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EDUCATIONAL INEQUALITY: AN EXPLORATION OF FAMILY, NEIGHBORHOOD, AND SCHOOL CONTEXTS

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Abstract

Despite decades of research and policy efforts, socioeconomic disparities in educational outcomes persist in the United States. In this dissertation, I examine these disparities, focusing on access to higher education during the later years and on academic achievement during elementary school. I explore the importance of family, neighborhood, and school contexts and introduce new approaches for conceptualizing, measuring, and analyzing educational disparities. My findings reveal significant neighborhood disparities in early academic achievement and widening gaps in college application and enrollment, underscoring the need to identify viable solutions. The dissertation begins with an overview of the research questions and theoretical framework in Chapter 1, and concludes with a discussion of implications and future research directions in Chapter 5.

In Chapters 2 and 3, I explore disparities in higher education application and enrollment, focusing on the family context. In Chapter 2, I expand upon prior research by examining trends in socioeconomic gaps in not just whether students enroll, but also where they apply and enroll. I find that, despite decades of efforts to broaden access, socioeconomic gaps have actually become more pronounced over time, even as aspirations for educational attainment increased across all family backgrounds. Chapter 3 explores the role of financial information to socioeconomic gaps in college application, and finds that equalizing information for both students and their parents reduces differences in the perceived affordability of 4-year colleges by about one-fourth and in college application by nearly one-fifth, though it actually increases socioeconomic differences in application to highly selective colleges.

In Chapter 4, coauthored with Geoffrey T. Wodtke, I focus on neighborhood disparities in elementary school achievement. We assess whether neighborhood differences in school contexts contribute to neighborhood test score gaps, challenging prior studies that draw on limited measures of school quality. Using 171 school context measures across five dimensions – composition, resources, instructional practices, climate, and effectiveness – and applying machine learning methods for high-dimensional data, we find that only school composition and climate vary meaningfully between high- and low-poverty neighborhoods, and that differences in school contexts account for just 4% to 8% of the neighborhood poverty gap in student test scores.

Chapter 1

Researching Socioeconomic Educational Inequality: An Introduction

An Overview of Socioeconomic Inequality in Education in the United States

Socioeconomic disparities in education are among the most enduring forms of inequality in the United States. From the time children enter kindergarten, differences in academic skills are already evident between students from different socioeconomic backgrounds. These disparities are shaped by the broader contexts within which children live, including the family, neighborhood, and school environments that provide access to critical resources and opportunities. As students progress through their educational careers, these early inequalities can compound, influencing not only their academic achievement but also their long-term educational trajectories. This dissertation aims to examine how specific contexts contribute to the reproduction of inequality at different stages across the educational pipeline.

This introductory chapter provides an overview of the literature on inequalities in educational outcomes. I first discuss social reproduction theory, which sociologists have long drawn upon to examine educational inequalities. I emphasize the field's evolution from focusing solely on socioeconomic differences and family background to incorporating the neighborhood and school contexts, which also play a critical role in shaping educational disparities. I then shift my discussion to the importance of a more nuanced conceptual framework of college access that recognizes horizontal stratification present within the level of college attendance. Finally, I address key methodological concerns in studying educational inequalities and introduce my approach.

Subsequently, I outline the three main empirical chapters of my dissertation, which are distinct but interconnected studies, all grounded in my proposed theoretical framework. My first two empirical chapters focus on the family context, examining socioeconomic disparities in access to higher education. The third empirical chapter shifts the focus backward to neighborhood and school contexts during early elementary school. Together, these studies contribute to the field of sociology by illustrating the multifaceted nature of the contexts shaping students' educational experiences and identifying potential leverage points for reducing disparities.

The Reproduction of Social Inequality through Education

The study of inequality is a key focus in the field of sociology. However, clearly identifying the specific factors contributing to these disparities remains complicated, despite decades of research on the topic. In the U.S., inequality is deeply embedded in family, neighborhood, and school contexts. From the early years of a child's schooling, these environments help to shape educational pathways by informing access to resources and opportunities. However, the extent to which specific contexts contribute to inequality – and the ways in which they reinforce one another – is difficult to determine. It is also possible that factors within each of these contexts could offer potential for disrupting the cycle of inequality. The trick is understanding which levers could be most effective in closing educational gaps at different time points.

Sociological theories on the reproduction of inequality explain educational disparities as the result of structures and mechanisms that perpetuate social advantage and disadvantage across generations. The social reproduction theory advanced by Bourdieu and Passeron (1990) aims to understand the processes through which certain students are rendered more or less likely to succeed in the educational system based on their socioeconomic backgrounds. Under this framework, access to economic, social, and cultural capital shape children's access to quality educational experiences (Aschaffenburg and Maas 1997; Bourdieu 1986; Bourdieu and Passeron 1990). Beyond simply increasing access to resources, Lareau's (2014) theory of concerted cultivation illustrates how higher-SES parents actively work to secure advantages for their children, leveraging their resources and social networks to ensure their children have better educational experiences.

While social reproduction theories have traditionally focused on family background and the transmission of different forms of capital, family context alone does not account for the full scope of educational inequality. Families operate within larger environmental contexts, making choices about where to live and which schools their children attend. As such, we as sociologists, must recognize neighborhood and school contexts as potential contributors to educational disparities, particularly during the earlier years when children's cognitive and social skills are most malleable (Duncan and Magnuson 2011). The quality of resources available in these environments can set children on either a trajectory of success or disadvantage (Jencks and Mayer 1990), and early disparities in educational achievement are particularly consequential because they can compound over time, shaping future opportunities in middle school, high school, and beyond (DiPrete and Eirich 2006). Thus, a pressing question emerges: How are a child's neighborhood and school contexts shaped by their socioeconomic background and how do they matter for educational outcomes?

Urban sociologists have long argued that family backgrounds do not act in isolation but are deeply intertwined with the neighborhoods in which families reside. Wilson (1987) was one of the first to systematically link family socioeconomic status with neighborhood contexts, arguing that broad structural shifts in the United States – such as deindustrialization and the flight of middle-class residents from cities – concentrated poverty in urban neighborhoods. This led to isolated, disadvantaged areas where children growing up were exposed to limited educational and economic opportunities, such that family resources, while important, may be insufficient to overcome the structural barriers posed by the neighborhoods in which families lived.

Sampson (2012) and other theorists have expanded on this work, emphasizing that socioeconomically advantaged families, who have access to greater resources, social networks, and information, are more able to move into neighborhoods that offer good opportunities for their children. This connects to Jencks and Mayer's (1990) institutional resources theory, which posits that one of the ways that neighborhoods influence child development is through local institutions, like schools. They argue that children growing up in disadvantaged neighborhoods often attend underfunded schools with fewer experienced teachers, leading to disparities in educational outcomes. Neighborhoods are often linked to the schools that students attend through residential zoning policies, and this can lead to inequality because local property taxes fund public schools (Arum 2000). As a result, scholars theorize that wealthier neighborhoods may have schools with more resources, while poorer neighborhoods may be more likely to have underfunded schools. Further, in addition to public funding, there may be differences in private funding across neighborhoods, given that wealthier families invest more in their children's schools (Kalil, Steimle and Ryan 2023). In turn, this means that the socioeconomic background of families can shape the quality of schools their children attend, which in turn matters for the educational trajectories of students (Jencks and Mayer 1990).

Schools serve as an important context for the reproduction of social inequality. Raudenbush and Bryk (2002) argue that schools are not just passive environments where children learn but are institutions that can either mitigate or exacerbate social inequalities.

According to institutional theories of schools, the school setting reflects broader societal inequalities, as they tend to reproduce existing social hierarchies by allocating resources unevenly across different populations (Bourdieu and Passeron 1990).

While the family, neighborhood, and school contexts in which students are situated during childhood play a crucial role in shaping their early academic achievement, they can also determine their academic trajectories. Early contexts often have compounding effects, because early advantages or disadvantages often persist or compound as students continue in school (DiPrete and Eirich 2006). By the time students reach high school, family resources, including parental aspirations, financial support, and cultural capital, become increasingly important since families guide children through the complicated processes of applying to college and financial aid (Conley 2001; Klasik 2012; Manski et al. 2014). As a result, even as students gain independence during the later years of school, the family context remains crucial for understanding disparities in college access (Crosnoe 2001). Socioeconomically advantaged families are more likely to have the resources necessary to guide their children through the complex college choice process, leveraging their social networks to secure information, which is not always the case for less socioeconomically advantaged families (George-Jackson and Gast 2015; Plank and Jordan 2001). The framework I advance in this dissertation conceptualizes educational disparities as stemming from specific contexts – family, neighborhood or school – that may operate in different ways at different stages of a child's life to shape their educational trajectories. My dissertation builds on these theories by considering how specific contexts shape disparities across the early schooling years and into the late high school years when students apply to college.

Horizontal Stratification in Higher Education

In the United States, attaining a college degree is one of the clearest predictors of economic success, health, and social wellbeing later in life (Gerber and Cheung 2008; Hout 2012). These benefits remain even after accounting for selection effects in who is more likely to pursue higher education in the first place (Hout 2012). In fact, those least likely to obtain a degree often experience the greatest benefits from doing so (Brand and Xie 2010). However, the extent of these advantages depends on two factors: (1) the type of degree attained, and (2) the institution from which the degree is obtained.

The type of degree obtained plays an important role in determining the economic and social benefits of higher education. Bachelor's degree holders experience much greater returns than those who attain an associate degree or no postsecondary degree at all. For example, Hout (2012) finds that those with a bachelor's degree earn, on average, 77% more over their lifetime compared to those with a high school diploma. Those who attain an associate degree see lifetime earnings approximately 20% higher than high school graduates, which is meaningful, although a smaller difference than that of a bachelor's degree. Community colleges are often considered by students and their parents a lower-cost entry point into postsecondary education, potentially providing students from less socioeconomically advantaged backgrounds a more accessible option. However, in addition to the economic rewards from associate degrees being much lower than that of a bachelor's degree, while many students enter community college with the goal of transferring to a 4-year college, actual transfer rates remain low. Only about 14% of community college students successfully transfer and complete a bachelor's degree within six years (Schudde and Goldrick-Rab 2015), a problem often attributed to a combination of poor alignment between community college curriculums and 4-year college requirements, limited access to academic advising, insufficient financial aid, and the need for many students to balance school with full-time work and family responsibilities (Goldrick-Rab 2006; Schudde and Brown 2019). Despite the fact that the majority of high school students in the U.S., along with their parents, aspire to attain a bachelor's degree, these aspirations are often unmet for low-income and first-generation students, even among those who take the first step to attend a community college (Schudde and Goldrick-Rab 2015). While the type of degree attained plays a critical role in the returns to college, the specific institution from which the degree is obtained also shapes students' outcomes.

Within 4-year college attendance, there is some evidence that graduating from elite and selective colleges leads to higher earnings, with graduates from elite universities earning approximately 10% more compared to graduates from less selective colleges (Hoxby 2009; Long 2008; Thomas 2000). However, others have questioned whether these observed benefits of selective college degrees are due to causal effects or are largely a result of selection effects, with students who attend more selective colleges already having advantages that make them more likely to earn higher incomes anyways (Dale and Krueger 2002), such as greater academic abilities or more advantageous social networks (Hout 2012). Despite this debate, it is clear that highly selective colleges provide students other advantages, including a higher chance of graduating (Alon and Tienda 2005; Bowen, Chingos and McPherson 2009) and of enrolling in graduate school (Mullen, Goyette and Soares 2003). This may be because selective colleges invest more into students by providing them access to more experienced faculty, comprehensive career counseling services, stronger alumni networks made up of advantaged peers, and a wider range of extracurricular opportunities (Bowen, Chingos and McPherson 2009; Davies and Zarifa 2012; Hoxby 2009; Michelman, Price and Zimmerman 2020).

Despite the robust findings on the differences in returns to various college degrees, much of the existing research on inequality in access to higher education has focused on the end result of whether students enroll in college. At best, some studies examine whether students enroll in a 4-year versus a community college. However, much less attention has been paid to a comprehensive conceptualization of *where* students enroll. This limited focus obscures the nuances of horizontal stratification – or the divergent pathways students take within the higher education system, depending on factors such as the type, selectivity, and quality of institution they attend (Charles and Bradley 2002; Gerber and Cheung 2008). Because these pathways can influence later labor market and life outcomes, understanding how and why students sort into these qualitatively different options within a quantitatively similar level of education is important.

Further, focusing on enrollment alone overlooks a critical earlier stage in the higher education decision-making process: the application stage. At this point, students and their families make pivotal decisions about whether and where to apply, which shapes their opportunities even before the enrollment stage. By the time college enrollment decisions are made, many of the socioeconomic inequalities in educational access have already been set in motion, based on where students were able to apply. Research shows that students from socioeconomically advantaged backgrounds apply to more colleges generally, and to a higher number of selective colleges (Bound, Hershbein and Long 2009; Hoxby and Turner 2013; Reardon, Baker and Klasik 2012), while less advantaged students often don't apply to selective colleges at all, even when they are qualified to do so (Avery et al. 2013). Disparities in college applications lead to different enrollment options, making it important to explore not just college enrollment, but the pre-enrollment behaviors that lead students to certain institutions and postsecondary pathways.

Despite the expansion of postsecondary education in the U.S. and significant policy efforts to reduce socioeconomic gaps, research comparing trends over the decades reveals that these gaps, particularly regarding the type and selectivity of institutions students attend, remained largely consistent through the early 1990s, with socioeconomically advantaged students continuing to disproportionately enroll in colleges that offer higher returns to a degree (Alon 2009; Karen 2002). In general, research on disparities in access to higher education related to family background has largely remained stagnant since the early 2000s, despite the fact that major contextual shifts have happened since that time, such as the rise of technology and the internet, significant changes in federal financial aid policies, and larger economic transformations like the Great Recession, which may have impacted students' college access, information seeking, and decision-making processes.

Advancements to technology during the 1990s and early 2000s made college-related information more widely available to families, providing information on specific colleges, college costs, and college admissions criteria online (Bound, Hershbein and Long 2009; Castleman and Page 2014; Hoxby and Turner 2013). However, it's possible that more socioeconomically advantaged families were better able to access computers and the internet, and to understand the complex information about financial aid and college costs that's available online, and thus, were better able to access and use this information to help advance their child's educational opportunities (Bound, Hershbein and Long 2009), making it unclear if changes in technology would truly reduce socioeconomic disparities. Websites like the U.S. News & World Report college rankings have also become increasingly important in shaping how families select specific colleges (Bound, Hershbein and Long 2009; Hoxby 2009). The presence of online college rankings could lead families to prioritize applying to and attending more elite colleges, particularly for families with the financial resources and knowledge to do so.

Around the same time, there were large economic shifts that could have influenced college enrollment disparities. The Pell Grant received additional funding in the early 2000s as policymakers worked to reduce barriers to higher education for low-income students. However, the Great Recession introduced major economic challenges in 2008, which may have changed how low-income families made decisions about college attendance. At the same time, college costs continued to rise (Baum, Kurose and McPherson 2013; Goldrick-Rab, Anderson and Kinsley 2017), which could lead families to re-weigh the immediate costs of college more heavily against any potential long-term benefits (Dynarski 2003).

Further, the Lucas (2001) theory of effectively maintained inequality argues that even if vertical stratification (i.e., access to a specific level of education) decreases over time, horizontal stratification can emerge. In the context of college education, socioeconomic disparities would then shift from informing *whether* students access a level of education to *what kind* of education they access within that same level of education. While the theory of effectively maintained inequality was originally applied to the context of secondary education, Alon (2009) extends this theory to higher education, arguing that from the 1970s through the 1990s, socioeconomic advantages did not simply determine *whether* students enroll in college, but also *where* they enrolled. During this period of postsecondary expansion, socioeconomically advantaged families were able to leverage their resources to secure both quantitative (e.g., enrollment) and qualitative (e.g., access to selective colleges) advantages, thereby widening the gap in higher education outcomes. As Alon (2009) extends Lucas's theory of effectively maintained inequality to higher education, it becomes clear that even when more students from across socioeconomic backgrounds access college, horizontal stratification could ensure that socioeconomically advantaged families maintain their dominance by securing access to more selective institutions, a form of social reproduction of inequality. As a result, educational inequalities become further entrenched across generations, despite the expansion of the higher education system.

Despite these broad societal shifts and growing efforts to reduce socioeconomic disparities in access to college, we lack updated research that systematically examines whether socioeconomic gaps in college application and enrollment have persistent or shifted in response to more recent societal changes. Additionally, it is possible that other factors that influence college outcomes, such as family values around education and students' academic preparation for college, may have changed and potentially impacted the stability of SES gaps. Recent evidence shows that income-based gaps in certain forms of parental involvement, such as attending school meetings, have narrowed over time, while inequalities in other forms, such as private tutoring or participation in extracurricular activities have either persisted or grown (Kalil, Steimle and Ryan 2023), highlighting the ways that resource disparities continue to shape the type of engagement families can provide. Further, parental values around education have also shifted over time, with income- and education-based differences in values around obedience and independent thinking narrowing across socioeconomic groups, showing that that some SES-based gaps in parental priorities may be closing (Ryan et al. 2020), though this has not been explored for educational attainment priorities specifically. Though these factors are widely known to influence educational outcomes, we lack research that traces their long-term trends. Understanding how these trends relate to SES gaps in college enrollment is important for addressing persistent inequalities in higher education access. It is also important to carefully consider the methodological approaches used to study educational disparities.

Methodological Considerations When Studying Educational Inequality

Randomized controlled trials (RCTs) and experimental methodologies are widely considered the gold standard for understanding causal effects of different factors on students' educational outcomes. These methods allow for precise estimates of causal relationships by taking into account potential confounding through the establishment of clear treatment and control groups. In the neighborhood effects literature, the Moving to Opportunity (MTO) study is a prominent large-scale experimental study that sought to examine how moving low-income families to less impoverished neighborhoods impacted various outcomes, including educational achievement.

Prior to the MTO study, the Gautreaux Program was one of the first large-scale housing mobility programs, where low-income Black families were relocated from public housing in Chicago to suburban or less segregated city neighborhoods in the 1970s and 1980s. Research on the program showed that children who moved to suburban neighborhoods were more likely to graduate from high school and attend college than their peers who remained in high-poverty neighborhoods (Rosenbaum 1995). However, this wasn't a randomized study, making it unclear the causal nature of the findings.

Building on the work of the Gautreaux study, the MTO study was a randomized controlled experiment in the 1990s with the goal of providing families in high-poverty neighborhoods with housing vouchers to move to lower-poverty neighborhoods. While MTO applied a stronger experimental design, the results from the study were mixed. Children who moved to lower-poverty neighborhoods did not show significantly improved academic achievement (Burdick-Will et al. 2011), though younger children in the study did experience other gains later on like increased college attendance rates and higher incomes (Chetty, Hendren and Katz 2016). The findings showed that while the treatment group moved to better neighborhoods, the schools they attended were not better in terms of quality (Ferryman et al. 2008). However, there were potential methodological limitations. First, while MTO is a large-scale experiment, its sample size is still relatively small to make broader generalizations and it was conducted in only five U.S. cities. Second, not all families who received vouchers moved to lower-poverty neighborhoods, affecting the overall treatment effect, and there was attrition during follow-up waves.

In contrast to the literature on K-12 education and neighborhood effects, large-scale randomized controlled trials in higher education are somewhat less common, though they have grown in prominence in recent years. One large-scale experiment is the University of Michigan study (Dynarski et al. 2021), which tested the effects of providing low-income students with personalized information about their eligibility for free tuition at the state's flagship university. The study found significant increases in both college application and enrollment rates for the treatment group. The results highlighted the importance of information, because even when free tuition was already available, students often didn't apply, either because they didn't know about it, or they didn't understand their chances of being admitted. However, the results from this large-scale experiment may not be generalizable to contexts where free tuition isn't already provided, and this is important given that most public 4-year universities don't offer free tuition guarantees.

Another higher education RCT is the H&R Block FAFSA Experiment (Bettinger et al. 2012), which explored the impact of providing assistance in filling out the FAFSA form. This study found that helping students to fill out the FAFSA increased their college enrollment rates. However, the study drew on a sample of H&R Block clients who were already completing their tax returns and who were eligible for free FAFSA assistance, and it's likely that this sample is not generalizable to the wider population of low-income families.

There are several key challenges to using the RCT design to study educational inequality. First, these types of studies often rely on specific contexts and might not be generalizable to broader populations. Another common limitation of RCTs is participant attrition, where members drop out or fail to adhere to the assigned study group. Finally, RCTs can be expensive and challenging to conduct, since they require securing buy-in to implement. There are also some topics that would not be feasible or ethical to study with an experimental design.

If we limited research to only topics that can be studied through large-scale experiments, many important areas would not be explored. As a result, sociologists commonly use observational designs, which provide samples generalizable to more broad populations and larger sample sizes. Observational designs in sociology often rely on survey data to study key mechanisms underlying educational inequalities. For example, many studies draw on national longitudinal surveys like the Early Childhood Longitudinal Study (ECLS), the National Longitudinal Study of Adolescent to Adult Health (Add Health), the Panel Study of Income Dynamics (PSID), the National Longitudinal Survey of Youth (NLSY), or the National Education Longitudinal Study (NELS) to identify mechanisms between students' socioeconomic background and their educational outcomes.

However, survey data has a few limitations when trying to study mechanisms. First, in observational studies, identifying causal effects is difficult due to potential confounding since these studies do not include random assignment. For example, low-income parents may be more likely to move to disadvantaged neighborhoods and also may have fewer resources to invest in their child's education, meaning the observed relationships between neighborhood disadvantage and educational achievement may be biased if family income is not taken into account. If the direct effect of contextual factors is misspecified, the identified indirect effects through mediators will also be unreliable, affecting findings about mediation. Further, many social categories, like family socioeconomic background, are not manipulable in the way policy interventions are, making it difficult to assign counterfactuals. We can't assign students to more or less socioeconomically advantaged families, for example. While there are some limitations to establishing causality due to potential confounding, observational methods can still provide valuable insights when key assumptions are carefully addressed.

Second, many studies using survey data to identify mechanisms related to student achievement or educational attainment do not formally decompose the total effect of a predictor on a given educational outcome into its direct and indirect effects through the hypothesized mechanisms, making it difficult to fully understand causal pathways. As a result, while these studies are seeking to explore mediation, they're often only able to measure the joint effects of different contextual factors on educational outcomes without determining the pathways that are most important. This limits the ability to determine specific mechanisms at play.

Finally, while understanding the theoretical role of mediators on educational outcomes is important, these findings may not provide practical insights for reducing disparities or provide insight actual observed disparities (Lundberg 2022). Mediation estimands target the direct and indirect effects of some exposure on a specific outcome by controlling for intermediate variables, and then decomposing the total effect of the exposure into components operating through these intermediates versus other mechanisms. This helps to explain how a given context influences an outcome. However, such estimands do not address the broader disparities that are actually observed and how they might be mitigated through potential interventions.

As a result, throughout my dissertation, I focus on observed socioeconomic disparities in educational outcomes. In two chapters, I draw on a gap-closing estimand, which allows for the estimation of how much a gap (e.g., educational achievement by neighborhood poverty) would close under an intervention to equalize a treatment (e.g., access to high-quality school contexts). Gap-closing estimands have several advantages over traditional mediation estimands. First, the gap-closing estimand allows for the consideration of important contextual factors like family background or residential neighborhood without requiring the identification of their direct effect on the educational outcome of interest. Second, gap-closing estimands allow researchers to draw on causal decomposition analyses, using advanced machine learning methods designed to estimate counterfactual outcomes. Third, gap-closing estimands represent more policy-relevant quantities in that they allow researchers to estimate how much observed disparities could be reduced if we intervened to equalize specific treatments, such as access to high-quality schools or high-quality information about college attendance. Fourth, unlike traditional mediation estimands, gap-closing estimands can be estimated under much weaker assumptions, making them more feasible for evaluating potential interventions.

While there are limitations to using survey data, this work employs more advanced techniques to mitigate these issues, allowing for more reliable estimates than prior work. The use of nationally representative data further allows for the ability to generalize the findings more broadly. Thus, while RCTs may provide stronger internal validity, the feasibility and generalizability of this work provides a valuable lens for understanding educational disparities.

Structure of the Dissertation

To contribute to the field, in this dissertation, I explore socioeconomic inequality in educational outcomes in the United States, with a focus on how specific contexts – family, neighborhood, or school – contribute to these disparities. In Chapter 2, I start by providing a comprehensive analysis of trends in socioeconomic gaps in college application and enrollment from the 1970s to the mid-2010s. I extend upon previous studies by investigating not only whether students enroll in college but also where they apply and enroll, thereby exploring horizontal stratification within higher education, an underexplored area in the literature. Using data from over 95,000 high school students across five cohorts from National Center for Education Statistics (NCES) surveys – including the National Longitudinal Study (NLS) of the high school class of 1972, the High School and Beyond (HS&B) study of the class of 1982, the National Education Longitudinal Study (NELS) of the class of 1982, the Education Longitudinal Study (ELS) of the class of 2004, and the High School Longitudinal Study of the class of 2014 – I link these data to information on the institutional selectivity of each college to which students apply from the NCES Barron's Admissions Competitiveness Index and the Integrated Postsecondary Education Data System (IPEDS). To ensure comparability across cohorts and survey datasets, I standardize all variables, use multiple imputation for missing data, and weight results to reflect the population of graduating seniors in each cohort. Additionally, I extend prior research on trends in college enrollment gaps by also considering concurrent trends in pre-enrollment factors like academic preparation, priorities in selecting a college, and college aspirations of both students and their parents to theorize about reasons behind observed trends in enrollment gaps over the decades.

In the third chapter, I explore current socioeconomic disparities in college application behavior, focusing on the contribution of financial information to these gaps. If students do not have information about college costs, they may believe that college is not a realistic option, and this may especially be the case for students from less advantaged backgrounds. While previous research has mostly focused on the impact of providing financial information directly to students, this chapter expands on this work by considering the impact of providing both students and their parents information about college expenses and financial aid on socioeconomic gaps in college application behavior. Understanding the impact of providing parents financial information is important because families play a major role in the college choice process, particularly when it comes to financial decisions. Building on prior research, I go beyond considering general application behavior and also look at how information shapes perceptions of different college pathways as affordable (or not) and how this connects to ultimate application behavior. To do so, I draw on data from more than 21,000 students in the 2009 High School Longitudinal Study, linked with Barron's Admissions Competitiveness Data and IPEDS data on college costs, and simulate hypothetical interventions equalizing financial information for students and their parents.

In the fourth chapter, coauthored with Geoffrey T. Wodtke, I shift focus from higher education disparities to inequalities present during the early elementary school years. In this chapter, I move from a focus on just the family context to also consider how neighborhood and school contexts experienced early on in life contribute to inequalities in academic achievement. In particular, we explore disparities in student test scores between students from high- versus low-poverty neighborhoods and ask how differences in the school context they encounter during 1st grade contribute to test score gaps across the elementary school years. While prior research has typically focused on a limited set of school inputs or outputs, we develop a comprehensive conceptualization of the school context encompassing five dimensions: composition, resources, instructional practices, climate, and effectiveness. In our analysis, we incorporate more than 170 distinct school context measures across these five dimensions, providing a more comprehensive understanding of the school's role in shaping neighborhood poverty disparities. We draw on data from approximately 18,000 students in the Early Childhood Longitudinal Study, Kindergarten Cohort of 2010-11 (ECLSK:2011) and link students to U.S. Census data on their neighborhood contexts and to Common Core of Data (CCD) and Private School Universe Survey (PSS) data on their school contexts. We employ novel machine learning methods designed for high-dimensional data to simulate hypothetical interventions equalizing school contexts that students across neighborhoods experience and explore the extent to which these interventions could potentially reduce test score disparities. We also provide the most comprehensive descriptive portrait of how early elementary school contexts differ by neighborhood poverty level.

In the fifth chapter, I end the dissertation by discussing the empirical findings from the previous chapters, and considering their broader theoretical and policy implications. I discuss how my dissertation contributes to the existing sociological literature, and I go over key limitations and directions for future research to further identify contributors and solutions to the pervasive socioeconomic disparities present in education in the United States.

Chapter 2

Trends in Socioeconomic Gaps in College Enrollment Across Five Cohorts, 1972-2014

Introduction

A college education has long been recognized as one of the key pathways to upward social mobility in the United States. A bachelor's degree provides better employment opportunities, higher earnings, improved marriage prospects, and enhanced health and wellbeing (Gerber and Cheung 2008; Hout 2012; Torche 2011), and can be especially advantageous for those from socioeconomically disadvantaged backgrounds (Brand and Xie 2010). Degrees from prestigious universities in particular can yield the highest benefits (Borgen and Mastekaasa 2018; Long 2008; Thomas 2000). While prior research has documented ongoing socioeconomic disparities in college enrollment in the United States (Alon 2009; Bailey and Dynarski 2011), gaps remain in our understanding of how these disparities have evolved (or not) over the decades, particularly when considering the decisions students make about whether and where to apply.

The higher education system in the United States underwent a significant expansion during the late twentieth century, offering the possibility to reduce existing socioeconomic disparities. During that time, the percent of high school graduates enrolling in college increased from 45% in 1960 to a high of almost 70% in 2005 (De Brey et al. 2021), and the number of postsecondary institutions doubled. Investments in higher education by federal, state, and local government also sharply increased, with a specific emphasis placed on facilitating access to college for low-income students. The most notable federal investment came in the form of the Higher Education Act of 1965, which introduced programs designed to help low-income students attend college. States and local governments also pushed for the establishment and enhancement of public universities and community colleges, which provide local and more affordable postsecondary education options for students (Baum, Kurose and McPherson 2013).

While the expansion of the postsecondary education system coupled with increased investments by federal, state, and local governments theoretically could have led to more equitable educational outcomes by increasing access for lower income students, the reality is more complex. Scholars have documented continued socioeconomic gaps in college enrollment (Alon 2009; Bailey and Dynarski 2011). These continued disparities are concerning given concurrent rises in income inequality and its association with children's later life chances (Chetty et al. 2014; Duncan, Kalil and Ziol-Guest 2017). Further, although there were investments to make a college education more accessible for low-income students, the cost of college tuition sharply increased starting around the 1980s and continuing into the 1990s and beyond, making college affordability a key concern (Baum, Kurose and McPherson 2013). While financial aid programs, such as Pell Grants and federal student loans were expanded during this time, the growth of tuition outpaced increases in aid and low-income families are not always aware of financial aid options (Dynarski and Scott-Clayton 2013; Goldrick-Rab, Anderson and Kinsley 2017). As community colleges emerged as a prominent lower-cost option, and as applications to selective 4-year colleges have dramatically increased among socioeconomically advantaged students in the recent years (Hoxby 2009), it's possible that socioeconomic disparities in college enrollment have actually drastically increased when taking into account not just *whether* but also *where* students enroll, and yet trends in socioeconomic gaps across the decades in choices between community colleges, non-selective 4-year colleges, and selective 4-year colleges have been underexplored in the literature.

To address this gap, in this study, I draw on data from five cohorts of high school seniors in the United States to explore trends in socioeconomic gaps in college enrollment between 1972 and 2014 using National Center for Education Statistics (NCES) nationally representative survey data. Specifically, I address four research questions: (1) To what extent does the U.S. experience socioeconomic gaps in college enrollment? (2) How do socioeconomic gaps in college enrollment differ by the level and selectivity of the institution? (3) How have socioeconomic gaps in college enrollment changed over the decades? Further, to go beyond merely considering trends in college enrollment and toward an understanding of the stages in the college choice process at which these gaps emerge, I also ask, (4) How do trends in college enrollment gaps correspond with trends in pre-enrollment stages, including academic preparation, college aspirations, institutional priorities, and college application?

In this chapter, I make three contributions to the literature. First, by considering both *whether* and *where* students enroll in college, I am able to capture not only vertical stratification in access to college, but also potential horizontal stratification within the level of college enrollment, which has been underexplored in the field, but which is necessary to accurately identify socioeconomic disparities and trends across the decades. Second, by drawing on data from five survey datasets and standardizing dozens of variables, I am able to explore trends across four decades, the most expansive and long-term dataset used to explore these questions. Finally, by exploring trends not only in college enrollment but also earlier stages in the college choice process, I am able to pinpoint the stages at which gaps emerge and are most salient, which has been unexplored in the literature looking at trends in socioeconomic disparities in college enrollment.

Stratification Within the Higher Education System

In response to the rise in college applications and enrollment between the 1950s and 1970s, the higher education system in the United States expanded rapidly to meet student demand. The number of postsecondary institutions almost doubled, and new institutions focused on providing affordable options close to home emerged as especially important, including community colleges and other public 4-year college locations (Baum, Kurose and McPherson 2013). This meant that suddenly, there were more options than ever for students to choose from, making the question of *where* a student chooses to attend important to understand.

The type of college a student attends can impact their college and post-college outcomes. While the purpose of community colleges was to increase access to higher education by providing more affordable and local options, the benefits of an associate degree are much lower than that of a bachelor's degree, with the economic returns to a bachelor's degree being almost double that of an associate degree (Hout 2012; Kim and Tamborini 2019). Community colleges, despite being a potential starting point for students intending to transfer to 4-year institutions later on, may actually provide a lower level of academic rigor compared to 4-year colleges (Hout 2012) and tend to have low graduation rates (Schudde and Goldrick-Rab 2015) and low transfer rates (Lee and Frank 1990; Schudde and Brown 2019). Recent data suggest that only about 13% of community college students both transfer to a 4-year college and earn a bachelor's degree within six years of transferring (Shapiro et al. 2017). As such, some argue that community colleges may cause a diversionary effect by diverting students who would otherwise enter a 4-year college into the community college system, decreasing their probability of bachelor's degree attainment than if they had initially entered a 4-year college (Schudde and Brown 2019; Schudde and Goldrick-Rab 2015). Others contend that community colleges play a critical role in expanding access to higher education for students who don't have the financial resources or academic qualifications to start a 4-year college, providing a pathway to eventually earn a bachelor's degree

By the mid-1980s, college application numbers spiked dramatically, which led to more competition within the higher education field (Bound, Hershbein and Long 2009; Hoxby 2009). Around the same time, U.S. News & World Report released the first "America's Best Colleges" report, which ranked U.S. colleges. This annual ranking of colleges was quickly adopted by students and their parents, and research shows that increases in a college's ranking are associated with increased applications, while a drop in ranking led to fewer applications, suggesting that the institutional selectivity or prestige is an important consideration for families (Bastedo and Bowman 2011; Bowman and Bastedo 2009).

Beyond differences in the benefits provided by a 4-year college compared to a community college, even within the 4-year college setting, there is evidence that highly selective, elite colleges lead to distinct advantages for students. This is especially the case for students from low-income backgrounds who are high-achieving, and who benefit the most from the better financial aid packages offered by more elite colleges (Cohodes and Goodman 2014; Dale and Krueger 2002). First, selective colleges often have better financial aid packages, particularly for high-achieving students, meaning college affordability is determined by more than just the "sticker" price of tuition (Cohodes and Goodman 2014; Hoxby 2009; Hoxby and Avery 2012). This is important given the sharp increases in college tuition, even at in-state public 4-year colleges, starting in the 1980s and continuing into the 2000s (Baum, Ma and Payea 2010). Second, selective colleges can provide better learning experiences as a result of the presence of more academically prepared peers (Kane 1998). Third, college completion rates are higher at more selective colleges (Bowen, Chingos and McPherson 2009; Shamsuddin 2016), even for students from underrepresented backgrounds (Alon and Tienda 2005). While this may be due partially to a selection effect, meaning that students admitted to selective colleges have stronger academic backgrounds making them more likely to graduate, there's also evidence of an effect holding student characteristics constant (Dale and Krueger 2002). Attending selective colleges can also lead to better post-graduation outcomes, like improved employment outcomes and potentially greater economic returns (Chetty, Deming and Friedman 2023; Davies and Guppy 1997; Long 2008; Thomas 2000).

Despite clear evidence of the advantages conferred by a bachelor's degree, and particularly one from a selective institution, socioeconomic gaps remain in enrollment at both 4-year and selective 4-year colleges. Students from lower socioeconomic backgrounds who do pursue higher education tend to enroll in community colleges (Alon 2009). And notably, even the highest-achieving low-income students rarely apply to selective colleges, despite the potential benefits of doing so (Cabrera and La Nasa 2001; Dynarski and Scott-Clayton 2013; Hoxby and Avery 2012).

