispanic*General Orientation	0.06	0.09	0.03						
		(0.70)	(0.71)	(0.74)						
	Hispanic*Most Vocationally Oriented	-0.44	-0.41	-0.49						
		(0.76)	(0.77)	(0.81)						
	Hispanic*More Experienced but Less Satisfied Teachers				0.25	0.27	-0.01			
					(0.62)	(0.62)	(0.66)			
	Hispanic*Moderate Physical Resource Problems							0.09	0.11	0.07
								(0.42)	(0.43)	(0.44)
	Hispanic*Most Physical Resource Problems							0.38	0.47	0.34
								(0.86)	(0.88)	(0.93)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes

	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	0.42	0.44	0.52	0.46	0.48	0.56	0.51	0.57	0.62
	Std. Dev. of Intercept	0.72	0.59	0.53	0.75	0.59	0.53	0.69	0.52	0.40
	Correlation	-0.46	-0.25	0.02	-0.48	-0.31	-0.03	-0.45	-0.42	-0.17
N	Students	2,239	2,239	2,189	2,211	2,211	2,161	1,909	1,909	1,874
	Schools	136	136	135	134	134	133	112	112	111
Model Fit Statistics	AIC	1,384.5	1,350.6	1,286.5	1,366.0	1,325.2	1,259.1	1,133.9	1,094.7	1,062.7
	Log-likelihood	-683.3	-662.3	-626.3	-676.0	-651.6	-614.5	-558.0	-534.4	-514.4
	R-squared	0.11	0.12	0.13	0.11	0.12	0.13	0.09	0.10	0.11

Classes based on membership probabilities. *$p < .05$, †$p < .10$

Table 8c. Variation by Resource Classes in the Difference between Black and White Students' Odds of High School Graduation

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Black	2.84	3.48	4.61	1.22†	1.69*	2.07*
		(2.16)	(2.29)	(2.84)	(0.72)	(0.74)	(0.83)
	Intercept	3.46*	3.04*	1.65*	3.37*	3.13*	2.76*
		(0.44)	(0.45)	(0.63)	(0.29)	(0.31)	(0.40)
School Resource Classes	Less Positive Student-Staff Relationships	-1.38*	-0.79†	0.88			
		(0.46)	(0.46)	(0.61)			
	Less Academically Oriented Peers				-1.50*	-1.02*	-0.42
					(0.33)	(0.33)	(0.43)
Cross-Level Interactions	Black*Less Positive Student-Staff Relationships	-2.93	-3.29	-4.29			
		(2.19)	(2.32)	(2.88)			
	Black*Less Academically Oriented Peers				-1.42†	-1.64*	-1.90*
					(0.77)	(0.79)	(0.88)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Black Slope	0.94	0.99	1.06	0.95	1.00	1.06
	Std. Dev. of Intercept	0.57	0.53	0.42	0.51	0.50	0.42
	Correlation	-0.29	-0.38	-0.35	-0.42	-0.46	-0.41
N	Students	2,693	2,693	2,602	2,693	2,693	2,602
	Schools	156	156	153	156	156	153
Model Fit Statistics	AIC	1,973.2	1,917.5	1,800.1	1,945.0	1,898.9	1,794.7
	Log-likelihood	-979.6	-947.8	-885.1	-965.5	-938.4	-882.4
	R-squared	0.14	0.15	0.15	0.13	0.14	0.15

Classes based on membership probabilities. *p < .05, †p < .10

Table 8d. Variation by Resource Classes in the Difference between Hispanic and White Students' Odds of High School Graduation

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-1.20	-0.80	-0.65	-1.64*	-1.43†	-1.43†
		(0.73)	(0.73)	(0.74)	(0.74)	(0.74)	(0.78)
	Intercept	4.11*	3.69*	2.69*	5.15*	4.80*	4.51*
		(0.59)	(0.57)	(0.64)	(0.60)	(0.60)	(0.68)
School Resource Classes	Less Positive Student-Staff Relationships	-1.49*	-1.04†	-0.14			
		(0.61)	(0.59)	(0.64)			
	Less Academically Oriented Peers				-2.92*	-2.48*	-2.28*
					(0.64)	(0.63)	(0.70)
Cross-Level Interactions	Hispanic*Less Positive Student-Staff Relationships	0.41	0.47	0.40			
		(0.76)	(0.76)	(0.77)			
	Hispanic*Less Academically Oriented Peers				1.01	1.19	1.25
					(0.79)	(0.79)	(0.83)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	0.43	0.46	0.54	0.44	0.48	0.54
	Std. Dev. of Intercept	0.74	0.60	0.54	0.49	0.44	0.45
	Correlation	-0.43	-0.27	0.01	-0.27	-0.13	-0.03
N	Students	2,239	2,239	2,189	2,239	2,239	2,189
	Schools	136	136	135	136	136	135
Model Fit Statistics	AIC	1,390.3	1,351.7	1,284.9	1,350.7	1,326.4	1,269.8
	Log-likelihood	-688.2	-664.8	-627.5	-668.4	-652.2	-619.9
	R-squared	0.11	0.12	0.13	0.10	0.11	0.12

Classes based on membership probabilities. *p < .05, †p < .10

Table 9a. Variation by School Type in the Difference between Black and White Students' Odds of Immediate Enrollment in a Four-Year Institution

		Model 1	Model 2	Model 3
Student-Level Variables	Black	-0.37	0.10	0.18
		(0.25)	(0.26)	(0.27)
	Intercept	-0.79*	-0.68*	-0.48*
		(0.20)	(0.19)	(0.22)
School Types	Well-Maintained Middle-of-the-Road Schools	0.52†	0.61*	0.62*
		(0.30)	(0.26)	(0.24)
	Most Academically Advantaged Schools	2.03*	1.49*	0.63*
		(0.32)	(0.28)	(0.30)
	Poorly Maintained Schools	0.26	0.26	0.20
		(0.36)	(0.32)	(0.29)
	Middle-of-the-Road Schools w/ Less Experienced Teachers	0.14	0.16	0.23
		(0.33)	(0.29)	(0.26)
	Most Vocationally Oriented Schools	0.06	0.11	0.21
		(0.39)	(0.36)	(0.32)
	Schools with Most Positive Student-Staff Relationships	0.62	0.58	-0.24
		(0.42)	(0.36)	(0.36)
	Less Well-Maintained, Academically Advantaged Schools	2.06*	1.87*	1.47*
		(0.37)	(0.33)	(0.31)
Cross-Level Interactions	Black*Well-Maintained Middle-of-the-Road Schools	-0.28	-0.32	-0.41
		(0.35)	(0.36)	(0.37)
	Black*Most Academically Advantaged Schools	0.12	0.21	0.21
		(0.42)	(0.43)	(0.44)
	Black*Poorly Maintained Schools	0.24	0.32	0.29
		(0.41)	(0.42)	(0.43)
	Black*Middle-of-the-Road Schools w/ Less Experienced Teachers	0.30	0.13	0.08
		(0.39)	(0.41)	(0.42)
	Black*Most Vocationally Oriented Schools	0.17	0.21	0.19
		(0.47)	(0.48)	(0.49)
	Black*Schools with Most Positive Student-Staff Relationships	-0.36	-0.42	-0.50
		(0.53)	(0.54)	(0.55)
	Black*Less Well-Maintained, Academically Advantaged Schools	-0.83†	-0.76	-0.76
		(0.45)	(0.46)	(0.48)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Black Slope	0.36	0.28	0.33
	Std. Dev. of Intercept	0.77	0.56	0.36
	Corr. between Intercept and Slope	-0.49	-0.11	0.34
N	Students	2,376	2,376	2,305

	Schools	146	146	144
Model Fit Statistics	AIC	2,933.4	2,660.2	2,554.8
	Log-likelihood	-1,447.7	-1,307.1	-1,249.4
	R-squared	0.24	0.31	0.30

School types based on class membership probabilities. *p < .05, †p < .10

Table 9b. Variation by School Type in the Difference between Hispanic and White Students' Odds of Immediate Enrollment in a Four-Year Institution

		Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-0.87*	-0.49*	-0.45
		(0.28)	(0.20)	(0.30)
	Intercept	-0.54*	-0.43	-0.46†
		(0.20)	(0.29)	(0.23)
School Types	Well-Maintained Middle-of-the-Road Schools	0.16	0.29	0.35
		(0.31)	(0.30)	(0.28)
	Most Academically Advantaged Schools	1.40*	1.07*	0.37
		(0.30)	(0.29)	(0.31)
	Poorly Maintained Schools	-0.14	-0.19	-0.04
		(0.40)	(0.39)	(0.36)
	Middle-of-the-Road Schools w/ Less Experienced Teachers	-0.30	-0.25	-0.09
		(0.38)	(0.37)	(0.34)
	Most Vocationally Oriented Schools	-0.63†	-0.48	-0.24
		(0.36)	(0.35)	(0.32)
	Schools with Most Positive Student-Staff Relationships	1.08*	0.60†	0.04
		(0.37)	(0.35)	(0.35)
	Less Well-Maintained, Academically Advantaged Schools	1.75*	1.31*	0.71†
		(0.42)	(0.41)	(0.40)
Cross-Level Interactions	Hispanic*Well-Maintained Middle-of-the-Road Schools	-0.71†	-0.81†	-0.84†
		(0.42)	(0.43)	(0.45)
	Hispanic*Most Academically Advantaged Schools	0.25	0.04	0.11
		(0.40)	(0.41)	(0.42)
	Hispanic*Poorly Maintained Schools	0.01	0.22	0.00
		(0.59)	(0.62)	(0.66)
	Hispanic*Middle-of-the-Road Schools w/ Less Experienced Teachers	0.04	0.22	0.16
		(0.50)	(0.51)	(0.52)
	Hispanic*Most Vocationally Oriented Schools	-0.32	-0.25	-0.22
		(0.57)	(0.58)	(0.59)
	Hispanic*Schools with Most Positive Student-Staff Relationships	-0.07	0.18	0.20
		(0.49)	(0.51)	(0.53)
	Hispanic*Less Well-Maintained, Academically Advantaged Schools	0.38	0.29	0.37
		(0.57)	(0.59)	(0.62)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	0.36	0.34	0.44
	Std. Dev. of Intercept	0.70	0.61	0.46

	Corr. between Intercept and Slope	0.32	0.27	0.52
N	Students	1,946	1,946	1,910
	Schools	128	128	127
Model Fit Statistics	AIC	2,274.7	2,119.4	2,062.8
	Log-likelihood	-1,118.3	-1,036.7	-1,004.4
	R-squared	0.28	0.33	0.33

School types based on class membership probabilities. *$p < .05$, †$p < .10$

Table 10a. Variation by Resource Classes in the Difference between Black and White Students' Odds of Immediate Enrollment in a Four-Year Institution

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Black	-0.81*	-0.25	-0.14	-0.41	-0.11	0.04	-0.51*	-0.05	-0.01
		(0.33)	(0.34)	(0.35)	(0.31)	(0.31)	(0.32)	(0.19)	(0.20)	(0.20)
	Intercept	1.88*	1.53*	1.06*	0.43	0.36	-0.10	0.11	0.10	0.24
		(0.26)	(0.24)	(0.29)	(0.31)	(0.27)	(0.29)	(0.20)	(0.18)	(0.23)
School Resource Classes	General Orientation	-2.40*	-1.93*	-1.27*						
		(0.29)	(0.25)	(0.30)						
	Most Vocationally Oriented	-2.28*	-1.82*	-1.20*						
		(0.35)	(0.31)	(0.33)						
	More Experienced but Less Satisfied Teachers				-0.69*	-0.59*	0.09			
					(0.34)	(0.28)	(0.26)			
	Moderate Physical Resource Problems							-0.53†	-0.45†	-0.37†
								(0.29)	(0.25)	(0.20)
	Most Physical Resource Problems							-0.24	-0.01	-0.08
								(0.74)	(0.64)	(0.52)
Cross-Level Interactions	Black*General Orientation	0.38	0.27	0.19						
		(0.37)	(0.38)	(0.39)						
	Black*Most Vocationally Oriented	0.67	0.61	0.56						
		(0.43)	(0.45)	(0.46)						
	Black*More Experienced but Less Satisfied Teachers				-0.08	0.17	0.08			
					(0.33)	(0.34)	(0.35)			
	Black*Moderate Physical Resource Problems							0.08	0.13	0.12
								(0.28)	(0.28)	(0.28)
	Black*Most Physical Resource Problems							0.69	0.69	0.63
								(0.74)	(0.75)	(0.74)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes

Variance Parameters	Std. Dev. of Black Slope	0.37	0.31	0.33	0.44	0.34	0.37	0.52	0.44	0.42
	Std. Dev. of Intercept	0.75	0.52	0.44	1.08	0.78	0.51	1.18	0.91	0.59
	Correlation	-0.45	-0.13	0.10	-0.63	-0.33	0.10	-0.67	-0.59	-0.14
N	Students	2,376	2,376	2,305	2,327	2,327	2,256	2,003	2,003	1,947
	Schools	146	146	144	144	144	142	121	121	119
Model Fit Statistics	AIC	2,917.6	2,639.4	2,553.3	2,907.8	2,619.4	2,494.7	2,487.4	2,249.2	2,146.5
	Log-likelihood	-1,449.8	-1,306.7	-1,258.6	-1,446.9	-1,298.7	-1,231.3	-1,234.7	-1,111.6	-1,055.2
	R-squared	0.24	0.31	0.31	0.26	0.32	0.32	0.27	0.33	0.33

Classes based on membership probabilities. *p < .05, †p < .10

Table 10b. Variation by Resource Classes in the Difference between Hispanic and White Students' Odds of Immediate Enrollment in a Four-Year Institution

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-0.70*	-0.42	-0.39	-0.61	-0.21	-0.25	-1.31*	-0.93*	-0.89*
		(0.34)	(0.34)	(0.35)	(0.31)	(0.31)	(0.32)	(0.23)	(0.24)	(0.24)
	Intercept	1.67*	1.20*	0.52†	0.51†	0.19	-0.55†	0.11	-0.03	-0.27
		(0.26)	(0.26)	(0.30)	(0.28)	(0.26)	(0.28)	(0.20)	(0.19)	(0.28)
School Resource Classes	General Orientation	-2.14*	-1.65*	-1.00*						
		(0.30)	(0.28)	(0.29)						
	Most Vocationally Oriented	-2.42*	-1.84*	-1.07*						
		(0.35)	(0.33)	(0.33)						
	More Experienced but Less Satisfied Teachers				-0.80*	-0.48†	0.23			
					(0.31)	(0.28)	(0.26)			
	Moderate Physical Resource Problems							-0.35	-0.29	-0.05
								(0.28)	(0.25)	(0.22)
	Most Physical Resource Problems							-1.78*	-1.72*	-0.93
								(0.72)	(0.65)	(0.58)
Cross-Level Interactions	Hispanic*General Orientation	-0.36	-0.14	-0.19						
		(0.40)	(0.40)	(0.40)						
	Hispanic*Most Vocationally Oriented	-0.48	-0.22	-0.22						
		(0.52)	(0.52)	(0.52)						
	Hispanic*More Experienced but Less Satisfied Teachers				-0.53	-0.42	-0.37			
					(0.35)	(0.35)	(0.36)			
	Hispanic*Moderate Physical Resource Problems							0.22	0.41	0.39
								(0.32)	(0.33)	(0.33)
	Hispanic*Most Physical Resource Problems							1.03	1.47	0.96
								(0.92)	(0.95)	(1.02)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes

Variance Parameters	Std. Dev. of Hispanic Slope	0.43	0.39	0.47	0.43	0.40	0.49	0.49	0.44	0.47
	Std. Dev. of Intercept	0.71	0.59	0.42	0.98	0.78	0.51	1.03	0.81	0.55
	Correlation	0.44	0.35	0.49	0.46	0.30	0.53	0.61	0.54	0.54
N	Students	1,946	1,946	1,910	1,922	1,922	1,886	1,672	1,672	1,644
	Schools	128	128	127	126	126	125	105	105	104
Model Fit Statistics	AIC	2,261.6	2,103.0	2,042.2	2,290.7	2,124.9	2,041.6	1,978.8	1,833.9	1,765.7
	Log-likelihood	-1,121.8	-1,038.5	-1,004.1	-1,138.3	-1,051.5	-1,005.8	-980.4	-903.9	-865.9
	R-squared	0.28	0.33	0.33	0.29	0.33	0.33	0.29	0.34	0.34

Classes based on membership probabilities. *p < .05, ǂp < .10

Table 10c. Variation by Resource Classes in the Difference between Black and White Students' Odds of Immediate Enrollment in a Four-Year Institution

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Black	-0.43	0.19	0.30	-0.66*	-0.05	0.01
		(0.51)	(0.53)	(0.53)	(0.28)	(0.29)	(0.29)
	Intercept	2.12*	1.46*	0.45	1.84*	1.41*	1.20*
		(0.38)	(0.35)	(0.41)	(0.19)	(0.20)	(0.26)
School Resource Classes	Less Positive Student-Staff Relationships	-2.48*	-1.71*	-0.46			
		(0.41)	(0.36)	(0.39)			
	Less Academically Oriented Peers				-2.59*	-1.97*	-1.66*
					(0.23)	(0.22)	(0.28)
Cross-Level Interactions	Black*Less Positive Student-Staff Relationships	0.00	-0.17	-0.24			
		(0.54)	(0.55)	(0.56)			
	Black*Less Academically Oriented Peers				0.32	0.11	0.07
					(0.33)	(0.34)	(0.35)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Black Slope	0.43	0.33	0.35	0.43	0.35	0.35
	Std. Dev. of Intercept	0.91	0.71	0.52	0.57	0.45	0.38
	Correlation	-0.57	-0.36	0.04	-0.61	-0.42	-0.18
N	Students	2,376	2,376	2,305	2,376	2,376	2,305
	Schools	146	146	144	146	146	144
Model Fit Statistics	AIC	2,942.3	2,671.1	2,568.1	2,862.1	2,609.1	2,530.4
	Log-likelihood	-1,464.2	-1,324.6	-1,268.0	-1,424.1	-1,293.6	-1,249.2
	R-squared	0.25	0.31	0.31	0.23	0.30	0.30

Classes based on membership probabilities. *p < .05, †p < .10

Table 10d. Variation by Resource Classes in the Difference between Hispanic and White Students' Odds of Immediate Enrollment in a Four-Year Institution

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-0.56	-0.18	-0.09	-0.55†	-0.42	-0.41
		(0.40)	(0.41)	(0.41)	(0.28)	(0.29)	(0.30)
	Intercept	1.47*	0.96*	-0.20	1.61*	1.18*	0.89*
		(0.35)	(0.33)	(0.35)	(0.19)	(0.20)	(0.27)
School Resource Classes	Less Positive Student-Staff Relationships	-1.88*	-1.35*	-0.18			
		(0.39)	(0.35)	(0.34)			
	Less Academically Oriented Peers				-2.35*	-1.87*	-1.43*
					(0.24)	(0.23)	(0.25)
Cross-Level Interactions	Hispanic*Less Positive Student-Staff Relationships	-0.53	-0.41	-0.54			
		(0.45)	(0.46)	(0.46)			
	Hispanic*Less Academically Oriented Peers				-0.54	-0.16	-0.19
					(0.36)	(0.37)	(0.38)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	0.42	0.39	0.48	0.44	0.46	0.52
	Std. Dev. of Intercept	0.90	0.73	0.50	0.53	0.42	0.30
	Correlation	0.41	0.22	0.49	0.11	0.39	0.49
N	Students	1,946	1,946	1,910	1,946	1,946	1,910
	Schools	128	128	127	128	128	127
Model Fit Statistics	AIC	2,294.6	2,125.2	2,052.4	2,217.6	2,072.2	2,019.9
	Log-likelihood	-1,140.3	-1,051.6	-1,011.2	-1,101.8	-1,025.1	-995.0
	R-squared	0.29	0.33	0.33	0.27	0.32	0.32

Classes based on membership probabilities. *p < .05, †p < .10

Table 11a. Variation by School Type in the Difference between Black and White Students' Odds of Any Postsecondary Enrollment

		Model 1	Model 2	Model 3
Student-Level Variables	Black	-0.18	0.22	0.30
		(0.32)	(0.32)	(0.33)
	Intercept	1.87*	2.23*	2.36*
		(0.20)	(0.21)	(0.28)
School Types	Well-Maintained Middle-of-the-Road Schools	-0.43	-0.41	-0.40
		(0.28)	(0.26)	(0.27)
	Most Academically Advantaged Schools	2.17*	1.60*	0.96†
		(0.51)	(0.50)	(0.54)
	Poorly Maintained Schools	0.09	0.09	0.02
		(0.35)	(0.34)	(0.36)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.22	-0.16	-0.09
		(0.31)	(0.30)	(0.31)
	Most Vocationally Oriented Schools	-0.34	-0.27	-0.26
		(0.41)	(0.40)	(0.41)
	Schools with Most Positive Student-Staff Relationships	0.50	0.44	-0.16
		(0.44)	(0.42)	(0.46)
	Less Well-Maintained, Academically Advantaged Schools	0.92*	0.66	0.31
		(0.45)	(0.44)	(0.45)
Cross-Level Interactions	Black*Well-Maintained Middle-of-the-Road Schools	0.30	0.39	0.30
		(0.43)	(0.44)	(0.45)
	Black*Most Academically Advantaged Schools	-0.38	-0.14	-0.11
		(0.84)	(0.85)	(0.87)
	Black*Poorly Maintained Schools	0.29	0.40	0.43
		(0.53)	(0.54)	(0.57)
	Black*Middle-of-the-Road Schools with Less Experienced Teachers	0.59	0.46	0.30
		(0.51)	(0.53)	(0.54)
	Black*Most Vocationally Oriented Schools	0.49	0.52	0.37
		(0.61)	(0.63)	(0.65)
	Black*Schools with Most Positive Student-Staff Relationships	1.06	0.99	1.01
		(0.94)	(0.96)	(0.98)
	Black*Less Well-Maintained, Academically Advantaged Schools	-0.16	-0.08	-0.11
		(0.72)	(0.73)	(0.74)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Black Slope	0.57	0.63	0.63
	Std. Dev. of Intercept	0.44	0.28	0.25
	Correlation between Intercept and Slope	-0.17	-0.29	-0.22
N	Students	2,335	2,335	2,256

	Schools	142	142	139
Model Fit Statistics	AIC	1,755.7	1,633.1	1,568.0
	Log-likelihood	-858.9	-793.6	-757.0
	R-squared	0.10	0.13	0.13

School types based on class membership probabilities. *p < .05, †p < .10

Table 11b. Variation by School Type in the Difference between Hispanic and White Students' Odds of Any Postsecondary Enrollment

		Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-0.50	0.06	0.09
		(0.36)	(0.37)	(0.37)
	Intercept	2.10*	2.23*	2.10*
		(0.29)	(0.27)	(0.30)
School Types	Well-Maintained Middle-of-the-Road Schools	0.03	0.12	0.10
		(0.43)	(0.38)	(0.36)
	Most Academically Advantaged Schools	1.06*	0.63	-0.04
		(0.46)	(0.42)	(0.43)
	Poorly Maintained Schools	0.47	0.47	0.57
		(0.58)	(0.54)	(0.50)
	Middle-of-the-Road Schools with Less Experienced Teachers	-0.32	-0.27	0.01
		(0.50)	(0.45)	(0.44)
	Most Vocationally Oriented Schools	-0.62	-0.48	-0.46
		(0.44)	(0.39)	(0.36)
	Schools with Most Positive Student-Staff Relationships	1.74*	1.16†	0.55
		(0.71)	(0.67)	(0.66)
	Less Well-Maintained, Academically Advantaged Schools	2.06*	1.60†	1.13
		(0.89)	(0.84)	(0.84)
Cross-Level Interactions	Hispanic*Well-Maintained Middle-of-the-Road Schools	-0.05	0.06	0.14
		(0.52)	(0.52)	(0.52)
	Hispanic*Most Academically Advantaged Schools	0.95	0.96	1.17
		(0.74)	(0.75)	(0.77)
	Hispanic*Poorly Maintained Schools	-0.03	0.33	0.20
		(0.77)	(0.80)	(0.79)
	Hispanic*Middle-of-the-Road Schools with Less Experienced Teachers	0.54	0.64	0.35
		(0.62)	(0.62)	(0.63)
	Hispanic*Most Vocationally Oriented Schools	0.16	0.17	0.27
		(0.58)	(0.58)	(0.58)
	Hispanic*Schools with Most Positive Student-Staff Relationships	-0.82	-0.45	-0.25
		(0.90)	(0.91)	(0.92)
	Hispanic*Less Well-Maintained, Academically Advantaged Schools	-1.79†	-1.80†	-1.10
		(1.03)	(1.03)	(1.12)
Covariates	Student-Level		Yes	Yes
	School-Level			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	0.71	0.71	0.65
	Std. Dev. of Intercept	0.83	0.58	0.39
	Correlation between Intercept and Slope	-0.87	-0.89	-0.79
N	Students	1,913	1,913	1,870

	Schools	123	123	122
Model Fit Statistics	AIC	1,319.5	1,242.9	1,205.7
	Log-likelihood	-640.7	-598.5	-575.9
	R-squared	0.12	0.13	0.13