The expansion of the higher education system have likely led to not only vertical stratification in educational outcomes but also apparent stratification within the higher education system based on the type of institution attended (Charles and Bradley 2002). The consequences of these disparities can matter not only for individual trajectories but also for broader patterns of social mobility (Pfeffer and Hertel 2015). As a result, while college enrollment rates have generally risen over time, understanding socioeconomic gaps in both *whether* and *where* students attend college is important for understanding inequality in higher education.

The College Choice Process

The sociological literature draws on several theories to understand how students make decisions about postsecondary pathways. The college choice model developed by Hossler and Gallagher (1987) is among the most cited. This model includes three stages of decision-making: (1) predisposition to college, (2) gathering information about colleges, and (3) deciding which college to attend and enrolling. Building on this model, Klasik (2012) highlighted the importance of academic preparation for college as another key stage, since college enrollment often requires taking college entrance exams and meeting other academic requirements, like graduating from high school. While college choice models have been extensively studied when considering inequalities in student outcomes, their application to understanding trends in college enrollment gaps has been limited, leaving it unclear at which stage socioeconomic gaps are most pronounced and how changes over time in socioeconomic gaps in earlier stages of the college choice process correspond with changes in college enrollment gaps.

Exploring Explanations for Changing Disparities in College Destinations

In exploring trends in racial gaps in college enrollment across the decades, Baker, Klasik and Reardon (2018) consider concurrent trends that may be related to the observed racial disparities over time. In this study, I apply a similar approach to the study of trends in socioeconomic disparities, examining concurrent trends in different stages of the college choice process, including the formation of college aspirations and expectations, the values students draw on when making college decisions, their academic preparation, and their college application behavior.

College aspirations and expectations. Sociologists have long emphasized the role of parents when considering how socioeconomic background shapes educational attainment, arguing that highly educated parents are more likely to form college aspirations for their child and as a result to pass on college-going mindsets (Perna 2000; Sewell, Haller and Portes 1969), while also being better able to prepare for these educational pathways (Carolan and Wasserman 2015; Coleman 1988; Crosnoe, Mistry and Elder Jr. 2002; Dumais 2002). As a result, in this study, I compare trends in parental aspirations and student expectations for educational attainment to trends in college enrollment to better understand their connection over time in the United States. Some scholars have argued that typical measures of students' college expectations don't fully capture their true intentions for attending college, but merely pick up on perceived values of a college degree (Alexander and Cook 1979; Manski 1995). As a result, I also examine students' immediate plans for college attendance post-high school.

College choice criteria. Students consider several factors when making decisions about future education. The cost and perceived affordability of attendance, particularly for low-income students, can drastically shape their college choices (Avery and Kane 2004; Grodsky and Jones 2007). If college costs are a major factor students consider, they may either opt out of applying to 4-year colleges or pick less selective institutions with lower tuition prices. Proximity to home also plays an important role in the college decision making process, especially for students from lower socioeconomic backgrounds (Turley 2006; Turley 2009). Research indicates that low-income students are more likely to apply to college if there are colleges near their home (Hirschl and Smith 2020; Turley 2009). Finally, the importance students place on an institution's academic rigor can guide their enrollment decisions (Hoxby 2009). This study, therefore, looks at how socioeconomic gaps in these specific choice criteria have evolved over time.

Academic preparation. Academic performance during high school is important for admission to selective colleges, though many public 4-year institutions have relatively accessible admissions criteria (Klasik, Proctor and Baker 2015). Given persistent findings of income-based disparities in academic achievement (Duncan, Kalil and Ziol-Guest 2017), it is important to consider trends in disparities in academic achievement that may relate to college enrollment patterns. Socioeconomically advantaged parents have increasingly prioritized college planning and preparation (Bound, Hershbein and Long 2009), which may account for some of the widening of the socioeconomic gap in college enrollment over time (Belley and Lochner 2007). Beyond considering trends in academic achievement, exploring patterns in ACT and SAT test-taking behavior is important, as college entrance exams are often a prerequisite to applying to 4-year colleges, and some research suggests that income-based gaps in student test-taking slightly widened between the 1990s and early 2000s, even as overall rates of test-taking increased (Mbekeani 2023). Graduating from high school is another prerequisite for college enrollment, so it is important to assess whether trends in graduation rates align with those in college enrollment disparities. Baker, Klasik and Reardon (2018) discovered that the narrowing of college enrollment racial gaps was partially a result of closing high school graduation gaps.

College application. Enrolling in a 4-year college begins with the application process. While some students may apply to 4-year colleges and not gain admission, research suggests that enrollment disparities are more reflective of application behavior than actual admissions decisions (Hoxby and Turner 2013). Notably, high-achieving students from low-income backgrounds are much less likely than students from high-income families to apply to any 4-year institutions (Cabrera and La Nasa 2001; Manski and Wise 1983), and very few students from low-income backgrounds apply to any selective colleges (Hoxby and Avery 2012; Mullen and Goyette 2019). A comprehensive understanding of trends in college enrollment disparities requires examining whether those patterns are due to shifts in college application behavior.

Data and Methods

Data

To explore trends in socioeconomic gaps in college enrollment across the decades, this study draws on survey data from five nationally representative cohorts of high school senior aged students, including both enrolled students and those who had dropped out, for the graduating classes of 1972, 1982, 1992, 2004, and 2014. The National Longitudinal Study (NLS) of the High School Class of 1972 surveyed approximately 19,000 students. Nearly ten years later, the High School and Beyond (HS&B) surveyed close to 15,000 sophomores in 1980, following up in 1982 when they were high school seniors. The National Education Longitudinal Study (NELS) began with a cohort of approximately 25,000 8^{th} graders first surveyed in 1988 who were then surveyed again as high school seniors in 1992. The Education Longitudinal Study (ELS) surveyed approximately 15,000 10^{th} graders in 2002, following up when they were seniors in high school in 2004. Finally, the High School Longitudinal Study (HSLS) began with a sample of more than 21,000 9^{th} grade students, following up when they were seniors in high school in 2014.

All five surveys followed students over time, including a wave during their senior year of high school and two years after intended high school graduation. The NLS (1972) began data collection during students' senior year of high school, which means that students who had already dropped out prior to their senior year were not included in the study. The other four surveys started tracking students earlier in middle school or high school, which allowed for data collection on students who later dropped out of high school. While high school students were included in the four later surveys, survey response rates are known to be lower among marginalized populations, including high school dropouts (Groves 2006), including in NCES survey datasets (Ingels et al. 2014). Each of the five datasets also incorporated information from students' parents, their high school administrators, and from students' high school transcripts. To track trends across the decades, I uniformly coded all variables across each of the five datasets. I also replaced missing data in each dataset using multiple imputation, which includes predictive data from baseline waves as well, ensuring that those who didn't respond in later waves are not fully excluded from the analytic sample. I then appended the five datasets, creating a flag indicating the cohort.

To capture the institutional selectivity of colleges that students applied to, I match the listed college from each survey dataset to data from the relevant graduation year of NCES Barron's Admissions Competitiveness Index Data File using Federal Interagency Committee on Education (FICE) codes to link the data sources. Because three of the NCES survey datasets – HS&B, NELS, and ELS – did not include FICE codes, I first merge each of those listed colleges to data from the Integrated Postsecondary Education Data System (IPEDS) using the college UnitID and secure the FICE code for each college from IPEDS data before then merging the survey data with Barron's competitiveness data. The Barron's institutional competitiveness index categorizes 4-year colleges in the United States based on the selectivity of admissions criteria at each school during a given year, including information on grade point average, class rank, college entrance exam scores, and the percentage of applicants accepted at a given institution the previous year (Schmitt 2015). As Table 2.1 shows, there were no major changes over time in how institutions are classified in the Barron's data.

Measures

To measure the outcome of interest, student college enrollment, I create a standardized measure in each of the five datasets that captures whether students enrolled in: (1) any college, (2) a 4-year college, and (3) a selective 4-year college during the fall following high school graduation. In Appendix Table A1, I list all variables used in this study for each of the five datasets. For the first college that students enrolled in, NCES provided either a FICE code, or a UnitID code, which provides information about the level of each college. I then use the FICE code to link to Barron's selectivity data, allowing me to capture the selectivity of college students applied to. Table 2.1 shows the criteria for rating colleges across each of the decades using the Barron's classification. In general, a selective 4-year college is one where high school grades of admitted students typically ranges from Bs to As, students rank in at least the top 35% of their high schools, and fewer than 50% of applicants are admitted (Schmitt 2015).

To measure differences in outcomes by socioeconomic status, I use a family socioeconomic status composition variable created by NCES. The SES measure relies on self-reports of parents' educational attainment, occupation, and family income (Ingels, Dalton and LoGerfo 2008). The composite variable is the mean of the standardized z-scores for each individual measure within each dataset, referring to a period-specific distribution of SES. I split this continuous variable into SES terciles, with students being classified as from low, middle, or high SES backgrounds. To understand socioeconomic disparities, I compare the top and bottom SES terciles, although I still include the middle SES tercile in all analyses. While the composite measure of SES is beneficial because it can provide a fuller understanding of socioeconomic backgrounds, it's possible that specific aspects of SES, like the importance of parent education, could change over time. As a result, in Appendix Figure A1, I also look at trends in college enrollment gaps using a measure of family income standardized to 2014 dollars, and I find the main results from this chapter are robust.

Table 2.1. Barron's Rating Criteria for Selective 4-year Colleges

	1972	1982	1992	2004	2014
GPA	B to A	B to A	B to A	B to A	B to A
Class rank (top %)	10-30%	10-35%	10-35%	10-35%	10-35%
Median SAT	600-800	575-800	575-800	620-800	620-800
Median ACT	26-28	26-27	27-29	27-29	27-29
Applicants admitted	<25%	<50%	<50%	<50%	<50%

Notes: Results combine rating criteria across Barron's highly competitive and most competitive categories.
Source: Schmitt, C.M. (2015). *Documentation for the Restricted-Use NCES-Barron's Admissions Competitiveness Index Data Files: 1972, 1982, 1992, 2004, 2008, and 2014* (NCES 2015-333). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

To measure college application, I use measures from spring of students' senior year, when students were asked to denote the colleges to which they had applied. Using the FICE code, I then link the student survey data to Barron's data, which allowed me to identify the selectivity of college students applied to. In this study, I consider whether students applied to a 4-year college and whether they applied to a selective 4-year college.

To measure students' academic preparation for college, I include variables for high school graduation, college entrance exam test taking, and high school GPA. To measure high school graduation, I use a binary measure of whether students had graduated from high school on time. To measure college entrance exam test taking, I draw on a binary measure of whether students had taken a college entrance exam by the end of high school. Each survey included students' SAT and ACT test scores, which I used to determine whether each student had taken at least one of the two college entrance tests by the end of high school. I use a measure of student GPA during high school that I code into a binary measure of whether the student had a GPA of 3.0 or higher.

To measure how students prioritized different factors in the college choice process, I use self-reported ratings by students of the importance of different factors for their choice of college, including the cost of attendance, the academic reputation of a school, and being able to live at home while attending college. Students were asked "How important to you [will/would] [the given factor] be when choosing a school or college to attend after high school?" Response options included "not at all important," "somewhat important," and "very important," and I created binary measures for whether students rated each factor as very important for their college choice.

To measure the formation of college aspirations and expectations, I draw on three binary variables. The first captures whether a student's parent reported wanting their child to attain a bachelor's degree. The second captures whether students reported expecting to attain a bachelor's degree. The third captures whether students reported that they would attend college immediately following high school graduation.

Analysis

In this study, to understand patterns in socioeconomic gaps in college enrollment, I begin by documenting changes in college enrollment between 1972 and 2014, focusing on differences across each cohort. I focus on trends in three outcomes. The first is whether students enrolled in any college. The second considers whether students enrolled in a 4-year college specifically, and the third is whether students enrolled in a selective 4-year college. I primarily focus on non-conditional college enrollment outcomes to avoid the potential for selection bias, where only those who have already overcome certain barriers are included in the subsequent analyses, though I also examine conditional outcomes, looking at 4-year college enrollment gaps, conditional on enrolling in any college, and selective college enrollment gaps, conditional on enrolling in a 4-year college to help identify whether SES disparities are due to initial access to college or to access to more selective institutions.

I next explore other pre-enrollment gaps across the college-choice process to understand the stages at which socioeconomic disparities emerge and are most prevalent and how these gaps shift across the decades with the expansion of the postsecondary education system. If students do not graduate from high school, they have little to no chance of enrolling in college. In this sense, differences across socioeconomic groups over time in high school completion rates could explain some of the observed gaps in college enrollment. This does not mean these are causal effects. It's likely that the same social and economic forces that determine whether a student completes high school will also affect college enrollment decisions. However, understanding descriptively where in the pipeline socioeconomic gaps emerge is valuable. Beyond high school completion, there are other key stages that are important to consider, including whether students applied to college, whether they took a college entrance exam, the factors they prioritize when selecting a college, and the formation of college plans in the first place. As such, I compare socioeconomic gaps in college enrollment to concurrent gaps in these other stages in the college choice process. The 95% confidence intervals for all SES gaps can be found in Appendix Tables A1-A6 and were notably narrow, indicating a high level of precision in the estimates.

A limitation of this work is that I rely on data from five cohorts to explore trends over a 40-year time period. The problem is that each cohort is about a decade apart, making the results less precise. However, the longitudinal nature of the data still provides valuable insights into the evolution of enrollment and college choice gaps, offering a more comprehensive picture of changes over time than would otherwise be possible with existing data sources like IPEDS data, which capture annual postsecondary enrollment, but do not account for those who never enrolled in the first place.

Results

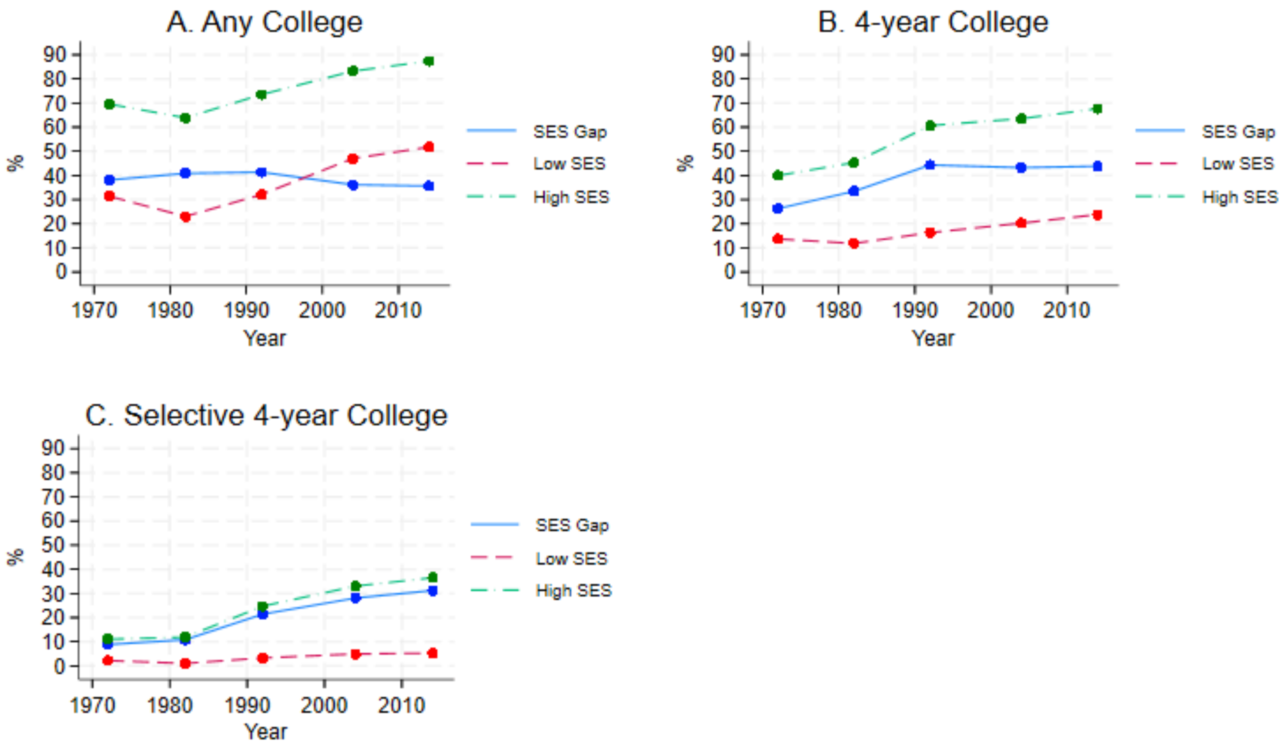
Socioeconomic Disparities in College Enrollment

Figure 2.1 presents the college enrollment patterns of high school seniors from 1972, 1982, 1992, 2004, and 2014 during the fall semester following high school graduation. The dashed lines present the overall percentage of seniors who enrolled among students from low SES and high SES backgrounds, while the solid line presents the gap in enrollment between students from high compared to low SES families. Panel A presents trends for enrollment in any college, Panel B focuses on 4-year college enrollment, while Panel C displays trends for selective 4-year college enrollment.

Figure 2.1 Panel A shows that overall enrollment in college generally increased across the decades for all students, rising about 20 percentage points from the early 1970s to the early

2010s, dipping between the 1970s and 1980s, and then consistently rising across each remaining decade. The trends looked very similar for students from low compared to high SES

Figure 2.1. High-Low Socioeconomic Status Gap in College Enrollment, 1972 to 2014



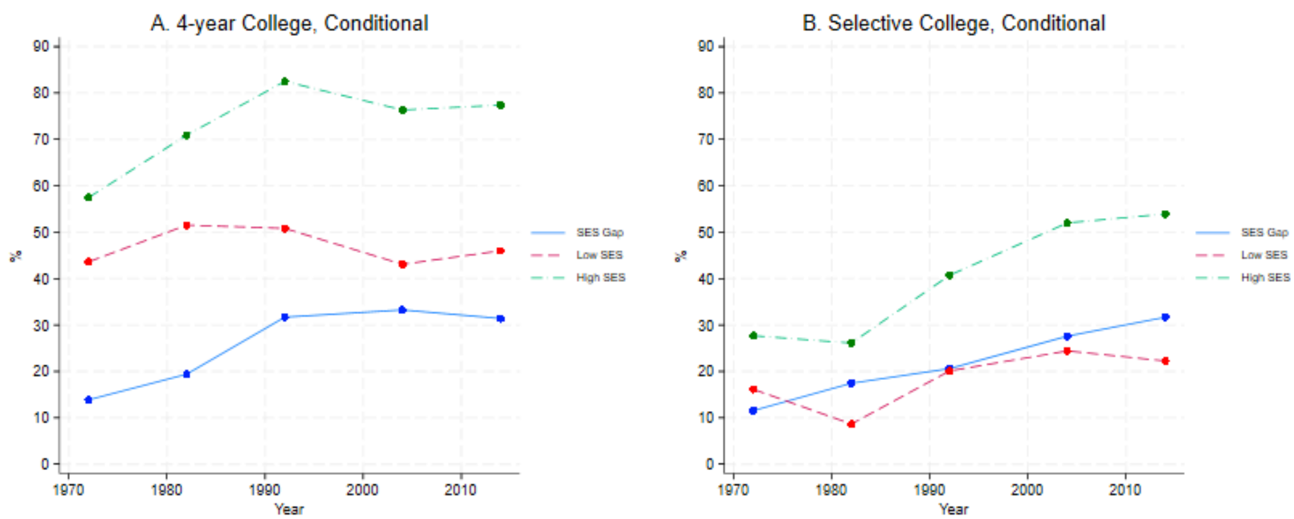
Notes: Observed percentages are presented of high school seniors in each cohort who enrolled in college the fall after high school graduation. The dots represent the data points for each cohort. All results are weighted to target graduating seniors in the given year and combined across five imputations. Confidence intervals for the SES gap point estimates can be found in Table A2.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

backgrounds. The high-low SES gap, which started at about 38 percentage points in 1972 slightly increases through the 1980s and 1990s before slightly dropping in the early 2000s and ultimately dropping to about 36 percentage points in 2014, only two percentage points lower than it started in 1972. This means that despite the expansion of the postsecondary education system, the plethora of policies enacted to improve access for low-income students, and the increase in the number of community colleges available, socioeconomic disparities in college enrollment did not ultimately decrease across the four decades in this study.

Beyond general enrollment in college, Figure 2.1, Panel B shows trends in 4-year college enrollment specifically. Similar to trends in general college enrollment, enrollment in a 4-year college saw a net increase between 1972 and 2014, though the increase looked very different in this case across socioeconomic backgrounds. Socioeconomically advantaged students saw an increase of almost 30 percentage points across the decades while those from low socioeconomic backgrounds saw an increase closer to only 10 percentage points. Students from high SES backgrounds saw the sharpest increase between the early 1970s and early 1990s and then another gradual increase between the 1990s and 2010s, while those from low SES backgrounds saw a slower and steady increase between the 1980s and 2010s. While socioeconomic gaps remained stable for enrollment in any college, the high-low SES gap dramatically increased when considering 4-year college enrollment, going from about 26 percentage points in the early 1970s to a high of 44 percentage points in the early 2010s. Figure A2 in the appendix confirms that as college enrollment rates increased over the decades for all students, a higher proportion of those from low SES backgrounds were enrolling in community colleges rather than 4-year colleges.

In Figure 2.1, Panel C shows that when looking at selective 4-year college enrollment, there is a general increase in selective 4-year college enrollment, again with those from high SES backgrounds benefitting the most. In 1972, about 11% of high SES students enrolled in a selective 4-year college, which increased to 38% in 2014, a 29 percentage-point increase – or a 246% increase - across the decades. Low SES students were much less likely to enroll in a selective college originally, with only 1% enrolling in a selective college in 1972, which increased to about 6% in 2014, a 5 percentage-point increase – or a 500% increase. High SES students saw the largest increase between the 1980s and early 2010s, which led to a dramatic increase in the SES gap from about 11 percentage points in 1982 to 30 percentage points in 2014. Figure A3 in the appendix similarly shows that socioeconomic gaps between high SES and middle SES students and those between middle SES and low SES students increased across the decades for both 4-year college enrollment and selective college enrollment, showing that the increased disparities in college enrollments are not isolated to the high-low SES gap.

Figure 2.2. Conditional High-Low Socioeconomic Status Gap in College Enrollment, 1972 to 2014



Notes: Observed percentages are presented of high school seniors in each cohort who enrolled in college the fall after high school graduation. All results are weighted to target graduating seniors in the given year and combined across five imputations. Confidence intervals for the SES gap point estimates can be found in Table A2.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

While the 4-year and selective 4-year gaps presented in Figure 2.1 are most accurate for understanding observed socioeconomic disparities, Figure 2.2 additionally shows 4-year college enrollment gaps conditional on having enrolled in any college, and selective college enrollment gaps conditional on having enrolled in a 4-year college, to provide insight into the decision-making process among college-bound students. In Panel A, of those who enrolled in a college, the socioeconomic gap in 4-year college enrollment increased from about 14 percentage points in 1972 to about 31 percentage points in 2014, which is a substantial increase, though is a smaller increase than the unconditional gap in Figure 2.1 showed, suggesting that once students from low SES backgrounds make the decision to attend college, the gap in accessing a 4-year institution, though still large and growing, is slightly less pronounced as the initial gap in accessing any college education at all.

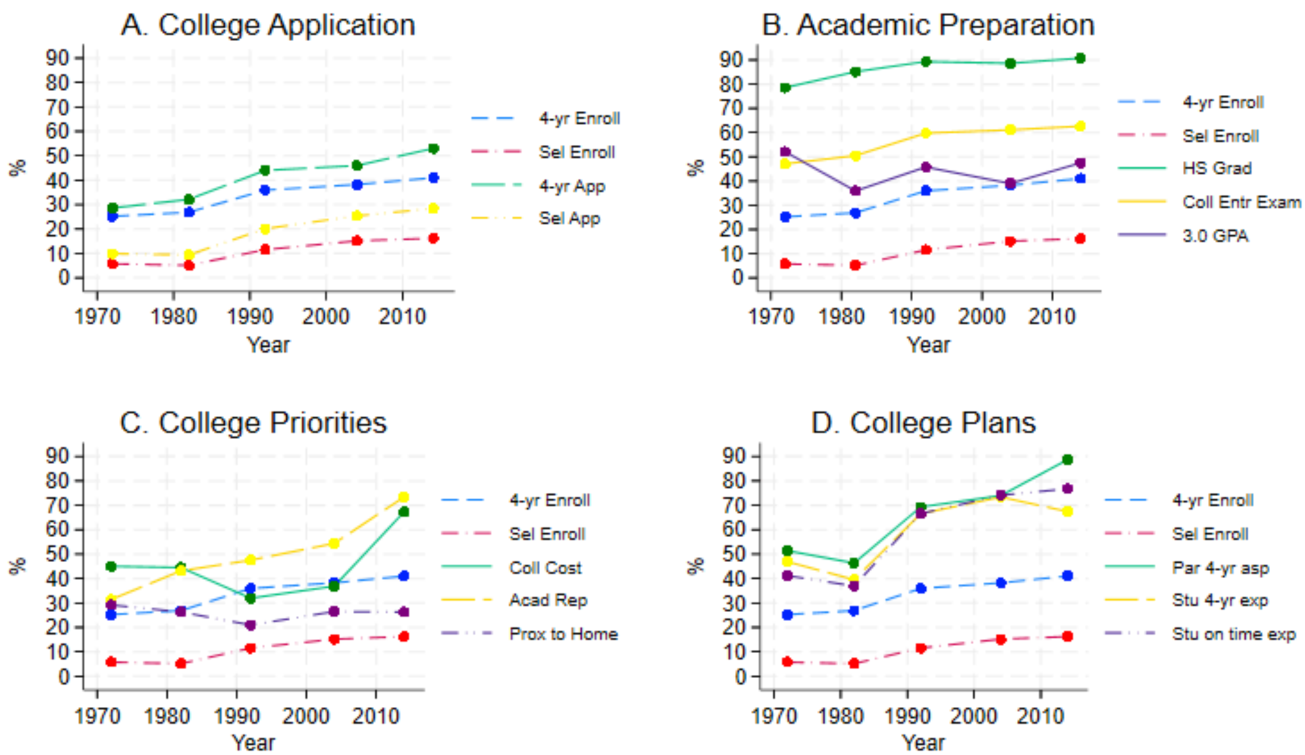
Figure 2.2 Panel B shows the disparities present after the initial hurdle of getting into a 4-year college has been overcome. In contrast to the 4-year college enrollment gap, which was less pronounced in the conditional model, for selective college enrollment, the SES gap is similar in the unconditional and conditional model, suggesting that even among those who make the decision to enroll in a 4-year college, the SES gap in selective enrollment is persistent, identifying the decision to enroll in a selective 4-year college as a key contributor to socioeconomic disparities in college enrollment.

Overall Trends Across Stages of the College Choice Process

Next, before examining trends in SES gaps across stages of the college choice process, I explore the overall trends in Figure 2.3, including college application behavior (Panel A), academic preparation for college (Panel B), setting college priorities (Panel C), and forming college plans

(Panel D). Each panel includes the 4-year and selective 4-year college enrollment trends as a comparison.

Figure 2.3. Overall Trends Across Stages of the College Choice Process, 1972 to 2014



Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Panel A shows that college application trends mirror trends in students' college enrollment. In the early 1970s, about 29% of students applied to a 4-year college, and 23% of students enrolled in one. About 10% of students applied to a selective college though while only 5% enrolled in one, suggesting that for selective college enrollment post-application factors come into play. As college application behavior steadily increased over the decades, so too did college enrollment rates, though the gap between application and enrollment behavior slightly widened, suggesting either that more students were applying to "reach" colleges and were not being admitted, or that students were deciding not to enroll in a given level of college even after applying and being admitted.

Panel B shows that high school graduation rates steadily increased between the early 1970s and early 1990s, showing a similar trend as 4-year and selective 4-year college enrollment rates across the same time period. However, while almost 90% of students graduated from high school in 2014, only about 41% enrolled in a 4-year college the following fall semester. College entrance exam test taking also closely matched the trends for college enrollment across the decades, increasing steadily before leveling off in the 1990s and early 2000s. The proportion of students with a GPA of 3.0 or higher fluctuated over the decades, but there was no consistent upward or downward trend across the four decades.

Panel C shows that the proportion of students who considered college costs very important to their college attendance decision decreased between the 1970s and 1990s before sharply increasing between the early 2000s and 2010s. As the importance placed on college costs decreased between the 1970s and 1990s, 4-year and selective 4-year college enrollment increased. When the importance placed on costs sharply spiked between 2004 and 2014, college enrollment rates remained stagnant though. The importance of a college's academic reputation steadily increased across each of the decades, closely following the 4-year and selective college enrollment trends between the 1970s and early 2000s before sharply increasing between the early 2000s and early 2010s. As such, while the importance placed on college costs sharply spiked, so too did the importance of the academic rigor of the institution attended. The importance placed on attending a college close to home generally seemed to follow the trend of the importance placed on college costs, falling between the 1970s and early 1990s. However, whereas the importance of college costs spiked between the early 2000s and early 2010s, the importance of attending a college close to home remained stagnant during that time period.

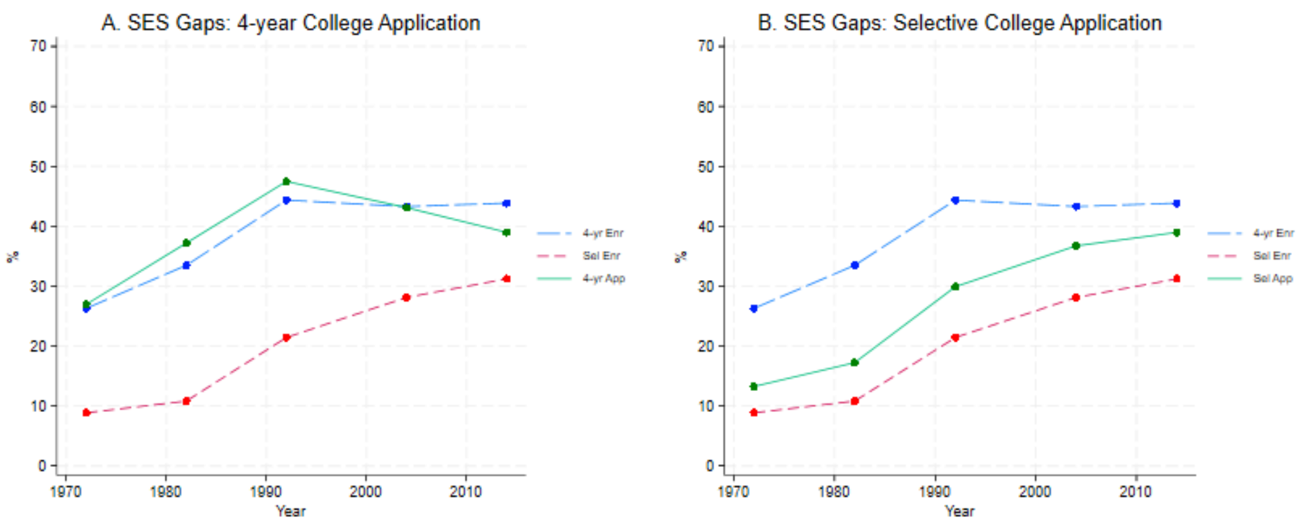
In Panel D, we see that as 4-year and selective 4-year college enrollment rates steadily increase across the decades, college plans also increase. The proportion of parents with bachelor's degree aspirations for their child, the proportion of students who expect to attain a bachelor's degree, and the proportion of students who expect to attend college right after high school increase from between 40-45% in 1982 to approximately 74% in 2004, almost doubling across the two-decade time span. Parents' college aspirations then spike to almost 90% in 2014, while students' college expectations go down. While trends in college plans increased similarly to 4-year and selective college enrollment across the decades, almost double the amount of students expected to attain a bachelor's degree as those who enrolled in a 4-year college in the early 1970s, and the same was true in the early 2010s. The gap between parental bachelor's degree aspirations and 4-year college enrollment only increased across the decade, starting with about a 30 percentage-point difference in 1972, and ending with about a 46 percentage-point difference in 2014 as students' 4-year college enrollment didn't keep pace with increasing parental aspirations. About 68% of students expected to attain a bachelor's degree in 2014, and roughly the same percentage of students took a college entrance exam, as shown in Panel B.

Socioeconomic Disparities Across Stages of the College Choice Process

Next, I explore trends in socioeconomic gaps across the different stages of the college choice process and compare these trends to those in college enrollment behavior. Each figure illustrates trends in outcomes at different stages of the college choice process among high school seniors from the years 1972, 1982, 1992, 2004, and 2014. In each figure, the blue dashed line represents SES gaps in 4-year college enrollment, the red dashed line represents gaps in selective college enrollment, and the green solid line represents SES gaps in the given college choice stage.

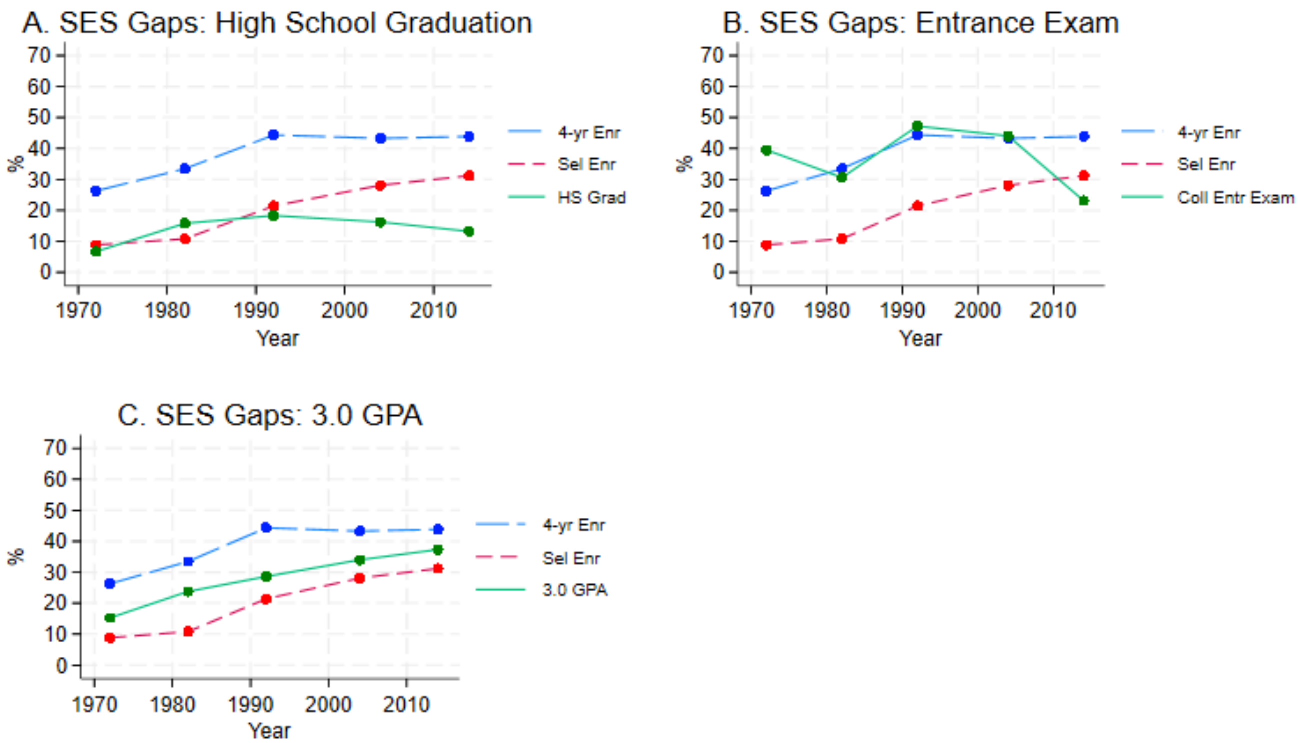
Figure 2.4 presents trends in SES disparities in college application behavior. Panel A focuses on disparities in 4-year college application, and Panel B on gaps in selective college application. Panel A shows that socioeconomic disparities in 4-year college application almost exactly mirror 4-year college enrollment gaps across each decade. Similarly, Panel B shows that

Figure 2.4. High-Low SES Enrollment Gaps Compared to College Application Gaps, 1972 to2014



Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations. Confidence intervals for the SES gap point estimates can be found in Table A3.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Figure 2.5. High-Low SES Enrollment Gaps Compared to Academic Preparation Gaps, 1972-2014

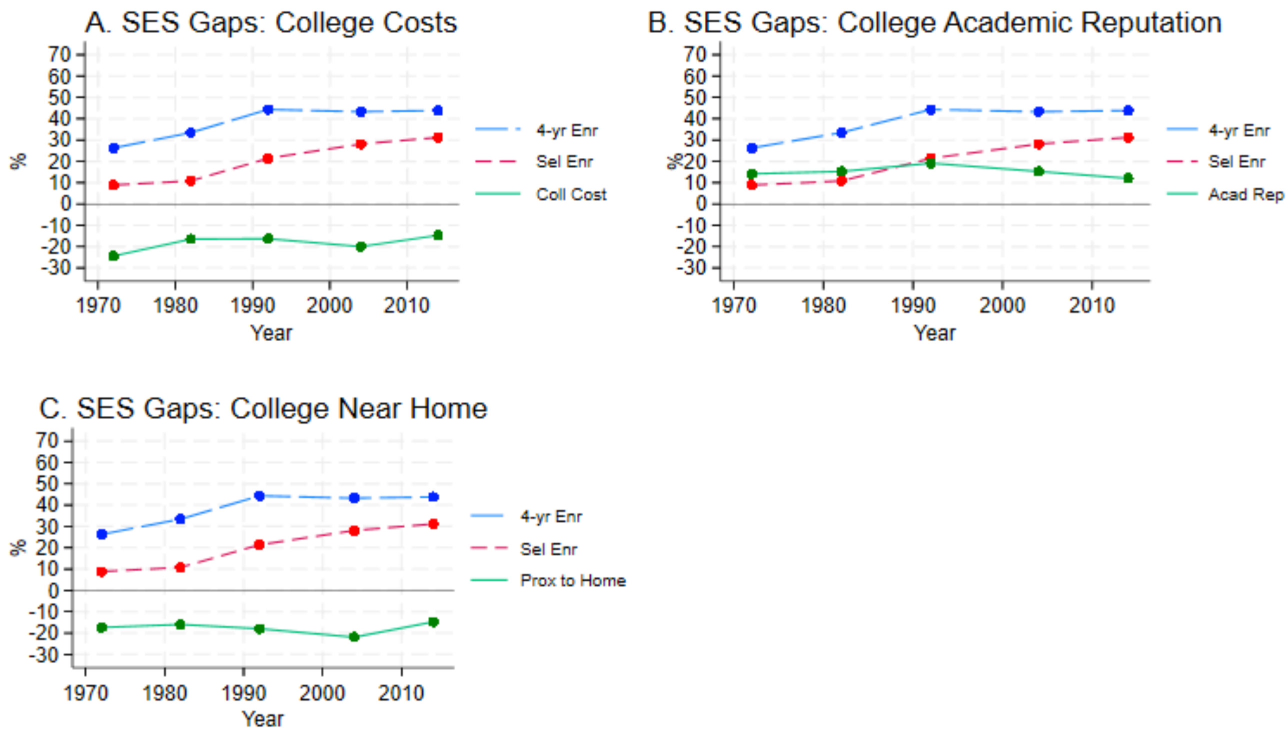


Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations. Confidence intervals for the SES gap point estimates can be found in Table A4.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

the selective college gaps also closely mirror the selective enrollment rates, although the SES gap was higher for selective application than for selective enrollment, suggesting that some of the socioeconomic disparities in selective college enrollment emerge after the application stage, either during the admissions process or when students are making the decision of which college to attend. While Figure 2.3 showed that the overall trends in college application and college enrollment rates closely mirrored each other over the decades, Figure 2.4 demonstrates that this is also true for socioeconomic gaps in college application and enrollment. This suggests that the widening socioeconomic disparities in 4-year college enrollment over the decades are largely driven by differences in college application behavior rather than disparities in acceptance rates or willingness to enroll. In other words, the issue is not that students from lower socioeconomic backgrounds applied and did not get in; it is that they often do not apply at all.

Next, Figure 2.5 presents trends in socioeconomic disparities in academic preparation for college. Panel A focuses on high school graduation gaps, Panel B on college entrance exam test taking gaps, and Panel C on grade point average gaps. Panel A shows that socioeconomic disparities in high school graduation actually doubled between the early 1970s and early 1980s before slightly dropping and remaining stagnant across the remaining decades. Panel B presents trends in SES disparities in college entrance exam behavior, specifically whether students took the ACT or SAT during high school. In the early 1970s, the SES gap in college entrance exam test taking was larger than the SES gap in 4-year college enrollment, by about 13 percentage points. Between the early 1980s and early 2000s, the college entrance test taking gap was almost equal to the 4-year college enrollment gap, with SES disparities increasing between the early 1980s and early 1990s before slightly dipping in the early 2000s. Between the early 2000s and early 2010s, socioeconomic disparities in taking a college entrance exam sharply dropped, almost by half, even as the 4-year college enrollment gap remained stagnant, suggesting that even the decreased SES disparities in college entrance exam test taking, a prerequisite to applying to most 4-year colleges, did not lead to a corresponding decrease in disparities in enrollment. Panel C shows that the socioeconomic gap among students with a 3.0 GPA or higher steadily increased across the decades, largely following the upward trends in 4-year and selective college enrollment.

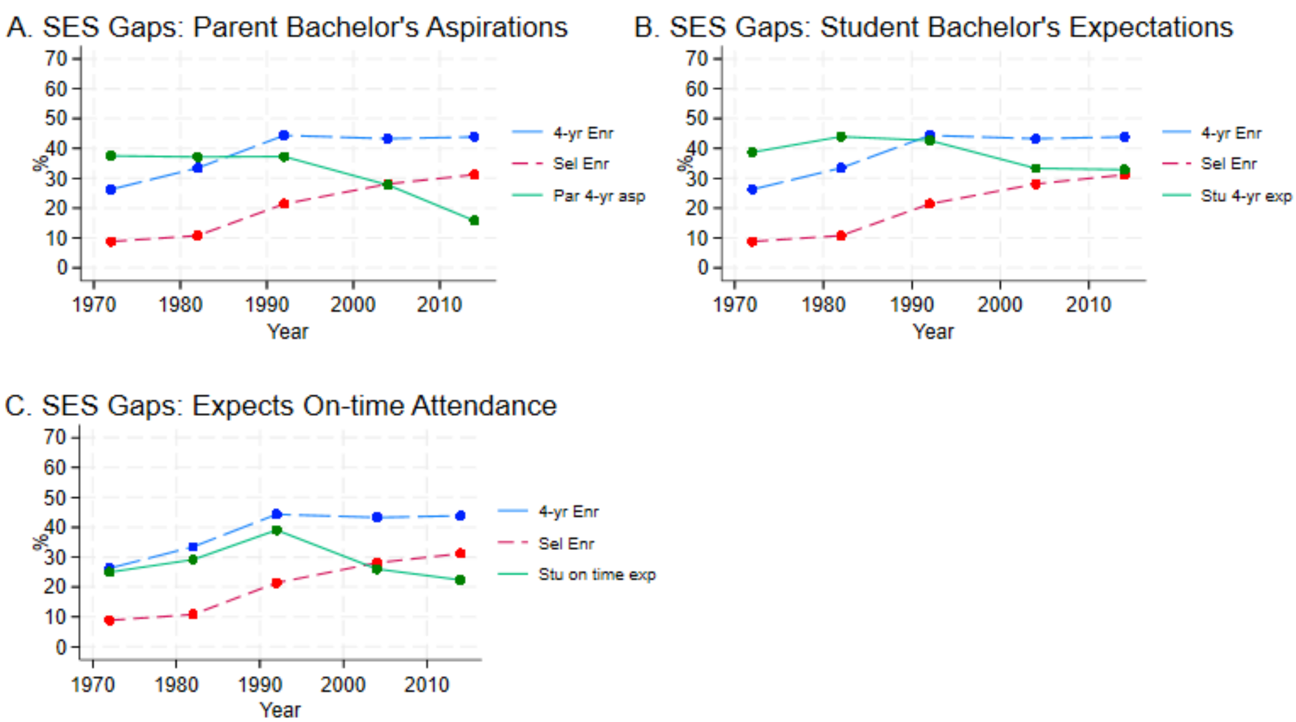
Figure 2.6. High-Low SES Enrollment Gaps Compared to College Priorities Gaps, 1972 to 2014



Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations. Confidence intervals for the SES gap point estimates can be found in Table A5.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Figure 2.6 presents trends in SES disparities regarding the factors students prioritized when making a college decision. Panel A focuses on the importance of college costs, Panel B on the importance of an institution's academic rigor, and Panel C on the importance of a college's proximity to home. Panel A shows that the high-low SES gap in the importance placed on college costs is negative, meaning that a higher proportion of low SES students considered college costs very important in their college attendance decision compared to high SES students. This concern was persistent over time, although the SES gap narrowed significantly decreasing from approximately -24 percentage points to about -15 percentage points over the decades. Panel B shows that the trends in the SES gap in the importance placed on the academic reputation of an institution closely mirrored that of 4-year college enrollment. Panel C shows that the high-low SES gap in the importance placed on attending a college near home is negative, meaning a higher proportion of low SES students felt this was important for their college attendance decision. The SES gap remained relatively stable over the decades.

Figure 2.7. High-Low SES Enrollment Gaps Compared to College Planning Gaps, 1972 to 2014



Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations. Confidence intervals for the SES gap point estimates can be found in Table A6.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Figure 2.7 presents trends in SES disparities in college plans. Panel A focuses on parental bachelor's degree aspirations, Panel B on students' bachelor's degree expectations, and Panel C on students' expectations for on-time college attendance. SES disparities in parents forming bachelor's degree aspirations sharply dropped between the early 1990s and early 2010s, going from about 38 percentage points to 16 percentage points. At the same time, the SES gap in 4-year college enrollment remained stagnant at approximately 44 percentage points, and the selective college enrollment gap actually slightly increased from 21 percentage points to about 31 percentage points. Panel B shows that the SES gap in student expectations dropped between the early 1980s and the early 200s, from about 43 percentage points to about 33 percentage points in the early 2010s. Finally, in Panel C, we can see that the SES gap in student expectations for on-time college enrollment very closely mirrored the 4-year college enrollment gap, with disparities actually increasing between the 1970s and 1990s before dropping between the 1990s and early 2000s.

Conclusion

This study explores socioeconomic disparities in college enrollment over four decades, revealing increasing inequality in U.S. higher education. Even though college enrollment generally increased and there were policy efforts specifically aimed at increasing access to higher education for low-income students, socioeconomic gaps have not just persisted, but in many cases, have actually widened over time.

The divergence in college enrollment trajectories for students from varying socioeconomic backgrounds is striking when it comes to 4-year and selective college enrollment patterns. While enrollment at community colleges and less selective 4-year colleges has increased across all SES groups, the representation of high SES students at 4-year colleges has grown at a much faster rate. While students from socioeconomically advantaged backgrounds are increasingly applying to and enrolling in selective colleges across the decades, the same is not true for their less advantaged counterparts, which led to a growing enrollment gap for selective colleges.

Most of the changes in socioeconomic disparities occurred between the 1970s and 1990s, after which the rates of enrollment and the corresponding disparities largely plateaued. This means that the expansion of the higher education system may have actually reinforced the importance of socioeconomic background in shaping educational opportunities for students. Rather than providing equal access, disparities widened for access to different tiers of postsecondary institutions. This has significant implications for students' long-term outcomes, given the benefits associated with attending more selective institutions (Borgen and Mastekaasa 2018; Gerber and Cheung 2008; Long 2008).

The complexities of the college choice process highlighted in this suggest its potential influence on enrollment patterns. Increases in parental aspirations and students' expectations over the decades reflect shifting societal values regarding higher education. At the same time, the importance attributed to the academic rigor of institutions has surged, mirrored by an uptick in college entrance exam test-taking. While overall high school graduation rates and college application rates have risen as well, they have done so to a lesser extent.

While overall rates increased across stages in the college choice process, socioeconomic gaps in college aspirations, college expectations, and test-taking declined over time. However, there was not a corresponding decrease in college enrollment gaps, which means there may be a mismatch between aspirations and actual enrollment outcomes that policymakers could better target with interventions. This is especially important for college application decisions as the appeal of attending a college close to home remains an important consideration for lower SES students, even after policy reforms aimed at improving college affordability and accessibility (Baum, Kurose and McPherson 2013). An important finding in this chapter is that there was not a reduction in socioeconomic gaps in the earlier stages in the college choice process, besides the reduced disparities in college expectations. This highlights the need for policy or interventions to address factors that shape college decisions before the application or enrollment stage.

A key limitation of this study is that while the four later survey datasets include high school dropouts in the sample, survey response rates among this population are known to be low (Groves 2006; Ingels et al. 2014), which could mean that some of those who are least likely to apply to and enroll in college on time, who are often from more socioeconomically disadvantaged families (Chapman et al. 2011), were already excluded from the sample by the time 12th grade aged students were surveyed. To prevent the loss of those who were non-responsive in later waves of data collection, I conducted multiple imputation for each survey dataset using not just 12th grade data, but also baseline data, meaning that students who were part of earlier waves of data collection could be retained. However, this does not fully eliminate the possibility of the underrepresentation of high school dropouts, especially in the NLS 1970 survey dataset, which initiated data collection starting in 12th grade, and so does not include high school dropouts at all. As a result, these estimates could be downwardly biased, meaning that it's possible the SES disparities could be even larger than what is reported in this analysis.

In sum, while increasing access to college for all students is positive, this study shows that access to college alone is not enough to reduce the persistent inequalities in access to higher education in the U.S. Despite decades of policy and research efforts on this topic, the socioeconomic gap in whether students enroll in any college has largely remained the same since the early 1970s. This unique contribution of this study is to show that when focusing on gaps in where students enroll across the decades, socioeconomic gaps have actually widened substantially, revealing areas for further study and policy intervention. This study is also the first to explore trends in socioeconomic educational gaps and other concurrent trends, This study contributes to theoretical understandings of inequality in higher education by highlighting the importance of considering horizontal stratification within the higher education system.

Chapter 3

The Impact of Financial Information on Socioeconomic Disparities in College Application

Introduction

College enrollment remains highly stratified by socioeconomic background in the United States, both in terms of whether students enroll and where they go (Alon 2009). These differences in enrollment are largely reflective of students' application behavior (Hoxby and Turner 2013), and low-income, high-achieving students are much less likely to apply to 4-year colleges than their more advantaged counterparts (Cabrera and La Nasa 2001; Manski and Wise 1983). Very few low-income students apply to even one selective college (Hoxby and Avery 2012; Mullen and Goyette 2019) despite the documented benefits that selective colleges can provide through reducing costs (Cohodes and Goodman 2014), increasing the chances of completing a degree, and improving future wages (Gerber and Cheung 2008; Hout 2012). Because perceptions of college affordability play an important role in students' college decisions, especially for those from socioeconomically disadvantaged backgrounds (Manski and Wise 1983; St. John, Paulsen and Starkey 1996), researchers have commonly hypothesized that providing students and parents with financial information could reduce college application disparities (George-Jackson and Gast 2015; Grodsky and Jones 2007), though there is limited empirical evidence. While the University of Michigan study highlights the impact of financial information on both application and enrollment, it focused specifically on testing the effect of informing students and their parents that they qualified for free tuition, which is distinct from simply providing detailed cost or aid information (Dynarski et al. 2021).

While students rely on friends, teachers, and high school counselors when making college decisions (Vesper, Hossler and Schmit 2003), parents remain the most influential source shaping a student's college-going intentions (Crosnoe, Mistry and Elder Jr. 2002; Manski and Wise 1983). College-educated parents are more likely to have the necessary knowledge to guide students through the college application process, both as a result of having prior experience with the higher education system and from having social networks they can draw on for relevant information (Coleman 1988). As a result, students and their parents from socioeconomically advantaged backgrounds have more information about college costs and financial aid options (Bell, Rowan-Kenyon and Perna 2009; Grodsky and Jones 2007; Horn, Chen and Chapman 2003).

While disparities in college financial information are thought to contribute to the socioeconomic gap in college application, there are surprisingly few studies that examine this empirically. Some scholars have found that providing specific samples of low-income, high achieving students with information about net college costs at highly selective colleges leads to small increases in college enrollment behavior (Hoxby and Turner 2013; Hyman 2020), while others have found that providing net tuition information does not change enrollment patterns (Gurantz et al. 2019). In a novel study, Dynarski et al. (2021) found that a large-scale intervention providing a treatment group of low-income students with information that they qualified for a guaranteed commitment of free tuition to attend the in-state flagship university substantially increased both applications and enrollment. Because all low-income students in the study already qualified to receive free tuition, while the intervention picked up on the effects of providing students with information, the results are likely not widely applicable to other settings without free tuition guarantees. Further, many prior interventions only targeted students to receive college information (Gurantz et al. 2019; Hoxby and Turner 2013; Hyman 2020), despite the known influence of parents on college decisions (Vesper, Hossler and Schmit 2003). While the Dynarski et al. (2021) study focused on an intervention providing both students and parents with financial information, there was no way to differentiate the importance of providing students compared to parents with financial information. Understanding the effects of providing financial information to students versus parents matters for structuring interventions. If parents are key levers, targeting them directly for information could more effectively reduce socioeconomic disparities.

In this study, I use longitudinal survey data from more than 21,000 high school freshman in the 2009 High School Longitudinal Study to explore the explanatory role of providing college financial information to students, parents, or both, on SES gaps in college application behavior. I link HSLS data to information on college selectivity from Barron's Admissions Competitiveness data and to information on college prices from the Integrated Postsecondary Education Data System data to ask the following questions: (1) How does the information that students and parents have about college finances differ by socioeconomic background? (2) To what extent do differences in financial information explain socioeconomic gaps in perceptions of college affordability? (3) To what extent do differences in financial information explain socioeconomic differences in college application behavior? (4) How does the importance of student financial information compare to that of parent information in explaining gaps in college application behavior?

To answer these questions, I use gap-closing estimands to explore how SES gaps in college outcomes would change if students and their parents had information about college costs and financing. In this study, I operationalize 'availability of college financial information' as the sources parents can draw on for financial aid information and the extent to which families are generally aware of college expenses and financial aid processes. This work contributes to the literature by demonstrating the importance of information in shaping perceptions of affordability and college application behavior (Cabrera and La Nasa 2000; Hossler and Gallagher 1987).

Models of College Choice

It can be difficult to decide whether and where to attend college, requiring an understanding of different options and their costs and benefits (Vesper, Hossler and Schmit 2003). In the education literature, the college choice process is typically defined by three main stages: (1) predisposition to college attendance, (2) search for information, and (3) college choice (Cabrera and La Nasa 2000; Hossler and Gallagher 1987). In this study, I focus on the latter two stages, which typically occur during the high school years (Cabrera and La Nasa 2000), exploring how financial information contributes to the choice stage. While conceptual models of college choice suggest that these stages are not distinct and that the search for information informs the choices students make both about whether and where to attend college (Alexander and Eckland 1975), there is a debate in the field about whether information received during the high school years can change students' college-going trajectories or if their predisposition to college attendance is set by the time they reach high school.

Rational action theorists argue that college intentions are formed as a result of a cost-benefit analysis that students and their parents undertake when weighing options for the future (Breen and Goldthorpe 1997; Morgan 2005; Raftery and Hout 1993). In this perspective, students and parents draw on information to make decisions about education continuation (Morgan 1998). A second set of scholars argues that families already have set expectations for a child's educational attainment long before the high school years, challenging rational action theorists who see educational decisions as a cost-benefit analysis based on available information (Andrew and Hauser 2012; Bozick et al. 2010; Grodsky and Riegle-Crumb 2010).

While family educational expectations may be set early on, even before children are born, in socioeconomically advantaged families (Grodsky and Riegle-Crumb 2010), this is not typically the case for less advantaged families, who tend to have less stable college expectations even during the high school years (Bozick et al. 2010). As a result, less advantaged families may be more inclined to draw on information to make decisions about educational continuation. Further, even if college going intentions are already set by the time students reach high school, college information can still inform decisions about the specific colleges students consider and apply to (McDonough 1997), which could thus still contribute to socioeconomic gaps.

College Information Disparities

Scholars have long outlined the fact that college-educated parents tend to have more relevant information they can draw on – such as knowledge about navigating the school system and accessing resources – to benefit their child's future educational opportunities (Coleman 1988). This is partially because of the ability to draw on personal experiences with the higher education system, but is also a result of socioeconomically advantaged parents having deeper social networks they can rely on for college-related information (Carbonaro 1998; Coleman 1988; Teachman, Paasch and Carver 1997). Parent networks matter a lot for gaining access to beneficial information about educational opportunities (Horvat, Weininger and Lareau 2003; Lewis-McCoy 2014). There is also variation in the informational resources that children's high school provides to parents, often reflecting differences in socioeconomic background (Horvat, Weininger and Lareau 2003).

Since affordability is a key factor in college decisions (Manski and Wise 1983; St. John, Paulsen and Carter 2005), understanding the disparities in how affordable college is perceived to be and the reason behind them is important. Perceptions of college affordability can influence behavior, regardless of their accuracy (Kim, DesJardins and McCall 2009; Tierney 1980). Some research has suggested that low-income students who believe college is affordable are most likely to aspire to attend college, and to therefore enroll (Perna 2006b). On the other hand, students from wealthier families tend to be less concerned with the specifics of paying for college (George-Jackson and Gast 2015). There is a general lack of clear information about college costs, which may contribute to perceptions about college affordability (Horn, Chen and Chapman 2003).

Despite the majority of students and their parents having college aspirations, many lack information about college costs and financing options (Bell, Rowan-Kenyon and Perna 2009; La Rosa, Luna and Tierney 2006). Students don't receive official information from colleges about costs until after they submit their FAFSA form and hear back about college acceptances. As a result, students and their parents typically make decisions about applying to college without knowing the exact costs of attendance (Perna 2006a).

Disadvantaged students, who are likely the least able to afford college, are also the least likely to have college financial information (Grodsky and Jones 2007; Horn, Chen and Chapman 2003; La Rosa, Luna and Tierney 2006). They are less likely to have information about the sticker price of colleges (Grodsky and Jones 2007; Horn, Chen and Chapman 2003), the net costs of college (Bell, Rowan-Kenyon and Perna 2009), or about specific financial aid packages (Perna 2006a) than their more advantaged counterparts, making them less financially aware overall (George-Jackson and Gast 2015). Even among those who have some awareness of college costs, both students and their parents tend to greatly overestimate even the sticker price of college attendance (Bell, Rowan-Kenyon and Perna 2009; Horn, Chen and Chapman 2003), and there is some evidence that those from disadvantaged backgrounds may have slightly larger overestimates of college costs (Grodsky and Jones 2007), which could lead to perceptions of college being unaffordable. A key component of understanding college financial information is understanding the information sources available to different families.

Low-SES students and their parents tend to have fewer sources to draw on for college financial information than high SES families (George-Jackson and Gast 2015; McDonough 1997; Tierney 1980). Parents tend to be the most important source of information and support for children (George-Jackson and Gast 2015; Plank and Jordan 2001), and some research has found that parents' knowledge about college finance is highest when they draw on information from several sources (Olson and Rosenfeld 1984), and that they are more confident in the accuracy of their knowledge (Bell, Rowan-Kenyon and Perna 2009). While some sources, like private college counselors, are expensive, other school-based resources for providing college information may be better situated to level the field, though access and quality can also vary across school and state contexts (Perna and Steele 2011; Tierney 1980).

Despite the plethora of research highlighting disparities in financial information for both students and parents, the empirical evidence is less clear when it comes to whether providing financial information can reduce socioeconomic gaps in application behavior. In general, interventions providing information about financial aid to low-income students have found pretty limited effects when looking at application for financial aid, although they have been less focused on effects for college application more specifically (Bettinger et al. 2012; Dynarski and Wiederspan 2012). Results about providing information to high-achieving low-income students have produced mixed results. Some have found that there are either no effects or very small effects of providing information about costs at flagship schools (Gurantz et al. 2019; Hoxby and Turner 2013; Hyman 2020). In other work, Dynarski et al. (2021) found large effects from providing low-income high-achieving students with cost information for a flagship state university, though the university in question was providing a free-tuition promise, making it difficult to extrapolate the results more broadly. Further, the focus on providing low-income students only with information about costs at highly selective institutions to try to improve the college ‘match’ (Gurantz et al. 2019) does not take into account the fact that students consider a range of factors when selecting a college, such as location, campus environment, majors offered, potential career options, and social fit. Therefore, this type of intervention may miss how providing more general information about how college costs could improve application behavior (Kurlaender and Grodsky 2013).

Data and Methods

Data

To explore how college financial information contributes to SES gaps in college application, this study draws on data from the restricted-use National Center for Education Statistics (NCES) High School Longitudinal Study of 2009 (HSLS:09). The HSLS is a nationally representative longitudinal survey, which follows more than 21,000 students, starting in fall of 2009 during their freshman year of high school. Follow-up waves occurred during spring of junior and senior years of high school, as well as three years post-high school. During the freshman and junior year waves, each student respondent and one of their parents were surveyed. The study also collected data from school administrators and teachers. Survey topics include family background, academic achievement, and postsecondary planning. In spring of senior year of high school, students were also asked about college applications.

To capture the institutional selectivity of colleges that students applied to, I match each listed college to data from the 2014 NCES Barron's Admissions Competitiveness Index Data File using Federal Interagency Committee on Education (FICE) codes to link the data sources. Barron's institutional competitiveness index categorizes 4-year colleges in the United States based on the selectivity of admissions criteria at each school, including grade point average, class rank, and college entrance exam scores (Schmitt 2009).

Additionally, to descriptively explore student and parent perceptions of college costs, I match each HSLS student with publicly available data from the Integrated Postsecondary Education Data System (IPEDS) on the published in-state tuition and total college costs for 4-year colleges in their state. The U.S. Department of Education collects institution-level data through IPEDS, including general institution-level characteristics and cost information, from all colleges in the United States that are eligible to receive federal student aid (Ginder, Kelly-Reid and Mann 2016).

Measures

The two main outcomes of interest in this study are whether students applied to a 4-year college and whether they applied to a highly selective 4-year college. During spring of their senior year, students were asked to list the colleges to which they had applied. For students who had applied to college, NCES used the FICE code for each institution to determine the level of the college, which I use to capture whether students applied to a 4-year college by the end of high school.

Using the FICE codes, I then match each institution students applied to with data on the Barron's competitiveness index to capture whether students applied to a highly selective 4-year college. The Barron's competitiveness index includes six categories: noncompetitive, less competitive, competitive, very competitive, highly competitive, and most competitive, which I reduce to a binary measure of whether students applied to a highly competitive 4-year college. At institutions classified as highly selective, high school grades of admitted students typically range from Bs to As, students rank at least in the top 35% at their high schools, and fewer than 50% of applicants are admitted, and this classification includes colleges like University of Texas at Austin, Boston University, University of California at Berkeley, and Yale University (Lee et al. 2017). I focus on the somewhat broad 'highly selective' category because very few students, especially those from low socioeconomic backgrounds apply to the most competitive institutions, and so the 'highly selective' outcome is more relevant for capturing what could be feasibly changed.

The other two outcomes of interest in this study are whether students perceived they could afford to attend: (1) a 4-year college, and (2) a highly selective 4-year college. During 11th grade, students were asked the following question, "Considering all sources of funds including scholarships, grants, loans, and savings, do you think your family [will/would] be able to afford to send you to…" about different types of institutions, including 4-year public colleges in their state, 4-year public colleges out of their state, 4-year private colleges, and highly selective 4-year colleges. To capture whether students perceived they could afford to attend a 4-year year college, I create a binary measure coded "yes" if the student responded that they could afford to attend any type of 4-year college. I create a second binary measure for whether the student said they could afford to attend a highly selective 4-year college specifically.

To capture students' socioeconomic background, I use a family socioeconomic status composition variable created by NCES, which relies on self-reported parental educational attainment, occupation, and family income during the baseline year of data collection (Ingels et al. 2004). The composite variable is the mean of the standardized z-scores for each individual measure. I split this continuous variable into SES terciles, classifying students as being from low, middle, or high SES backgrounds.

I measure college financial information as a combination of students' and parents' awareness of college financing and the sources from which parents receive information about financial aid. During spring of the junior year of high school wave, HSLS included a series of questions about college financial information. Survey respondents were asked whether they were able to provide an estimate of 4-year public college costs in their state, and whether they were able to provide an estimate of 4-year private college costs, and I include binary measures of each for both students and for their parents. Doing so captures a general awareness and engagement with trying to understand the financial requirements of college, which is critical in planning for college. I also include binary indicators of whether students and their parents know about the FAFSA process. In total, awareness of college financing is captured through these three binary measures for each student, and then separately for their parent. To capture the information sources about financial aid that parents rely on, I include five binary measures for whether parents received information about financial aid from each of the following sources: (1) other parents, family, or friends, (2) the financial aid office at a college, (3) staff at the student's high school, (4) an informational meeting at the student's high school, and (5) the internet. Appendix Table B1 provides additional information about the creation of these college financial information measures.

To account for potential confounding, I control for a series of baseline measures, assessed during fall of students' freshman year of high school. I include measures of a student's race and ethnicity and sex. I control for whether a student lives with both parents, and the number of siblings in their household. I also take into account student grade point average and math standardized test scores. Finally, I control for whether a student attends a public high school and the urbanicity and region where they reside.

Estimands

To understand the extent to which differences in financial information explain socioeconomic gaps in college application, I use a gap-closing estimand, to compare a set of observed gaps in application outcomes to a set of counterfactual gaps under a hypothetical intervention to equalize college financial information (Lundberg 2022). The methods in this paper closely follow those applied in Schachner and Wodtke (2023b). I start by comparing the observed gaps in 4-year and selective college application between those from high and low SES backgrounds:

$$\mu_{x,x'} = E(Y_i|X_i = x) - E(Y_i|X_i = x'),$$

where Y_i denotes whether or not student *i* applied to college, *X* represents the SES background of student i, such that x denotes a high SES background, and x' denotes a low SES background. This estimand captures the difference in probabilities of applying to college between students from high and low SES backgrounds.

Next, to understand how a hypothetical intervention equalizing financial information would contribute to each gap, I consider a set of counterfactual gaps (Lundberg 2022), which can be formally defined as:

$$\tau_{x,x'}(\boldsymbol{A}) = E(Y_i(\boldsymbol{A})|X_i = x) - E(Y_i(\boldsymbol{A})|X_i = x'),$$

Where $\boldsymbol{A}$ denotes the vector of college financial information measures. As such, $\tau_{x,x'}(\boldsymbol{A})$ Represents the average difference in the probability of college application between high and low SES backgrounds if all financial information characteristics were equalized at level $\boldsymbol{A}$. To understand the contribution of financial information to the SES gap, I compare the observed gap in college application to the counterfactual gap, which can be expressed as:

$$\mu_{x,x'} - \tau_{x,x'}(\boldsymbol{A}),$$

where $\mu_{x,x'}$ represents the set of observed gaps and $\tau_{x,x'}(\boldsymbol{A})$ represents the counterfactual gap. This shows the difference between the observed gap and the gap that would exist if financial information were equalized at the same level for everyone.

Identification Assumptions

Gap-closing estimands involve potential outcomes that are unobserved, making it important to consider the identification assumptions involved. A benefit of the gap-closing estimand is that there are no set assumptions about the causal nature of the gap-closing category itself, here captured by student SES, which allows for a range of more plausible assumptions about that category (Lundberg 2022). Gap-closing estimands rely on the assumption of conditional independence, which means that after controlling for observed covariates, treatment assignment is independent of potential outcomes. This is a strong assumption that may be difficult to meet using survey data. It would not be met if there are unobserved factors that affect both financial information and college application net of the observed controls. To attempt to meet the identification assumptions, I control for a range of baseline measures that are theoretically important predictors of receiving financial information and applying to college. I also conduct a sensitivity analysis to understand the amount of bias due to unobserved confounding that would have to be present for the results to be null as a robustness check.

Estimation Strategy

To estimate the counterfactual gaps of interest, I start by modeling observed outcomes using logistic regression models. I next use g-computation to impute potential outcomes Y_i under a hypothetical scenario where all individuals had access to a high level of college financial information (Lundberg 2022; Robins and Hernan 2008). I then average the imputed outcomes within each socioeconomic subpopulation and derive counterfactual gaps by comparing high versus low SES imputed outcomes.

To estimate socioeconomic gaps in college application behavior, I consider a set of 3 hypothetical interventions under which college financial information is equalized. The first hypothetical intervention provides all students with awareness of college costs and financial aid. The second additionally provides each student's parent with awareness of college costs and financial aid. The final hypothetical intervention additionally ensures that parents receive financial aid information from several different sources. Each of these interventions equalizes college information across socioeconomic background. In the main set of estimates presented in this study, I focus on high versus low SES tercile gaps in college application behavior, though middle SES data are included in all estimates.

Results

SES Differences in College Application, Perceived Affordability, and Financial Information

Table 3.1 presents information on college application, perceived affordability, and financial information separately for low SES and high SES students, and among the total sample. Looking at application outcomes for students from high compared to low SES backgrounds shows that there are large disparities. While approximately three-quarters of students from high SES backgrounds (77.4%) applied to a 4-year college, only about one-third of low SES students did so (37.5%). While very few students applied to a highly selective college, the SES gap remains present, with close to 30% of high SES students applying and only 5% of low SES students applying to a highly selective college.

In terms of perceptions of college affordability, a higher proportion of students perceived they could afford to attend a 4-year college than actually applied to a 4-year college, by about 10 percentage points. High SES students were much more likely to perceive that they could afford to attend a 4-year college (85.3%) compared to low SES students (46.7%), though both were more likely to perceive they could afford to attend a 4-year college than they were to actually apply to one. However, for highly selective colleges, only about 5% of low SES students perceived they could afford to attend one, which is in line with the fact that about 5% of low SES students applied to one. For high SES students, only 19% perceived they could afford to attend a highly selective college, while about 30% applied to one, suggesting high SES students are either less concerned with the affordability component when deciding where to apply or that they receive outside encouragement to apply despite affordability concerns.