School types based on class membership probabilities. *p < .05, †p < .10

Table 12a. Variation by Resource Classes in the Difference between Black and White Students' Odds of Any Postsecondary Enrollment

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Black	-0.14	0.40	0.61	0.49	0.92	1.04†	-0.24	0.34	0.34
		(0.69)	(0.68)	(0.73)	(0.56)	(0.57)	(0.60)	(0.27)	(0.27)	(0.27)
	Intercept	3.66*	3.48*	2.56*	2.63*	2.70*	2.30*	2.19*	2.37*	2.33*
		(0.39)	(0.37)	(0.46)	(0.34)	(0.31)	(0.38)	(0.20)	(0.20)	(0.28)
School Resource Classes	General Orientation	-1.89*	-1.37*	-0.29						
		(0.41)	(0.37)	(0.46)						
	Most Vocationally Oriented	-1.50*	-0.99*	-0.06						
		(0.47)	(0.43)	(0.52)						
	More Experienced but Less Satisfied Teachers				-0.59†	-0.46	-0.01			
					(0.36)	(0.32)	(0.34)			
	Moderate Physical Resource Problems							-0.11	-0.01	0.01
								(0.28)	(0.24)	(0.23)
	Most Physical Resource Problems							0.17	0.38	0.13
								(0.74)	(0.61)	(0.59)
Cross-Level Interactions	Black*General Orientation	0.14	0.09	-0.11						
		(0.72)	(0.70)	(0.76)						
	Black*Most Vocationally Oriented	0.35	0.28	0.08						
		(0.80)	(0.79)	(0.85)						
	Black*More Experienced but Less Satisfied Teachers				-0.60	-0.41	-0.49			
					(0.57)	(0.58)	(0.62)			
	Black*Moderate Physical Resource Problems							0.40	0.35	0.44
								(0.36)	(0.37)	(0.38)
	Black*Most Physical Resource Problems							-0.18	-0.42	-0.32
								(1.02)	(1.02)	(1.01)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes

	School-Level			Yes			Yes			Yes
Variance Parameters	Std. Dev. of Black Slope	0.57	0.65	0.65	0.57	0.64	0.67	0.60	0.62	0.60
	Std. Dev. of Intercept	0.57	0.35	0.29	0.77	0.42	0.29	0.87	0.52	0.34
	Correlation	-0.26	-0.28	-0.22	-0.32	-0.14	-0.13	-0.45	-0.34	-0.32
N	Students	2,335	2,335	2,256	2,284	2,284	2,205	1,966	1,966	1,898
	Schools	142	142	139	140	140	137	118	118	115
Model Fit Statistics	AIC	1,761.5	1,631.8	1,559.5	1,738.3	1,600.1	1,513.9	1,511.7	1,390.9	1,312.1
	Log-likelihood	-871.7	-802.9	-762.8	-862.1	-789.0	-741.9	-746.8	-682.4	-639.1
	R-squared	0.11	0.13	0.14	0.13	0.14	0.14	0.13	0.14	0.14

Classes based on membership probabilities. *p < .05, †p < .10

Table 12b. Variation by Resource Classes in the Difference between Hispanic and White Students' Odds of Any Postsecondary Enrollment

		Instructional Resources			Teacher Resources			Physical Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-0.84	-0.16	0.34	0.01	0.77	0.65	-0.73†	0.02	0.28
		(0.79)	(0.80)	(0.85)	(0.73)	(0.73)	(0.77)	(0.37)	(0.36)	(0.36)
	Intercept	4.42*	3.88*	2.96*	3.65*	3.23*	2.77*	2.92*	2.78*	2.41*
		(0.57)	(0.54)	(0.56)	(0.50)	(0.45)	(0.52)	(0.31)	(0.28)	(0.34)
School Resource Classes	General Orientation	-2.19*	-1.54*	-0.78						
		(0.61)	(0.56)	(0.58)						
	Most Vocationally Oriented	-2.55*	-1.85*	-1.10†						
		(0.64)	(0.59)	(0.60)						
	More Experienced but Less Satisfied Teachers				-1.31*	-0.82†	-0.55			
					(0.52)	(0.46)	(0.51)			
	Moderate Physical Resource Problems							-0.55	-0.37	-0.09
								(0.39)	(0.33)	(0.30)
	Most Physical Resource Problems							-0.42	-0.06	0.61
								(0.92)	(0.82)	(0.75)
Cross-Level Interactions	Hispanic*General Orientation	0.40	0.36	-0.10						
		(0.83)	(0.83)	(0.88)						
	Hispanic*Most Vocationally Oriented	0.34	0.37	-0.02						
		(0.87)	(0.88)	(0.92)						
	Hispanic*More Experienced but Less Satisfied Teachers				-0.67	-0.70	-0.42			
					(0.75)	(0.75)	(0.79)			
	Hispanic*Moderate Physical Resource Problems							0.31	0.31	0.02
								(0.46)	(0.46)	(0.46)
	Hispanic*Most Physical Resource Problems							0.52	0.66	0.10
								(1.25)	(1.28)	(1.27)
Covariates	Student-Level		Yes	Yes		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes			Yes

Variance Parameters	Std. Dev. of Hispanic Slope	0.78	0.75	0.70	0.84	0.80	0.76	0.88	0.91	0.87
	Std. Dev. of Intercept	0.90	0.60	0.41	1.07	0.72	0.45	1.11	0.74	0.46
	Correlation	-0.82	-0.84	-0.78	-0.87	-0.87	-0.79	-0.72	-0.86	-0.83
N	Students	1,913	1,913	1,870	1,889	1,889	1,846	1,621	1,621	1,589
	Schools	123	123	122	121	121	120	100	100	99
Model Fit Statistics	AIC	1,315.1	1,235.6	1,193.1	1,297.4	1,211.5	1,165.4	1,100.4	1,018.3	985.0
	Log-likelihood	-648.5	-604.8	-579.6	-641.7	-594.8	-567.7	-541.2	-496.1	-475.5
	R-squared	0.13	0.13	0.13	0.14	0.14	0.14	0.15	0.14	0.13

Classes based on membership probabilities. *$p < .05$, †$p < .10$

Table 12c. Variation by Resource Classes in the Difference between Black and White Students' Odds of Any Postsecondary Enrollment

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Black	2.06	3.09	3.17	-0.74	-0.13	-0.30
		(2.52)	(2.75)	(2.69)	(0.61)	(0.63)	(0.66)
	Intercept	4.56*	4.05*	2.90*	4.26*	4.04*	3.75*
		(0.66)	(0.64)	(0.74)	(0.39)	(0.40)	(0.49)
School Resource Classes	Less Positive Student-Staff Relationships	-2.69*	-1.86*	-0.60			
		(0.68)	(0.66)	(0.73)			
	Less Academically Oriented Peers				-2.75*	-2.10*	-1.79*
					(0.42)	(0.42)	(0.51)
Cross-Level Interactions	Black*Less Positive Student-Staff Relationships	-2.05	-2.62	-2.67			
		(2.55)	(2.78)	(2.72)			
	Black*Less Academically Oriented Peers				0.91	0.69	0.88
					(0.66)	(0.67)	(0.71)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Black Slope	0.58	0.65	0.66	0.59	0.67	0.66
	Std. Dev. of Intercept	0.58	0.37	0.29	0.39	0.30	0.25
	Correlation	-0.24	-0.23	-0.22	-0.22	-0.36	-0.32
N	Students	2,335	2,335	2,256	2,335	2,335	2,256
	Schools	142	142	139	142	142	139
Model Fit Statistics	AIC	1,756.9	1,629.4	1,554.3	1,719.1	1,606.4	1,541.1
	Log-likelihood	-871.5	-803.7	-762.2	-852.6	-792.2	-755.6
	R-squared	0.11	0.14	0.14	0.09	0.13	0.14

Classes based on membership probabilities. $*p < .05$, $\dagger p < .10$

Table 12d. Variation by Resource Classes in the Difference between Hispanic and White Students' Odds of Any Postsecondary Enrollment

		Student-Staff Resources			Student-Peer Resources		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Student-Level Variables	Hispanic	-0.90	-0.16	0.15	-0.96	-0.61	-0.40
		(0.90)	(0.89)	(0.89)	(0.80)	(0.79)	(0.80)
	Intercept	4.53*	3.88*	2.75*	5.00*	4.56*	3.90*
		(0.68)	(0.62)	(0.64)	(0.57)	(0.55)	(0.59)
School Resource Classes	Less Positive Student-Staff Relationships	-2.31*	-1.58*	-0.56			
		(0.71)	(0.64)	(0.65)			
	Less Academically Oriented Peers				-3.21*	-2.57*	-1.96*
					(0.61)	(0.58)	(0.61)
Cross-Level Interactions	Hispanic*Less Positive Student-Staff Relationships	0.42	0.37	0.14			
		(0.93)	(0.92)	(0.93)			
	Hispanic*Less Academically Oriented Peers				0.63	0.94	0.76
					(0.85)	(0.84)	(0.85)
Covariates	Student-Level		Yes	Yes		Yes	Yes
	School-Level			Yes			Yes
Variance Parameters	Std. Dev. of Hispanic Slope	0.78	0.77	0.73	0.81	0.77	0.72
	Std. Dev. of Intercept	0.97	0.66	0.44	0.72	0.53	0.41
	Correlation	-0.82	-0.83	-0.76	-0.89	-0.88	-0.83
N	Students	1,913	1,913	1,870	1,913	1,913	1,870
	Schools	123	123	122	123	123	122
Model Fit Statistics	AIC	1,322.2	1,238.3	1,194.7	1,276.2	1,211.0	1,179.7
	Log-likelihood	-654.1	-608.2	-582.3	-631.1	-594.5	-574.9
	R-squared	0.13	0.13	0.13	0.12	0.13	0.13

Classes based on membership probabilities. *p < .05, †p < .10

Chapter 6. Conclusions and Implications

This dissertation examined how gender, socioeconomic, and racial/ethnic differences in educational outcomes vary across contexts, as well as what school contexts are more or less unequal for students from particular backgrounds. Lee and Bryk pioneered much of the initial research on how the relation between students' characteristics and their outcomes varies across schools, arguing that "the causes of such heterogeneity should be a central concern in research on school effects" (1989: 173). Though Lee, Bryk, and colleagues conducted an impressive amount of work on this subject in the 1980s and 90s, since then, research on how the relation between educational outcomes and students' demographic characteristics varies across contexts has been relatively isolated and unconnected, with researchers examining the effects of individual resources on different samples for different outcomes.

Using more recent, nationally representative data, this dissertation aimed to quantify variability in gender, socioeconomic, and racial/ethnic inequalities in educational achievement and attainment and to provide a more comprehensive look at the way resources are associated with the degree of these inequalities in U.S. high schools. My goal was to document the distribution of inequalities, as well as the potentially manipulable school characteristics associated with that distribution.

SUMMARY OF FINDINGS

For all subgroups and outcomes, I first examined the degree of variation across schools in the relation between a particular demographic characteristic and students' outcomes. The magnitude of this variation was easiest to understand for math achievement: across student subgroups, the standard deviations of the slopes for math achievement were about one to two points, or about 10 to 20 percent of the test's standard deviation. Across outcomes, the standard deviations of the gender slopes were consistently smallest, indicating that, of the demographic characteristics examined, the relation between students' gender and their outcomes was the least variable across schools. For most outcomes, the standard deviations of the SES and race/ethnicity slopes were similar, at least after conditioning on other student characteristics; for example, the standard deviations of the SES, Black, and Hispanic slopes for on-time four-year enrollment were all around 0.34 to 0.48. The exception to the relatively consistent size of the standard deviations for the SES and race/ethnicity slopes was that the standard deviation of the Black slope for high school graduation was 0.96 to 1.09, whereas the standard deviations of both the SES and Hispanic slopes were between 0.44 and 0.54. Thus, the degree of inequality between Black and White students' graduation odds varied substantially among the high schools with relatively integrated student populations that were included in this sample.

I examined correlations between the random intercepts and school slopes to gain a preliminary understanding of the relation between schools' average level of achievement or attainment and the degree of demographic inequality at the school. On average, schools with higher math achievement had *larger* gender inequalities, while schools with higher graduation and college enrollment rates had *smaller* gender inequalities. Across outcomes, on average, schools with higher achievement and attainment had *larger* Black-White inequalities (favoring White students).[1] For the Hispanic-White sample, the correlational pattern was the same as for the Black-White sample when measuring students' odds of any postsecondary enrollment and, depending on the control variables included, their odds of high school graduation. In contrast, schools with higher average on-time four-year enrollment rates had *smaller* Hispanic-White

[1] The one exception was that, conditional on both student and school covariates, the correlation between schools' average rate of on-time four-year enrollment and the magnitude of the Black-White difference in on-time four-year enrollment was near zero.

differences in the odds of on-time four-year enrollment. In the SES chapter, correlations were near zero for three of four outcomes because group mean-centering student SES removed most of the relation between schools' intercepts and their SES slopes. Though the correlation was weak-to-moderate, schools with higher average rates of on-time four-year enrollment had *less* SES-based differentiation in students' probability of on-time four-year enrollment. In sum, schools with higher average outcomes had smaller demographic-based inequalities for some outcomes and some demographic subgroups but certainly not all.

School Types

Two school types, "schools with the most positive student-staff relationships" and "less well-maintained but academically advantaged schools," were most often found to have relations between students' demographic characteristics and outcomes that differed from those in middle-of-the-road schools. Compared to middle-of-the-road schools, both of these school types generally had higher average achievement and attainment, but they differed in their patterns of subgroup inequality. Schools with the most positive student-staff relationships had *smaller* than average gender inequalities in high school graduation and perhaps any postsecondary enrollment but *larger* than average gender inequalities in math achievement and on-time four-year enrollment. These schools had *less* SES-based differentiation in math achievement and possibly on-time four-year enrollment, and a *smaller* than average difference between Hispanic and White students' math achievement. In a mostly contrasting pattern, less well-maintained but academically advantaged schools had *larger* gender inequalities in high school graduation and on-time four-year enrollment and *more* SES-based differentiation in on-time four-year enrollment. In this school type, White students' odds of four-year enrollment were particularly high relative to Black students', as were White students' odds of any postsecondary enrollment relative to Hispanic students'. In sum, although both schools with the most positive student-staff relationships and less well-maintained but academically advantaged schools generally had higher average outcomes than middle-of-the-road schools, their patterns for subgroup inequality were largely opposite: schools with the most positive student-staff relationships tended to have less inequality by students' demographic characteristics, while less well-maintained but academically advantaged schools tended to have more.

Most of the other differences in the relation between students' demographic characteristics and their outcomes by school type were outcome- and sample-specific. The only school type that never exhibited statistically distinguishable differences in the degree of inequality compared to middle-of-the-road schools was the most vocationally-oriented schools. Apparently, "average" schools (i.e., the modal type) and those with more vocationally-oriented instruction than average have similar degrees of inequality regardless of outcome or student subgroup.

School Resources

In each chapter, I then examined how individual school resources were related to the degree of inequality in high schools. In terms of instructional resources, although the magnitude and significance of the coefficients varied, the patterns were generally quite similar for schools with a general versus more vocational orientation to instruction (mirroring the findings for the most vocationally-oriented school type discussed above). Compared to schools with a more general or vocational orientation, schools with the **most academically-oriented instruction** had *larger* gender inequalities in math achievement; *less* SES-based differentiation in math achievement and on-time four-year enrollment[2]; and *smaller* Hispanic-White, and possibly

---

[2] But possibly *more* SES-based differentiation in any postsecondary enrollment, though none of the interactions were statistically significant

Black-White, inequalities in math achievement. Black students also may have been advantaged, relative to White students, in terms of high school graduation in schools with the most academically-oriented instruction. In general, then, traditionally less-advantaged groups often had particularly positive outcomes (relative to their predicted performance in other schools) in schools with the most academically-oriented instruction, but there were important exceptions.

Although there were rarely statistically significant differences by **teacher resource classes** in the degree of inequality, when differences existed, they suggested that schools with more experienced but less satisfied teachers were associated with larger *inequality* among students of different socioeconomic and ethnic backgrounds, even though these schools often had higher average levels of achievement and attainment. Specifically, schools with more experienced but less satisfied teachers had *more* SES-based differentiation in math achievement and on-time four-year enrollment and *larger* Hispanic-White differences in math achievement. Perhaps teachers' dissatisfaction particularly harms disadvantaged students, or perhaps teachers are particularly dissatisfied when they work in schools with disadvantaged students who are performing poorly relative to their more advantaged counterparts.

The results for **physical resource classes** were not as consistent across student subgroups and outcomes. Compared to schools with the most physical resource problems, schools with few to moderate problems had *smaller* gender inequalities in high school graduation but *more* SES-based differentiation in math achievement. Among the relatively integrated schools examined in Chapter 5, a puzzling finding was that Black students' math achievement (and possibly Black students' odds of on-time four-year enrollment) seemed to differ *less* than White students' did between schools with the most physical resource problems and those with the fewest problems. Similarly puzzling was that, while in schools with the fewest physical resource problems, Hispanic students' odds of on-time four-year enrollment were significantly *lower* than White students', Hispanic and White students' odds of on-time four-year enrollment were nearly equal in schools with the most physical resource problems. These results suggest that, at least for some outcomes and at least within the relatively select group of schools in the sample (i.e., those I call "relatively integrated"), White students may benefit more than Black or Hispanic students from attending schools with the fewest physical resource problems. Perhaps more resources are directed at White rather than Black or Hispanic students when there is no resource shortage.

Schools with **more positive student-staff relationships** had *larger* gender inequalities in math achievement but *smaller* gender inequalities in high school graduation. These schools had *less* SES-based differentiation in math achievement and on-time four-year enrollment and *smaller* Hispanic-White inequalities in math achievement. Black students' odds, relative to White students', of graduating high school and of any postsecondary enrollment were particularly high in schools with more positive student-staff relationships. Thus, all students generally had higher average outcomes in schools with more positive student-staff relationships, but disadvantaged students' outcomes were particularly high (consistent with the findings for the "most positive student-staff relationships" school type discussed above). The one important exception, however, was for female students' math achievement. As I discussed in previous chapters, in schools with more positive student-staff relationships, staff may spend more time and effort helping traditionally disadvantaged students.

In contrast to the patterns for student-staff relationships, patterns for student-peer relationships varied across samples and outcomes, which is perhaps not surprising given that the peer effects literature has proposed at least two different theories that imply contradictory outcomes for disadvantaged students attending schools with more privileged students. Schools with **more academically-oriented peers** had *larger* gender inequalities in math achievement, and also had *more* SES-based differentiation in students' odds of any postsecondary enrollment. In these schools, differences between Hispanic and White students' math achievement were *smaller*, but differences between Hispanic and White students' odds of graduating and odds of any postsecondary enrollment might have been *larger*. Black students' odds of high school graduation were particularly high in schools with more academically-oriented peers compared to schools with less academically-oriented peers, but Black students' odds of any postsecondary enrollment differed less by schools' peer resource class than White students' did. Thus, although the results may provide evidence of both normative and frog pond dynamics at play in U.S. high schools, it is difficult to discern a clear pattern or theory about why normative versus frog pond dynamics operate for different outcomes or samples.

Ultimately, schools have some control over how they allocate resources, but their resources are certainly finite, and some types of resource allocations are more common than others. By first examining empirically occurring bundles of resources, or "school types," I was able to explore the relation between different, real-world resource allocations and inequality in student outcomes. Then, looking at the individual resources independently allowed me to more closely investigate possible mechanisms. While the findings here are limited in ways I have already discussed, they provide preliminary insights into the link between school-level variability in student outcome disparities and manipulable school resources.

FUTURE WORK

Using ELS data allowed me to examine multiple outcomes, interpersonal as well as structural school resources, and resources and demographic inequalities across the range of U.S. high schools. Although the data and methods did bring challenges and limitations, there is much more that could be done within my existing framework and approach to strengthen and clarify the results I have discussed here. First, however, I need to reiterate that the small within-school sample sizes and limited power at the school level restricted the precision of estimates and my ability to find statistically significant relationships and that the fact that Black and Hispanic students mostly do not attend the same schools as White students, which led me to focus only on relatively integrated schools in Chapter 5, meant that Chapter 5 did not take advantage of the ELS' nationally representative nature.

Sensitivity Analyses

The first set of future work I plan to conduct is additional analyses to assess the robustness of the results presented here. First, while estimating within-school inequality between students from different subgroups necessarily requires at least one student per subgroup from each school, requiring more students per school entails tradeoffs. I chose to restrict the sample to schools with at least three students from each subgroup (five students total in the SES chapter) as a compromise between sample representativeness and precision of estimates. In the future, I plan to estimate the models requiring only one student from each subgroup per school (to increase the school-level sample's representativeness) and then five students from each subgroup per school (to increase the estimates' precision). This would provide information about how robust the results are to different sample restrictions.

Relatedly, I plan to explore whether and how modeling changes to the race/ethnicity models affect my conclusions. In this vein, the first step is to include students from all races/ethnicities in the race/ethnicity models, rather than splitting the sample into only Black and White or Hispanic and White students; this revision would increase the sample size while keeping the baseline the same. While it should not affect the pattern of results, it offers the possibility of increasing power to find statistical significance. The second step is to run similar models but keep all schools in the sample, rather than omitting schools with fewer than three Black, Hispanic, or White students; again, the primary advantage of this approach would be to increase statistical power. In discussing these models, I will be sure to clarify that the coefficients for the cross-level interactions are estimated only from schools that have at least one student in that subgroup. In my current approach, the Black-White and Hispanic-White results are not strictly comparable because the parameters come from different school samples; the approach I just discussed would improve comparability. In addition, I plan to run some analyses that group Black and Hispanic students together into a “minority” group, and that also include multiracial students or students from other racial/ethnic categories in that category, to explore whether the models and presentation of results could be simplified or clarified by focusing on minority students as a group, rather than Black and Hispanic students as separate categories.

Next, given that estimates of cross-level interactions can be sensitive to the variables included in the student-level model, I plan to review papers that have used similar approaches to determine whether I have omitted any student-level variables that are available in the ELS and that are included in the student-level models shown in related papers; if so, I will explore whether including any of these variables changes the conclusions I draw.

The final sensitivity analysis I plan to conduct is to compare the estimates shown here to those from a supplementary analysis focused only on traditional public schools. Concerns about unidentified selection effects are much greater for the main effects of student background characteristics and school resources than for the interactions between student characteristics and resources that I focus on here (Bryk and Thum 1989; Lee and Bryk 1989). Lee and Bryk wrote that, for an unidentified variable to confound the cross-level interactions, “the unmeasured selection factor must be related to the student outcome…, the relationship between the unmeasured variable and those student variables already included in the model must vary across schools…, [and] this slope variability must be systematically related to the specific school factors considered here" (1989: 187). Nevertheless, I would like to provide clearer bounding of my estimates by including results based on traditional public schools only. Although students are not randomly sorted in traditional public schools, there should be less selectivity than when the full set of schools (including private, magnet, and charter schools) is used, which could provide some insights into the degree of selectivity concerns.

Modeling Extensions

I see the future work discussed above as a series of sensitivity analyses for the existing models. In this section, I discuss ways to extend the models in different but closely related directions.

First, for this dissertation, I used nearly identical models, including the same outcome and school resource measures, across chapters in order to compare similar patterns for different demographic subgroups. The models shown here should be thought of as exploratory and as offering preliminary insights toward estimating more constrained models that are informed by this initial work and that focus on cross-level interactions that are theoretically and/or empirically interesting. I plan to refine and prune these models, in part based on the model fit statistics shown here. Many of the cross-level interactions I included in this dissertation did not explain additional variance; in the future, I will think and write carefully about which models – across outcomes, resource measures, and demographic subgroups – are best supported by the data and are the strongest at predicting meaningful variation.

Second, I will extend the resource measures employed here in multiple ways. To explore student-peer relationships more thoroughly, I would like to create measures that differentiate students' perceptions of the school as a whole versus students' perceptions of their own friends. This approach might lead to insights into which, if any, students have a gap between what they perceive to be true with regard to the academic orientation of their specific friends versus the school as a whole. Additionally, I would like to use a group mean-centering approach to examine whether the absolute versus relative level of peer resources matters differently. For example, is it the school average peer culture – as I have tried to capture here – that is important for students' outcomes, or does a student's position relative to the school average matter more or differently? Further exploration of more refined peer resource measures could provide insight into the different patterns through which peer resources are related to the distribution of attainment or math achievement and about how, and when, peer effects operate.

As I mentioned in Chapter 3, I also plan to examine gender-specific resource measures. Aggregating students' reports of school resources assumes that students from different subgroups experience the school in relatively similar ways, or have relatively similar perceptions of the school. As I discussed in each chapter, there is ample prior literature documenting that students within the same school often do not have a common experience. Unfortunately, my ability to investigate within-school differences in experience is generally severely limited by the small within-school sample sizes; the exception may be differences in within-school experiences by gender. Because of the relatively even distribution of male and female students across schools, I could explore gender-specific resource perceptions for most schools in the ELS. Thus, in the future, I plan to explore whether male and female students' subgroup-specific resource perceptions are associated with gender inequalities in ways that differ from the aggregate resource measures I have included here.