When it comes to the sources from which parents receive financial aid information, there are large disparities across high and low SES backgrounds. A higher proportion of socioeconomically advantaged students had a parent who received financial aid information from friends or family, the internet, or a high school information session. The most common source of

Table 3.1. Weighted proportions of College Outcomes and Financial Information Among Total HSLS 2009 Sample, and Separately by High and Low SES Terciles

	Low SES	High SES	Total
College Application			
4-year college	.3746	.7739	.5557
Selective college	.0514	.3187	.1591
Perceived College Affordability			
4-year college	.4670	.8529	.6521
Selective college	.0521	.1912	.1066
Parent Financial Aid Information Sources			
Friends or family	.3948	.5567	.4702
High school staff	.2539	.2940	.2707
College financial aid office	.2309	.2402	.2372
Internet	.3485	.5020	.4190
High school information session	.2359	.4285	.3210
Student and Parent Financial Awareness			
Provide 4-year college cost estimate			
Neither able	.3773	.1171	.2477
Student able	.4122	.5866	.4954
Parent able	.4281	.7905	.6017
Both able	.2176	.4942	.3448
Provide private college cost estimate			
Neither able	.4366	.1355	.2901
Student able	.3781	.5760	.4714
Parent able	.3590	.7564	.5471
Both able	.1736	.4680	.3086
FAFSA form			
Neither aware	.0878	.0468	.0678
Student aware	.5544	.5173	.5366
Parent aware	.8373	.8831	.9206
Both aware	.4795	.4847	.4847

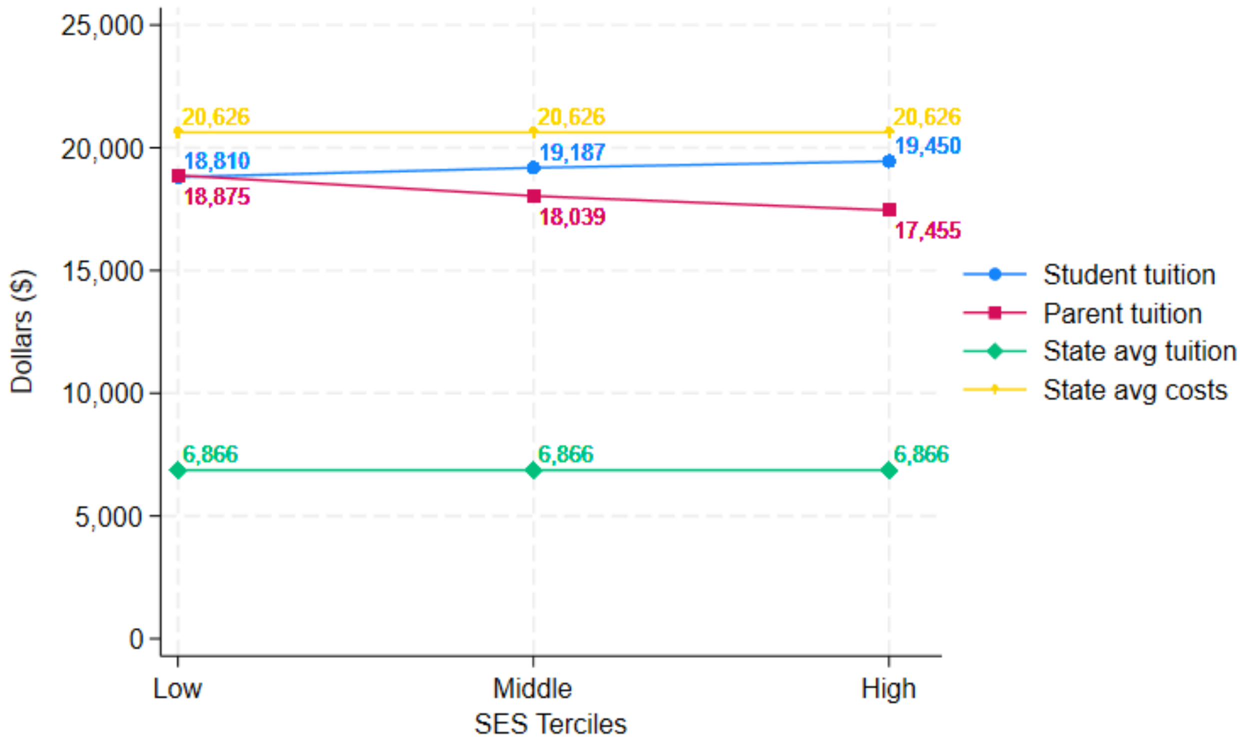
Notes: Results are combined across 5 multiply imputed datasets. The student awareness proportions include cases where only the student was aware and where the student and their parent were both aware. The same is true for the parent awareness proportions.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013, 2016; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

information across socioeconomic background was friends or family members, followed by the internet, suggesting that parents are more frequently receiving information from less official sources. There are not observable differences by socioeconomic background in receiving information from high school staff or college financial aid offices, with about a quarter of all parents reporting receiving information from each of these sources.

When it comes to students' and parents' financial awareness, we see similar gaps by socioeconomic background. For about half of those from high SES families, both the student and the parent felt sufficiently aware of college costs in their state to provide a cost estimate, which was only true for just under a quarter of those from low SES families. Among those from high SES backgrounds, a higher proportion of parents than students were able to provide an estimate of college costs, while it was more equal among parents and students from low SES backgrounds. The socioeconomic gaps are largest for parents, with a 36 percentage-point gap between high and low SES parents. The patterns are similar when considering the ability of students and their parents to provide a cost estimate.

For knowledge of the FAFSA form, the pattern looks quite different though. A higher proportion of students from less socioeconomically advantaged backgrounds have FAFSA information than their counterparts from more advantaged backgrounds, though only by about 4 percentage points. However, for parents, a higher proportion of those from high SES backgrounds had FAFSA information than did those from low SES backgrounds. Another key difference for FAFSA information is that among those from low SES backgrounds, parents were much more likely to have FAFSA information than were high school students, by a gap of about 28 percentage points. The proportion of those from low SES backgrounds with both student and parent awareness of FAFSA was more in line with the proportion of those from high SES backgrounds, which makes sense given that those from less advantaged backgrounds may be more likely to rely on financial aid for college attendance.

Figure 3.1. Respondent Tuition Estimates for Public In-state 4-year College Attendance Compared to IPEDS Estimates, by SES Tercile



Notes: Results draw on a subsample of HSLS:09 students who provided an estimate of college costs. The "cost" measures capture the overall attendance costs, including tuition, required fees, on-campus housing, books and supplies, and other typical costs at the average tuition college in each student's state, and "tuition" measures capture the costs only for tuition and mandatory fees. *Source*: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

While Table 3.1 presents information on ability to provide a cost estimate, the prior literature has suggested that both students and parents tend to dramatically overestimate college costs even when they are able to provide a cost estimate (Bell, Rowan-Kenyon and Perna 2009; Grodsky and Jones 2007; La Rosa, Luna and Tierney 2006). As such, Figure 3.1 compares the average tuition estimates by socioeconomic background among students and parents who felt they had enough information to provide an estimate for the in-state tuition at the average priced public, 4-year college in their state. Figure 3.1 also includes overall in-state cost estimates at the average priced college, which includes the price of room and board, books and supplies, and other relevant fees (Ginder, Kelly-Reid and Mann 2016). Figure 3.1 shows that on average, students from low SES backgrounds provide lower tuition estimates ($18,810) than those from high SES backgrounds ($19,450), by about $640. However, it is difficult to interpret the meaning between these differences because the literature shows that high SES students tend to consider and apply to more selective, and likely more expensive in terms of the sticker price of tuition, colleges, which means they may be drawing on a different frame of reference compared to low SES students even when thinking about the costs of a 4-year public college within their state (Cabrera and La Nasa 2000; Mullen and Goyette 2019; St. John, Paulsen and Starkey 1996). For parents, those from low SES backgrounds provide cost estimates that are higher than those from more socioeconomically advantaged backgrounds, by about $1,400.

Students and parents were asked to provide an estimate of only tuition and mandatory fees, excluding room and board, books and supplies, and other fees. Comparing both student and parent estimates to the state average tuition costs, we can see that student and parent estimates are about $12,000 more than average yearly tuition prices. In Figure Appendix B1, I further compare student and parent tuition estimates to the tuition prices at the most expensive public 4-year college within their state, to reflect that students and parents may be more likely to draw on the state flagship university as a frame of reference, though I find that student and parent estimates are still between $7,000 and $9,000 higher than the in-state maximum yearly tuition prices. However, in Figure 3.1, I find that the average student and parent estimates are fairly close to the average in-state costs, which includes prices of room and board, books and supplies, and other relevant college fees that students and parents were explicitly asked to exclude from their estimate. It is possible that students and their parents are more likely to have heard about college costs that include all of these fees, meaning they may have more of an understanding of college costs than the prior literature suggests. As a whole, these results suggest that the largest SES gaps when it comes to information about college costs are for whether or not students and parents have information versus differences in the accuracy of cost estimates. As such, it is important to understand how equalizing college financial information can explain SES gaps in college outcomes.

A Descriptive Decomposition of the College Application Gap

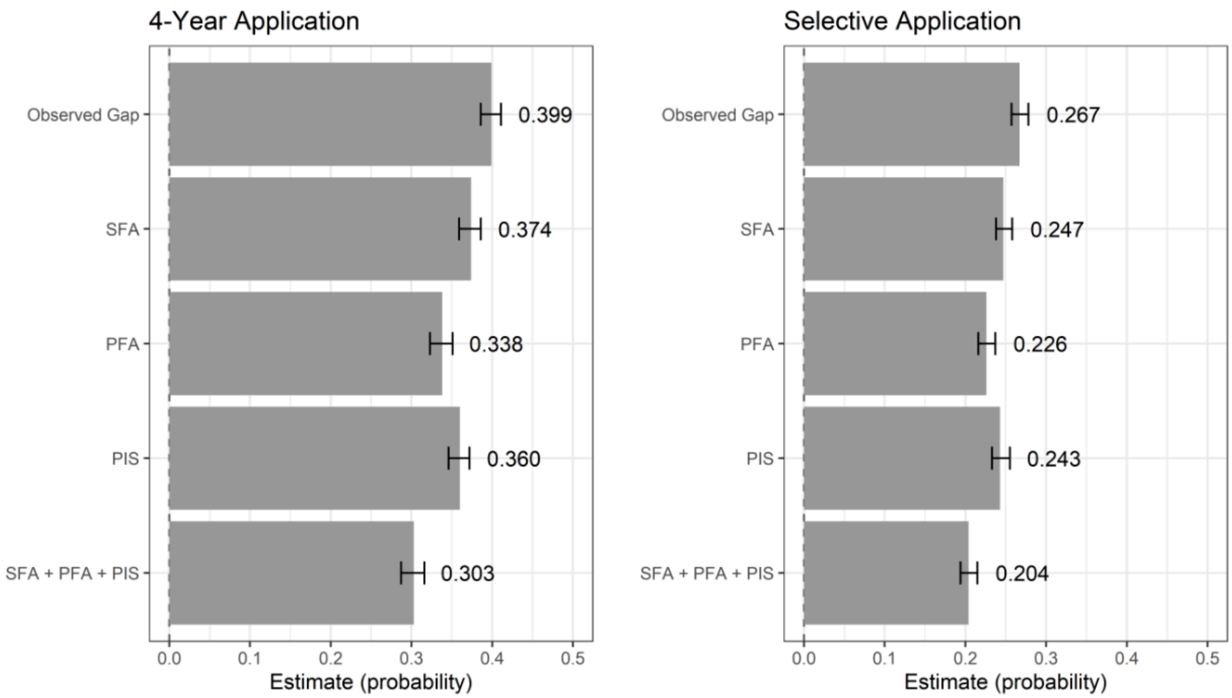
Figure 3.2 illustrates the step-by-step decomposition of the college application gap for both 4-year and selective college application behavior, with a focus on the role of financial information. The initial observed gap demonstrates the disparity in college application between students from high SES and low SES backgrounds. Subsequently, I equalize the availability of financial information across both groups, adjusting for specific elements of financial knowledge in a staged approach. For the first adjusted gap, I simulate a scenario where students from all socioeconomic backgrounds possess financial awareness – this involves imputing college application probabilities as if every student was able to provide estimates of college costs and knew about the FAFSA form. Next, I simulate a scenario where parents can provide estimates of college costs and have awareness of the FAFSA process. The third gap simulates the effect of all parents having access to diverse sources of financial aid information, including from other parents, school staff, financial aid offices, and online resources. In the final adjusted gap, I consider the cumulative effect of setting both student and parent financial awareness, along with parent information sources, to be universally high across all SES groups. This hypothetical scenario accounts for the combined influence of all measured aspects of college financial information. The results from this descriptive decomposition do not control for baseline differences in other characteristics between students, and thus provides an upper bound on the potential of financial information to equalize college application rates.

The results in Figure 3.2 show that the observed college application gaps by SES are high. The probability of students from high SES backgrounds applying to a 4-year college is about 40 percentage points higher than that of students from low SES backgrounds. For application to a selective college, the gap is about 27 percentage points. Looking at the explanatory power of each component of financial information, it appears that for both 4-year application and selective college application, equalizing parent financial awareness does the most to reduce the SES gaps. Setting only parents to have financial awareness reduces the SES gap by about 15% for both 4-year and selective application. Setting only students to have financial awareness also reduces the SES gap meaningfully, though only by about 6 or 7%. Equalizing student financial awareness and parent information sources in addition to equalizing parent financial awareness does very little above and beyond equalizing parent financial awareness alone, possibly because this descriptive finding may be driven in part due to other dimensions of parental motivation and involvement, rather than seeking information alone. The results in this figure suggest that if all students and their parents had financial information, the most the SES gap could be reduced by is about 24% for both 4-year college application and selective college application. However, these results are descriptive, and do not adjust for potential confounding.

The Explanatory Role of College Financial Information

Table 3.2 shows the impact of hypothetical interventions aimed at equalizing college financial information on socioeconomic disparities in perceptions of college affordability. The point estimates and 95% confidence intervals represent differences between the observed SES gaps

Figure 3.2. Descriptive Decomposition of the College Application Gaps by College Financial Information



Notes: Estimates are reported in probability units and are computed using g-computation, from logistic regression models; results are combined across 5 imputations. Different vectors of college financial information are represented, where "SFA" stands for student financial awareness, "PFA" stands for parent financial awareness, and "PIS" stands for parent information sources.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013, 2016; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

and those that would exist if financial information was uniformly distributed. The first intervention scenario, ObsGap-CnfGap(SFA), assumes that all students have financial awareness, operationalized by setting all students to be able to provide college cost estimates and to be aware of the FAFSA process. The second hypothetical intervention, ObsGap-CnfGap(SFA, PFA), builds on the first by simulating awareness among parents as well. The third scenario, ObsGap-CnfGap(SFA, PFA, PIS), further assumes that all parents receive financial information from each listed source. These counterfactual gaps adjust for a comprehensive set of baseline confounders to isolate the effect of financial information on gaps in perceived affordability.

Table 3.2. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps in Perceptions of College Affordability

	Point Estimate	95% Confidence Interval
4-year College Affordability		
ObsGap	0.386	[0.372, 0.399]
ObsGap-CnfGap(SFA)	0.043	[0.037, 0.050]
ObsGap-CnfGap(SFA, PFA)	0.074	[0.063, 0.084]
ObsGap-CnfGap(SFA, PFA, PIS)	0.098	[0.083, 0.111]
Selective College Affordability		
ObsGap	0.139	[0.139, 0.148]
ObsGap-CnfGap(SFA)	-0.014	[-0.018, -0.010]
ObsGap-CnfGap(SFA, PFA)	-0.014	[-0.019, -0.009]
ObsGap-CnfGap(SFA, PFA, PIS)	-0.008	[-0.017, 0.001]

Notes: Estimates are reported in probability units and are computed using g-computation, from logistic regression models; results are combined across 5 imputations. "ObsGap" stands for observed gap, which compares application outcomes between high SES and low SES backgrounds. "CnfGap" stands for the counterfactual gap. Different vectors of college financial information are represented, where "SFA" stands for student financial awareness, "PFA" stands for parent financial awareness, and "PIS" stands for parent information sources.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

The results suggest a moderate effect of equalizing financial information on reducing the SES gap for 4-year college affordability. The counterfactual scenario where both students and parents have financial awareness, and where parents have access to all information sources, narrows the gap by about 25%. Considering a hypothetical intervention where only students are provided financial awareness reduces the gap by just 11%, while additionally setting parents to have awareness reduces the gap by 19% total. While the SES gap in perceived affordability of 4-year college attendance remains even after equalizing all measured dimensions of college financial information, a reduction by one-quarter of the gap simply by equalizing financial information is quite substantial. When looking at perceived affordability of selective colleges though, equalizing financial information does not meaningfully change the SES gap at all.

To further understand the contribution of financial information to SES gaps in college application behavior, Table 3.3 presents an analysis following the same hypothetical intervention framework. The findings indicate that providing students and their parents with college financial information contributes to closing the SES gap in 4-year college application. Specifically, when the financial awareness of all students and parents is equalized, and when parents are informed from several sources, the SES gap reduces by approximately 18%. Here, in the counterfactual scenario where only students are provided with financial awareness, the gap is only reduced by about 5%, while additionally providing parents with financial awareness reduces the gap by 11%. The results suggest that financial information matters for reducing the SES gap in 4-year college application, though primarily as a result of equalizing information for both students and their parents. Additionally, equalizing financial information appears to bridge not only the high-low SES gap, but also narrows the high-middle SES gap by 13%, as shown in Appendix Table B3.

Table 3.3 suggests that after taking into account the full set of baseline confounders, equalizing college financial information does not reduce the SES gap in selective college application at all. In fact, the point estimates suggest there is an increase in the SES gap, with the gap increasing by about 15% when students and parents are financially aware and parents have several information sources. The primary benefit of equalizing financial information seems to come at the stage when students decide whether or not to apply to a 4-year college. These findings are in line with those in Table 3.2, which showed that equalizing financial information does not reduce the SES gap in perceived affordability of selective college

Table 3.3. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps in College Application Outcomes

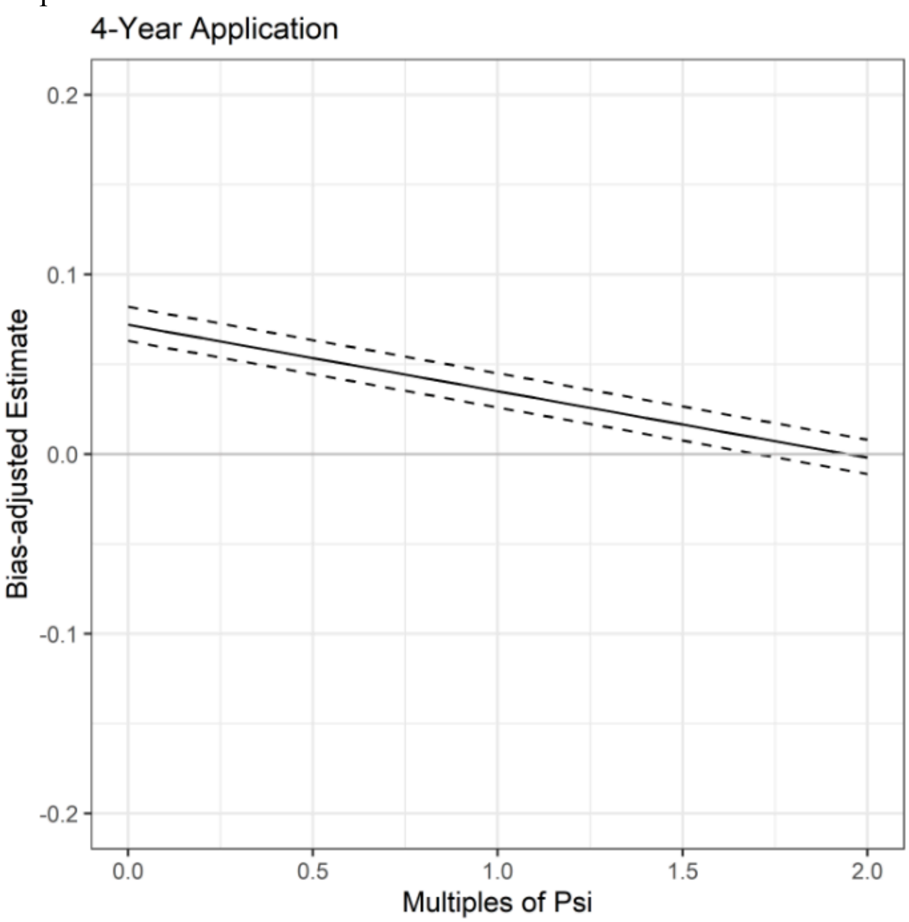
	Point Estimate	95% Confidence Interval
4-year College Application		
ObsGap	0.399	[0.386, 0.414]
ObsGap-CnfGap(SFA)	0.020	[0.016, 0.024]
ObsGap-CnfGap(SFA, PFA)	0.044	[0.037, 0.051]
ObsGap-CnfGap(SFA, PFA, PIS)	0.072	[0.063, 0.082]
Selective College Application		
ObsGap	0.267	[0.257, 0.278]
ObsGap-CnfGap(SFA)	-0.024	[-0.030, -0.018]
ObsGap-CnfGap(SFA, PFA)	-0.026	[-0.033, 0.020]
ObsGap-CnfGap(SFA, PFA, PIS)	-0.040	[-0.052, 0.029]

Notes: Estimates are reported in probability units and are computed using g-computation, from logistic regression models; results are combined across 5 imputations. "ObsGap" stands for observed gap, which compares application outcomes between high SES and low SES backgrounds. "CnfGap" stands for the counterfactual gap. Different vectors of college financial information are represented, where "SFA" stands for student financial awareness, "PFA" stands for parent financial awareness, and "PIS" stands for parent information sources.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

attendance. Even considering a more expansive definition of "selective colleges," including those that are moderately selective, instead of only those that are classified as highly selective, the results in Appendix Table B4 suggest that the overall findings are substantively the same. Equalizing information does not reduce SES gaps in the perceived affordability of attendance and increases gaps in application behavior.

While Table 3.3 findings suggest that college financial information plays an explanatory role for the SES gap in 4-year college application, using a hypothetical intervention to assign students and their parents to receive college financial information is limited because these claims rely on identification assumptions about no unobserved findings. If those assumptions are not

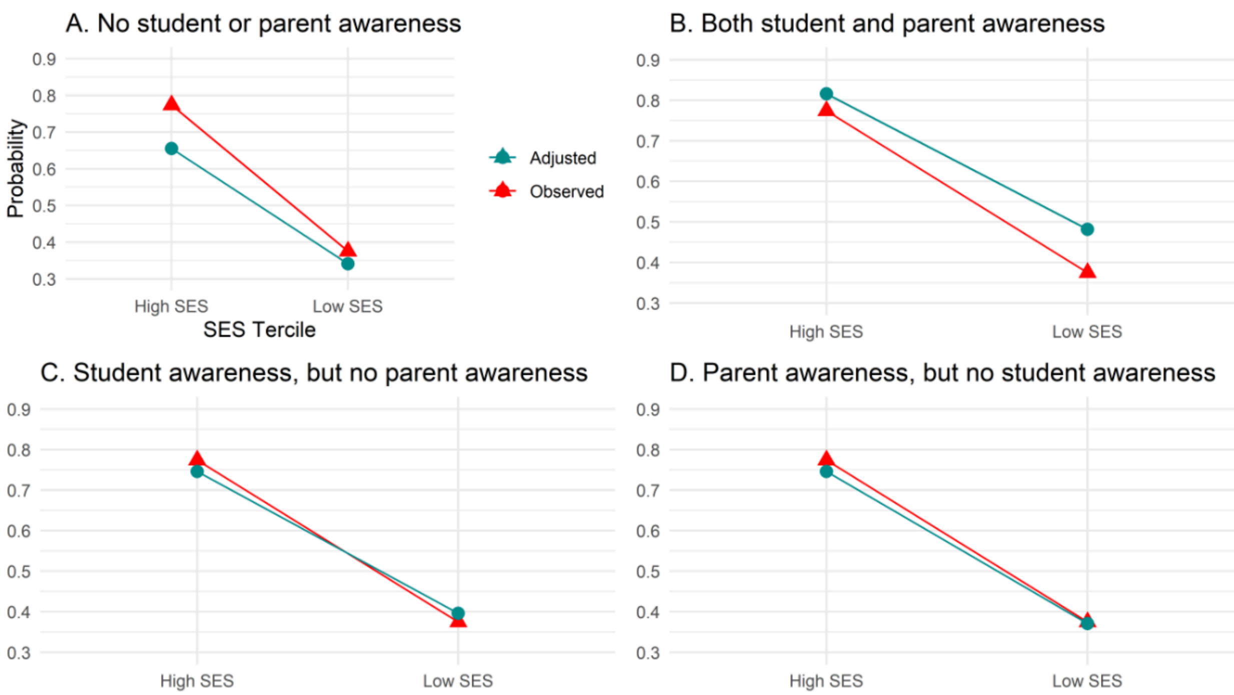
Figure 3.3. Bias-adjusted Estimates of the Difference between Observed and Counterfactual Gaps



Notes: Estimates are reported in probability units and are computed using g-computation, from logistic regression models; results are combined across 5 imputations. The x-axis shows the difference in bias due to a hypothetical confounder was that many times as large as that from omitting GPA from the model.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013, 2016; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

met, this could lead to biased estimates. Figure 3.3 extends the analysis from Table 3.3, presenting bias-adjusted estimates to evaluate the robustness of the findings regarding the SES gap in 4-year college applications. These bias-adjusted estimates serve to explore the potential impact of unobserved confounders on the estimates previously outlined. To compute the bias-adjusted estimates, I adopted a sensitivity analysis approach to estimate the change in the observed versus the counterfactual gap when a known predictor of importance – here, student grade point average, which is highly predictive of college outcomes (Massey et al. 2011; Sewell, Haller and Portes 1969) – is omitted from the model. This sensitivity analysis provides a reference for the degree of unmeasured confounding that would be necessary to undermine the validity of the findings.

Figure 3.4. High vs. Low SES Observed Gaps and Adjusted Gaps in 4-year College Application Outcomes



Notes: Estimates are reported in probability units and are computed using g-computation, from logistic regression models; results are combined across 5 imputations.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013, 2016; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

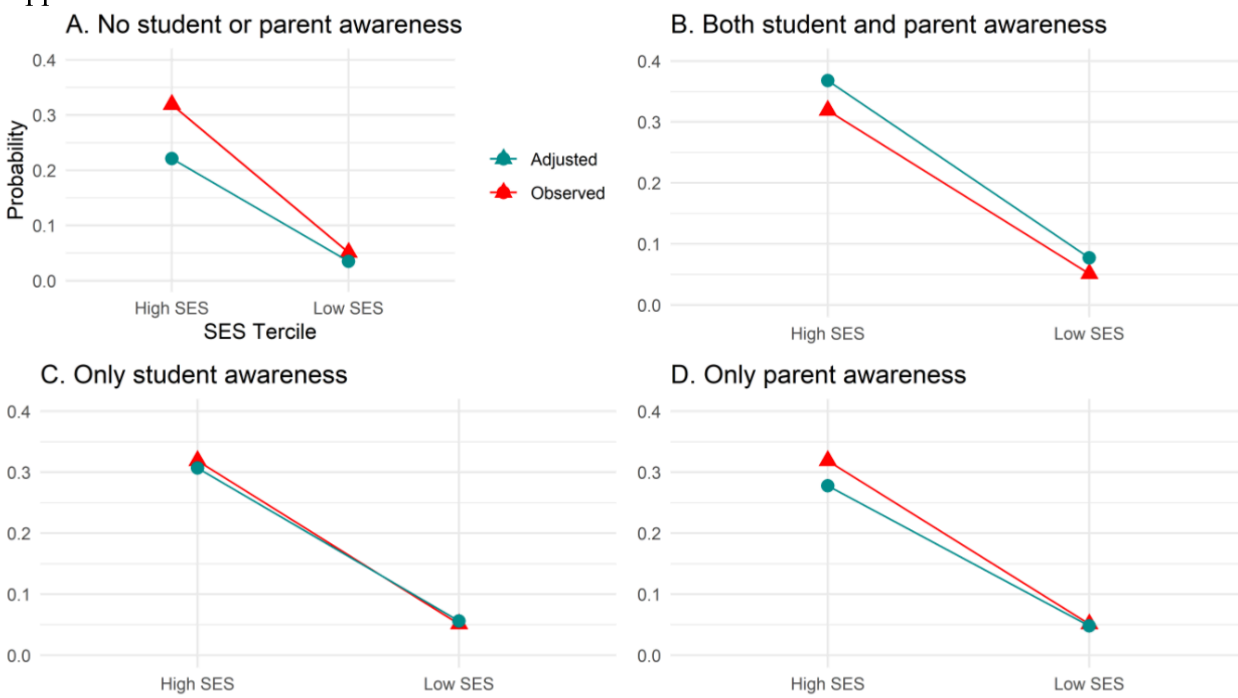
The x-axis quantifies the level of bias introduced by hypothetical unobserved confounders in multiples of the size of the effect of student GPA. In other words, this figure plots the difference between the estimated gaps when financial information is equalized, against scenarios where the effect of an unmeasured confounder is between 0 to 2 times as large as the effect of GPA. The plotted line indicates the point at which the effect of financial information on the 4-year college application gap becomes statistically insignificant. The findings suggest that the confounding influence would need to be twice as strong as the effect of GPA to nullify the effect of equalizing financial information. As such, while the estimates are sensitive to unobserved confounders, the effect of financial information on the SES gap in 4-year college application remains unless the bias is substantial.

Next, to better understand the relationship between how equalizing students' and parents' college financial awareness contributes to 4-year college application, Figure 3.4 presents observed and adjusted point estimates for high and low SES students under four different hypothetical interventions, using a thought experiment to explore how the presence of student and parent information matters. The intervention in Panel A sets all students and their parents to have no financial information. This is not meant to be a realistic intervention that could ever be conducted but rather represents a theoretical exploration. Panel B sets both students and their parents to have financial information. Panel C sets students to have financial information and parents to not have information, while Panel D sets parents to have financial information and students to not have information. These hypothetical interventions are meant to explore how the presence and absence of information across students and their parents matters for those from low and high SES backgrounds.

The results from Figure 3.4 show that what is most important for reducing the SES gap is both students and their parents having information. In Panel A, setting students and their parents to have no information, the adjusted point estimate for 4-year college application among high SES students is about 12 percentage points lower than the observed point estimate. The adjusted point estimate is barely different from the observed point estimate for low SES students, which means the SES gap is reduced when no students or parents have financial information, though only as a result of high SES students having a lower predicted probability of applying to a 4-year college with no information. Conversely, in Panel B, setting both students and their parents to have financial information increases the probability of 4-year application for low SES students by about 10 percentage points, while doing very little for high SES students. In this way, increasing student and parent information reduces the SES gap by increasing the predicted probability of applying to a 4-year college among those from low SES backgrounds. Panels C and D test whether setting all students to have information while setting all parents to not have information, and vice versa, reduces the SES gap. The results suggest very little would change for low or high SES students if only parents had information or only students had information, which is interesting to understand theoretically, though again, is not a realistic intervention, because providing only students or only parents with information would likely lead to spillover effects where the other would also benefit from that information.

Next, to explore why increasing financial information does not reduce the SES gap in selective college application, Figure 3.5 presents similar information. The results from Figure 3.5 suggest that when it comes to selective college application, financial information provides a greater benefit to high SES students, while having only a minimal effect on predicted probabilities of selective college application for those from low SES backgrounds. In Panel A, simulating a scenario where no students or parents have financial information, the SES gap is actually reduced, though again only as a result of lowering the probability of applying to a selective college among those from high SES backgrounds, which leads to a reduction by about 10 percentage points. On the other hand, in Panel B, setting all student and parents to have financial information leads to an increase in the probability of applying for those from

Figure 3.5. High vs. Low SES Observed Gaps and Adjusted Gaps in Selective College Application Outcomes



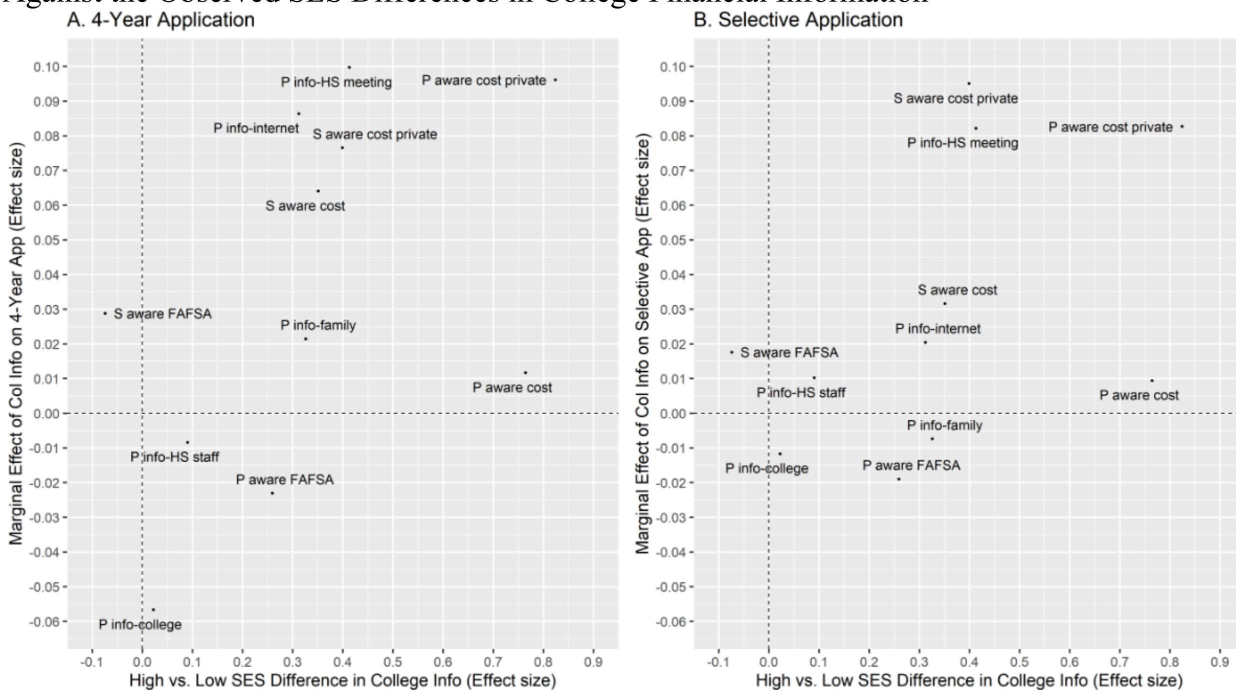
Notes: Estimates are reported in probability units and are computed using g-computation, from logistic regression models; results are combined across 5 imputations.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013, 2016; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

low SES backgrounds (~3 percentage points), while also leading to a larger probability of applying for those from high SES backgrounds (~8 percentage points). This helps to explain the results from Table 3.3, by showing that increasing student and parent financial information may very slightly increase the SES application gap because high SES students seem to benefit more from financial information when it comes to applying to selective colleges than their less socioeconomically advantaged counterparts. In Panel C and D, setting students to have awareness and parents to not does not change much for low SES students.

Finally, Figure 3.6 presents the marginal effects of college financial information on college application, classified against the observed SES differences in college financial information. The estimates are all presented in standard deviation units using Cohen's h, an effect size measure for binary variables. Panel A presents the results for 4-year college application, and Panel B presents the results for selective college application. Financial information variables in the upper right quadrant of the plot are those with the largest marginal effects for application while also being strongly predicted by socioeconomic background. The results suggest that most of the financial information measures have a very small positive association with 4-year college application. The largest effect sizes were for parent receipt of information from a high school meeting, parent awareness of private college costs, parent receipt of information from the internet, and student awareness of private college costs, though each measure had an effect size smaller than 0.10 standard deviations. On the other hand, there were large SES differences in college financial information, especially when it came to parent information about private college costs (0.83 SDs) and parent information about 4-year college costs (0.75 SDs), though parent information on 4-year college costs had very low point estimate for application (~0.01 SD).

When it comes to selective college application, the results are similar, showing that student information on private costs, parent information on private costs, and parent receipt of information from a high school meeting are among the strongest predictors of selective college application, while also being strongly predicted by SES background. For selective college application, parent receipt of information from the internet had a much smaller effect size for application (~0.02) than was the case for 4-year application (~0.08).

Figure 3.6. Marginal Effects of College Financial Information on College Application Classified Against the Observed SES Differences in College Financial Information



Notes: Effect sizes are presented based on Cohen's h. Results are combined across 5 multiply imputed datasets.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013, 2016; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

Conclusion

Students and their parents draw on perceptions of affordability when making decisions about college attendance, and this is particularly the case for socioeconomically disadvantaged families, for whom college costs are likely more difficult (George-Jackson and Gast 2015; Manski and Wise 1983; Vesper, Hossler and Schmit 2003). Given the large socioeconomic disparities in financial information about college (Bell, Rowan-Kenyon and Perna 2009; Grodsky and Jones 2007; Horn, Chen and Chapman 2003), examining the contribution of financial information to socioeconomic gaps in perceived affordability and college application is an important step for understanding not only reasons behind these gaps but also interventions to address those inequalities. This study uses data on 21,000 students from the 2009 HSLS to understand the extent to which students' and parents' college financial information contribute to socioeconomic gaps in perceptions of affordability and college application for 4-year colleges and highly selective 4-year colleges. I further ask about the importance of students' compared to parents' information about college costs and financial aid.