Additionally, I plan to break down the resource measures into their individual components and spend some time exploring how consistent the patterns documented here are across the individual items that make up each school resource class. Latent class analysis provided an empirical method of clustering schools and allowed me to explore how certain types of common, joint resource allocations are related to variation in outcomes. However, using latent classes as predictors sometimes raised questions about whether particular items might be driving results, or obscured what specifically about the class mattered. Therefore, additional information on the robustness of the results to different measures of each resource type would strengthen confidence in the findings and might point to specific aspects of instructional, teacher, school physical, student-staff, or student-peer resources that should be further investigated in future studies.

Beyond the extensions to the resource measures proposed above, I also would like to extend my analyses of socioeconomic inequalities by analyzing patterns for not only the SES composite measure but also the individual components of SES – that is, parents' education and income. Inequalities related to parent education may have different implications than those related to parent income; for example, if inequalities are related to parents' education, schools may be able to shift those inequalities by raising students' aspirations or by providing specific knowledge that is more often possessed by college-educated parents. However, if inequalities are related to parent income, schools may have fewer openings to reduce these inequalities. Thus, a focus on specific aspects of SES – not solely the SES composite – could be valuable.

The final modeling extension I would like to make is to take greater advantage of the latent class aspect of the models. Up to this point, I have treated the latent classes as school-level covariates. In the future, I plan to take the latent class analysis in a different but related direction by treating the latent classes as subpopulations of schools and exploring the degree of inequality within each of these (more) homogenous groups. For example, within the school type of "most academically advantaged schools," which type of inequalities (e.g., gender, racial/ethnic, socioeconomic) are larger and which are smaller than they are in "middle-of-the-road schools"? This type of approach has the potential to offer important insights into which inequalities we should be most concerned about in which schools and perhaps which school types are associated with the best (and worst) outcomes for particular types of students.

Improvements in Theory and Framing

In future revisions and extensions of this work, I plan to improve the theory and framing in several ways. First, I will provide a clearer discussion of the mechanisms through which gender differences in the association between school resources and student outcomes may occur. In this version of the work, I have discussed why racial/ethnic and socioeconomic differences in the resource-outcome relation may occur but have provided less justification for why school characteristics may be differentially related to outcomes for male and female students. Relatedly, I will provide a stronger theory of school resources that more carefully describes the basis for asserting that certain school characteristics are at least partially within schools' control and, therefore, can be thought of as potentially manipulable school resources. In doing so, I will be certain to stress that, in my viewpoint, time and labor, not just money, are resources.

Second, I plan to more carefully compare my work to existing research when appropriate. For example, when drawing on Bryk and Lee's findings, I will discuss in greater detail the similarities and differences between my models and findings and theirs in order to both more transparently connect my work to the existing literature and to make clearer what is unique about my work.

Third, I plan to provide additional details about the latent classes and slightly alter the way I discuss the classes. By referring to the latent classes as denoting "school types," I may inadvertently give the impression that I used modal categories, rather than posterior probabilities, from the LCA as predictors. In the future, to avoid giving the impression that schools are unambiguously of one type or another, I plan to talk about schools as having stronger *tendencies* toward some characteristics (e.g., satisfied teachers, academically oriented instruction) than others. This change in language should help make clearer to readers that the tendencies and traits identified via LCA are probabilistic. Along these lines, I also plan to provide more details about how I used the observed indicators and latent classes, as well as their characteristics (e.g., the extent to which the response patterns were bimodal, though technically continuous).

I also plan to bolster my substantive and theoretical justification for the use of latent classes. For example, I will more forcefully argue that, when selecting schools for their children, parents usually do not have fine-tuned data on every aspect of schools and, therefore, often view schools holistically; thus, the "typology" approach I employ may be very consistent with how non-social scientists think about schools.

Another improvement I hope to make to the framing of this work is to more clearly discuss how unobserved selectivity may affect the results shown here, and when it is unlikely to do so. Though I discussed at multiple points the concern that the patterns shown here may be the result of which students attend which schools, not of the influence of schools themselves, in the future, I plan to provide more concrete examples of possible omitted variables and how they might affect results. This should help readers see what is and is not a limitation of the data and analysis. Where appropriate, I also plan to include more information about the extent to which there is prior literature on how particular families select into schools; for example, there is much more existing literature on how middle- and upper-middle-class Black students' parents select schools than there is on how boys' versus girls' parents select schools. Thus, we may have a better sense of omitted variables that for the race/ethnicity chapter than for the gender chapter.

Extensions to Other Data

All of the future work discussed above could be done using the ELS data. I would also like to use other data to further investigate one of the most intriguing findings of this dissertation: that more positive student-staff relationships were relatively consistently associated with both higher and more equitable outcomes. In the future, I plan to look for opportunities to test interventions related to improving relationships between students and adult members of the school community to learn whether experimental manipulation of student-staff relationships can improve equity and, if so, for which students and what outcomes.

CONCLUSION

Reducing the relation between ascriptive characteristics and educational outcomes is, at least normatively, a central goal of schooling. While the majority of students from advantaged backgrounds do well academically regardless of the school they attend, schools have a greater role to play in improving the educational achievement and attainment of students from disadvantaged subgroups (Rumberger and Palardy 2005a). This dissertation showed that "good schools," when defined as those with high average achievement or attainment, do not always have correspondingly low levels of inequality, nor do schools with higher levels of resources always have lower levels of inequality. In some cases, schools with higher levels of specific resources have *greater* inequalities. While this was most commonly the case for the school resources of “experienced teachers” and “academically-oriented peers,” higher levels of all of the resources were associated with greater inequalities for at least some subgroups and outcomes.

Although the findings cannot provide strong evidence for particular policy prescriptions, they do provide insight into *manipulable* school resources that are associated with more positive outcomes for students from traditionally less-advantaged subgroups. Most importantly, students from traditionally less-advantaged subgroups may be particularly helped by attending schools with the most academically-oriented instruction and most positive student-staff relationships. Across outcomes and subgroups, student-staff relationships had the most consistent, positive, and equitable associations, which is a particularly important finding given the current prioritization of instructional improvement of schools over teachers’, students’, and staff’s relational and socioemotional well-being. A greater focus on strengthening within-school relationships may be a particularly promising approach that schools could adopt in striving toward both higher average achievement and attainment and greater equity by gender, socioeconomic status, and race/ethnicity.

Ultimately, much more remains to be learned about the causal effects of particular resources on inequalities in student outcomes. Yet, quantifying the degree of variation in these inequalities across contexts and documenting the characteristics associated with smaller or larger inequalities is an important step on the path toward understanding – and then reducing – gender, socioeconomic, and racial/ethnic inequalities.

References

Acker, Joan. 2006. "Inequality Regimes: Gender, Class, and Race in Organizations." *Gender & Society* 20(4):441-64.

Aguinis, Herman, Ryan K. Gottfredson, and Steven Andrew Culpepper. 2013. "Best-Practice Recommendations for Estimating Cross-Level Interaction Effects Using Multilevel Modeling." *Journal of Management* 39(6):1490-528.

Akiba, Motoko, Gerald K. LeTendre, and Jay P. Scribner. 2007. "Teacher Quality, Opportunity Gap, and National Achievement in 46 Countries." *Educational Researcher* 36(7):369-87.

Arum, Richard. 1998. "Invested Dollars or Diverted Dreams: The Effect of Resources on Vocational Students' Educational Outcomes." *Sociology of Education* 71(2):130-51.

Attewell, Paul. 2001. "The Winner-Take-All High School: Organizational Adaptations to Educational Stratification." *Sociology of Education* 74(4):267-95.

Attewell, Paul, and Thurston Domina. 2008. "Raising the Bar: Curricular Intensity and Academic Performance." *Educational Evaluation and Policy Analysis* 30(1):51-71.

Bailey, Martha J., and Susan M. Dynarski. 2011. "Gains and Gaps: Changing Inequality in U.S. College Entry and Completion." Cambridge, MA: National Bureau of Economic Research.

Balfanz, Robert, and Vaughan Byrnes. 2012. "Chronic Absenteeism: Summarizing What We Know from Nationally Available Data." Baltimore, MD: Johns Hopkins University Center for Social Organization of Schools.

Barone, Carlo. 2011. "Some Things Never Change: Gender Segregation in Higher Education across Eight Nations and Three Decades." *Sociology of Education* 84(2):157-76.

Bertrand, Marianne, and Jessica Pan. 2013. "The Trouble with Boys: Social Influences and the Gender Gap in Disruptive Behavior." *American Economic Journal* 5(1):32-64.

Bidwell, Charles E., and John D. Kasarda. 1980. "Conceptualizing and Measuring the Effects of School and Schooling." *American Journal of Education* 88(4):401-30.

Billings, Stephen B., David J. Deming, and Jonah E. Rockoff. 2012. "School Segregation, Educational Attainment and Crime: Evidence from the End of Busing in Charlotte-Mecklenburg." *Quarterly Journal of Economics* 129(1):435-76.

Black, Sandra E., Jane Arnold Lincove, Jenna Cullinane, and Rachel Veron. 2014. "Can You Leave High School Behind?" Cambridge, MA: National Bureau of Economic Research.

Borman, Geoffrey D., and Jerome V. D'Agostino. 1996. "Title I and Student Achievement: A Meta-Analysis of Federal Evaluation Results." *Educational Evaluation and Policy Analysis* 18(4):309-26.

Borman, Geoffrey D., and Maritza Dowling. 2010. "Schools and Inequality: A Multilevel Analysis of Coleman's Equality of Educational Opportunity Data." *Teachers College Record* 12(5):1201-46.

Borman, Kathryn M., Tamela McNulty Eitle, Deanna Michael, David J. Eitle, Reginald Lee, Larry Johnson, Deirdre Cobb-Roberts, Sherman Dorn, and Barbara Shircliffe. 2004. "Accountability in a Postdesegregation Era: The Continuing Significance of Racial Segregation in Florida's Schools." *American Educational Research Journal* 41(3):605-31.

Bowditch, Christine. 1993. "Getting Rid of Troublemakers: High School Disciplinary Procedures and the Production of Dropouts." *Social Problems* 40(4):493-509.

Bowers, Alex J., and Angela Urick. 2011. "Does High School Facility Quality Affect Student Achievement?: A Two-Level Hierarchical Linear Model." *Journal of Education Finance* 37(1):72-94.

Bozick, Robert, and Stefanie DeLuca. 2005. "Better Late Than Never? Delayed Enrollment in the High School to College Transition." *Social Forces* 84(1):531-54.

Bozick, Robert, Erich Lauff, and John Wirt. 2007. "Education Longitudinal Study of 2002 (ELS:2002): A First Look at the Initial Postsecondary Experiences of the Sophomore Class of 2002 (NCES 2008-308)." Washington, D.C.: National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education.

Bray, Bethany C., Stephanie T. Lanza, and Xianming Tan. 2015. "Eliminating Bias in Classify-Analyze Approaches for Latent Class Analysis." *Structural Equation Modeling: A Multidisciplinary Journal* 22(1):1-11.

Bryk, Anthony S., and Mary Erina Driscoll. 1988. "The High School as Community: Contextual Influences and Consequences for Students and Teachers." Madison, WI: National Center on Effective Secondary Schools.

Bryk, Anthony S., Valerie E. Lee, and Peter B. Holland. 1993. *Catholic Schools and the Common Good*. Cambridge, MA: Harvard University Press.

Bryk, Anthony S., and Barbara Schneider. 2002. *Trust in Schools: A Core Resource for Improvement*. New York, NY: Russell Sage Foundation.

Bryk, Anthony S., and Yeow Meng Thum. 1989. "The Effects of High School Organization on Dropping Out: An Exploratory Investigation." *American Educational Research Journal* 26(3):353-83.

Buchmann, Claudia, and Thomas A. DiPrete. 2006. "The Growing Female Advantage in College Completion: The Role of Family Background and Academic Achievement." *American Sociological Review* 71(4):515-41.

Camburn, Eric M., and Seong Won Han. 2011. "Two Decades of Generalizable Evidence on U.S. Instruction from National Surveys." *Teachers College Record* 113(3):561-610.

Carbonaro, William. 2005. "Tracking, Students' Effort, and Academic Achievement." *Sociology of Education* 78(1):27-49.

Carbonaro, William, and Elizabeth Covay. 2010. "School Sector and Student Achievement in the Era of Standards Based Reforms." *Sociology of Education* 83(2):160-82.

Carbonaro, William, and Adam Gamoran. 2002. "The Production of Achievement Inequality in High School English." *American Educational Research Journal* 39(4):801-27.

Cherng, Hua-Yu Sebastian, Jessica McCrory Calarco, and Grace Kao. 2013. "Along for the Ride: Best Friends' Resources and Adolescents' College Completion." *American Educational Research Journal* 50(1):76-106.