Results show that increasing the level of financial information among both students and parents, thereby equalizing information across socioeconomic backgrounds, reduces SES gaps in perceived affordability of 4-year college attendance by about one-fourth (25%) and application to 4-year colleges by almost one-fifth (18%). While these are moderate gap reductions, for an intervention like providing information, which is considered a light-touch intervention, these are actually fairly large (Hyman 2020). The gap reduction is driven by the increase in application behavior among low SES students. This finding supports existing research that providing information could increase application behavior for less advantaged students (Dynarski et al. 2021). The gap reduction is driven mostly by providing both students and their parents with financial information, rather than only targeting one or the other. This is in line with research suggesting that student-parent alignment is important for student enrollment behavior (Kim and Schneider 2005), but provides additional insight into the way that providing both students and their parents with information can lower perceptions that college is unaffordable and increase application behavior among less advantaged students.

While equalizing information reduced 4-year college affordability and application gaps, I find that this was not the case when it comes to selective colleges. Increasing information about college costs, financial aid, and the number of financial information sources for parents did not substantially change the gap in perceptions of affordability and may even have increased the gap in selective college application. This is driven in large part by the fact that increasing information did not change the probability that low SES students apply to selective colleges, though did increase the probability of application for high SES students. This is related to the Matthew Effect, where providing additional resources, or in this case, information, disproportionately benefits those who are already more advantaged, and can lead to the widening of existing disparities. These findings are in line with the literature, which suggests that providing low-income students with college cost information does not substantially increase their enrollment at selective colleges (Gurantz et al. 2019; Hyman 2020). Despite providing general information to students and parents about college attendance costs not moving the needle on disparities in selective college application, the most advantageous college option, the fact that it does move the needle on 4-year college application behavior by increasing the probability that low SES students apply is noteworthy given it is such a low-touch, low-cost type of intervention.

This study has a few key limitations. First, the measures of college financial information offer a single point in time understanding of information during junior year of high school. However, existing research has found that the later high school years are when most students and their parents receive concrete information about financial preparation for college (Cabrera and La Nasa 2000). It is possible though that students who were already predisposed to attending college are the ones who specifically seek out college information during the later high school years. To better capture the effect of financial information on students' intentions to go to college, an experimental design would better isolate this effect. A second limitation is that students and their parents are only asked whether they are able to provide estimates of annual tuition and fee costs at specific types of schools. It remains less clear whether they can provide information about costs at specific colleges, and whether these estimates are accurate. However, some research suggests that students and their parents form mental pictures about the types of college that are feasible to attend based on general understandings of costs (St. John, Paulsen and Starkey 1996), so the measures used in this study may more accurately pick up on how students make decisions about whether and where to apply.

Nevertheless, this study shows that equalizing well-documented socioeconomic gaps in college financial information can reduce socioeconomic gaps in 4-year college affordability perceptions and in 4-year college application. Low-SES students are at a significant disadvantage during the college choice process as a result of having less information about college. While parents are a key source students draw on for information and motivation (George-Jackson and Gast 2015), parents of low-SES high schoolers tend to have less information about college costs and fewer sources from which to receive information about financial aid. Interventions providing financial information should specifically target both students and their parents to have the most impact on disparities in 4-year college application behavior. Future research should focus more on whether there are other types of information interventions that could decrease the selective college application gap.

Chapter 4

Poor Neighborhoods, Bad Schools? A High-dimensional Model of Place-based Disparities in Academic Achievement, with Geoffrey T. Wodtke

Introduction

By the end of third grade, students from high-poverty neighborhoods demonstrate a significant disadvantage in academic achievement compared to their peers from low-poverty neighborhoods. In this study, our estimates, based on data from the Early Childhood Longitudinal Study, Kindergarten Class of 2011 (ECLS-K), show that the gap in reading test scores between these groups of students has an effect size of -0.480, and for math, it is slightly larger, at -0.533. These test score gaps highlight substantial neighborhood inequality in academic achievement, even during the early elementary years.

These observed differences in students' test scores could be a result of many different factors, including the background characteristics of students' families. For example, high-income families often live in low-poverty neighborhoods, while those with fewer resources may be disproportionately found in high-poverty neighborhoods (Owens 2016; Reardon and Bischoff 2011). Socioeconomic background can also shape the educational support that families are able to provide their child in ways that influence their academic success (Coleman 1988; Duncan and Murnane 2011). As a result, family background can both shape the neighborhood where a student lives while also impacting their academic achievement. At the same time, beyond the influence of families, the neighborhoods where students live can also play a role in determining their academic success. Institutional resource theory posits that differences in access to local institutions like high-quality schools plays a role in students' educational outcomes (Jencks and Mayer 1990). In the United States, many students enroll in local elementary schools, meaning the school they attend is linked to the neighborhood they live in. As a result, children from high-poverty neighborhoods may attend schools with fewer resources and less supportive learning environments than their peers from low-poverty neighborhoods (Arum 2000; Johnson 2012), which could in turn affect their education, likely partially a result of selection of families into different types of neighborhoods..

Despite the prominence of institutional resource theory, empirical evidence from the neighborhood effects literature does not fully support the claim that neighborhood disparities in academic achievement are driven by differences in school quality. Research examining the combined effects of neighborhoods and schools has produced mixed results on their relative importance (Ainsworth 2002; Card and Rothstein 2007; Owens 2010; Sanbonmatsu et al. 2006). Only two studies have specifically decomposed the total neighborhood effect on student learning into its indirect effects through schools, and this work suggest that school quality does not mediate the impact of neighborhood poverty on student achievement (Wodtke et al. 2023; Wodtke and Parbst 2017). However, these studies face two limitations.

First, while understanding the theoretical role of schools in mediating neighborhood effects is valuable, it may not translate into practical insights for how interventions aimed at equalizing school experiences across neighborhoods could reduce achievement gaps (Lundberg 2022). Further, isolating neighborhood effects is challenging due to the complex interplay of factors influencing both student outcomes and their place of residence (Harding 2003). As a result, prior research may not be able to fully capture the complicated ways that school contexts could be adapted to reduce achievement disparities.

Second, while extensive research on school effects shows that schools contribute substantially to variation in student achievement (Konstantopoulos and Borman 2011;

Raudenbush and Bryk 1986), these effects are multifaceted and cannot be reduced to a single measure of the school environment (Borman and Dowling 2010; Hanushek 2003). As such, because Wodtke and Parbst (2017) focus primarily on a measure of school poverty, and Wodtke et al. (2023) rely mainly on school value-added to measure the impact of schools on student learning, both may be overlooking other potentially important determinants of student achievement, such as school expenditures (Jackson, Johnson and Persico 2016), class size (Boyd-Zaharias 1999; Krueger 2002), teacher quality (Clotfelter, Ladd and Vigdor 2010; Hanushek and Rivkin 2010), classroom pedagogy (Crosnoe et al. 2010), the curriculum (Raudenbush 2008), or administrative leadership (Borman and Dowling 2008; Raudenbush and Willms 1995). Further, there is only limited evidence about the specific aspects of schools that differ across neighborhoods (Owens and Candipan 2019), making it difficult to determine which school factors both vary by neighborhood poverty and affect student achievement. As a result, by not considering the broader school context, these studies may underestimate the role that schools play in contributing to neighborhood disparities in academic achievement.

In this study, we provide a comprehensive evaluation of whether and how elementary schools contribute to gaps in academic achievement between students from high- versus low-poverty neighborhoods. To do so, we conceptualize the school context as including five main components: 1) composition, 2) resources, 3) instructional practices, 4) climate, and 5) effectiveness. Composition refers to the demographic and socioeconomic makeup of the student body and staff. Resources encompass the funding, staffing, materials, and facilities that support student learning. Instructional practices include the teaching methods, curriculum, classroom management techniques, and assessment practices used by teachers. Climate captures the social and emotional environment of the school, measured through factors like student safety, parent involvement, administrative leadership, and teacher morale. Lastly, effectiveness measures the impact of the school on student learning. To capture the complexity of these dimensions and school context as a whole, we include more than 170 distinct features of the school context in our models. Instead of focusing on specific inputs or outputs of schools, our study investigates how hypothetical interventions across these five dimensions of school context could affect neighborhood disparities in reading and math test scores.

To examine how school contexts contribute to neighborhood achievement disparities, we draw on nationally representative data from the ECLS-K, which follows students from kindergarten through fifth grade and link this to U.S. census data on residential neighborhood composition. Our study provides a detailed comparison of school characteristics across neighborhoods, highlighting how the school context varies by neighborhood poverty level. We then conduct a descriptive decomposition to connect these differences in school characteristics to observed achievement gaps. Finally, we apply machine learning methods to estimate counterfactual outcomes, evaluating the effects of hypothetical school-based interventions on reducing the size of neighborhood achievement gaps (Lundberg 2022). In doing so, we are also able to identify the specific aspects of the school context that vary across neighborhoods, while also exploring how equalizing different dimensions of the school context could reduce educational disparities.

Developing a More Comprehensive Conceptual Model of the School Context

Institutional resource theory suggests that access to quality local schools is a critical factor influencing neighborhood disparities in students outcomes. For this theory to hold, two conditions must be met: first, there must be meaningful variation in school contexts across neighborhood poverty levels; second, these school contexts must influence student achievement. Yet, prior research in each of these areas shows the answers to these questions are complicated.

Regarding the first condition, the rise of the school choice movement over the past several decades has introduced new dynamics into the educational landscape. School choice programs, including public charter schools, magnet schools, and other open enrollment policies, provide families with alternatives to their designated neighborhood schools, theoretically allowing them to select schools that best meet their children's educational needs (Berends 2015). These policies have somewhat weakened the direct link between a child's neighborhood of residence and the school they attend, though most students, particularly at the elementary level, still attend schools within their local neighborhoods (Hoxby 2003; Rich, Candipan and Owens 2021). Further, while school choice is intended to give parents access to higher-quality schools, parents may not effectively identify high quality schools, instead sorting into schools based on student demographics, such as race (Rich, Candipan and Owens 2021). As such, the lasting connection between residence and school assignment implies that the neighborhood where students live may continue to shape their educational experiences within the school system, though there's a lack of consensus on exactly how school contexts vary across neighborhoods.

Regarding the second condition, education scholars continue to debate about the extent to which specific aspects of the school contribute to disparities in student outcomes. The Coleman Report (Coleman et al. 1966), actually argued that many of the observed 'school effects' are in fact due to differences in characteristics of students' families, such as family income and education, and that schools don't have much of a direct effect at all. However, the education literature argues that schools account for a substantial amount of the variation present in student test scores (Borman and Dowling 2010; Raudenbush and Bryk 1986), there is less agreement on how certain school factors in isolation affect student learning. The lack of clarity about exactly how schools vary across neighborhood poverty levels and which aspects of the school context contribute directly to student learning highlight the need for a comprehensive approach to conceptualizing the school context, as we outline below.

School Composition

School composition refers to the demographic and socioeconomic characteristics of the students and staff within a school. Because a student's place of residence is often linked to the school they attend, schools in high-poverty neighborhoods tend to have a higher concentration of low-income students (Owens 2010). Further, due to long-standing racial residential segregation in the United States and the fact that many school districts historically assigned children to schools by race before it was outlawed in the 1950s (Reardon et al. 2018), neighborhood racial segregation is still high, which means that the racial and economic disparities found within neighborhoods could continue to bleed into the school context (Frankenberg 2013; Owens and Candipan 2019).

Since the Coleman Report (Coleman et al. 1966), scholars have discussed the role of school poverty and racial segregation in shaping student achievement. Peer effects theory argues that students are influenced by the behaviors and academic performance of their peers, potentially leading to higher educational expectations and outcomes in schools with more advantaged students (Borman and Dowling 2010; Hanushek 2003). However, the impact of these compositional factors on achievement is often small and may be influenced by broader contextual factors rather than causation (Lauen and Gaddis 2013; Vigdor and Ludwig 2008). Further, attending schools with higher-ability peers may actually negatively affect educational outcomes, as students may compare themselves more harshly to their higher-achieving peers, leading to diminished self-esteem and lower academic aspirations (Alexander and Eckland 1975; Davis 1966). School composition can also indirectly affect student outcomes by shaping other dimensions of the school environment, including the availability of resources, the quality of instruction, and the overall academic climate. These interconnected dynamics underscore the importance of considering a more comprehensive framework that includes multiple dimensions of the school context beyond just the socioeconomic and demographic composition.

School Resources

School resources include the tangible and intangible assets within a school that support student learning, including funding, expenditures, materials, facilities, and staffing. Schools in more affluent neighborhoods may benefit from greater resources including better facilities, high-quality materials, and more experienced teachers (Baker 2017; Owens 2010). This advantage is partly due to school funding being tied to local property taxes, though school finance reforms in the 1970s largely reduced financial disparities between districts (Arum 2000) and recent research suggests that school district funding does not vary substantially across neighborhood income levels (Owens and Candipan 2019). However, schools in high-poverty neighborhoods tend to have larger class sizes (Baker 2017; Clotfelter, Ladd and Vigdor 2010) and face greater challenges in hiring and retaining qualified teachers, partially due to lower offered salaries, fewer instructional resources, and less overall support for teachers provided by administrators (Borman and Dowling 2008; Boyd et al. 2005).

Since the 1960s, significant attention has been devoted to understanding how school resources matter for student outcomes, though the findings remain mixed. Increased per-pupil spending has been shown to improve some school inputs, such as lowering student-teacher ratios

(Jackson, Johnson and Persico 2016), enhancing teacher retention (Borman and Dowling 2010), and raising teacher salaries (Jackson, Johnson and Persico 2016). However, despite improvement in school resources between the 1960s and early 2000s – like a sharp increase in teachers with graduate degrees and the rise in per-pupil expenditures – there has been no corresponding increase in student test scores (Hanushek 2003). The impact of specific interventions, such as reducing class sizes (Boyd-Zaharias 1999; Krueger 2002) or raising teacher credential requirements (Clotfelter, Ladd and Vigdor 2010), has generally been modest.

These findings highlight the challenge of isolating individual measures of school resources that significantly impact student achievement directly, even though there are differences in resources across neighborhoods. Increased spending and resources alone do not necessarily translate into better student performance, particularly when not accompanied by effective instructional practices (Hanushek 2003). Given the strong link between teacher quality and student achievement in the literature (Rivkin, Hanushek and Kain 2005), it is important to also consider instructional practices and curriculum quality when considering how the school context contributes to neighborhood disparities.

School Instructional Practices

Instructional practices encompass a range of factors including instructional time, teaching practices, classroom management techniques, curriculum content, and assessment practices. Due to differences in student composition and school resources, it's possible that schools in disadvantaged neighborhoods may face unique challenges that affect their instructional practices. For example, as a result of serving students who begin with lower academic baselines, these schools may adopt a slower pace of instruction or offer a less rigorous curriculum (Kahlenberg

2001; Lauen and Gaddis 2013; Willms 2010). Further, because schools serving disadvantaged neighborhoods sometimes encounter difficulties in recruiting and retaining experienced teachers (Boyd et al. 2011; Owens and Candipan 2019) and receive larger classes sizes (Clotfelter, Ladd and Vigdor 2010), the quality of instructional techniques and practices may be affected, though there is a lack of prior research in this area.

Research indicates that students tend to perform better on reading and math assessments when they are taught by high-quality teachers who can adapt their instruction to meet diverse student needs (Raudenbush 2008; Rivkin, Hanushek and Kain 2005). Effective instructional practice identified in the literature include implementing higher-order instructional strategies, using efficient classroom management techniques, and providing students with individualized instruction (Crosnoe et al. 2010; Hanushek 2003; Willms 2010). While increased instructional time has been shown to benefit student learning, it is most effective when accompanied by high-quality teaching (Rivkin and Schiman 2015). While there's at least some suggestive evidence that instructional practices may vary by neighborhood and could impact student achievement, instructional practices are also closely linked to a broader set of factors within the school context. Elements such as teacher morale, administrative support, and overall school climate can play a significant role in shaping these practices (Borman and Dowling 2008; Raudenbush 2008), highlighting the importance of considering instructional practices within a broader framework that accounts for various dimensions of the school context.

School Climate

The school climate refers to the social and emotional environment that students experience within a school, and include factors like student attendance, school safety, community involvement, parental involvement, administrative leadership, and teacher morale. Administrators at schools located within higher-income neighborhoods report more positive school climates than those in lower-income neighborhoods, which may face challenges due to differences in the student body or differences in factors in the larger neighborhood, like local violent crime. Neighborhood violent crime can affect student behavior substantially (Sharkey and Faber 2014) and lead to more authoritarian disciplinary approaches among staff (Arum and Velez 2012). There may also be a lower level of trust among teachers, students, and parents, which can lower student engagement (Bryk 2002). When it comes to student engagement, schools serving low-income neighborhoods experience higher levels of chronic student absenteeism, suspension rates, and grade retention than schools in high-income neighborhoods (Owens and Candipan 2019). Such schools may also have more disorderly classrooms, which can make maintaining a conducive learning environment difficult (Kahlenberg 2001; Willms 2010).

While specific components of school climate, like student attendance, have clear impacts learning (Gottfried 2014), the general effect of school climate remain less clear. Positive student-teacher relationships help to create a safe and engaging learning environment (Crosnoe et al. 2010; Hallinan 2008), and strong administrative leadership is known to boost teacher morale and retention (Black 2001; Borman and Dowling 2008; Moller et al. 2013). A positive school climate can also ensure students feel safe and supported, allowing them to focus on their schoolwork (Burdick-Will 2013; Burdick-Will et al. 2011). However, while these aspects of the school climate are often intertwined and influence one another, their direct effect on student learning is less clear. This underscores the need for an approach that considers how school contexts as a whole matter for student learning.

School Effectiveness

In response to the difficulty in identifying specific aspects of the school environment that contribute substantially to student learning, scholars have increasingly turned to measures of overall school effectiveness in promoting student learning. In particular, value-added models, which are designed to estimate the effect of a school on student academic progress have become increasingly popular in education research (Downey, von Hippel and Hughes 2008; Rivkin, Hanushek and Kain 2005). Schools serving the most economically advantaged neighborhoods have drastically higher average levels of student achievement than those serving economically disadvantaged neighborhoods (Owens and Candipan 2019). However, when taking into account overall school effectiveness in promoting student learning through value-added models, there is little variation by neighborhood advantage (Hanushek and Rivkin 2010; Wodtke et al. 2023), suggesting either that schools don't contribute meaningfully to neighborhood disparities in achievement, or that the school-value added models are not fully able to capture aspects of the school environment that do vary by neighborhood, and which also affect student achievement.

One limitation of value-added models is that they can be quite noisy, especially when derived from surveys like the ECLS-K, which includes data from about 20 students per school to estimate each school's value-added (Kane and Staiger 2002). This noisiness makes it difficult to determine the actual influence of schools on student learning, and thus measures of student achievement. Although Wodtke et al. (2023) advanced the literature by examining how school value-added mediates neighborhood effects on student outcomes, their reliance on potentially noisy school value-added measures may oversimplify the complex ways in which different dimensions of the school context vary across neighborhoods and influence student achievement.

In sum, the school effects literature has documented a wide range of features of the school context that seem to matter, though to varying degrees, for student learning. Further, the literature shows that different components of the school contextual environment have complex, and often interconnected relationships, making it difficult to disentangle exactly which features of the school matter for student achievement outcomes and which vary across neighborhood poverty levels. As a result, a defensible proxy for school context should consider different aspects of the school context, while also allowing for the complex interactions that likely exist between different components. In the present study, we overcome these limitations by merging nationally representative survey data with U.S. census data on neighborhood composition to draw on 171 measures across five dimensions of the school context. We use novel machine learning methods for high dimensional data to estimate the effects of equalizing different dimensions of school context on differences in achievement between students living in high- versus low-poverty neighborhoods, allowing for complex interactions and non-linearities. This informs our methodological strategy, outlined below.

Data and Methods

Data

To explore whether differences in schools attended by students from high- versus low-poverty neighborhoods account for disparities in academic achievement, we use data from the Early Childhood Longitudinal Study, Kindergarten Cohort of 2010-11 (ECLS-K:2011) linked to U.S. census data on the composition of neighborhoods where children lived and to information from the U.S. National Center for Education Statistics (NCES) on the characteristics of the school each child attended. ECLS-K 2011 is a nationally representative, longitudinal survey beginning in fall 2010 when students were starting kindergarten and following them through spring of fifth grade in 2016. The study includes waves of data at fall and spring of kindergarten (2010 and 2011), fall and spring of first grade (2011 and 2012), fall and spring of second grade (2012 and 2013), spring of third grade (2014), spring of fourth grade (2015), and spring of fifth grade (2016). The waves of data at fall of first grade and second grade only include a random subsample of about 30% of the original sample of students, while all other waves included data collection from the full sample. ECLS-K contains extensive data in each wave on student and family background characteristics, student academic achievement, and the school environment. The analytic sample for this study includes all n = 18,170 children in j = 970 schools who were enrolled in the study in fall of kindergarten.

The ECLS-K is especially suited to the examination of the school contexts that students experience, containing hundreds of measures related to the school a student attends. The ECLS-K also provides reading and math test scores at each wave, allowing for the exploration of student learning over time. The ECLS-K 1998 and 2011 surveys are commonly used by researchers trying to understand the effects of schools on student learning (Downey and Condron 2016; Downey, von Hippel and Hughes 2008). The restricted-use ECLS-K includes geographical and school identifiers, allowing us to link each child with data on their residential neighborhood and their school environment.

Using ECLS-K residential census tract measures, we match children to data from the U.S. Census Bureau on the demographic composition of their residential area during fall of kindergarten. These indicators are drawn from the NCDB (version 2.0), which contains harmonized tract-level data on population characteristics collected as part of the 2010 U.S. Census and the 2010 American Community Surveys (Geolytics 2012).

Using the ECLS-K school identifier codes for the school students attended during spring of first grade, we match students to data from the 2011/2012 school-year Common Core of Data (CCD) if they attended a public school or to 2011/2012 school-year Private School Universe Survey (PSS) data if they attended a private school. While the ECLS-K already includes a comprehensive list of school environment measures, CCD and PSS data provide additional information on the number of students and teachers at each school and on expenditures for each school district.

Measures

Our outcomes of interest include two indicators of academic achievement: math and reading test scores. We measure each of these outcomes using item-response theory (IRT) theta scores from ECLS-K assessments taken during spring of third grade. The IRT theta scores provide vertical, equal-interval measures of achievement, allowing for comparison across time. The reading test assesses basic reading skills, vocabulary, and reading comprehension. The math test assesses grade-level appropriate skills in five content categories, including number properties and operation, measurement, geometry, data analysis and probability, and algebra (Najarian et al. 2019). The reading and math IRT theta scores in the ECLS-K have high reliability, high construct validity, and low differential item functioning (Najarian et al. 2019).

To measure neighborhood poverty, we use the linked NCDB data on neighborhood composition in 2010, at spring of kindergarten. We define neighborhoods as census tracts, which is consistent with other quantitative neighborhood research (Harding 2003; Owens and Candipan 2019; Sampson, Sharkey and Raudenbush 2008). Neighborhood poverty is measured as the ratio of families falling below the federal poverty threshold to the total number of families in a given census tract area. While neighborhood disadvantage is multidimensional and could be measured using several indicators of neighborhood composition, this study focuses on neighborhood poverty because of its demonstrated effects on the social processes theorized to matter in this study. Additionally, it is simple to interpret and highly correlated with other measures of neighborhood disadvantage. As detailed below, we also control for other measures of neighborhood disadvantage.

For our exposure of interest, we focus on the school context in the spring of 1st grade. To capture the multidimensional school contexts that students experience, we include more than 170 measures. These measures span critical aspects of the school context, including the demographic composition of students and staff, resource allocation such as funding and expenditures per pupil, and key indicators of instructional quality like class sizes, staff qualifications, and teaching methods. Recognizing the importance of the broader school climate, we also include measures of student attendance, school communication with parents, teacher morale, and the school's overall effectiveness in fostering student learning. Before deciding to include each individual measure of school context in our main set of models, we first explored various clustering and dimension reduction methods to determine whether these measures could be aggregated into a smaller number of components (see Figure C1 and Figure C2). However, we found that school context could not be effectively reduced, indicating that the individual measures captured distinct and important aspects of the school context.

We categorize the 171 measures into five conceptual dimensions of school context: 1) composition, 2) resources, 3) instructional practices, 4) climate, and 5) overall effectiveness, while still including each measure individually in our models (see Appendix Table C1). While we have included an extensive set of measures to capture the multifaceted nature of school contexts, we recognize that there may be individual aspects of the school context that we do not fully capture or that aren't measured perfectly here. To address these potential limitations, we also consider overall school effectiveness in promoting student learning through school value-added measures, which help to account for any potential gaps in our specific measures of school context.

The primary purpose of school value-added measures is to estimate how much additional learning a school provides to its student beyond what would be expected based on their prior academic achievement and demographic characteristics. To estimate school value-added, we estimate multilevel models with school random effects for students' reading and math test scores at the end of 1st grade, controlling for their test scores at both the beginning and end of kindergarten, as well as for student gender, race, and parental education. Additionally, to account for differences in the timing of assessments across schools (Downey, von Hippel and Hughes 2008), we include a control for the number of months between spring of kindergarten and spring of the 1st grade assessments. A schools value-added is given by the empirical Bayes estimate of its random effect on test scores at the end of 1st grade, net of student gender, race, parental education, and prior test scores measured during kindergarten.

In our main set of models, we control for potential confounding by adjusting for wide range of individual, family, and neighborhood characteristics measured at baseline, fall of kindergarten (see Appendix Table C2). At the individual level, we control for gender, race, and weight at birth. Gender is coded as 0 for female and 1 for male. Race is coded as a series of binary variables that captures whether a child is white, Black, Hispanic, or another race. Birth weight in ounces is measured continuously. We also adjust for fall kindergarten reading and math test scores, along with other developmental indicators at school entry, including behavioral problems, attention issues, student motivation, and health.

Family controls include parental age, marital status, income, education, employment status, language spoken at home, household size, parental involvement in education, and receipt of government assistance. Mother age is measured in years, marital status as a binary indicator (0 for not married, 1 for married), and income as a continuous variable using midpoint averages (in 2010 dollars) from categorical data. Employment status is captured categorically (0 for not in labor force, 1 for working fewer than 35 hours per week, 2 for working 35 hours or more per week), and parental educational attainment is categorized from less than high school to graduate degrees. The language spoken at home is a binary variable (0 for non-English, 1 for English), and household size is the total number of residents. Parental involvement is measured by the frequency of reading to and practicing numbers with their child, each ranging from "not at all" to "every day." Receipt of government assistance is measured by binary variables for receipt of WIC, SNAP, and TANF benefits.

At the neighborhood level, in addition to the poverty rate, we control for education level, racial composition, household structure, and unemployment using NCDB data. Specifically, we include the percentage of residents with varying levels of education, racial demographics, female-headed households, and the neighborhood unemployment rate.

Estimands

This section outlines our approach to evaluating whether disparities in academic achievement across neighborhood poverty levels can be attributed to differences in school contexts. We do this by comparing the observed gaps in reading and math test scores to a series of counterfactual gaps that arise under hypothetical scenarios in which various dimensions of the school context are equalized across neighborhoods (Lundberg 2022; Nguyen, Schmid and Stuart 2020; Schachner and Wodtke 2023a).

The observed gap in student test scores can be expressed as follows:

$$\mu(x, x') = E(Y_i|X_i = x) - E(Y_i|X_i = x'),$$

where Y_i denotes the observed test score of child i, X_i denotes neighborhood poverty level, and $E(\cdot)$ is the expectation operator. Here, $\mu(x, x')$ represents the population average difference in student test scores observed between two different neighborhood poverty levels, defined by $X_i = x$ versus $X_i = x'$. In this case, x corresponds to a neighborhood poverty rate of 20% or higher, while x' corresponds to a neighborhood poverty rate of less than 20%. Thus, $\mu(x, x')$ captures the mean difference in test scores between children residing in high-poverty neighborhoods and those in low-poverty neighborhoods.

To explore the impact of school context on the observed gap in student test scores across neighborhood poverty levels, we compare it to a set of counterfactual gaps under hypothetical stochastic interventions to equalize the distribution of school characteristics across neighborhoods. These counterfactuals can be formally expressed as follows:

$$\eta(x, x', \boldsymbol{\mathcal{S}}) = E(Y_i(\boldsymbol{\mathcal{S}})|X_i = x) - E(Y_i(\boldsymbol{\mathcal{S}})|X_i = x'),$$

where $Y_i(\boldsymbol{\mathcal{S}})$ denotes a child's potential outcome under exposure to a vector of school characteristics, denoted by $\boldsymbol{\mathcal{S}}$, randomly drawn from some prescribed distribution. For example, when $\boldsymbol{\mathcal{S}}$ is randomly drawn from $f(\mathbf{S}|X = x')$, the joint distribution of school characteristics observed among students in low-poverty neighborhoods, then $\eta(x, x', \boldsymbol{\mathcal{S}})$ would represent the average difference in test scores that would persist between students from high-poverty versus low-poverty neighborhoods, if all students were exposed to a set of school characteristics selected from their distribution observed in low-poverty neighborhoods. In other words, it represents the gap in tests scores after an intervention at the population level to shift the distribution of all school characteristics contained in $\mathbf{S}$ to that observed in low-poverty neighborhoods. Instead of setting each school context measure to a specific fixed value, we adopt an alternative approach where $\boldsymbol{S}$ represents a random vector of values randomly drawn from an observed joint distribution. This allows us to emulate the consequences of hypothetical interventions at the population level, such as the implementation of a strict school lottery, where $\boldsymbol{S}$ would be drawn from $f(\mathbf{S})$—that is, the marginal distribution of school characteristics—for all students, thereby equalizing the distribution of measured school characteristics across students living in poor versus non-poor neighborhoods.

Identification Assumptions

Unlike observed gaps, counterfactual gaps involve unobserved values that can only be identified under certain conditional independence assumptions. Specifically, $\eta(x, x', \boldsymbol{S})$ can be identified under the assumption that the potential outcomes $Y_i(\boldsymbol{s})$ are conditionally independent of a child's observed vector of school characteristics $\mathbf{S}_i$ given their neighborhood poverty level X_i and their set of baseline characteristics $\mathbf{C}_i$ (Lundberg 2022; Nguyen, Schmid and Stuart 2020). The assumption can be formally expressed as:

$$Y_i(\mathbf{s}) \perp \mathbf{S}_i \mid X_i, \mathbf{C}_i,$$

meaning that the effect of school context on student test scores is not confounded by unobserved factors that affect both. This is a strong assumption that may not be met even given the strong set of baseline controls $\mathbf{C}_i$ included here. As such, we perform a sensitivity analysis to assess the robustness of our findings to unobserved confounding.

Estimation

We estimate the counterfactual gaps of interest by employing a g-computation approach, which is a flexible algorithm designed to estimate potential outcomes, supplemented with supervised machine learning techniques (Lundberg 2022; Nguyen, Schmid and Stuart 2020). The process for g-computation involves:

1. **Modeling the conditional mean**: we first fit a model to estimate the conditional mean of the observed outcome, $E(Y_i|X_i, \mathbf{C}_i, \mathbf{S}_i) = h(X_i, \mathbf{C}_i, \mathbf{S}_i)$, where $h(\cdot)$ represents the function connecting the outcome with the predictors.
2. **Imputing potential outcomes**: Using the fitted model, we then generate potential outcomes under a hypothetical scenario where the values of each school context measure within the vector $\mathbf{S}_i$ are randomly drawn from a particular empirical distribution. For each student, we hold all other predictors at their observed values while resetting their observed vector $\mathbf{S}_i$ to a new vector, $\boldsymbol{S}$, randomly drawn from a particular empirical distribution in the sample, thereby computing $\hat{h}(X_i, \mathbf{C}_i, \boldsymbol{S})$;
3. **Calculating the counterfactual gap**: Finally, we compute the counterfactual gap by averaging these imputed potential outcomes within each level of neighborhood poverty, specifically where $X_i = x$ and $X_i = x'$, or high-poverty and low-poverty levels. The difference between the high neighborhood poverty and low neighborhood poverty averages then represents the estimated counterfactual gap.

Under the previously stated ignorability assumption and provided that $h(X_i, \mathbf{C}_i, \mathbf{S}_i)$ is correctly specified, g-computation will yield consistent estimates for the counterfactual gaps of interest. Because of the challenges of correctly specifying the functional form of $h(X_i, \mathbf{C}_i, \mathbf{S}_i)$, traditional parametric models, like linear regression, might not capture the complexity of the relationship between school context and student academic achievement, particularly when the set of predictors $\{X_i, \mathbf{C}_i, \mathbf{S}_i\}$ is high-dimensional, meaning it includes a large number of variables that could interact in complex ways. This potential misspecification could introduce bias, particularly when dealing with so many school context measures. To mitigate these risks, we leverage supervised machine learning methods, which allow us to flexibly model these relationships and improve the robustness of our estimates.

We start with a traditional linear regression model to estimate $h(X_i, \mathbf{C}_i, \mathbf{S}_i)$. However, because this model may not fully capture the complexity of the data due to its simplicity, we subsequently apply a series of more sophisticated tree-based machine learning algorithms. These include recursive partitioning (Breiman et al. 1984), gradient boosting (Friedman 2001), and random forests (Breiman 2001).

Recursive partitioning creates a decision tree by iteratively splitting the dataset into smaller subgroups, or nodes, based on binary decisions about the predictors (Breiman et al. 1984). The algorithm selects the optimal binary split at each step by minimizing the sum of squared deviations from the mean of the outcome within each node. While recursive partitioning can model complex interactions and nonlinearities, which is ideal for a study with so many predictors, it can also overfit the data, leading to predictions that are highly variable and potentially imprecise.

Gradient boosting and random forests enhance the recursive partitioning approach by addressing its tendency to overfit (Breiman 2001; Friedman 2001). These methods create ensembles of decision trees to improve the accuracy of predictions. In gradient boosting, trees are built sequentially, with each new tree aimed at reducing the errors of the previous ones. The final model is a weighted combination of all trees. In contrast, random forests construct each tree from a bootstrap sample of the data and use a random subset of predictors to reduce the likelihood of overfitting by averaging the predictions across many trees.

To draw on the strengths of these various methods, we use a super learner algorithm (Naimi and Balzer 2018; Van der Laan, Polley and Hubbard 2007). This approach combines the predictions from the linear regression and the tree-based models into a weighted average, with the goal of leveraging the strengths of each method while mitigating their individual weaknesses. The resulting predictions are designed to be at least as accurate as the best-performing method would be in isolation, with the potential to improve upon any single model. With this estimation approach, finite sample bias is a potential concern, as machine learning methods, like the SuperLearner algorithm, only converge to target estimates with a large enough sample size. Although we draw on a sample of more than 20,000 students, there is still a potential for finite sample bias. To mitigate this risk, we applied bootstrap bias correction methods to estimate all confidence intervals, though it's possible this will not fully eliminate potential bias from the plug-in machine learning estimators.

We estimate counterfactual neighborhood test score gaps by emulating a set of four hypothetical interventions:

1. **Strict school lottery**: Under the first hypothetical intervention, we adjust the distribution of all school context factors to be consistent across all children, including school composition, resources, instructional practices, culture, and effectiveness. This is equivalent to a strict school lottery system where students are randomly assigned to schools, irrespective of their background or neighborhood. Specifically, we assign $\boldsymbol{S}$ based on draws from $f(\mathbf{S})$, its empirical marginal distribution.

2. **Decoupling Neighborhood Poverty and School Composition**: Under the second hypothetical intervention, we equalize the distribution of school composition that students are exposed to, assigning students to schools at random, drawing from the existing distribution of school composition. In this way, we are decoupling school assignment from neighborhood poverty levels, though because the existing distribution of schools tends to be fairly segregated on factors like race or student socioeconomic background, students would still be exposed to segregated schools under this hypothetical intervention. Specifically, we assign $\boldsymbol{S}_1$ based on draws from $f(\mathbf{S_1})$, where $\mathbf{S_1}$ denotes the vector of characteristics measuring school composition.
3. **School finance reform**: The third hypothetical intervention equalizes school resources across schools, ensuring that students attending schools in high-poverty neighborhoods have access to the level of funding, materials, and facilities that those attending schools in low-poverty neighborhoods do. This could be seen as an intervention like school finance reforms that aim to distribute resources more equitably across districts and schools but would go beyond traditional reforms that equalize funding only, which wouldn't necessarily account for historical differences in funding that may have led to unequal materials and facilities that schools are starting with. Specifically, we assign $\boldsymbol{S}_2$ based on draws from $f(\mathbf{S_2}|X = x')$, where $\mathbf{S_2}$ denotes the vector of characteristics measuring school resources and $f(\mathbf{S_2}|X = x')$ denotes the empirical distribution of these characteristics among students in low-poverty neighborhoods.
4. **Standardized instruction**: The final hypothetical intervention equalizes instructional practices across schools, ensuring that students attending schools in high-poverty neighborhoods have access to the same teaching and curriculum as those attending

schools in low-poverty neighborhoods. This is roughly equivalent to an effort to alter instructional practices in high-poverty neighborhood schools by standardizing instructional practices based on those offered already in low-poverty neighborhood schools. Specifically, we assign $\boldsymbol{S}_3$ based on draws from $f(\mathbf{S_3}|X = x')$, where $\mathbf{S_3}$ denotes the vector of characteristics measuring instructional practices and $f(\mathbf{S_3}|X = x')$ denotes the empirical distribution of these characteristics among students in low-poverty neighborhoods.

To explore the impact of these changes under the potential outcomes framework, we focus on hypothetical interventions that could at least conceivably be implemented. While other dimensions of school context, such as school effectiveness or school culture, are crucial, they are more challenging to target through specific, realistic interventions, and so weren't included in their own direct hypothetical intervention outside the strict school lottery scenario. Therefore, our analysis concentrates on interventions that are both theoretically grounded and conceivably actionable: equalizing the distribution of school characteristics across students from different neighborhoods (strict school lottery), equalizing school composition only (desegregation bussing), equalizing school resources at the distribution observed in low-poverty neighborhoods (equitable funding programs), and equalizing instructional practices at the distribution observed in low-poverty neighborhoods (standardized instruction).

Each of the four hypothetical interventions compares students living in neighborhoods with a neighborhood poverty rate of 20% or higher to those in neighborhoods with a poverty rate below 20%, after adjusting the distribution of school context factors to be consistent across students from different neighborhoods. We draw on an extensive set of measures for each dimension of school context, totaling 171 school context variables across dimensions. As a result, for each hypothetical intervention, we equalize the distribution of the relevant subset of these school context measures rather than selecting specific values for each variable. For example, in the hypothetical school lottery, we equalize the distribution of all 171 school context measures. In the bussing desegregation program hypothetical intervention, we equalize only the distribution of the 11 school composition measures. A similar approach is used for the other hypothetical interventions.

To equalize distributions of many school characteristics, we compute predictions via g-computation after replacing student's observed values on these characteristics with a random vector selected with replacement from the appropriate empirical distribution. Specifically, we fit a model for the mean of the outcome given all the relevant school context measures and controls for the given intervention. We then compute predictions from this model after randomly selecting vectors of school context values from the empirical distribution among the total sample of students and substituting them for students' observed values on these variables. We repeat this step many times for each student and average the predictions from each iteration together. Finally, averaging these predictions together again across sample members approximates the counterfactual means under the intervention that adjusts the distribution of school context factors across neighborhoods.

For the last two hypothetical interventions – school finance reform and standardized instruction – we sample from the empirical distribution of these characteristics among students from low-poverty neighborhoods specifically. This approach reflects that these interventions would be intended to elevate the resources and instructional quality in high-poverty schools to match those typically found in low-poverty schools. By drawing from the conditional distribution in low-poverty neighborhoods, we aim to emulate a scenario where schools serving high-poverty neighborhoods can receive the same level of resources and the same instructional practices as those serving low-poverty neighborhoods, addressing disparities by trying to improve the experiences of students attending schools in high-poverty neighborhoods.

Results

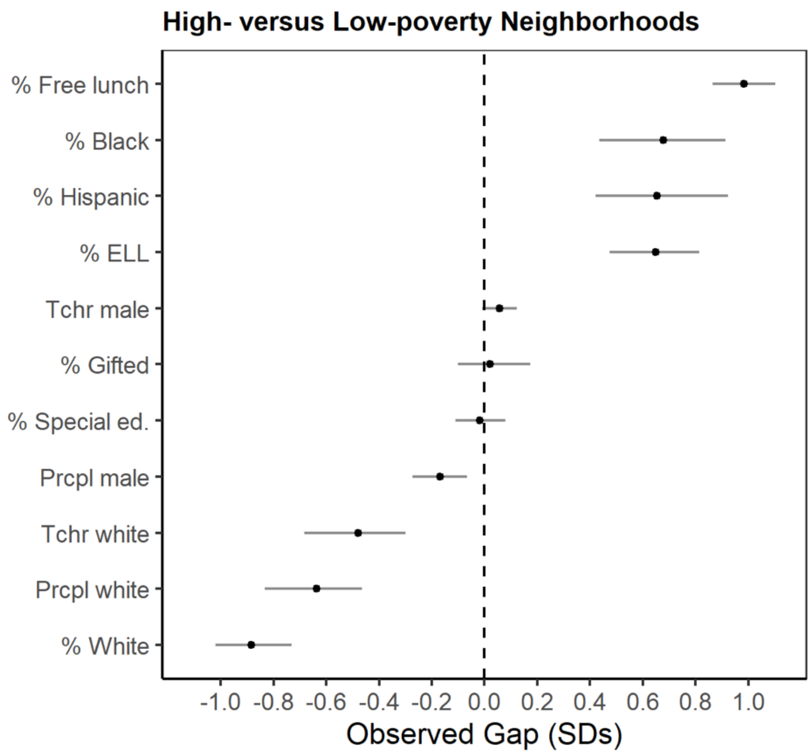
Observed Differences in School Context by Neighborhood Poverty

We first explore differences in the school contextual environments students are exposed to, by residential neighborhood poverty level. Figure 4.1, Figure 4.2, Figure 4.3, and Figure 4.4 each display a dot-and-whisker plot showing the observed neighborhood achievement gap in exposure to each dimension of school characteristics considered in this analysis. These gaps contrast exposure for children from a neighborhood with a poverty rate greater than or equal to 20% (high-poverty), compared to those from a neighborhood with a poverty rate less than 20% (low-poverty). The horizontal axis of each figure displays the observed gaps and 95% confidence intervals (CIs) in standard deviation (SD) units, and the vertical axis displays each measure of school context sorted in descending order by effect size. Figure 4.1 illustrates the observed gaps for 11 measures of school composition, while Figure 4.2 focuses on 41 measures of school resources, Figure 4.3 examines 91 measures of instructional practices, and Figure 4.4 focuses on 26 measures of school climate. Appendix Table C1 provides descriptions and basic statistics for each school context variable.

Figure 4.1 shows that the composition of the school students attend varies dramatically between high-poverty and low-poverty neighborhoods. Students from high-poverty neighborhoods attend schools with more peers who are impoverished (0.99 SDs; % Free lunch), Black (0.68 SDs; % Black), Hispanic (0.66 SDs; % Hispanic), and English Language Learners

(0.65 SDs; % ELL) than do students from low-poverty neighborhoods. They also have less exposure to white peers (-0.89 SDs; % White), principals (-0.64 SDs; Prcpl white), and teachers (-0.48 SDs; Tchr white). There are no appreciable differences in the percentage of students who are in special education (% Special ed.) or gifted and talented education (% Gifted) at schools attended by students from high-poverty versus low-poverty neighborhoods.

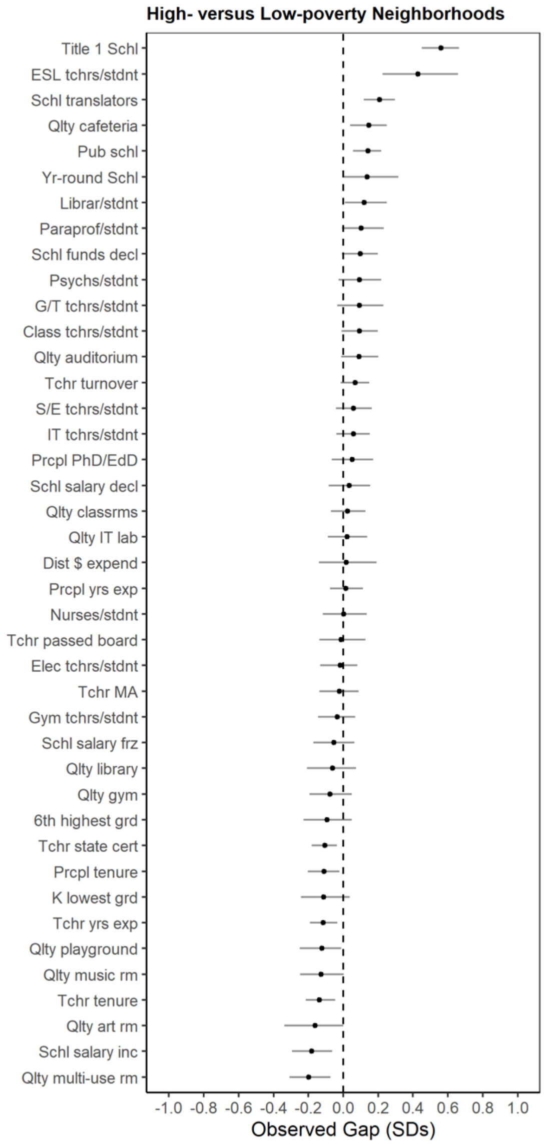
Figure 4.1. Observed Neighborhood Poverty Gaps in School Composition



Notes: Observed gaps contrast residence in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20%. Confidence intervals are based on the repeated half-sample bootstrap with 200 replications and include bootstrap bias correction. Results are combined across 5 imputations.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File.

Figure 4.2 shows much smaller differences in school resources by residential neighborhood poverty than were present for school composition. When looking at school

Figure 4.2. Observed Neighborhood Poverty Gaps in School Resources

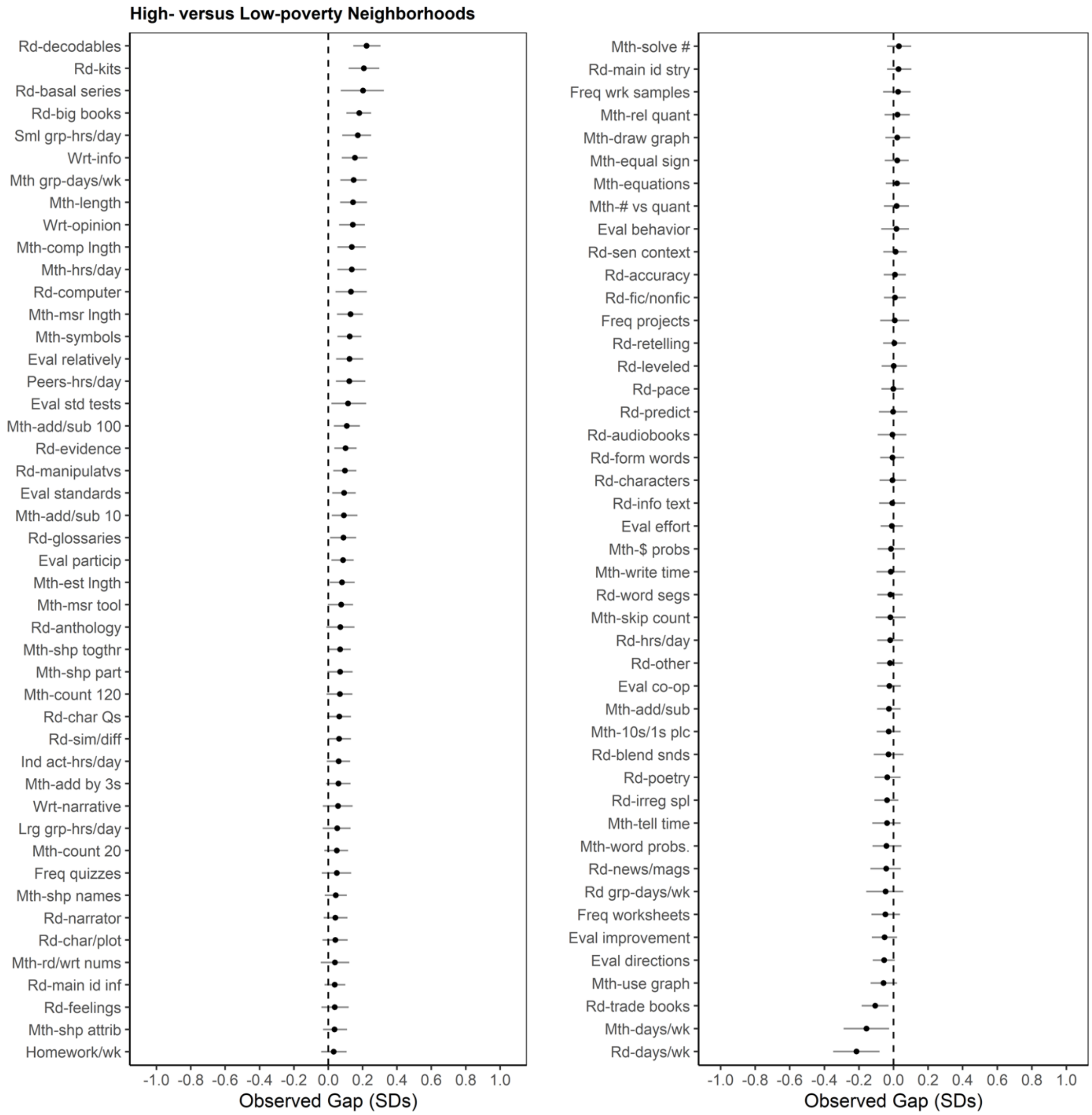


Notes: Observed gaps contrast residence in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20%. Confidence intervals are based on the repeated half-sample bootstrap with 200 replications and include bootstrap bias correction. Results are combined across 5 imputations.

Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), “School District Finance Survey (F-33),” fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), “Local Education Agency Universe Survey,” “Public Elementary/Secondary School Survey,” 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

funding, a higher proportion of children from high-poverty neighborhoods attend a Title 1 school (Title 1 Schl) than those from low-poverty neighborhoods (0.56 SDs), though there are no appreciable neighborhood differences in the district expenditures per-pupil (Dist $ expend). A lower proportion of students from high-poverty neighborhoods attend schools where staff had been given a salary increase over the past year (-0.18 SDs; Schl salary inc) than those from low-poverty neighborhoods. In terms of class sizes, there were no appreciable differences in the number of classroom teachers per 100 students (Class tchrs/stdnt) experienced by students from high-poverty compared to low-poverty neighborhoods. Students from high-poverty neighborhoods attended schools with more ESL teachers per 100 students (0.43 SDs; ESL tchrs/stdnt) than those from low-poverty neighborhoods, which is a byproduct of these students attending schools with more English Language Learner students. In line with this, a higher proportion of students from high-poverty neighborhoods attend a school with translators (0.21 SDs; Schl translators) by neighborhood poverty level. When looking at neighborhood differences in staff qualifications, the results suggest few differences in the educational background and certifications of teachers and principals at schools attended by students from high-poverty compared to low-poverty neighborhoods. Students in high-poverty neighborhoods attended schools with teachers who had slightly fewer years of experience (-0.12; Tchr tenure), though this effect size is small. Finally, students from high-poverty neighborhoods attend schools where the administrator rated some of the school facilities as lower in quality, including the multi-use room (-0.20 SDs; Qlty multi-use rm), the art room (-0.16 SDs; Qlty art rm), the music room (-0.13 SDs; Qlty music rm), and the playground (-0.12 SDs; Qlty playground), though these differences are small and there were no differences in ratings of regular classroom quality by neighborhood poverty level.

Figure 4.3. Observed Neighborhood Poverty Gaps in Instructional Practices

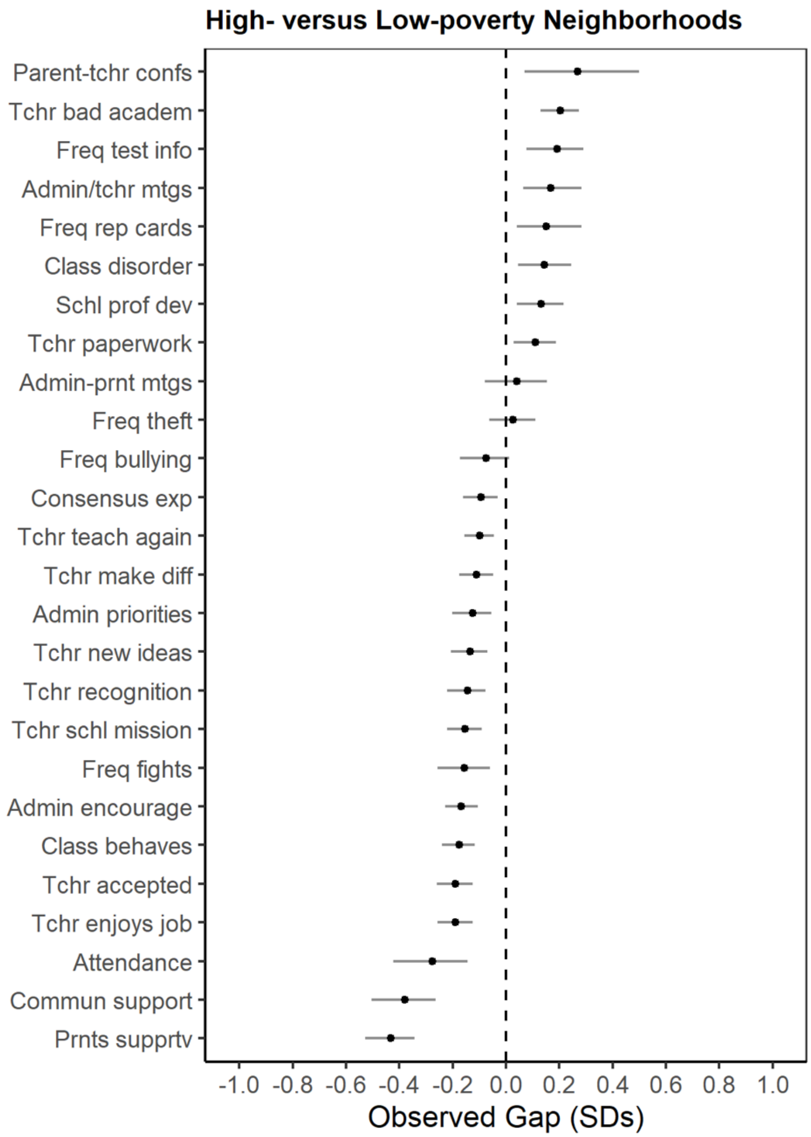


Notes: Observed gaps contrast residence in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20%. Confidence intervals are based on the repeated half-sample bootstrap with 200 replications and include bootstrap bias correction. Results are combined across 5 imputations.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File.

Figure 4.3 suggests there are also few differences in school instructional practices that students are exposed to, by neighborhood poverty. The differences that are present are all quite small, even when considering 91 measures of instructional practices that capture in-depth information about the teaching methods and curriculum students are exposed to. Of the small observed differences, some do not provide a clear indication of one group of students being exposed to higher quality instruction than the other. For example, children from high-poverty neighborhoods are more likely to be exposed to teacher practices that include use of decodables (Rd-decodables), kits (Rd-kits), basal series (Rd-basal series), and big books (Rd-big books) during reading instruction, about one-fifth of a standard deviation each, compared to children from low-poverty neighborhoods. However, the results do suggest that children from high-poverty neighborhoods are exposed to less instructional time, both for days of reading (-0.21 SDs; Rd-days/wk) and math (-0.16 SDs; Mth-days/wk) instruction per week than those from low-poverty neighborhoods. However, those from high-poverty neighborhoods are exposed to more math instruction time per day (0.14 SDs; Mth-hrs/day) than those from low-poverty neighborhoods, suggesting math instructional time may balance out over the course of a week. While these effect sizes are fairly small, even small differences in instructional time can add up over the course of a school year and have broader consequences for student learning and development.

Figure 4.4 indicates several larger differences in school climate exposure by neighborhood poverty. Children from high-poverty neighborhoods are less exposed to schools where administrators perceive parents (-0.43 SDs; Prnts supprtv) or the community (-0.38 SDs; Commun support) to be supportive. Fewer students from high-poverty neighborhoods have a teacher with high morale. For example, fewer have a teacher who reported liking their job (-0.19 SDs; Tchr enjoys job). Fewer attend a school with strong administrator support and leadership, where they have a teacher who feels accepted at the school (-0.19 SDs; Tchr accepted), encouraged by administrators (-0.17 SDs; Admin encourage), clear about the school mission (-0.15 SDs; Tchr schl mission), recognized by administrators (-0.15 SDs; Tchr recognition),

Figure 4.4. Observed Neighborhood Poverty Gaps in School Climate



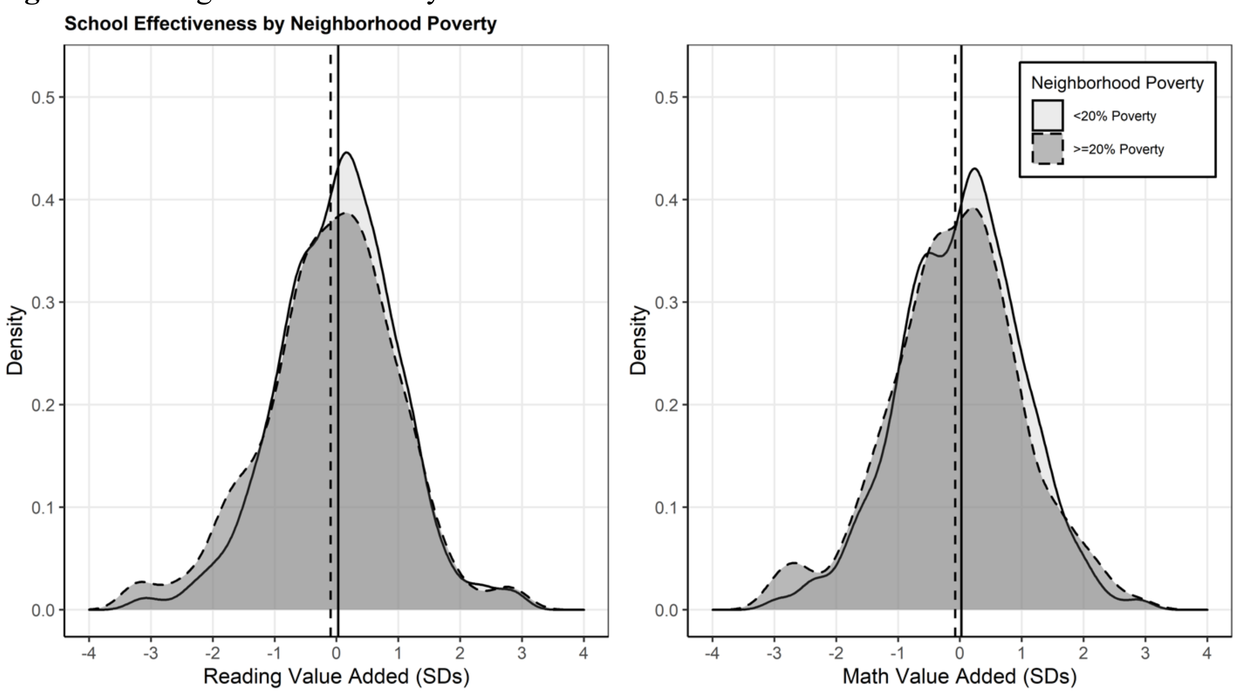
Notes: Observed gaps contrast residence in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20%. Confidence intervals are based on the repeated half-sample bootstrap with 200 replications and include bootstrap bias correction. Results are combined across 5 imputations.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File.

supported in coming up with new ideas (-0.14 SDs; Tchr new ideas), or clear about administrator priorities (-0.13 SDs; Admin priorities). Students from high-poverty neighborhoods attend schools that experience greater average student absenteeism (-0.28 SDs; Attendance) than those from low-poverty neighborhoods. Conversely, children from high-poverty neighborhoods attend schools with more frequent school communication with parents through conferences (0.27 SDs; Parent-tchr confs) and sending home report cards (0.15 SDs; Freq rep cards) and test information (0.19 SDs; Freq test info). Principal reports of classroom disorder (0.14 SDs; Class disorder) are somewhat higher in schools attended by high-poverty students, and teacher reports of positive classroom behavior are lower (-0.18 SDs; Class behaves), though the size of these differences are relatively small. There are no appreciable differences by neighborhood poverty level in exposure to school theft or bullying, and only small differences in the frequency of school fights (-0.16 SDs; Freq fights).

Figure 4.5 displays kernel density plots for school effectiveness in reading and math at the schools attended by students from high-poverty and low-poverty neighborhoods. School effectiveness is captured by assessing student learning through school value-added scores from reading and math assessments. This figure suggests there are only very small neighborhood differences in school effectiveness, with those from high-poverty neighborhoods attending schools with slightly lower average school effectiveness. Overall though, students from high-poverty and low-poverty neighborhoods are exposed to fairly similar distributions of school value-added.

In sum, the results across Figures 4.1-4.5 indicate that the primary differences in school context by neighborhood poverty are in school composition, with students from high-poverty neighborhoods having more exposure to Black, Hispanic, and impoverished peers than those from low-poverty neighborhoods, as expected given prevailing patterns of residential and school segregation. There is also evidence of modest differences in school climate by neighborhood poverty level, with children from high-poverty neighborhoods being less likely to attend schools where administrators feel supported by parents and community members, with high teacher morale, and with high daily attendance. There are few clear, consistent, or sizable differences by neighborhood poverty level in the resources, instructional practices, and effectiveness at the schools that students attend.

Figure 4.5. Neighborhood Poverty Differences in School Effectiveness



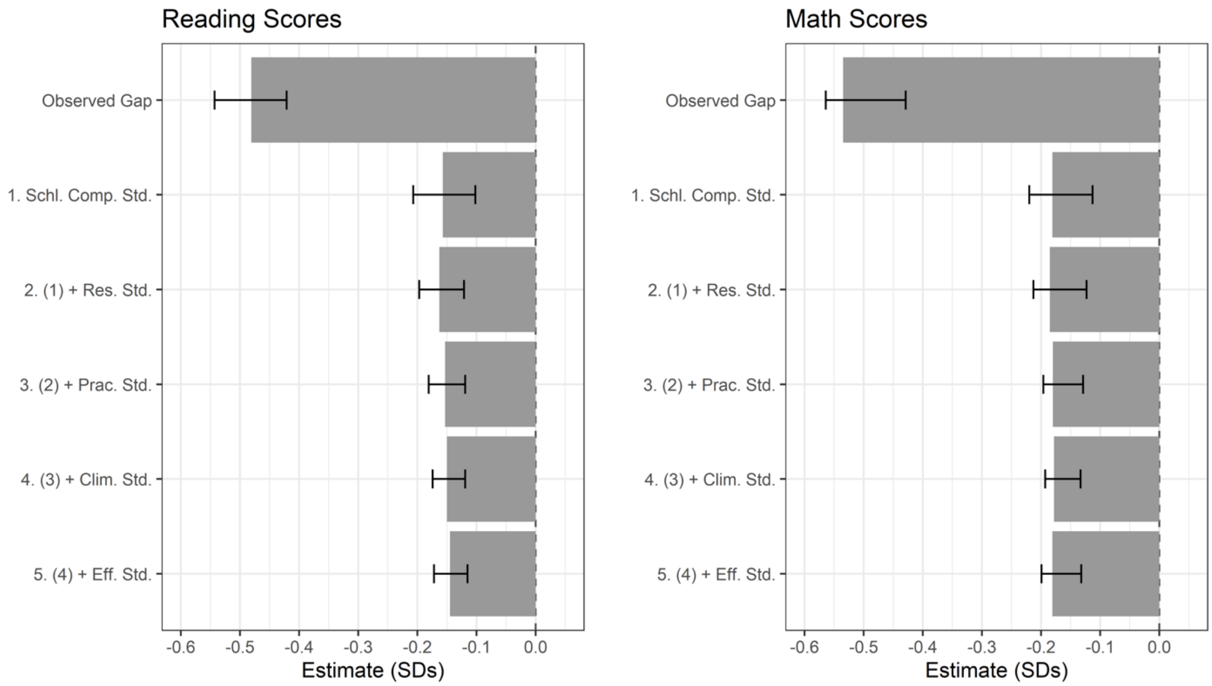
Notes: This plot contains kernel densities contrasting school effectiveness based on residence in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20%.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File.

The Contribution of School Context to the Neighborhood Test Score Gap

While the previous set of analyses explored observed differences in exposure to school context by neighborhood poverty, the subsequent analyses investigate the extent to which differences in school contexts account for neighborhood disparities in student achievement. To start, Figure 4.6 summarizes results from a descriptive decomposition of the unadjusted neighborhood test score gap. First, we present the observed gap in test scores, comparing students from high-poverty neighborhoods to those from low-poverty neighborhoods. In each of the subsequent gaps, we standardize those living in high- and low-poverty neighborhoods to have the same distribution of school context characteristics, starting with only adjusting the distribution for school composition, and successively adding each school context component until the final gap adjusts for school composition, school resources, instructional practices, school climate, and school effectiveness. Estimates are reported in standard deviation units and are computed by combining results from linear modeling, recursive partitioning, random forests, and gradient boosting using the "Super Learner" stacking algorithm. This is merely a descriptive, rather than causal, decomposition because we do not adjust for any baseline differences between students, their families, or neighborhoods at the time of school entry that may confound the effects of the school environment on their achievement.

Figure 4.6 indicates that observed reading and math test score gaps by neighborhood poverty are high. Children from high-poverty neighborhoods score about half of a standard deviation below those from low-poverty neighborhoods in both reading and math assessments. After equalizing the distribution of school composition across neighborhood poverty levels, the test score gap is reduced by about two-thirds. Successively standardizing each of the other four school context vectors does very little to further close the gap, suggesting that after taking into account school composition, the other 160 measures of school context do not seem to move the needle much at all. Equalizing exposure to all school context components statistically explains approximately 74% of the reading test score gap and 72% of the math test score gap by

Figure 4.6. Descriptive Decomposition of the Neighborhood Test Score Gap by School Composition, Resources, Instructional Practices, Climate, and Effectiveness



Notes: Estimates are reported in standard deviation units and are computed by combining results from linear modeling, recursive partitioning, random forests, and gradient boosting using a stacking algorithm super learner; they are combined across 5 imputations; confidence intervals are based on the [2.5, 97.5] percentiles simulated via the repeated half-sample bootstrap with 200 replications per imputation and include bootstrap bias correction. The estimates reflect demographic standardization. "Schl. Comp." denotes school composition, "Res." is school resources, "Prac" is instructional practices, "Clm" is school climate, and "Eff." is school value-added.

Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Table 4.1. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps in Test Scores

Estimands	Point Estimate	[2.5, 97.5] Percentile Bootstrap Interval
Reading Test Scores		
ObsGap	-0.480	[-0.543, -0.418]
ObsGap-CnfGap(All~tot)	-0.037	[-0.071, -0.004]
ObsGap-CnfGap(Comp~tot)	-0.017	[-0.044, 0.006]
ObsGap-CnfGap(Res~low)	-0.037	[-0.053, -0.018]
ObsGap-CnfGap(Prac~low)	-0.018	[-0.030, -0.007]
Math Test Scores		
ObsGap	-0.533	[-0.582, -0.437]
ObsGap-CnfGap(All~tot)	-0.021	[-0.045, 0.014]
ObsGap-CnfGap(Comp~tot)	0.007	[-0.015, 0.034]
ObsGap-CnfGap(Res~low)	0.038	[0.019, 0.055]
ObsGap-CnfGap(Prac~low)	0.020	[0.011, 0.037]

Notes: Estimates are reported in standard deviation units and are computed using g-computation, combining results from linear modeling, recursive partitioning, random forests, and gradient boosting using a stacking algorithm super learner; they are combined across 5 imputations; confidence intervals are based on the [2.5, 97.5] percentiles simulated via the repeated half-sample bootstrap with 200 replications per imputation and bootstrap bias correction. "ObsGap" stands for the observed gap, which contrasts residence in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20%. "ConfGap" stands for the counterfactual gap. Different vectors of school characteristics are represented, where "All" stands for all dimensions of school context, "Comp" stands for school composition; "Res" stands for school resources; and "Prac" stands for instructional practices. The first two counterfactual gap presented equalizes the distribution of all school characteristics at the marginal distribution among all students ("tot"). For the two subsequent counterfactual gaps, we set students residing in high-poverty neighborhoods to have the same distribution of the denoted vector(s) of school characteristics as those residing in low-poverty neighborhoods ("low").

Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

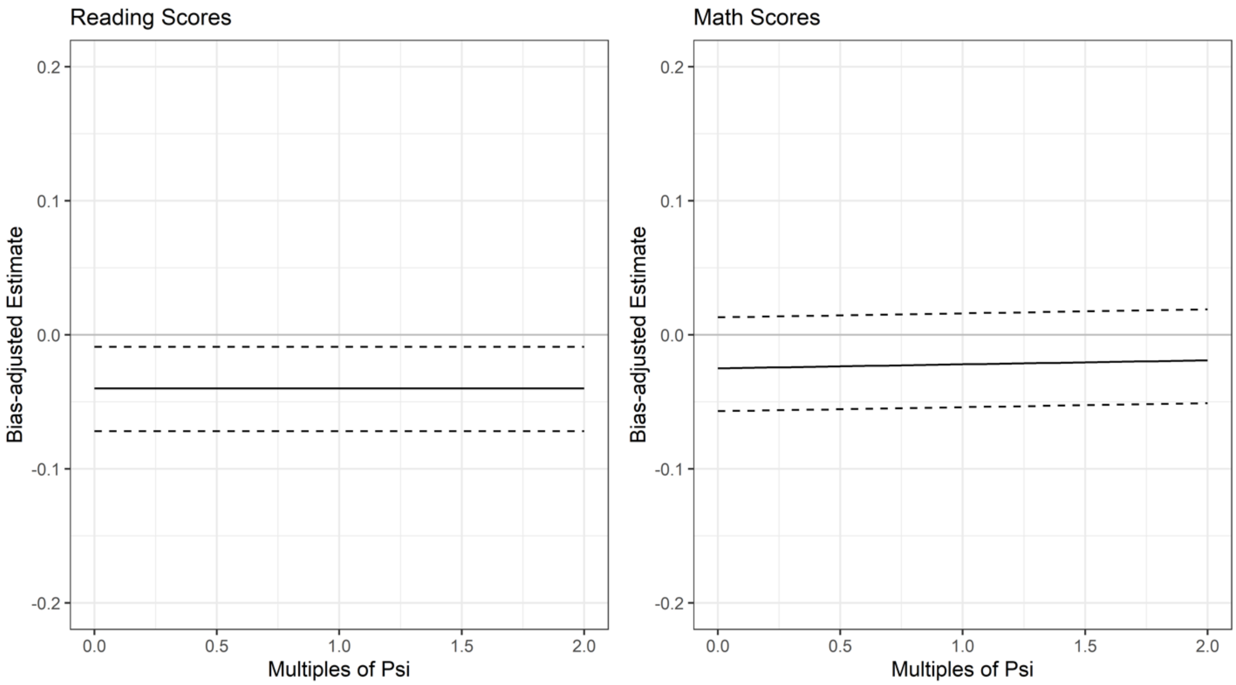
neighborhood poverty level. However, these results are purely descriptive, and do not adjust for potential confounding.

Table 4.1 presents point estimates (in standard deviation units) and 95% confidence intervals for the differences between the counterfactual and observed gaps in reading and math test scores under hypothetical interventions aimed at equalizing various components of school context. As outlined in the methods section, these hypothetical interventions include equalizing all school context components (emulating a strict school lottery), equalizing school composition (emulating a bussing program), equalizing school resources (emulating a finance equity reform), and equalizing instructional practices (emulating standardized instruction). All estimates adjust for a comprehensive set of baseline confounders, including baseline student achievement, as well as family and neighborhood characteristics at school entry.

The results suggest that equalizing the distribution of all school context components would reduce the neighborhood test score gap by 7.7% for reading (from -0.48 SDs to -0.44 SDs) and by 4.3% for math (from -0.53 SDs to -0.51 SDs). Although these reductions are nontrivial, they are much smaller than those indicated in the descriptive decomposition. Equalizing only school composition reduces the reading test score gap by 3.5% but has little effect on the math test score gap.