Chung, Yeojin, Sophia Rabe-Hesketh, Andrew Gelman, Jingchen Liu, and Vincent Dorie. 2012. "Avoiding Boundary Estimates in Linear Mixed Models through Weakly Informative Priors." *U.C. Berkeley Division of Biostatistics Working Paper Series*. Berkeley, CA: U.C. Berkeley.

Clotfelter, Charles T., Helen F. Ladd, and Jacob L. Vigdor. 2010. "Teacher Credentials and Student Achievement in High School: A Cross-Subject Analysis with Student Fixed Effects." *Journal of Human Resources* 45(3):655-81.

Cohen, David K., Stephen W. Raudenbush, and Deborah Loewenberg Ball. 2003. "Resources, Instruction, and Research." *Educational Evaluation and Policy Analysis* 25(2):119-42.

Coleman, James S., Ernest Q. Campbell, Carol J. Hobson, James McPartland, Alexander M. Mood, Frederic D. Weinfeld, and Robert L. York. 1966. "Equality of Educational Opportunity." Washington, D.C.: U.S. Department of Health, Education, and Welfare.

Coleman, James S., Thomas Hoffer, and Sally Kilgore. 1982. *High School Achievement: Public, Catholic, and Private Schools Compared*. New York, NY: Basic Books.

Collins, Linda M., and Stephanie T. Lanza. 2010. *Latent Class and Latent Transition Analysis with Applications in the Social, Behavioral, and Health Sciences*. Hoboken, NJ: John Wiley and Sons, Inc.

Condron, Dennis J. 2009. "Social Class, School and Non-School Environments, and Black/White Inequalities in Children's Learning." *American Sociological Review* 74(5):685-708.

Crosnoe, Robert. 2009. "Low-Income Students and the Socioeconomic Composition of Public High Schools." *American Sociological Review* 74(5):709-30.

Crosnoe, Robert, Monica Kirkpatrick Johnson, and Glen H. Elder, Jr. 2004. "Intergenerational Bonding in School: The Behavioral and Contextual Correlates of Student-Teacher Relationships." *Sociology of Education* 77(1):60-81.

Dee, Thomas S., and Sarah R. Cohodes. 2008. "Out-of-Field Teachers and Student Achievement: Evidence from Matched-Pairs Comparisons." *Public Finance Review* 36(1):7-32.

Deming, David J., Justine S. Hastings, Thomas J. Kane, and Douglas O. Staiger. 2011. "School Choice, School Quality, and Postsecondary Attainment." Cambridge, MA: National Bureau of Economic Research.

Desimone, Laura, and Daniel Long. 2010. "Teacher Effects and the Achievement Gap: Do Teacher and Teaching Quality Influence the Achievement Gap between Black and White and High- and Low-SES Students in the Early Grades?" *Teachers College Record* 112(12):3024-73.

DiPrete, Thomas A., and Claudia Buchmann. 2013. *The Rise of Women: The Growing Gender Gap in Education and What It Means for American Schools*. New York, NY: Russell Sage Foundation.

Downey, Douglas B., and Anastasia S. Vogt Yuan. 2005. "Sex Differences in School Performance during High School: Puzzling Patterns and Possible Explanations." *The Sociological Quarterly* 46(2):299-321.

Downey, Douglas B., Paul T. von Hippel, and Beckett A. Broh. 2004. "Are Schools the Great Equalizer? Cognitive Inequality during the Summer Months and the School Year." *American Sociological Review* 69(5):613-35.

Doyle, William R. 2009. "The Effect of Community College Enrollment on Bachelor's Degree Completion." *Economics of Education Review* 28(2):199-206.

Duncan, Greg J., and Richard J. Murnane (Eds.). 2011. *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*. New York, NY: Russell Sage Foundation.

Elliott, Marta. 1998. "School Finance and Opportunities to Learn: Does Money Well Spent Enhance Students' Achievement?" *Sociology of Education* 71(3):223-45.

Elliott, Philip, and Jennifer Agiesta. 2013. "AP-NORC Poll: Race, Income Divide Views of Schools." Washington, D.C.: ABC News.

Engberg, Mark E., and Gregory C. Wolniak. 2010a. "Access to Postsecondary Education: The Interrelationships among High School Contexts and Socioeconomic Status." Tallahassee, FL: Association for Institutional Research.

—. 2010b. "Examining the Effects of High School Contexts on Postsecondary Enrollment." *Research in Higher Education* 51(2):132-53.

Ensminger, Margaret E., and Kate E. Fothergill. 2003. "A Decade of Measuring SES: What It Tells Us and Where to Go from Here." Pp. 13-27 in *Socioeconomic Status, Parenting, and Child Development,* edited by M. H. Bornstein and R. H. Bradley. New York, NY: Routledge.

Entwisle, Doris R., Karl L. Alexander, and Linda S. Olson. 2007. "Early Schooling: The Handicap of Being Poor and Male." *Sociology of Education* 80(2):114-38.

Erickson, Lance D., Steve McDonald, and Glen H. Elder. 2009. "Informal Mentors and Education: Complementary or Compensatory Resources?" *Sociology of Education* 82(4):344-67.

Espenshade, Thomas J., Lauren E. Hale, and Chang Y. Chung. 2005. "The Frog Pond Revisited: High School Academic Context, Class Rank, and Elite College Admission." *Sociology of Education* 78(4):269-93.

Fall, Anna-Mária, and Greg Roberts. 2012. "High School Dropouts: Interactions between Social Context, Self-Perceptions, School Engagement, and Student Dropout." *Journal of Adolescence* 35(4):787-98.

Fan, Weihua, Cathy M. Williams, and Danya Marie Corkin. 2011. "A Multilevel Analysis of Student Perceptions of School Climate: The Effect of Social and Academic Risk Factors." *Psychology in the Schools* 48(6):632-47.

Ferguson, Ann Arnett. 2001. *Bad Boys: Public Schools in the Making of Black Masculinity*. Ann Arbor, MI: University of Michigan Press.

Ferguson, Ronald F. 2003. "Teachers' Perceptions and Expectations and the Black-White Test Score Gap." *Urban Education* 38(4):460-507.

Finn, Jeremy D., and Charles M. Achilles. 1999. "Tennessee's Class Size Study: Findings, Implications, Misconceptions." *Educational Evaluation and Policy Analysis* 21(2):97-109.

Fletcher, Jason M. 2011. "Social Identity as a Determinant of College Enrollment." *Rationality and Society* 23(3):267-303.

Frost, Michelle Bellessa. 2007. "Texas Students' College Expectations: Does High School Racial Composition Matter?" *Sociology of Education* 80(1):43-65.

Fryer, Roland G., Jr., and Steven D. Levitt. 2004. "Understanding the Black-White Test Score Gap in the First Two Years of School." *Review of Economics and Statistics* 86(2):447-64.

—. 2006. "The Black-White Test Score Gap through Third Grade." *American Law and Economics Review* 8(2):249-81.

Gamoran, Adam. 1992. "The Variable Effects of High School Tracking." *American Sociological Review* 57(6):812-28.

—. 1996. "Student Achievement in Public Magnet, Public Comprehensive, and Private City High Schools." *Educational Evaluation and Policy Analysis* 18(1):1-18.

—. 2010. "Tracking and Inequality: New Directions for Research and Practice." Pp. 213-28 in *The Routledge International Handbook of the Sociology of Education*, edited by M. Apple, S. J. Ball, and L. A. Gandin. London: Routledge.

Gamoran, Adam, and Brian P. An. 2016. "Effects of School Segregation and School Resources in a Changing Policy Context." *Educational Evaluation and Policy Analysis* 38(1):43-64.

Gamoran, Adam, Ana Cristina Collares, and Sarah Barfels. 2016. "Does Racial Isolation in School Lead to Long-Term Disadvantages? Labor Market Consequences of High School Racial Composition." *American Journal of Sociology* 121(4):1116-67.

Gamoran, Adam, and Robert D. Mare. 1989. "Secondary School Tracking and Educational Equality: Compensation, Reinforcement, or Neutrality." *American Journal of Sociology* 94(5):1146-83.

Gelman, Andrew, and Jennifer Hill. 2007. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. New York, NY: Cambridge University Press.

Gerber, Theodore P., and Sin Yi Cheung. 2008. "Horizontal Stratification in Postsecondary Education: Forms, Explanations, and Implications." *Annual Review of Sociology* 34:299-318.

Goldhaber, Dan D., and Dominic J. Brewer. 2000. "Does Teacher Certification Matter? High School Teacher Certification Status and Student Achievement." *Educational Evaluation and Policy Analysis* 22(2):129-45.

Goldrick-Rab, Sara, and Seong Won Han. 2011. "Accounting for Socioeconomic Differences in Delaying the Transition to College." *The Review of Higher Education* 34(3):423-45.

Goldschmidt, Pete, and Jia Wang. 1999. "When Can Schools Affect Dropout Behavior? A Longitudinal Multilevel Analysis." *American Educational Research Journal* 36(4):715-38.

Goldsmith, Pat Antonio. 2004. "Schools' Racial Mix, Students' Optimism, and the Black-White and Latino-White Achievement Gaps." *Sociology of Education* 77(2):121-47.

Goldsmith, Pat Rubio. 2009. "Schools or Neighborhoods or Both? Race and Ethnic Segregation and Educational Attainment." *Social Forces* 87(4):1913-41.

—. 2011. "Coleman Revisited: School Segregation, Peers, and Frog Ponds." *American Educational Research Journal* 48(3):508-35.

Gordon, Nora. 2004. "Do Federal Grants Boost School Spending? Evidence from Title I." *Journal of Public Economics* 88(9–10):1771-92.

Gordon, Nora, and Sarah Reber. 2015. "The Quest for a Targeted and Effective Title I ESEA: Challenges in Designing and Implementing Fiscal Compliance Rules." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 1(3):129-47.

Greenwald, Rob, Larry V. Hedges, and Richard D. Laine. 1996. "The Effect of School Resources on Student Achievement." *Review of Educational Research* 66(3):361-96.

Gregory, Anne, and Rhona S. Weinstein. 2004. "Connection and Regulation at Home and in School: Predicting Growth in Achievement for Adolescents." *Journal of Adolescent Research* 19(4):405-27.

Grubb, W. Norton. 2008. "Multiple Resources, Multiple Outcomes: Testing the 'Improved' School Finance With NELS88." *American Educational Research Journal* 45(1):104-44.

Guryan, Jonathan. 2004. "Desegregation and Black Dropout Rates." *The American Economic Review* 94(4):919-43.

Hallinan, Maureen, and Warren N. Kubitschek. 2012. "A Comparison of Academic Achievement and Adherence to the Common School Ideal in Public and Catholic Schools." *Sociology of Education* 85(1):1-22.

Hallinan, Maureen T. 1992. "The Organization of Students for Instruction in Middle School." *Sociology of Education* 65(2):114-27.

—. 2001. "Sociological Perspectives on Black-White Inequalities in American Schooling." *Sociology of Education* 74(Extra issue):50-70.

—. 2008. "Teacher Influences on Students' Attachment to School." *Sociology of Education* 81(3):271-83.

Halpern, Diane F. 2013. *Sex Differences in Cognitive Abilities*. New York, NY: Psychology Press.

Hanushek, Eric A. 1996. "School Resources and Student Performance." Pp. 43-73 in *Does Money Matter? The Effect of School Resources on Student Achievement*, edited by G. T. Burtless. Washington, D.C.: Brookings Institution.

—. 1997. "Assessing the Effects of School Resources on Student Performance: An Update." *Educational Evaluation and Policy Analysis* 19(2):141-64.

—. 2010. "How Well Do We Understand Achievement Gaps?" *Focus* 27(2):5-12.

Hanushek, Eric A., and Steven G. Rivkin. 2006. "School Quality and the Black-White Achievement Gap." Cambridge, MA: National Bureau of Economic Research.

Hanushek, Eric A., John F. Kain, and Steven G. Rivkin. 2009. "New Evidence about Brown v. Board of Education: The Complex Effects of School Racial Composition on Achievement." *Journal of Labor Economics* 27(3):349-83.

Harris, Douglas N. 2007. "High-Flying Schools, Student Disadvantage, and the Logic of NCLB." *American Journal of Education* 113(3):367-94.

Harris, Douglas N., and Carolyn D. Herrington. 2006. "Accountability, Standards, and the Growing Achievement Gap: Lessons from the Past Half-Century." *American Journal of Education* 112(2):209-38.

Hauser, Robert M., and William H. Sewell. 1986. "Family Effects in Simple Models of Education, Occupational Status, and Earnings: Findings from the Wisconsin and Kalamazoo Studies." *Journal of Labor Economics* 4(3):S83-S115.