Equalizing school resources at the distribution observed among students from low-poverty neighborhoods decreases the neighborhood reading test score gap by 7.7%, mirroring the effect of the strict school lottery. However, this same hypothetical intervention is estimated to increase the math test score gap by 7.1%. One possible explanation for this counterintuitive result is that (naively) equalizing resources might unintentionally reduce access to resources that are more commonly present in schools serving those from high-poverty neighborhoods and that benefit them in particular, such as ESL teachers and school translators, even as it increases other school resources students from high-poverty neighborhoods are exposed to. Finally, providing

Figure 4.7. Bias-adjusted Estimates of the Difference between Observed and Counterfactual Gaps



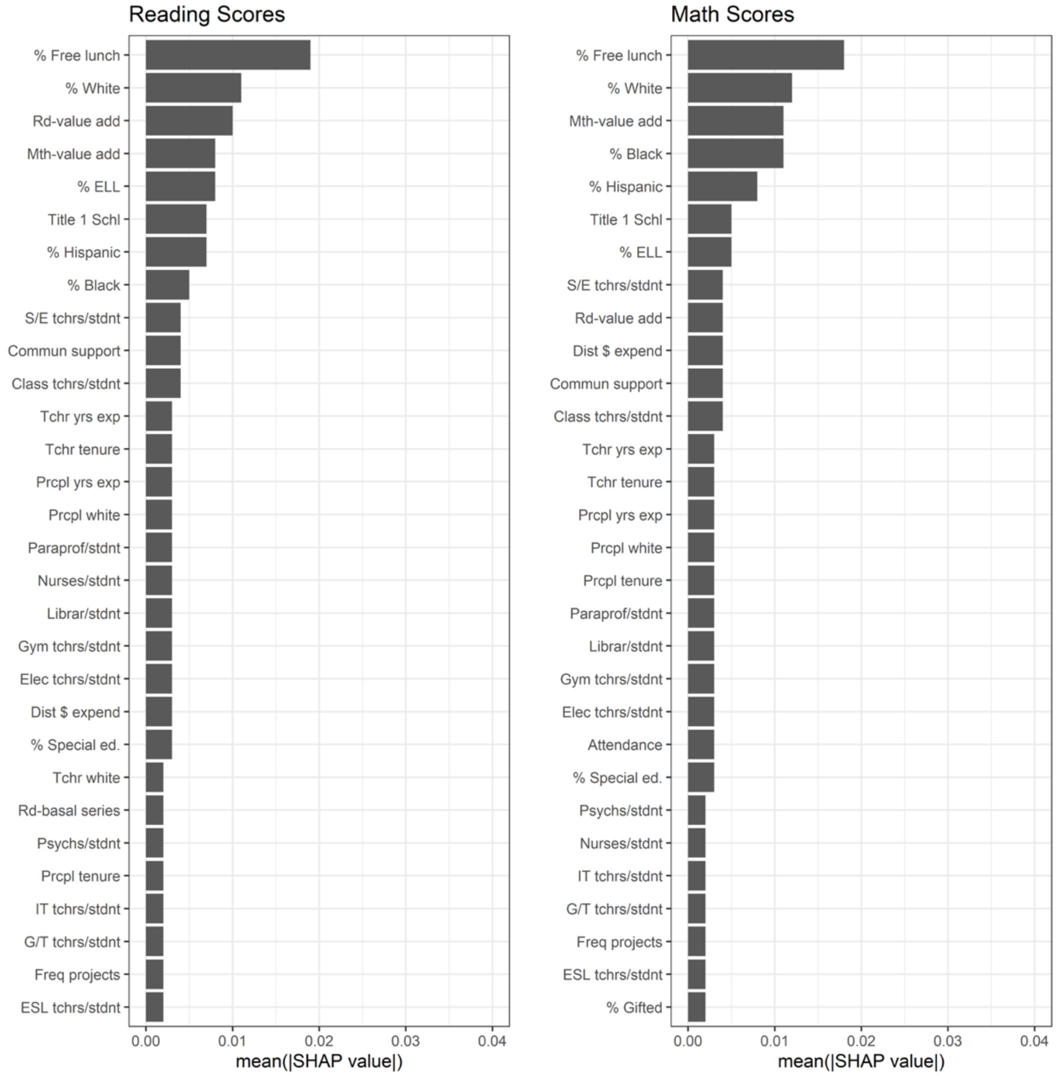
Notes: Estimates are reported in standard deviation units and are computed by combining results from linear modeling, recursive partitioning, random forests, and gradient boosting using a stacking algorithm super learner; they are combined across 5 imputations; confidence intervals are based on the [2.5, 97.5] percentiles simulated via the repeated half-sample bootstrap with 200 replications per imputation and bootstrap bias correction. The x-axis shows the difference if bias due to a hypothetical confounder was that many times as large as that from omitting SES from the model.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

students from high-poverty neighborhoods with exposure to the same instructional practices as those in low-poverty neighborhoods reduces the reading test score gap by 3.8% but increases the math test score gap by about the same percentage.

To assess the robustness of the results in the presence of omitted variable bias, Figure 4.7 presents a set of bias-adjusted estimates. These estimates adjust for hypothetical bias due to unobserved confounders whose confounding influence operates in exactly the same way as parental education, income, and occupation. Specifically, the x-axis represents multiples of the bias due to omitting a hypothetical covariate whose confounding influence emulates that of these three controls, which collectively capture family socioeconomic background. The y-axis shows the estimated difference between counterfactual and observed gaps in standard deviation units, after adjusting for this bias. The results indicate that for reading and math test scores, even if omitted variable bias is up to twice as large as that due to the confounding influence of family socioeconomic background, the estimated differences remain largely consistent, suggesting the results are fairly robust to unobserved confounding.

To further assess the robustness of our results, we conducted several additional checks. Table C3 in the appendix shows that the results remain substantively consistent when using fifth grade test scores instead of third grade test scores. Table C4 presents estimates using a neighborhood poverty threshold of 30% or higher for high-poverty and less than 30% for low-poverty, with results that are also substantively similar. Table C5 examines neighborhood disadvantage using an index that captures various factors in addition to neighborhood poverty, including racial and educational composition, female-headed households, and unemployment rate, comparing the top quintile of neighborhood disadvantage to those not in the top quintile, and finding that the results are also substantively consistent with the original results. Table C6

Figure 4.8. SHAP Values for Selected School Characteristics



Notes: This figure reports mean absolute SHAP values computed from random forests. Each random forest includes neighborhood poverty, the full set of controls, and the full set of school characteristics as predictors. Results are combined across 5 multiply imputed datasets.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

uses ECLS-K sampling weights, and shows there are a few differences, with the difference after equalizing school resources being smaller for reading test score gaps, about one-quarter the size of the original estimate. Additionally, for math test scores, the difference after adjusting for all school context components becomes larger. Finally, C7 details the point estimates and weight assigned to each model in the super learner for each of the main set of estimates.

While Figures 4.1-4.5 show the observed neighborhood poverty differences in each aspect of school context, next, to understand how each school context measure matters for reading and math test scores, Figure 4.8 presents the Shapley additive explanation (SHAP) values from random forests predicting reading and math test scores. The mean absolute SHAP values capture the predictive importance of each measure of school context, while also takinginto account any potential interactions and collinearities among them (Lundberg and Lee 2017). SHAP values are computed by comparing model predictions with and without each specific school context measure included. Larger differences in predictions thus indicate the greater predictive value of a specific measure. These comparisons are made over every possible combination of covariates and the differences are then averaged to produce each SHAP value. The top 30 SHAP values for both reading test score and math test scores are presented in Figure 4.8, while the full set of SHAP values for all 171 school context measures are presented in Appendix Figures C3 – C6.

The results suggest that of the 171 school context measures considered in the analysis, school poverty, racial composition, and value-added are the most important predictors of reading and math test scores in third grade. However, the importance of even these school context measures alone is relatively weak. For example, the mean absolute SHAP value for school poverty, the measure with the greatest predictive importance for both reading and math scores, is only about 0.02 standard deviations. Outside of these few specific aspects of school context, each of the other measures has a mean SHAP value that is less than 0.01 standard deviations. However, while the predictive importance of any single school context measure is low, it is

Figure 4.9. Marginal Effects of School Characteristics for Test Scores Classified Against the Marginal Effects of Neighborhood Poverty for Exposure to School Characteristics

Notes: The vertical axis displays standardized marginal effects for each school characteristic from a super learner combining estimates from linear modeling, recursive partitioning, random forests, and gradient boosting to predict test scores. On the horizontal axis, standardized marginal effects compare living in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20% for exposure to each school characteristic. Results are combined across 5 multiply imputed datasets.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

possible that collectively, some of these aspects of school context are still important for student achievement.

Next, to understand both the impact of each school characteristic on student test scores along with differences in observed exposure by neighborhood poverty level, Figure 4.9 presents a plot of marginal effects. The x-axis displays the standardized difference in each school characteristic comparing students from high-poverty versus low-poverty neighborhoods, while the y-axis shows the average marginal effects of each school characteristic on test scores. School context measures in the upper left or right quadrants of the plot are those with the largest marginal effects on test scores, coupled with the largest observed differences by neighborhood poverty level. The results show that there are not many single aspects of school context that both have large impacts on student test scores and that are substantially different by neighborhood poverty level. School average daily attendance has a small but nontrivial effect on math test scores (0.14 SDs), while also varying moderately by neighborhood poverty level (-0.28 SDs). Otherwise, the school context measures with the largest marginal effects on student achievement are estimates of school value-added, which do not differ much between schools serving high-poverty and low-poverty neighborhoods. School context measures that differ the most by neighborhood poverty level, such as aspects of school composition and climate, seem to have only very small marginal effects on student achievement. While specific measures of school composition do not have large marginal effects on achievement when considered individually, the results from Figure 4.6 and Table 4.1 suggest that they may matter slightly more when taken together. These results overall suggest that of the 171 measures of school context captured by this study, the majority do not vary much by neighborhood poverty and do not have large individual effects on student achievement. Further, even after taking into account the dimensions of school composition, resources, instructional practices, and climate, measures of school value-added still have the largest marginal effects on student than any more specific aspect of the school context.

Discussion

It is widely theorized that neighborhood disparities in student achievement stem from differences in the quality of elementary schools that students attend (Jencks and Mayer 1990; Leventhal and Brooks-Gunn 2000). However, prior empirical studies have failed to find substantial evidence supporting this theory (Wodtke et al. 2023; Wodtke and Parbst 2017). In this study, we build on this research by adopting a more comprehensive approach to assess whether neighborhood poverty gaps in student achievement can be explained by differences in the schools that students are exposed to, considering the school context as a whole rather than individual measures of school quality. Using nationally representative data on elementary students from the ECLS-K 2011, we examined 171 distinct features across five components of school context: composition, resources, instructional practices, climate, and effectiveness.

Our findings reveal that differences in school contexts contribute only marginally to disparities in student achievement between children from high- and low-poverty neighborhoods. Even with an expansive set of school measures, we estimate that equalizing the distribution of these characteristics between students from high- and low-poverty neighborhoods would reduce reading and math test score gaps by just 4% to 8%. Consistent with previous research, we find that the reason for these results is that the aspects of school context most influential for student achievement vary little by neighborhood poverty level, while those that do vary across high- versus low-poverty neighborhoods have small effects on achievement (Wodtke et al. 2023;

Wodtke and Parbst 2017). Our findings challenge the institutional resource theory, and suggest that factors outside of the school context likely play a more significant role in explaining neighborhood disparities in student achievement. Indeed, an emerging strand of research has found that environmental factors partially mediate the effects of neighborhood disadvantage on child development (Schachner and Wodtke 2023a; Wodtke et al. 2022). Future research should explore the contribution of other factors, like the contribution of parents, exposure to violent crime or differences in access to other neighborhood resources like health care or early childhood education (Jencks and Mayer 1990), to fully understand contributors and potential solutions to neighborhood inequalities in student outcomes.

Beyond finding that school context contributes only minimally to neighborhood disparities in student test scores, our results also challenge prevailing assumptions in the literature that schools serving students from high-poverty neighborhoods are lower in quality. Our findings indicate that in first grade, many aspects of the school context are very similar across neighborhoods, particularly in areas such as school resources and instructional practices. The main differences present are in the demographic makeup of students and staff, in select resources that schools appear to proactively tailor to meet the needs of students based on their demographic composition, and in the perceived climate of the school. Consistent with findings from Wodtke et al. (2023), we find there are not meaningful differences in school value-added between schools serving high-poverty and low-poverty neighborhood students. These findings challenge the common assumption that schools in high-poverty neighborhoods are lower in quality.

Although schools appear to play only a modest role in shaping neighborhood disparities in student achievement, and they don't differ uniformly across neighborhood poverty levels in their resources and instructional practices, they may still be part of the solution. Our analysis only considered the effects of equalizing school contexts, but this approach overlooks the reality that students from disadvantaged neighborhoods may require more than just equal resources – they may need additional, targeted support to close the achievement gaps with their more advantaged peers (Owens and Candipan 2019). For instance, our findings indicate that when instructional practices, such as math instruction time, or school resources, like access to ESL teachers and translators, which were initially higher for students from disadvantaged neighborhoods, are equalized, the math test score gap widens. This suggests that simply leveling the playing field is insufficient, as it overlooks the ways that students from high-poverty neighborhoods may benefit from additional, targeted, or different resources altogether. There is a growing recognition that addressing the unique and varied needs of students requires tailored resources and interventions, rather than a one-size-fits-all approach like equalizing school contexts for those coming from unequal backgrounds (Gamoran 2001; Jackson, Johnson and Persico 2016).

In this study, we also introduce novel methods for analyzing the contribution of schools to neighborhood disparities in student achievement. While many studies examine the combined effects of neighborhoods and specific school inputs on student outcomes (Ainsworth 2002; Card and Rothstein 2007; Carlson and Cowen 2015) or describe differences in school quality by neighborhood (Owens and Candipan 2019), they often do not explicitly isolate the effects of schools on neighborhood disparities. Other research focuses on how neighborhood effects are transmitted through school quality using a mediation framework (Wodtke et al. 2023; Wodtke and Parbst 2017). Our approach is different; in line with the work of (Lundberg 2022), we use a gap-closing framework to assess whether equalizing school contexts across neighborhoods can reduce achievement disparities between those from high- and low-poverty neighborhoods. Instead of asking how neighborhood disadvantage leads to poorer school quality, which in turn may harm student learning, we evaluate whether different types of school interventions could close these achievement gaps. Additionally, we apply a novel method by using random draws from an empirical distribution to approximate the range of school context variables across neighborhoods in different hypothetical interventions.

While this study has important implications, it is not without limitations. The first is that while we rely on a fairly robust set of school context measures, it is possible that we are still missing important aspects of the school that are difficult to capture with survey data. For example, scholars have argued that variation in teacher quality is often not captured by the teacher characteristics measured in either administrative data or survey data (Jennings and DiPrete 2010), and the same could be true for school effects. However, in recognition of this fact, in addition to 169 distinct features of the school context, we also considered two measures of school outputs, or school value-added, for math and reading learning, in order to pick up on other unmeasurable aspects of the schools that may impact student learning, and still find that schools do not contribute substantially to neighborhood disparities in test scores.

A second limitation is the potential finite sample bias from our estimation approach. Machine learning estimators, like the SuperLearner algorithm, are meant to improve predicted accuracy and are consistent with large samples, though there is a risk of bias in more moderately sized samples. In this study, even with a sample of more than 20,000 students, it's possible that the convergence to the target estimate might be slower than is optimal, which could lead to bias. To try to mitigate bias, we employed bootstrap bias correction methods for the confidence intervals, though it's not clear that this is enough to fully resolve potential bias associated with machine learning plug-in estimators. Future research should explore other advanced methods like de-biased machine learning (DML) to further address potential bias. These methods are not currently developed for gap-closing estimands with a high-dimensional set of exposures, like the one used in this study.

A third limitation is that our data focuses on differences in school contexts during first grade. It is likely that schools' role changes as children progress through the system (Gamoran and An 2016), and that the school environments that students experience in younger grades are more standardized across schools when students are learning basic information like how to read. On the other hand, as curricular differentiation and stratification increasingly occurs during the middle school and high school grades (Lucas 2001), there could be more opportunity for neighborhood differences in school quality to emerge. As a result, it will be important for future research to explore whether these findings hold in older grades.

A fourth consideration is that our data focuses on neighborhood-poverty test score disparities, exploring the contributions of schools to test score gaps between high-poverty and low-poverty neighborhoods. As such, this work does not address the entire spectrum of neighborhood socioeconomic disparities. It's possible that schools contribute more to disparities between the most elite, high-income neighborhoods, and the rest. Future research should further explore this possibility.

It is important to identify interventions that could reduce the persistent neighborhood achievement gaps. While scholars commonly hypothesize that schools contribute to neighborhood-based disparities, our findings show that equalizing the school contexts that students from different neighborhoods are exposed to is not enough to meaningfully reduce neighborhood poverty gaps in student achievement. Further exploring other potential contributors and solutions, like exposure to violent crime or unequal access to other neighborhood resources like health care or early childhood education is a crucial next step for research in the neighborhood effects literature.

Chapter 5

Concluding Thoughts

In this dissertation, I set out to explore socioeconomic inequality in educational outcomes across various stages of the educational pipeline in the United States, paying particular attention to the roles of family, neighborhood, and school contexts. Drawing on a combination of sociological theories – particularly the social reproduction theory (Bourdieu and Passeron 1990) the institutional resource theory (Jencks and Mayer 1990), and the theory of effectively maintained inequality (Lucas 2001) – this research seeks to deepen understandings of how intersecting contexts may contribute to the reproduction of inequality during the early stages of schooling and how the family context remains salient during the later stages. Through three distinct but interconnected empirical studies, this dissertation offers new insights into the levers underlying these disparities and suggests potential pathways for reducing socioeconomic inequality. Findings from each chapter reveal the complexity of educational inequality, demonstrating how early disadvantages continue over time, and highlighting the increase in educational disparities across the decades in the United States.

Overview of Findings

The empirical chapters explore different dimensions of socioeconomic inequality across key educational stages. In Chapter 2, I analyzed long-term trends in socioeconomic disparities in college application and enrollment, revealing widening gaps, particularly in access to 4-year and selective colleges. This underscores the importance of taking into account horizontal stratification in higher education, as the level and quality of the institutions students attend can significantly shape their post-graduation outcomes (Gerber and Cheung 2008).

Chapter 3 extends the analysis by exploring how financial information – or the lack thereof – contributes to socioeconomic disparities in college application behavior. The findings reveal that targeted interventions, such as providing both students and their parents with accurate financial information, can reduce gaps in perceived affordability and in 4-year college application rates. However, this type of intervention appears less effective in addressing disparities in selective college application, highlighting the limits of light-touch interventions for more entrenched forms of inequality.

In Chapter 4, coauthored with Geoffrey T. Wodtke, I go backward in the educational pipeline to the early elementary years. We explore how the school context contributes to neighborhood poverty disparities in student achievement. Contrary to common beliefs that schools serving high-poverty neighborhoods are uniformly low in quality, the empirical findings in this chapter suggest that differences in school contexts play only a minimal role in explaining neighborhood achievement gaps. This suggests that factors outside the school environment may have a greater influence on early student disparities.

Theoretical Contributions

The theoretical framework and empirical findings in this dissertation can contribute to understandings of how social inequalities are reproduced across generations through educational outcomes. In the social reproduction theory, schools are thought to perpetuate social inequalities by providing unequal access to resources and quality instruction (Bourdieu and Passeron 1990). In the neighborhood effects literature, the institutional resource theory posits that schools are a mechanism through which neighborhood disadvantages shape educational outcomes, especially during the early years of schooling (Jencks and Mayer 1990). Findings in Chapter 4 of this dissertation, however, challenge the extent to which schools explain neighborhood-based achievement gaps. Even after examining more than 170 distinct aspects of the school context – including composition, resources, instructional practices, climate, and overall effectiveness – differences in schools do not meaningfully explain achievement gaps between high- and low-poverty neighborhoods.

This calls into question the weight of the institutional resource theory in explaining neighborhood inequalities in student outcomes. While the institutional resource theory is commonly drawn on, the results here suggest two possible theoretical interpretations. First, it could be that equalizing school contexts for students coming from unequal backgrounds is simply not enough to close achievement gaps. In other words, schools, even when made more equal in terms of resources and instructional practices, may not be able to fully compensate for the disadvantages students face outside of school. Instead, it's possible that students from poor neighborhoods may need additional, tailored resources (Owens and Candipan 2019) – suggesting that equity, rather than equality, could be the more meaningful goal for reducing disparities in educational outcomes. Alternatively, it could be that school contexts themselves are not the most significant path for reducing disparities. Other neighborhood-level factors – such as exposure to violent crime, environmental toxins, or access to healthcare – might exert a stronger influence on early student achievement. These findings suggest the need for scholars to rethink the emphasis placed on school improvement as the primary strategy for addressing neighborhood disparities in education. A more holistic approach, which considers both school-based determinants and broader environmental factors, may be required to fully understand drivers – and potential solutions – to these achievement gaps.

Beyond contributing to understandings of the institutional resource theory, these findings also have implications for understandings of the role of parental choice in residential selection and school quality. Scholars have argued that higher-income parents strategically select neighborhoods of residence with higher-quality schools to ensure their children receive a better education, thus reinforcing socioeconomic advantages (Berends 2015). However, the findings here suggest that while elementary schools in wealthier neighborhoods may differ in composition and culture, these differences do not always translate into meaningful variations in resources, instructional practices, or the overall effect of the school on student learning. This may indicate that parents are not as successful at selecting high-quality schools based within neighborhoods as often assumed. Instead, they may be relying on superficial markers of school quality, such as the racial or socioeconomic makeup of students, or the school's reputation, rather than factors that directly impact the quality of education students receive.

Social reproduction also operates at later stages in the educational pipeline. A critical contribution of this dissertation is the argument that to understand postsecondary inequalities, we must move beyond solely considering vertical stratification – whether students attend college at all – to also examining horizontal stratification – where students enroll and the quality of education they receive. Findings in Chapter 2 suggest that this shift is essential for accurately capturing the reproduction of inequality in educational outcomes. This work builds upon the theory of effectively maintained inequality, developed by Lucas (2001), which posits that even if access to education expands, social inequalities may persist through stratification within that level of the education system. Traditionally, effectively maintained inequality has focused on how inequalities shift from whether students attend high school to the kind of education they receive within the high school context, where curricular tracking channels students into different academic pathways in ways that are tied to their socioeconomic background. I argue that this theory is also relevant for understanding inequality in postsecondary education as well. While increasing numbers of students across socioeconomic backgrounds now enroll in college, inequalities in postsecondary education have actually widened over the decades when considering horizontal stratification, or where students apply and enroll. Even as socioeconomically disadvantaged students increasingly access postsecondary education, they are more likely to enroll in less selective institutions, such as 2-year colleges or non-selective 4-year colleges, than their more advantaged peers. This distinction in institutional type and selectivity plays a critical role in the reproduction of social inequalities, as more selective colleges tend to offer better resources, career networks, and long-term economic returns (Hoxby 2009). This dissertation further underscores the importance of considering not just college enrollment but also college application behaviors, which provide more clarity on the timepoints at which disparities are most salient.

In this dissertation, I also contribute to the theoretical literature by exploring the role of information in shaping the ways that social inequalities are reproduced in the postsecondary education system in Chapter 3. According to the social reproduction theory, unequal access to information is a key determinant of educational outcomes (Bourdieu 1986). Going all the way back to Bourdieu's concept of cultural capital (Bourdieu 1986), scholars have argued that middle and upper class families possess knowledge and general educational know-how that allows them to navigate the school systems more effectively. In the college application setting, information becomes a form of capital that high-SES families are more likely to have and use to optimize their children's educational trajectories (George-Jackson and Gast 2015; Perna 2006a; Plank and Jordan 2001). This dissertation builds on the theoretical literature by demonstrating that high

SES parents have more knowledge about college attendance costs and financing than low SES parents and are able to draw on more diverse sources for financial aid information, which plays a meaningful role in shaping inequalities in students' college application behaviors when it comes to the decision to apply to 4-year versus 2-year colleges.

However, I find there are limits to the role of information as an equalizing mechanism in the social reproduction of educational inequalities. In the literature, information is often treated as a straightforward solution – something that, when increased, should reduce disparities. However, the findings here complicate that narrative. In the case of selective college applications, increasing information about college costs and financial aid for families does not close the SES gap, and in fact, slightly widens it. Students from more socioeconomically advantaged families may be better equipped to leverage information about college costs in ways that maximize their children's educational outcomes. This could be due to their stronger social networks, higher levels of familiarity with navigating complex bureaucracies, and greater financial resources that allow them to interpret and act upon the information they receive (Bourdieu 1986). Thus, while increasing access to information is often viewed as a potential equalizer in the social reproduction literature, this dissertation suggests that information is not always enough on its own to reduce inequalities, and may, in some cases, exacerbate them by further advantaging those who already possess the capital necessary to make the most of it.

Finally, this dissertation contributes to the literature by demonstrating the importance of student-parent alignment in information for shaping educational decision-making. The social reproduction theory heavily emphasizes the role of parents and how they pass on knowledge directly to their children. However, in this dissertation, I find that information gaps between low and high SES students is smaller than the corresponding gaps among parents. Students from less socioeconomically advantaged backgrounds may play a more active role in collecting information about college attendance to make up for the fact that their parents don't already have that knowledge. My findings suggest that even when students or parents alone have knowledge, the misalignment between student and parent knowledge can constrain the ability of students to fully leverage that information when making critical decisions about education continuation. This finding deepens our understanding of the social reproduction theory by revealing that intra-family dynamics, and particularly the congruence between student and parent knowledge, can be an important factor through which educational inequalities are perpetuated or alleviated. This suggests that beyond the linear transfer of resources from parents to children, there can be more complex interactions of shared and unshared knowledge that shapes decision-making processes and educational trajectories.

In addition to the above theoretical contributions, this dissertation also offers important methodological advancements for the study of educational gaps. By employing survey data and gap-closing estimands in Chapters 3 and 4, I provide a more nuanced approach to understanding how socioeconomic disparities manifest in educational outcomes. Unlike traditional causal mediation methods, which are often limited by the need to estimate accurate total effects that can then be decomposed into direct and indirect pathways, gap-closing estimands allow for the estimation of how much a given disparity would close if certain contextual factors were equalized (Lundberg 2022), which is particularly valuable for policy-relevant research, as it provides clearer insights into how interventions – such as improving school quality or increasing financial knowledge – could impact educational inequalities.

Further, by integrating machine learning approaches into the causal decomposition analysis, this dissertation goes beyond standard regression-based approaches by allowing a more robust exploration of the potential mechanisms driving these disparities. In chapter 4, we are able to consider the contribution of more than 170 distinct aspects of the school context, for example, offering an empirical approach for taking into account the full conceptual model that comprises the school context. This methodological framework has the potential to be adopted by sociologists seeking to study complex social phenomena.

Limitations and Future Research Directions

While the work in this dissertation provides important contributions, it is important to acknowledge some key limitations. The first limitation is that I rely on observational designs for all three empirical chapters. While there are some advantages to using observational designs, like the ability to study large, nationally representative samples, there are also challenges to estimating causal effects. As a result, there could be potential confounding that biases the main effect estimates.

For example, in Chapter 3, I explored how financial information contributes to college application gaps. It is possible that unobserved characteristics, like parental motivation, parental social networks, or peer influences shape both parental access to financial information and students' decisions about college. In Chapter 4, I explored how school contexts contribute to neighborhood achievement gaps. In this setting, it's possible that unobserved characteristics, like parental involvement, could impact both the quality of neighborhood schools that students attend and their academic achievement.

To attempt to address these limitations, I used machine learning approaches in Chapters 3 and 4, which allow me to include more potential confounders in the main models. However, survey data does not necessarily measure all potential confounders, and so there is still the potential for omitted variable bias. In both chapters, I ran sensitivity analyses, which show that the impact of omitted variables would have to be large to meaningfully change the main results. Observational designs could also result in selection-bias, where individuals who select into certain groups may differ in meaningful ways from those who don't. For example, parents who seek out financial information or who choose to have their child attend local elementary schools might differ in important ways from parents who do not, which makes it difficult to isolate the effects of receiving information or attending a specific school from pre-existing factors.

While observational methods relying on survey data have some limitations in comparison to randomized controlled trials, which allow researchers to more clearly isolate causal relationships, there are still key advantages and the contributions from this dissertation are still valuable. Observational designs often provide the most practical approach for studying important inequalities, especially when experiments would be unfeasible. Future research on educational disparities would benefit from a combination of experimental, quasi-experimental, and observational approaches to understand mechanisms at play behind educational inequalities.

A second limitation is the narrow focus of this dissertation when it comes to understanding contextual effects on postsecondary educational disparities. While Chapter 4, focused on elementary school academic achievement disparities considers multiple, interrelated contexts, including the family, neighborhood, and school, Chapter 3 which explores disparities in access to college focuses exclusively on the family context, and concentrates on a limited set of measures related to financial information disparities. This narrow focus may overlook other critical aspects of the family context that are important, but also misses how other contexts, like the neighborhood or school may matter for college disparities. While Chapter 4 found that the school context did not meaningfully contribute to neighborhood disparities in early academic achievement, this may be due to the fact that elementary schools are typically more standardized in terms of curriculum and instruction, which leaves less room for variation across neighborhoods. In elementary school, especially kindergarten and 1st grade, the focus is often on building more basic skills, like learning to read and write, and as a result, there may be less curricular differentiation (Duncan and Magnuson 2011). However, as students start high school, it's possible that the role of schools may become more important, especially as there are increasing differences in resources, curricular tracks, and college preparation resources, which can shape student outcomes. High schools serving more advantaged students tend to offer a wider variety of advanced placement courses, college counseling resources, and extracurricular opportunities that can improve a student's chances of navigating the college application process (Reed et al. 2023). This variability in school resources and supports could help shape disparities in postsecondary pathways, but could also be a key lever for reducing socioeconomic inequalities. Thus, while I find in Chapter 4 that the school context does not play a meaningful role in shaping neighborhood disparities in academic achievement, this does not necessarily mean that the school context is unimportant for shaping educational disparities, and future research should consider whether variation in the school contexts students are exposed to during high school shape inequalities in their postsecondary pathways.

A third limitation is that while this dissertation offers important insights into disparities in access to higher education, I do not explore what happens after students enroll in college. Many socioeconomically disadvantaged students initially start at community colleges with the goal of transferring to a 4-year college (Schudde and Goldrick-Rab 2015), and that is not something I'm able to account for in this dissertation. At the same time, prior research shows that many students who initially start at a community college do not ever transfer, even if they initially planned to do so (Schudde and Brown 2019). However, community colleges can provide students with the opportunity to avoid accruing large amounts of student loan debt by starting at a more affordable college, so it would be misleading to characterize enrollment in a community college as being necessarily a "bad" choice. Future research should further unpack this, and explore the financial and educational trade-offs that students make when deciding where to attend college.

Beyond the lack of consideration of transfer rates, this dissertation also does not explore graduation from college, despite the fact that the attainment of a degree, versus merely attending, is what confers long-term benefits (Hout 2012). Many students who initially attend college do not ever finish a degree, and some take on student loan debt in the process. As a result, future research should expand upon this work by exploring socioeconomic disparities in college graduation rates as part of the exploration of trends in socioeconomic gaps across the decades and conversations about moving the needle on the social reproduction of inequality.

A final limitation is that this dissertation relies solely on quantitative methodologies. While quantitative approaches provide important insights into broad patterns and the estimation of contextual effects on socioeconomic disparities, they may miss more rich nuances into factors that shape student experiences of inequality. For example, the reliance on survey data alone can reduce complex social processes to oversimplified quantitative measures, like "college financial information," and may overlook more nuanced pictures of what's behind that. Outside of a few noteworthy examples (McDonough 1997), research in this field tends to rely primarily on quantitative data. Future research should incorporate a mixed-methods approach, incorporating both quantitative and qualitative data, to provide a deeper understanding of drivers behind educational disparities and to unpack the complicated ways that students and their parents make decisions about future education.

Policy Implications

Despite these limitations, the findings from this dissertation offer several important policy implications, particularly regarding the need for multifaceted interventions that target both early educational disparities and persistent inequalities in postsecondary access. While education policymakers often focus on improving the schools that students attend, the findings here suggest that addressing early educational disparities will require a more holistic approach, one that goes beyond improving school quality alone. While equalizing resources across schools is important, the evidence from Chapter 4 indicates that such interventions are not enough to meaningfully reduce achievement gaps between students from high- and low-poverty neighborhoods. Instead, targeting additional, personalized resources to students from more disadvantaged backgrounds could be more effective in reducing disparities (Gamoran 2001). This perspective recognizes that students from lower-income families may face greater challenges and require more than just equal school contexts to catch up with their more advantaged peers. For example, students from high-poverty neighborhoods may benefit from enhanced support in areas like tutoring, mental health services, and family engagement programs to overcome the compounded barriers they currently face both inside and outside the classroom. However, the results also suggest that policymakers should broaden their focus to address neighborhood-level factors that contribute to educational inequality outside of the school setting. Recent research suggests that factors like exposure to violent crime (Burdick-Will et al. 2011) and to environmental toxins (Schachner and Wodtke 2023a; Wodtke et al. 2022) are important mediators through which neighborhood disadvantage leads to lower educational outcomes. As a result, it is important to target factors outside the school setting that research shows have more meaningful effects on these gaps.

To effectively address educational inequalities at later stages in students' academic journeys, policymakers must pay particular attention to the issues of horizontal stratification within higher education. Horizontal stratification refers to disparities that exist not just in whether students access higher education, but where they enroll. While policies aimed at expanding access to overall college enrollment and the emergence of low-cost options for college attendance increased enrollment in college generally, they overlooked the importance of ensuring that socioeconomically disadvantaged students gain access to not just the same level of education, but also the same quality of postsecondary educational opportunities as their more advantaged peers, which should be taken into consideration.

This dissertation also shows the importance of focusing policy efforts on the college application stage. While student achievement gaps are important to target and can affect college possibilities, this research shows that socioeconomic gaps remain even after taking into account academic preparation, and that inequalities in college enrollment outcomes are largely a result of differences in where students decide to apply. This is despite the fact that, over the decades, the majority of students and their parents have consistently aspired for students to attain a bachelor's degree, indicating that this issue extends beyond differences in values and priorities regarding college attendance.

One particular light-touch intervention that this dissertation finds could be a cost-effective way to lower the 4-year college application gap is providing students and their families with financial information about college. However, while this type of information-based intervention could slightly reduce the gap in 4-year college enrollment generally, it appears to be less effective when it comes to selective college enrollment. More comprehensive and robust policies – such as those that provide financial incentives, increase mentorship, or enhance college counseling – may be better suited to fully addressing disparities in access to elite institutions. However, this dissertation only considered very general information about college costs, but it's possible that interventions providing even slightly more customized information about net college costs after taking into account likely financial aid receipt could be more effective.

Final Thoughts

This dissertation highlights the persistent nature of socioeconomic disparities in education. By considering educational disparities across different time points in the educational pipeline – ranging from early academic achievement in elementary school to inequality in access to college – this dissertation makes clear that solving educational inequality will require interventions that take into account specific, and sometimes intersecting, contexts that students are exposed to and that can shape their educational opportunities in complex ways. This dissertation contributes to sociological theories on the intergenerational reproduction of social inequalities and underscores the importance of interventions targeting socioeconomic inequalities present at both the early and later stages of schooling.

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Appendix A. Supplementary Material for Chapter 2

Table A1. NCES Variables

	NLS 1972	HS&B 1982	NELS 1992	ELS 2004	HSLS 2014
College enrollment	fq82b, fq83b, fq84b	y4203b01, y4203d01	typdegct, delay	f2ilevel f3pstiming	fice_c1, s3clglvl
College application	fq82aa, fq83ab, fq84ab	y4203a01, sy14a1, sy14a2	refipeds, f2s60b1, f2s60b2	f2iiped, f1s51cd1, f1s51cd2	s3clgid, s3clgappid1, s3clgappid2
High school graduation	fq3b	sy12	f4hsdipl, f4dhsg	f2f1hsst	x3hscompstat
High school GPA	hsgrades	hsgrades	f2rgpa	f1ragp	x3tgpatot
College entrance exam	srfq2a, srfqd	fy8a, satm, satv, actcomp	f2s44b, f2s44c	f1s21c, txsatm	s2satnum, x3txsatcomp,
College cost priority	bq68a	fy123a	f2s59a	f1s52a	s2costattend
Academic reputation priority	bq68d	fy123d	f2s59l	f1s52k	s2reputation
Close to home priority	bq68k	fy123g	f2s59f	f1s52f	s2closehome
Parent bachelor's aspirations	bq91a, bq91b	fy81	f2s42a, f2s42b	f1s43a, f1s43b	p2eduasp
Student bachelor's expectations	bq29b	sexp10, sexp12	sexp10, sexp12	sexp10, sexp12	x2stuedexpct
Student on-time expectations	bq81	fy87f	f2s49	f1s45	s2clg2013
Socioeconomic status	sesraw	byses	byses	byses1	x1ses

Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09).