Heckman, James J., John Eric Humphries, and Nicholas S. Mader. 2010. "The GED." Cambridge, MA: National Bureau of Economic Research.

Hemphill, F. Cadelle, and Alan Vanneman. 2011. "Achievement Gaps: How Hispanic and White Students in Public Schools Perform in Mathematics and Reading on the National Assessment of Educational Progress." Washington, D.C.: National Center for Education Statistics.

Hill, Jason G., and Ben Dalton. 2013. "Student Math Achievement and Out-of-Field Teaching." *Educational Researcher* 42(7):403-05.

Hill, Lori Diane. 2008. "School Strategies and the 'College-Linking' Process: Reconsidering the Effects of High Schools on College Enrollment." *Sociology of Education* 81(1):53-76.

Hoffer, Thomas, Andrew M. Greeley, and James S. Coleman. 1985. "Achievement Growth in Public and Catholic Schools." *Sociology of Education* 58(2):74-97.

Ingels, Steven J., Daniel J. Pratt, Christopher P. Alexander, Donna M. Jewell, Erich Lauff, Tiffany L. Mattox, and David Wilson. 2014. "Education Longitudinal Study of 2002 (ELS:2002) Third Follow-Up Data File Documentation." Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

Ingels, Steven J., Daniel J. Pratt, James E. Rogers, Peter H. Siegel, and Ellen S. Stutts. 2004. "Education Longitudinal Study of 2002: Base Year Data File User's Manual." Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

—. 2005. "Education Longitudinal Study of 2002: Base-Year to First Follow-up Data File Documentation." Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

Ingels, Steven J., Daniel J. Pratt, David Wilson, Laura J. Burns, Douglas Currivan, James E. Rogers, and Sherry Hubbard-Bednasz. 2007. "Education Longitudinal Study of 2002: Base-Year to Second Follow-Up Data File Documentation." Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

Ingersoll, Richard M. 1999. "The Problem of Underqualified Teachers in American Secondary Schools." *Educational Researcher* 28(2):26-37.

James, Angela. 2008. "Making Sense of Race and Racial Classification." Pp. 31-46 in *White Logic, White Methods: Racism and Methodology*, edited by T. Zuberi and E. Bonilla-Silva. Lanham, MD: Rowman & Littlefield Publishers.

Jencks, Christopher, and Meredith Phillips (Eds.). 1998. *The Black-White Test Score Gap*. Washington, D.C.: Brookings Institution Press.

Jencks, Christopher, Marshall Smith, Henry Acland, Mary Jo Bane, David Cohen, Herbert Gintis, Barbara Heyns, and Stephan Michelson. 1972. *Inequality: A Reassessment of the Effect of Family and Schooling in America*. New York, NY: Basic Books.

Jennings, Jennifer L., David Deming, Christopher Jencks, Maya Lopuch, and Beth E. Schueler. 2015. "Do Differences in School Quality Matter More Than We Thought? New Evidence on Educational Opportunity in the Twenty-First Century." *Sociology of Education* 88(1):56-82.

Jennings, John F. 2000. "Title I: Its Legislative History and Its Promise." *Phi Delta Kappan* 81(7):516-22.

Johns, Michael, Toni Schmader, and Andy Martens. 2005. "Knowing Is Half the Battle: Teaching Stereotype Threat as a Means of Improving Women's Math Performance." *Psychological Science* 16(3):175-79.

Jones, Susanne M., and Kathryn Dindia. 2004. "A Meta-Analytic Perspective on Sex Equity in the Classroom." *Review of Educational Research* 74(4):443-71.

Kain, John F., and Kraig Singleton. 1996. "Equality of Education Opportunity Revisited." *New England Economic Review* Special issue(May/June):87-114.

Kalogrides, Demetra, and Susanna Loeb. 2013. "Different Teachers, Different Peers: The Magnitude of Student Sorting Within Schools." *Educational Researcher* 42(6):304-16.

Kane, Thomas J. 2004. "College Going and Inequality." Pp. 319-54 in *Social Inequality*, edited by K. Neckerman. New York, NY: Russell Sage Foundation.

Keith, Timothy Z., and Ellis B. Page. 1985. "Do Catholic High Schools Improve Minority Student Achievement?" *American Educational Research Journal* 22(3):337-49.

Kelly, Sean. 2009. "The Black-White Gap in Mathematics Course Taking." *Sociology of Education* 82(1):47-69.

Kelly, Sean, and Heather Price. 2011. "The Correlates of Tracking Policy: Opportunity Hoarding, Status Competition, or a Technical-Functional Explanation?" *American Educational Research Journal* 48(3):560-85.

Klugman, Joshua. 2012. "How Resource Inequalities among High Schools Reproduce Class Advantages in College Destinations." *Research in Higher Education* 53(8):803-30.

—. 2013. "Equalizing, but not Greatly: How Inverted Educational Opportunities in U.S. High Schools Contribute to Stratification in College Destinations." Working paper.

Ladson-Billings, Gloria, and William F. IV Tate. 1995. "Toward a Critical Race Theory of Education." *Teachers College Record* 97(1):47-68.

Lanza, Stephanie T., Xianming Tan, and Bethany C. Bray. 2013. "Latent Class Analysis with Distal Outcomes: A Flexible Model-Based Approach." *Structural Equation Modeling: A Multidisciplinary Journal* 20(1):1-26.

Lauen, Douglas Lee, and S. Michael Gaddis. 2013. "Exposure to Classroom Poverty and Test Score Achievement: Contextual Effects or Selection?" *American Journal of Sociology* 118(4):943-79.

Lee, Jaekyung, and Todd Reeves. 2012. "Revisiting the Impact of NCLB High-Stakes School Accountability, Capacity, and Resources: State NAEP 1990–2009 Reading and Math

Achievement Gaps and Trends." *Educational Evaluation and Policy Analysis* 34(2):209-31.

Lee, Valerie E., and Anthony S. Bryk. 1989. "A Multilevel Model of the Social Distribution of High School Achievement." *Sociology of Education* 62(3):172-92.

Lee, Valerie E., and David T. Burkam. 2003. "Dropping Out of High School: The Role of School Organization and Structure." *American Educational Research Journal* 40(2):353-93.

Lee, Valerie E., Todd K. Chow-Hoy, David T. Burkam, Douglas Geverdt, and Becky A. Smerdon. 1998. "Sector Differences in High School Course Taking: A Private School or Catholic School Effect?" *Sociology of Education* 71(4):314-35.

Lee, Valerie E., Robert G. Croninger, and Julia B. Smith. 1997. "Course-Taking, Equity, and Mathematics Learning: Testing the Constrained Curriculum Hypothesis in U.S. Secondary Schools." *Educational Evaluation and Policy Analysis* 19(2):99-121.

Lee, Valerie E., and Julia B. Smith. 1995. "Effects of High School Restructuring and Size on Early Gains in Achievement and Engagement." *Sociology of Education* 68(4):241-70.

—. 1996. "Collective Responsibility for Learning and Its Effects on Gains in Achievement for Early Secondary School Students." *American Journal of Education* 104(2):103-47.

—. 1997. "High School Size: Which Works Best and for Whom?" *Educational Evaluation and Policy Analysis* 19(3):205-27.

Lee, Valerie E., Julia B. Smith, and Robert G. Croninger. 1997. "How High School Organization Influences the Equitable Distribution of Learning in Mathematics and Science." *Sociology of Education* 70(2):128-50.

Legewie, Joscha, and Thomas A. DiPrete. 2011. "Gender Differences in the Effect of Peer SES: Evidence from a Second Quasi-Experimental Case Study." Working paper.

—. 2012. "School Context and the Gender Gap in Educational Achievement." *American Sociological Review* 77(3):463-85.

—. 2014. "The High School Environment and the Gender Gap in Science and Engineering." *Sociology of Education* 87(4):259-80.

Lewis-McCoy, R. L'Heureux. 2014. *Inequality in the Promised Land: Race, Resources, and Suburban Schooling*. Stanford, CA: Stanford University Press.

Lewis, Amanda E., and John B. Diamond. 2015. *Despite the Best Intentions: How Racial Inequality Thrives in Good Schools*. New York, NY: Oxford University Press.

Lleras, Christy. 2008. "Race, Racial Concentration, and the Dynamics of Educational Inequality across Urban and Suburban Schools." *American Educational Research Journal* 45(4):886-912.

Logan, John R., Deirdre Oakley, and Jacob Stowell. 2008. "School Segregation in Metropolitan Regions, 1970–2000: The Impacts of Policy Choices on Public Education." *American Journal of Sociology* 113(6):1611-44.

Long, Bridget Terry, and Michal Kurlaender. 2009. "Do Community Colleges Provide a Viable Pathway to a Baccalaureate Degree?" *Educational Evaluation and Policy Analysis* 31(1):30-53.

Lopez, Nancy. 2003. *Hopeful Girls, Troubled Boys: Race and Gender Disparity in Urban Education*. New York and London: Routledge.

Lubienski, Sarah Theule. 2002. "A Closer Look at Black-White Mathematics Gaps: Intersections of Race and SES in NAEP Achievement and Instructional Practices Data." *The Journal of Negro Education* 71(4):269-87.

Lubienski, Sarah Theule, and Christopher Lubienski. 2006. "School Sector and Academic Achievement: A Multilevel Analysis of NAEP Mathematics Data." *American Educational Research Journal* 43(4):651-98.

Lucas, Samuel R. 1999. *Tracking Inequality: Stratification and Mobility in American High Schools*. New York, NY: Teachers College Press.

Lucas, Samuel R., and Mark Berends. 2002. "Sociodemographic Diversity, Correlated Achievement, and De Facto Tracking." *Sociology of Education* 75(4):328-48.

Lucas, Samuel R., and Adam Gamoran. 2002. "Track Assignment and the Black-White Test Score Gap: Divergent and Convergent Evidence from 1980 and 1990 Sophomores." Pp. 171-98 in *Closing the Gap: Promising Strategies for Reducing the Achievement Gap*, edited by T. Loveless. Washington, D.C.: Brookings Institution.

Ludwig, Jens, and Laurie J. Bassi. 1999. "The Puzzling Case of School Resources and Student Achievement." *Educational Evaluation and Policy Analysis* 21(4):385-403.

Ma, Xin. 2008. "Within-School Gender Gaps in Reading, Mathematics, and Science Literacy." *Comparative Education Review* 52(3):437-60.

Ma, Xin, and J. Douglas Willms. 2004. "School Disciplinary Climate: Characteristics and Effects on Eighth Grade Achievement." *Alberta Journal of Educational Research* 50(2):169-88.

Magnuson, Katherine, and Jane Waldfogel (Eds.). 2008. *Steady Gains and Stalled Progress: Inequality and the Black-White Test Score Gap*. New York, NY: Russell Sage Foundation.

Manna, Paul. 2006. *School's In: Federalism and the National Education Agenda*. Washington, D.C.: Georgetown University Press.

Marks, Gary N. 2008. "Accounting for the Gender Gaps in Student Performance in Reading and Mathematics: Evidence from 31 Countries." *Oxford Review of Education* 34(1):89-109.

Martinez, Sylvia, and Yesenia Lucia Cervera. 2012. "Fulfilling Educational Aspirations: Latino Students' College Information Seeking Patterns." *Journal of Hispanic Higher Education* 11(4):388-402.

Massey, Douglas S. 2006. "Social Background and Academic Performance Differentials: White and Minority Students at Selective Colleges." *American Law and Economics Review* 8(2):390-409.

McDonough, Patricia M. 1997. *Choosing Colleges: How Social Class and Schools Structure Opportunity*. Albany, NY: State University of New York Press.

McGrady, Patrick B., and John R. Reynolds. 2013. "Racial Mismatch in the Classroom: Beyond Black-White Differences." *Sociology of Education* 86(1):3-17.

McGrath, Daniel J., and Peter J. Kuriloff. 1999. "'They're Going to Tear the Doors Off This Place': Upper-Middle-Class Parent School Involvement and the Educational Opportunities of Other People's Children." *Educational Policy* 13(5):603-29.

McKown, Clark, and Rhona S. Weinstein. 2002. "Modeling the Role of Child Ethnicity and Gender in Children's Differential Response to Teacher Expectations." *Journal of Applied Social Psychology* 32(1):159-84.

Mickelson, Roslyn Arlin. 2001. "Subverting Swann: First- and Second-Generation Segregation in the Charlotte-Mecklenburg Schools." *American Educational Research Journal* 38(2):215-52.

Miller, Raegen T., Richard J. Murnane, and John B. Willett. 2008. "Do Teacher Absences Impact Student Achievement? Longitudinal Evidence from One Urban School District." *Educational Evaluation and Policy Analysis* 30(2):181-200.

Moineddin, Rahim, Flora I. Matheson, and Richard H. Glazier. 2007. "A Simulation Study of Sample Size for Multilevel Logistic Regression Models." *BMC Medical Research Methodology* 7(1):34-43.

Morgan, Stephen L. 2001. "Counterfactuals, Causal Effect Heterogeneity, and the Catholic School Effect on Learning." *Sociology of Education* 74(4):341-74.

Mullen, Brian. 1983. "Operationalizing the Effect of the Group on the Individual: A Self-Attention Perspective." *Journal of Experimental Social Psychology* 19(4):295-322.

Muller, Chandra, Susan Roberta Katz, and L. Janelle Dance. 1999. "Investing in Teaching and Learning: Dynamics of the Teacher-Student Relationship from Each Actor's Perspective." *Urban Education* 34(3):292-337.

Murnane, Richard J. 1975. *The Impact of School Resources on the Learning of Inner City Children*. Cambridge, MA: Balinger Publishing Company.

National Center for Education Statistics. 2013. "Public School Graduates and Dropouts from the Common Core of Data: School Year 2009-10." Washington, D.C.: U.S. Department of Education.

Nye, Barbara, Spyros Konstantopoulos, and Larry V. Hedges. 2004. "How Large Are Teacher Effects?" *Educational Evaluation and Policy Analysis* 26(3):237-57.

Oakes, Jeannie. 2005. *Keeping Track: How Schools Structure Inequality*. New Haven, CT: Yale University Press.

Odden, Allan R., and Lawrence O. Picus. 2008. *School Finance: A Policy Perspective*. Boston, MA: McGraw-Hill.

Orfield, Gary, and Chungmei Lee. 2007. "Historic Reversals, Accelerating Resegregation, and the Need for New Integration Strategies." Los Angeles, CA: Civil Rights Project/Proyecto Derechos Civiles, UCLA.

Palardy, Gregory J. 2008. "Differential School Effects among Low, Middle, and High Social Class Composition Schools: A Multiple Group, Multilevel Latent Growth Curve Analysis." *School Effectiveness and School Improvement* 19(1):21-49.

—. 2013. "High School Socioeconomic Segregation and Student Attainment." *American Educational Research Journal* 50(4):714-54.

Palardy, Gregory J., and Russell W. Rumberger. 2008. "Teacher Effectiveness in First Grade: The Importance of Background Qualifications, Attitudes, and Instructional Practices for Student Learning." *Educational Evaluation and Policy Analysis* 30(2):111-40.

Park, Insim. 2005. "Teacher Commitment and Its Effects on Student Achievement in American High Schools." *Educational Research and Evaluation* 11(5):461-85.

Pascoe, Cheri J. 2011. *Dude, You're a Fag: Masculinity and Sexuality in High School, With a New Preface*. Berkeley, CA: University of California Press.

Patacchini, Eleonora, Edoardo Rainone, and Yves Zenou. 2011. "Dynamic Aspects of Teenage Friendships and Educational Attainment." *Centre for Economic Policy Research Discussion Paper No. 8223*.

Payne, Kevin J., and Bruce J. Biddle. 1999. "Poor School Funding, Child Poverty, and Mathematics Achievement." *Educational Researcher* 28(6):4-13.

Penner, Andrew M., and Marcel Paret. 2008. "Gender Differences in Mathematics Achievement: Exploring the Early Grades and the Extremes." *Social Science Research* 37(1):239-53.

Perna, Laura Walter, and Marvin A Titus. 2005. "The Relationship between Parental Involvement as Social Capital and College Enrollment: An Examination of Racial/Ethnic Group Differences." *Journal of Higher Education* 76(5):485-518.

Person, Ann E., and James E. Rosenbaum. 2006. "Chain Enrollment and College Enclaves: Benefits and Drawbacks of Latino College Students' Enrollment Decisions." *New Directions for Community Colleges* 2006(133):51-60.

Pike, Gary R., and Joseph L. Saupe. 2002. "Does High School Matter? An Analysis of Three Methods of Predicting First-Year Grades." *Research in Higher Education* 43(2):187-207.

Posey-Maddox, Linn. 2012. "Middle- and Upper-Middle-Class Parent Action for Urban Public Schools: Promise or Paradox?" *Teachers College Record* 114(1):1-43.

Quillian, Lincoln. 2014. "Does Segregation Create Winners and Losers? Residential Segregation and Inequality in Educational Attainment." *Social Problems* 61(3):402-26.

Quinn, David M. 2015. "Kindergarten Black–White Test Score Gaps: Re-examining the Roles of Socioeconomic Status and School Quality with New Data." *Sociology of Education* 88(2):120-39.

Raudenbush, Stephen W., and J. Douglas Willms. 1995. "The Estimation of School Effects." *Journal of Educational and Behavioral Statistics* 20(4):307-35.

Raudenbush, Stephen W., and Anthony S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods*. Thousand Oaks, CA: Sage.

Raudenbush, Stephen W., and Robert D. Eschmann. 2015. "Does Schooling Increase or Reduce Social Inequality?" *Annual Review of Sociology* 41(1):443-70.

Reardon, Sean. 2008. "Thirteen Ways of Looking at the Black-White Test Score Gap." *Stanford Institute for Research on Education Policy and Practice*.

Reardon, Sean F. 2011. "The Widening Academic Achievement Gap between the Rich and the Poor: New Evidence and Possible Explanations." Pp. 91-115 in *Whither Opportunity: Rising Inequality, Schools, and Children's Life Chances*, edited by G. J. Duncan and R. J. Murnane. New York, NY: Russell Sage Foundation.

Reardon, Sean F., and Claudia Galindo. 2009. "The Hispanic-White Achievement Gap in Math and Reading in the Elementary Grades." *American Educational Research Journal* 46(3):853-91.

Reardon, Sean F., Elena Tej Grewal, Demetra Kalogrides, and Erica Greenberg. 2012. "Brown Fades: The End of Court-Ordered School Desegregation and the Resegregation of American Public Schools." *Journal of Policy Analysis and Management* 31(4):876-904.

Reardon, Sean F., and Ann Owens. 2014. "60 Years After Brown: Trends and Consequences of School Segregation." *Annual Review of Sociology* 650:736-8517.

Ridgeway, Cecilia L. 2009. "Framed Before We Know It: How Gender Shapes Social Relations." *Gender & Society* 23(2):145-60.

Ridgeway, Cecilia L., and Shelley J. Correll. 2004. "Unpacking the Gender System: A Theoretical Perspective on Gender Beliefs and Social Relations." *Gender & Society* 18(4):510-31.

Riegle-Crumb, Catherine, and Eric Grodsky. 2010. "Racial-Ethnic Differences at the Intersection of Math Course-Taking and Achievement." *Sociology of Education* 83(3):248-70.

Riegle-Crumb, Catherine, and Melissa Humphries. 2012. "Exploring Bias in Math Teachers' Perceptions of Students' Ability by Gender and Race/Ethnicity." *Gender & Society* 26(2):290-322.

Robinson, John Paul, and Sarah Theule Lubienski. 2011. "The Development of Gender Achievement Gaps in Mathematics and Reading during Elementary and Middle School: Examining Direct Cognitive Assessments and Teacher Ratings." *American Educational Research Journal* 48(2):268-302.

Roderick, Melissa, Vanessa Coca, and Jenny Nagaoka. 2011. "Potholes on the Road to College: High School Effects in Shaping Urban Students' Participation in College Application, Four-Year College Enrollment, and College Match." *Sociology of Education* 84(3):178-211.

Romer, Thomas, and Howard Rosenthal. 1979. "Bureaucrats Versus Voters: On the Political Economy of Resource Allocation by Direct Democracy." *The Quarterly Journal of Economics* 93(4):563-87.

—. 1982. "Median Voters or Budget Maximizers: Evidence from School Expenditure Referenda." *Economic Inquiry* 20(4):556-78.

Rosin, Hanna. 2012. *The End of Men: And the Rise of Women*. New York, NY: Penguin Group.

Ross, Terris, Grace Kena, Amy Rathbun, Angelina KewalRamani, Jijun Zhang, Paul Kristapovich, and Eileen Manning. 2012. "Higher Education: Gaps in Access and Persistence Study." Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

Rowan, Brian, Richard Correnti, and Robert Miller. 2002. "What Large-Scale Survey Research Tells Us about Teacher Effects on Student Achievement: Insights from the Prospects Study of Elementary Schools." *Teachers College Record* 104(8):1525-67.

Rumberger, Russell W., and Gregory J. Palardy. 2005a. "Does Segregation Still Matter? The Impact of Student Composition on Academic Achievement in High School." *Teachers College Record* 107(9):1999-2045.

—. 2005b. "Test Scores, Dropout Rates, and Transfer Rates as Alternative Indicators of High School Performance." *American Educational Research Journal* 42(1):3-42.

Sadker, David, and Karen Zittleman. 2009. *Still Failing at Fairness: How Gender Bias Cheats Girls and Boys in School and What We Can Do about It*. New York, NY: Scribner.

Sax, Leonard. 2009. *Boys Adrift: The Five Factors Driving the Growing Epidemic of Unmotivated Boys and Underachieving Young Men*. New York, NY: Basic Books.

Shen, Jianping, Jeffrey M. Leslie, Jessaca K. Spybrook, and Xin Ma. 2012. "Are Principal Background and School Processes Related to Teacher Job Satisfaction? A Multilevel Study Using Schools and Staffing Survey 2003-04." *American Educational Research Journal* 49(2):200-30.

Sokatch, Andrew. 2006. "Peer Influences on the College-Going Decisions of Low Socioeconomic Status Urban Youth." *Education and Urban Society* 39(1):128-46.

Sommers, Christina Hoff. 2001. *The War Against Boys: How Misguided Feminism Is Harming Our Young Men*. New York, NY: Simon and Schuster.

Spillane, James P., Leigh Mesler Parise, and Jennifer Zoltners Sherer. 2011. "Organizational Routines as Coupling Mechanisms: Policy, School Administration, and the Technical Core." *American Educational Research Journal* 48(3):586-619.

Stanton-Salazar, Ricardo D. 2001. *Manufacturing Hope and Despair: The School and Kin Support Networks of U.S.-Mexican Youth*. New York, NY: Teachers College Press.

Stanton-Salazar, Ricardo D., and Sanford M. Dornbusch. 1995. "Social Capital and the Reproduction of Inequality: Information Networks among Mexican-Origin High School Students." *Sociology of Education* 68(2):116-35.

Steele, Claude M. 1997. "A Threat in the Air: How Stereotypes Shape Intellectual Identity and Performance." *American Psychologist* 52(6):613-29.

Stiefel, Leanna, Amy Ellen Schwartz, and Colin C. Chellman. 2007. "So Many Children Left Behind: Segregation and the Impact of Subgroup Reporting in No Child Left Behind on the Racial Test Score Gap." *Educational Policy* 21(3):527-50.

Sui-Chu, Esther Ho, and J. Douglas Willms. 1996. "Effects of Parental Involvement on Eighth-Grade Achievement." *Sociology of Education* 69(2):126-41.

Tach, Laura Marie, and George Farkas. 2006. "Learning-Related Behaviors, Cognitive Skills, and Ability Grouping When Schooling Begins." *Social Science Research* 35(4):1048-79.

Thompson, Angela. 2012. "Teacher Profiles and High School Mathematics Achievement: What Do We Know about the Teachers of Latino and ELL High School Students?" Santa Cruz, CA: University of California Santa Cruz.

Tyre, Peg. 2008. *The Trouble with Boys: A Surprising Report Card on Our Sons, Their Problems at School, and What Parents and Educators Must Do*. New York, NY: Three Rivers Press.

Van de Werfhorst, Herman G., and Jonathan J. B. Mijs. 2010. "Achievement Inequality and the Institutional Structure of Educational Systems: A Comparative Perspective." *Annual Review of Sociology* 36:407-28.

Vermunt, Jeroen K., and Jay Magidson. 2005. *Latent GOLD 4.0 User's Guide*. Belmont, MA: Statistical Innovations, Inc.

—. 2013. *Technical Guide for Latent GOLD 5.0: Basic, Advanced, and Syntax*. Belmont, MA: Statistical Innovations, Inc.

Watt, Toni Terling. 2003. "Are Small Schools and Private Schools Better for Adolescents' Emotional Adjustment?" *Sociology of Education* 76(4):344-67.

Wenglinsky, Harold. 2004. "Closing the Racial Achievement Gap: The Role of Reforming Instructional Practices." *Education Policy Analysis Archives* 12(64):1-22.

Wolniak, Gregory C., and Mark E. Engberg. 2010. "Academic Achievement in the First Year of College: Evidence of the Pervasive Effects of the High School Context." *Research in Higher Education* 51(5):451-67.