Table A2. College Enrollment Point Estimates and Confidence Intervals for SES Gaps

	Any enrollment	4-year enrollment	Selective enrollment	Conditional 4-year enrollment	Conditional selective enrollment
NLS 1972					
Point estimate	38.16	26.29	8.87	13.87	11.55
Lower 95% C.I.	37.55	25.74	8.55	13.22	11.02
Upper 95% C.I.	38.76	26.84	9.18	14.52	12.08
HS&B 1982					
Point estimate	40.87	33.47	10.81	19.41	17.45
Lower 95% C.I.	40.14	32.79	10.42	18.63	16.85
Upper 95% C.I.	41.61	34.16	11.21	20.18	18.06
NELS 1992					
Point estimate	41.39	44.36	21.43	31.70	20.60
Lower 95% C.I.	40.58	43.58	20.83	30.91	19.80
Upper 95% C.I.	42.20	45.13	22.02	32.49	21.41
ELS 2004					
Point estimate	36.18	43.28	28.11	33.27	27.60
Lower 95% C.I.	35.49	42.59	27.53	32.55	26.87
Upper 95% C.I.	36.87	43.98	28.70	33.99	28.33
HSLS 2014					
Point estimate	35.64	43.86	31.21	31.42	31.69
Lower 95% C.I.	35.12	43.30	30.74	30.84	31.12
Upper 95% C.I.	36.17	44.42	31.68	31.99	32.27

Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Table A3. College Application Point Estimates and Confidence Intervals for SES Gaps

	4-year application	Selective application
NLS 1972		
Point estimate	26.95	13.25
Lower 95% C.I.	26.38	12.86
Upper 95% C.I.	27.52	13.65
HS&B 1982		
Point estimate	37.19	17.23
Lower 95% C.I.	36.48	16.73
Upper 95% C.I.	37.91	17.73
NELS 1992		
Point estimate	47.48	29.91
Lower 95% C.I.	46.70	29.21
Upper 95% C.I.	48.27	30.61
ELS 2004		
Point estimate	43.11	36.73
Lower 95% C.I.	24.40	36.07
Upper 95% C.I.	43.82	37.39
HSLS 2014		
Point estimate	38.99	38.98
Lower 95% C.I.	38.43	38.44
Upper 95% C.I.	39.56	39.51

Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations.

Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09).

Table A4. Academic Preparation Point Estimates and Confidence Intervals for SES Gaps

	High school graduation	Took college entrance exam	High school GPA of 3.0 or higher
NLS 1972			
Point estimate	39.53	15.28	6.69
Lower 95% C.I.	38.93	14.64	6.16
Upper 95% C.I.	40.13	15.93	7.22
HS&B 1982			
Point estimate	30.61	23.80	15.81
Lower 95% C.I.	29.84	23.04	15.24
Upper 95% C.I.	31.39	24.55	16.38
NELS 1992			
Point estimate	47.22	28.62	18.34
Lower 95% C.I.	46.46	27.77	17.78
Upper 95% C.I.	47.99	29.48	18.90
ELS 2004			
Point estimate	44.05	34.03	16.25
Lower 95% C.I.	43.38	33.30	15.77
Upper 95% C.I.	44.72	34.76	16.73
HSLS 2014			
Point estimate	23.14	37.34	13.23
Lower 95% C.I.	22.56	36.76	18.88
Upper 95% C.I.	23.71	37.91	13.58

Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Table A5. College Priorities Point Estimates and Confidence Intervals for SES Gaps

	College costs	Academic reputation	College near home
NLS 1972			
Point estimate	-24.38	14.15	-17.34
Lower 95% C.I.	-25.01	13.56	-17.92
Upper 95% C.I.	-23.75	14.75	-16.77
HS&B 1982			
Point estimate	-16.45	15.29	-15.96
Lower 95% C.I.	-17.24	14.49	-16.65
Upper 95% C.I.	-15.65	16.08	-15.27
NELS 1992			
Point estimate	-16.29	19.12	-17.94
Lower 95% C.I.	-17.10	18.24	-18.64
Upper 95% C.I.	-15.48	20.00	-17.25
ELS 2004			
Point estimate	-20.70	15.27	-21.95
Lower 95% C.I.	-19.97	14.50	-22.60
Upper 95% C.I.	-19.23	16.04	-21.30
HSLS 2014			
Point estimate	-14.71	12.04	-14.74
Lower 95% C.I.	-15.29	11.51	-15.27
Upper 95% C.I.	-14.12	12.58	-14.21

Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations.
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

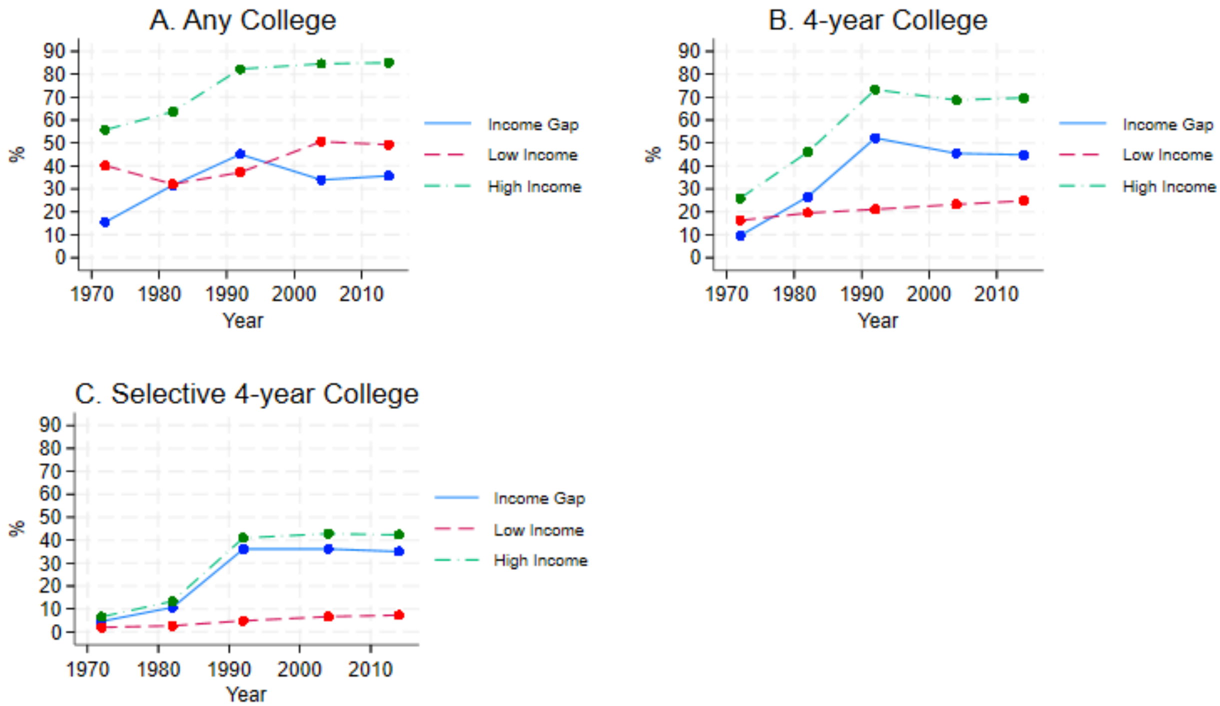
Table A6. College Planning Point Estimates and Confidence Intervals for SES Gaps

	Parent bachelor's aspirations	Student bachelor's expectations	Student expects on-time attendance
NLS 1972			
Point estimate	37.51	38.75	24.99
Lower 95% C.I.	36.91	38.15	24.36
Upper 95% C.I.	38.12	39.35	25.61
HS&B 1982			
Point estimate	37.17	43.96	29.17
Lower 95% C.I.	36.42	43.24	28.42
Upper 95% C.I.	37.92	44.68	29.93
NELS 1992			
Point estimate	37.30	42.69	39.09
Lower 95% C.I.	36.55	41.94	38.33
Upper 95% C.I.	38.04	43.43	39.85
ELS 2004			
Point estimate	27.75	33.35	26.04
Lower 95% C.I.	27.12	32.72	25.41
Upper 95% C.I.	28.38	33.97	26.68
HSLS 2014			
Point estimate	15.80	32.92	22.36
Lower 95% C.I.	15.43	32.39	21.87
Upper 95% C.I.	16.17	33.45	22.86

Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations.

Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

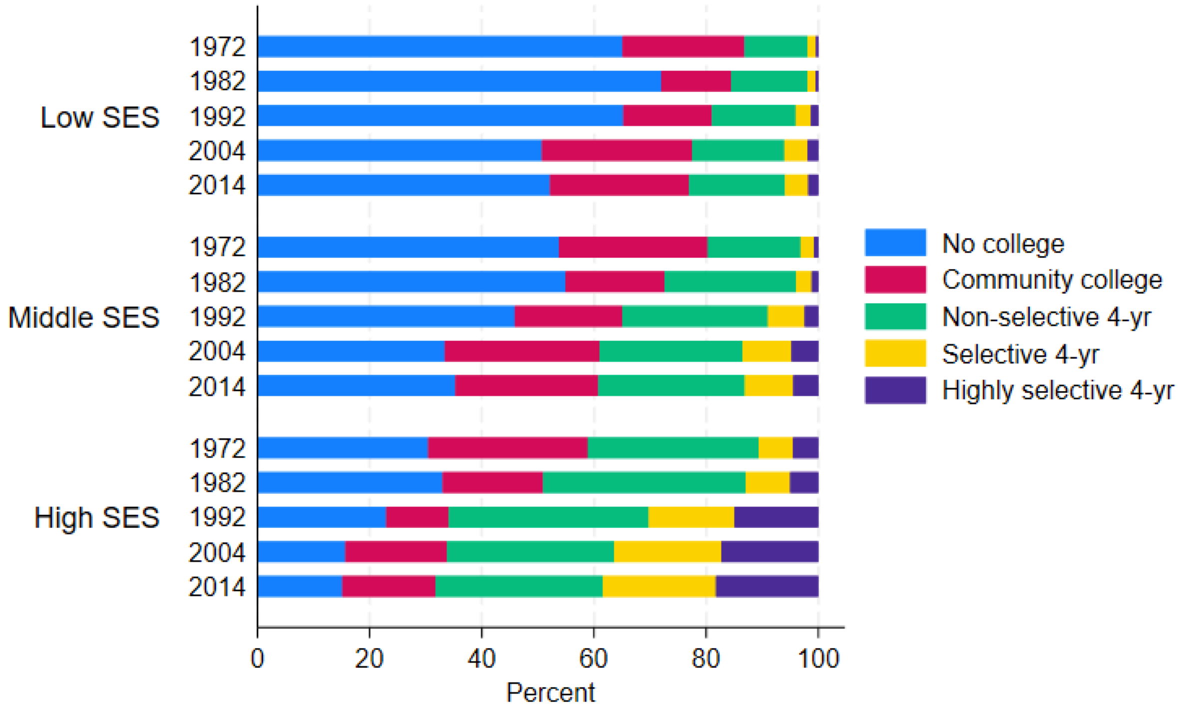
Figure A1. Family Income Gaps in College Enrollment, 1972 to 2014



Notes: Observed percentages are presented of high school seniors in each cohort who enrolled in college the fall after high school graduation. High income is defined as a family income in the top 20th percentile, and low income as a family income in the bottom 20th percentile. The dots represent the data points for each cohort. All results are weighted to target graduating seniors in the given year and combined across five imputations.

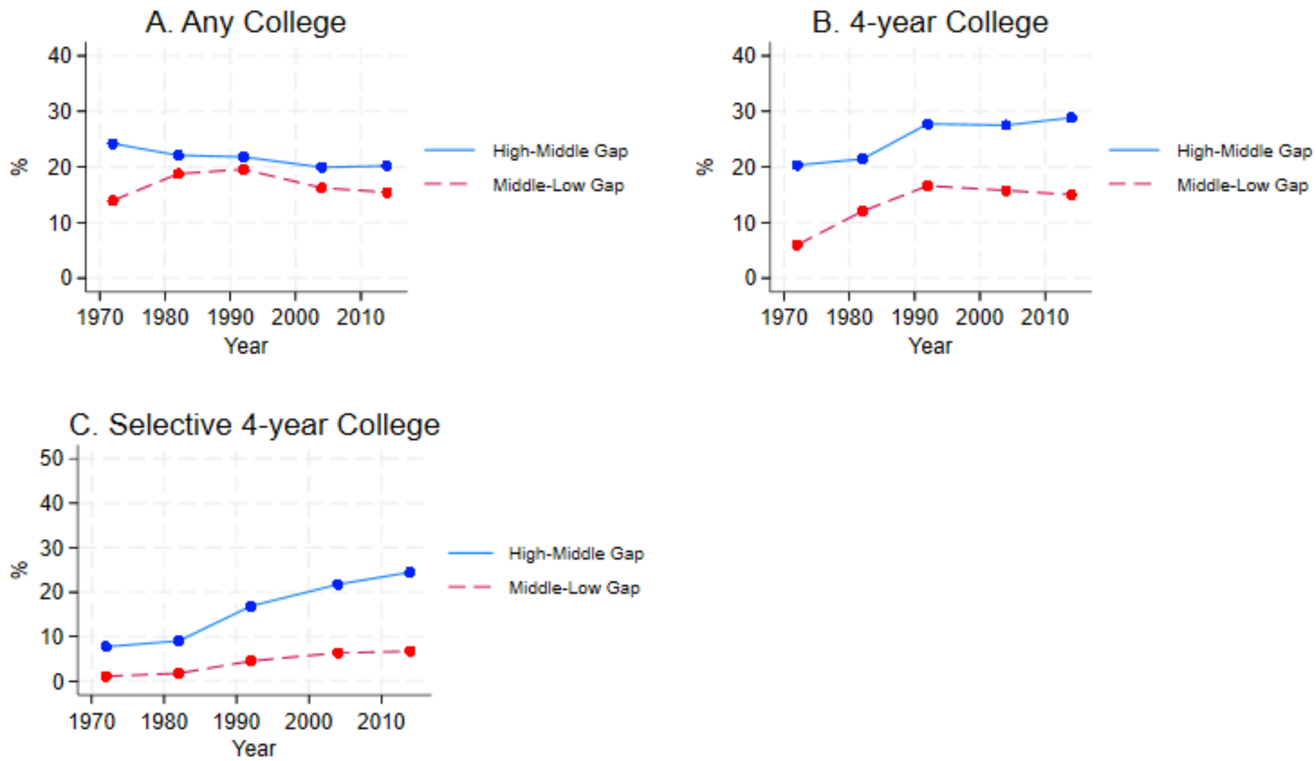
Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Figure A2. Postsecondary Enrollment Patterns by SES, 1972 to 2014



Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Figure A3. High-Middle and Middle-Low SES Gaps in College Enrollment, 1972 to 2014



Notes: All results are weighted to target graduating seniors in the given year and combined across five imputations.

Source: U.S. Department of Education, National Longitudinal Study of the High School Class of 1972 (NLS-72); U.S. Department of Education, High School and Beyond (HS&B); U.S. Department of Education, National Education Longitudinal Study of 1988 (NELS:88); U.S. Department of Education, Education Longitudinal Study of 2002 (ELS:2002); U.S. Department of Education, High School Longitudinal Study (HSLS:09); Barron's *Profile of American Colleges* 1972, 1982, 1992, 2004, 2014; IPEDS 1980, 1994, 2004.

Appendix B. Supplementary Materials for Chapter 3

Table B1. College Financial Information Variables

Variable	Variable description
Parent Financial Aid Information sources	
p2aidparent	Received info about financial aid from other parents, family, or friends
p2aidschstaff	Received info about financial aid from high school staff
p2aidoffice	Received info about financial aid from college financial aid office
p2aidinternet	Received info about financial aid on the internet
p2aidmeeting	Received info about financial aid from high school meeting
College Financial Awareness (students & parents)	
s(/p)2cost4ypub	Can provide annual cost estimate for in-state 4-year public college
s(/p)2cost4yprv	Can provide annual cost estimate for 4-year private college
s(/p)applyaid	Knows what FAFSA form is

Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2012.

Table B2. Weighted Descriptive Statistics Among Total HSLS 2009 sample, and Separately by High and Low SES Terciles

	Total %/mean (std. dev.)	Low SES %/mean (std. dev.)	High SES %/mean (std. dev.)
Race			
White	51.70	33.44	71.87
Hispanic	22.18	37.96	8.04
Black	13.64	18.01	6.76
Asian	3.58	2.45	5.21
Other	8.91	8.15	8.13
Female	49.66	48.87	49.42
Lives with both parents	55.63	42.10	73.30
Number of siblings	1.69 (1.50)	1.82 (1.68)	1.57 (1.28)
9^{th} grade GPA	2.69 (0.91)	2.31 (0.91)	3.12 (0.75)
9^{th} grade math test score	0.20 (0.97)	-0.45 (0.90)	0.53 (0.89)
Lives in a city	31.89	36.77	29.77
Lives in the South	37.59	38.42	35.41
Attends public high school	92.89	98.43	82.26

Notes: Results are weighted to account for HSLS sample design and combined across 5 multiply imputed datasets.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009.

Table B3. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps in College Application Outcomes for High vs. Middle and Middle vs. Low SES Terciles

	Middle vs. Low SES		High vs. Middle SES	
	Point Estimate	[2.5, 97.5] Percentile Bootstrap Interval	Point Estimat e	[2.5, 97.5] Percentile Bootstrap Interval
4-year College Application				
ObsGap	0.144	[0.129, 0.157]	0.256	[0.244, 0.270]
ObsGap-CnfGap(SFA)	0.003	[0.001, 0.004]	0.017	[0.014, 0.020]
ObsGap-CnfGap(SFA, PFA)	0.011	[0.008, 0.014]	0.033	[0.028, 0.038]
ObsGap-CnfGap(SFA, PFA, PIS)	0.018	[0.015, 0.022]	0.054	[0.047, 0.061]
Selective College Application				
ObsGap	0.056	[0.048, 0.063]	0.212	[0.201, 0.224]
ObsGap-CnfGap(SFA)	-0.008	[-0.010, -0.005]	-0.016	[-0.021, -0.012]
ObsGap-CnfGap(SFA, PFA)	-0.010	[-0.013, -0.007]	-0.016	[-0.021, -0.012]
ObsGap-CnfGap(SFA, PFA, PIS)	-0.016	[-0.022, -0.011]	-0.024	[-0.032, -0.016]

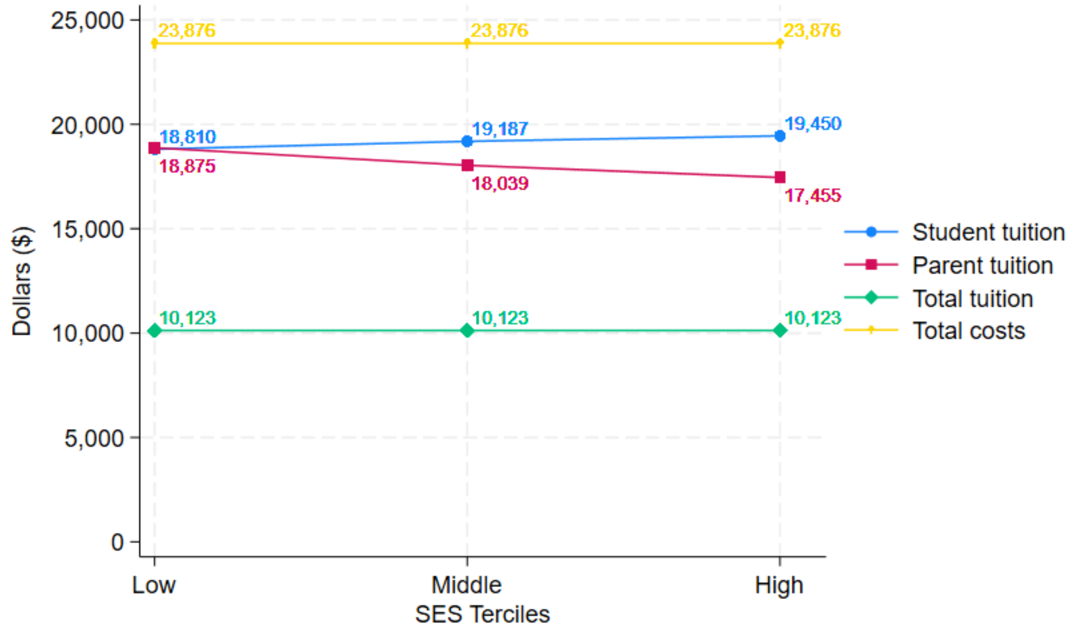
Notes: Estimates are reported in probability units and are computed using g-computation, from logistic regression models; results are combined across 5 imputations. “ObsGap” stands for the observed gap, which compares application outcomes between high SES and low SES backgrounds. “ConfGap” stands for the counterfactual gap. Different vectors of college financial information are represented, where “SFA” stands for student financial awareness, “PFA” stands for parent financial awareness, and “PIS” stands for parent information sources.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013; Barron’s *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

Table B4. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps in Moderately Selective College Application

	Point Estimate	[2.5, 97.5] Percentile Bootstrap Interval
Moderately Selective College Application		
ObsGap	0.414	[0.402, 0.427]
ObsGap-CnfGap(SFA)	-0.014	[-0.018, -0.009]
ObsGap-CnfGap(SFA, PFA)	-0.007	[-0.012, -0.003]
ObsGap-CnfGap(SFA, PFA, PIS)	-0.012	[-0.018, -0.006]

Notes: Estimates are reported in probability units and are computed using g-computation, from logistic regression models; results are combined across 5 imputations. Moderately selective is defined as greater than or equal to the Barron's category "very selective." "ObsGap" stands for the observed gap, which compares application outcomes between high SES and low SES backgrounds. "CnfGap" stands for the counterfactual gap. Different vectors of college financial information are represented, where "SFA" stands for student financial awareness, "PFA" stands for parent financial awareness, and "PIS" stands for parent information sources.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012, 2013; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

Figure B1. Respondent Tuition Estimates for Public In-state 4-year College Attendance Compared to IPEDS State Max Estimates, by SES Tercile



Notes: Sample of HSLS:09 students who provided an estimate of college costs; the "cost" measures capture the overall attendance costs, including tuition, required fees, on-campus housing, books and supplies, and other typical costs at the maximum tuition college in each student's state; the "tuition" measures capture the costs only for tuition and mandatory fees.
Source: U.S. Department of Education, High School Longitudinal Study (HSLS) 2009, 2012; Barron's *Profile of American Colleges* 2008; IPEDS 2010 to 2011.

Appendix C. Supplementary Materials for Chapter 4

Table C1. Descriptive Statistics for School Characteristics among the Total ECLS-K Sample and Separately among High vs. Low Poverty Neighborhoods

	Abbreviated label	Total sample	
		Mean	SD
School composition			
Student demographics			
% Free lunch	% Free lunch	0.502	0.311
% Black	% Black	0.146	0.226
% White	% White	0.513	0.342
% Hispanic	% Hispanic	0.226	0.276
% English Language Learner	%ELL	0.145	0.196
Student learning			
% Gifted/talented	% Gifted	0.012	0.036
% Special education	% Special ed.	0.061	0.059
Staff			
Teacher male	Tchr male	0.029	0.169
Teacher white	Tchr white	0.805	0.396
Principal male	Prcpl male	0.305	0.460
Principal white	Prcpl white	0.805	0.396
School resources			
School type			
Public school	Pub schl	0.913	0.281
Year-round school	Yr-round Schl	0.016	0.125
Kindergarten lowest grade at school	K lowest grd	0.604	0.489
6th grade highest grade at school	6th highest grd	0.362	0.481
Funding			
School funds declined from prior year	Schl funds decl	0.867	0.340
School salaries declined from prior year	Schl salary decl	0.189	0.391
School salaries frozen from prior year	Schl salary frz	0.427	0.495
School salaries increased from prior year	Schl salary inc	0.301	0.459
Title 1 school	Title 1 Schl	0.728	0.445
Expenditures			
District expenditures per-pupil	Dist $ expend	12,155.32	3,825.03
Staffing			
IT teachers per 100 students	IT tchrs/stdnt	0.078	0.132
Elective teachers per 100 students	Elec tchrs/stdnt	0.197	0.202
Gym teachers per 100 students	Gym tchrs/stdnt	0.166	0.167

Table C1 (Continued)

	Abbreviated label	Total sample	
		Mean	SD
ESL teachers per 100 students	ESL tchrs/stdnt	0.238	0.533
Librarians per 100 students	Librar/stdnt	0.109	0.113
Paraprofessionals per 100 students	Paraprof/stdnt	1.322	1.161
Psychologists per 100 students	Psychs/stdnt	0.064	0.128
Nurses per 100 students	Nurses/stdnt	0.010	0.118
Special education teachers per 100 students	S/E tchrs/stdnt	0.668	0.480
Gifted and talented teachers per 100 students	G/T tchrs/stdnt	0.099	0.252
School has translators	Schl translators	0.842	0.365
Class size			
Classroom teachers per 100 students	Class tchrs/stdnt	4.615	1.192
Staff qualifications			
Principal has doctoral degree	Prcpl PhD/EdD	0.420	0.494
Principal years teaching	Prcpl tenure	12.412	6.369
Principal years of experience	Prcpl yrs exp	8.890	6.591
Teacher has master's degree	Tchr MA	0.509	0.500
Teacher years of experience	Tchr yrs exp	15.040	9.827
Teacher has state certification	Tchr state cert	0.930	0.255
Teacher passed board	Tchr passed board	0.213	0.409
Staff retention			
Teacher years at school	Tchr tenure	9.719	7.763
School had teacher turnover from prior year	Tchr turnover	0.194	0.396
Quality of school facilities			
Classrooms always meets school needs	Qlty classrms	0.808	0.394
Auditorium always meets school needs	Qlty auditorium	0.231	0.421
Library always meets school needs	Qlty library	0.799	0.400
Gym always meets school needs	Qlty gym	0.613	0.487
Playground always meets school needs	Qlty playground	0.753	0.431
Music room always meets school needs	Qlty music rm	0.654	0.476
Art room always meets school needs	Qlty art rm	0.555	0.497
Computer lab always meets school needs	Qlty IT lab	0.646	0.478
Multi-use room always meets school needs	Qlty multi-use rm	0.336	0.472
Cafeteria always meets school needs	Qlty cafeteria	0.793	0.405
Instructional practices			
Instructional time			
Reading-days of instruction per week	Rd-days/wk	2.936	0.300
Reading-hours of instruction per day	Rd-hrs/day	3.924	1.370

Table C1 (Continued)

	Abbreviated label	Total sample	
		Mean	SD
Math-days of instruction per week	Mth-days/wk	2.917	0.337
Math-hours of instruction per day	Mth-hrs/day	2.254	0.895
Teaching practices			
Hours of small group work per day	Sml grp-hrs/day	1.787	0.747
Hours of large group work per day	Lrg grp-hrs/day	2.338	0.875
Hours of peer work per day	Peers-hrs/day	2.003	0.809
Hours of individual work per day	Ind act-hrs/day	2.419	0.827
Reading-days of group work per week	Rd grp-days/wk	5.932	1.722
Math-days of group work per week	Mth grp-days/wk	3.598	2.262
Reading-freq. teacher uses decodables	Rd-decodables	3.276	0.946
Reading-freq. teacher uses kits	Rd-kits	2.276	1.223
Reading-freq. teacher uses basal series	Rd-basal series	3.192	1.200
Reading-freq. teacher uses big books	Rd-big books	2.829	0.928
Reading-freq. teacher uses computer	Rd-computer	2.556	1.205
Reading-freq. teacher uses manipulatives	Rd-manipulatives	3.493	0.762
Reading-freq. teacher uses anthology	Rd-anthology	2.732	1.093
Reading-freq. teacher uses leveled books	Rd-leveled	3.786	0.560
Reading-freq. teacher uses audio books	Rd-audiobooks	2.743	1.121
Reading-freq. teacher uses glossaries	Rd-glossaries	4.439	1.395
Reading-freq. teacher uses newspapers	Rd-news/mags	1.742	0.812
Reading-freq. teacher uses trade books	Rd-trade books	3.379	0.903
Reading-freq. teacher uses other materials	Rd-other	3.153	0.832
Classroom management evaluation			
Importance of evaluating participation	Eval particip	3.419	0.658
Importance of evaluating behavior	Eval behavior	2.712	0.490
Importance of evaluating cooperativeness	Eval co-op	3.476	0.636
Importance of evaluating direction following	Eval directions	3.685	0.505
Curriculum content			
Reading-freq. using evidence	Rd-evidence	4.230	1.637
Reading-freq. character, setting, plot	Rd-char/plot	5.543	0.856
Reading-freq. similarities and differences	Rd-sim/diff	4.664	1.333
Reading-freq. identifying narrator in story	Rd-narrator	4.505	1.459
Reading-freq. character questions	Rd-char Qs	5.371	1.027
Reading-freq. main idea in informational text	Rd-main id inf	5.102	1.142
Reading-freq. identifying feelings/senses	Rd-feelings	4.772	1.256
Reading-freq. identifying main ideas in story	Rd-main id stry	5.274	1.091
Reading-freq. fiction vs non-fiction	Rd-fic/nonfic	5.287	1.099

Table C1 (Continued)

	Abbreviated label	Total sample	
		Mean	SD
Reading-freq. sentence context	Rd-sen context	5.166	1.111
Reading-freq. accuracy and fluency	Rd-accuracy	5.770	0.656
Reading-freq. retelling stories	Rd-retelling	5.473	0.921
Reading-freq. pace/intonation/expression	Rd-pace	5.719	0.716
Reading-freq. predicting what might occur	Rd-predict	5.605	0.819
Reading-freq. blending sounds to form words	Rd-blend snds	5.821	0.631
Reading-freq. describing character/events	Rd-characters	5.530	0.864
Reading-freq. using informational text	Rd-info text	5.192	1.070
Reading-freq. words into phonemes	Rd-word segs	5.683	0.809
Reading-freq. breaking words into sounds	Rd-form words	5.704	0.798
Reading-freq. reading prose/poetry	Rd-poetry	4.478	1.380
Reading-freq. irregularly spelled words	Rd-irreg spl	5.608	0.839
Writing-freq. writing informational piece	Wrt-info	4.176	1.380
Writing-freq. writing opinion piece	Wrt-opinion	3.635	1.641
Writing-freq. writing narrative	Wrt-narrative	4.700	1.362
Math-freq. arranging 3 objects by length	Mth-length	3.235	1.352
Math-freq. comparing objects with a 3rd	Mth-comp lngth	3.138	1.335
Math-freq. measuring length by copies	Mt-msr lngth	3.114	1.294
Math-freq. estimating length in standard unit	Mth-est lngth	2.886	1.372
Math-freq. measuring length using tools	Mth-msr tool	3.035	1.369
Math-freq. labeling relative quantity	Mth-rel quant	4.996	1.127
Math-freq. relative quantity using symbols	Mth-symbols	4.150	1.386
Math-freq. putting shapes together	Mth-shp togthr	3.051	1.360
Math-freq. counting to 120	Mth-count 120	4.637	1.559
Math-freq. solving addition of 3 numbers	Mth-add by 3s	4.125	1.582
Math-freq. solving word problems	Mth-word probs	5.261	0.991
Math-freq. identifying shape attributes	Mth-shp attrib	3.574	1.273
Math-freq. solving for unknown number	Mth-solve #	4.462	1.369
Math-freq. drawing graphs	Mth-draw graph	3.803	1.306
Math-freq. answering questions using a graph	Mth-use graph	4.037	1.272
Math-freq. meaning of equal sign	Mth-equal sign	5.109	1.334
Math-freq. both sides of equation equal	Mth-equation	4.338	1.510
Math-freq. numbers vs quantity	Mth-# vs quant	5.046	1.223
Math-freq. solving word problem with coins	Mth-$ probs	3.589	1.620
Math-freq. time in hours and half hours	Mth-write time	3.873	1.472
Math-freq. telling time - hours and half hours	Mth-tell time	4.001	1.470
Math-freq. skip counting by 5s, 10s, and 100s	Mth-skip count	5.270	1.094

Table C1 (Continued)

	Abbreviated label	Total sample	
		Mean	SD
Math-freq. identifying tens and ones place	Mth-10s/1s plc	5.163	1.078
Math-freq. counting, adding, subtracting	Mth-add/sub	5.311	1.011
Math-freq. counting to 20	Mth-count 20	5.306	1.187
Math-freq. add/subtract sums of 100	Mth-add/sub 10	4.056	1.662
Math-freq. add/subtract by quantities of 10	Mth-add/sub 10	4.160	1.421
Math-freq. describe portions of shapes	Mth-shp part	3.271	1.334
Math-freq. read/write numerals	Mth-rd/wrt nums	4.753	1.549
Math-freq. partition shapes in 2 and 4 shares	Mth-shp names	2.973	1.360
Assessment practices			
Days of homework assigned per week	Homework/wk	5.033	0.911
Frequency teacher assigns work samples	Freq wrk samples	4.924	0.999
Frequency teacher assigns projects	Freq projects	3.476	1.308
Frequency teacher assigns worksheets	Freq worksheets	5.138	1.218
Frequency teacher assigns standardized tests	Freq quizzes	2.489	1.088
Importance of evaluating relative to class	Eval relatively	2.862	0.940
Importance of evaluating to standards	Eval standards	3.185	0.797
Importance of evaluating effort	Eval effort	3.673	0.520
Importance of evaluating improvement	Eval improvement	3.739	0.471
Importance of evaluating standardized tests	Eval std tests	4.881	0.700
School climate			
Attendance			
Average daily attendance (%)	Attendance	0.957	0.021
Communication with parents			
Freq. of parent-teacher conferences	Parent-tchr confs	2.018	0.656
Freq. report cards sent to parents	Freq rep cards	1.805	0.633
Freq. of information on tests sent to parents	Freq test info	2.578	0.725
Hours/week administrators meet with parents	Admin-prnt mtgs	5.681	3.764
Community support			
Administrator - parents support school	Prnts supprtv	3.864	0.791
Administrator - community supports school	Commun support	4.267	0.706
Teacher morale			
Teacher - enjoys job	Tchr enjoys job	4.422	0.735
Teacher - can make a difference	Tchr make diff	4.545	0.574
Teacher - choose to teach again	Tchr teach again	4.285	0.945
Teacher - accepted at school	Tchr accepted	4.466	0.702
Administrator support and leadership			

Table C1 (Continued)

	Abbreviated label	Total sample	
		Mean	SD
School offers professional development	Schl prof dev	1.698	0.754
Hours per week meet with teachers	Admin/tchr mtgs	9.841	6.746
Teacher - administrator sets clear priorities	Admin priorities	4.011	0.875
Teacher - administrator welcomes new ideas	Tchr new ideas	4.243	0.760
Teacher - administrator is encouraging	Admin encourage	4.068	0.907
Teacher - recognized for work	Tchr recognition	3.802	0.954
Teacher - faculty aligned on school mission	Tchr schl mission	3.986	0.829
Teacher - paperwork gets in the way	Tchr paperwork	3.172	1.131
Teacher - consensus school expectations	Consensus exp	4.046	0.832
Student behavior and safety			
Classroom disorder is high	Class disorder	2.230	0.468
Classroom behavior is low	Class behaves	2.432	0.811
Frequent thefts occur at school	Freq theft	2.815	0.485
Frequent bullying occurs at school	Freq bullying	2.360	0.923
Frequent fights occur at school	Freq fights	2.522	0.832
School Effectiveness			
Student learning at school			
Reading value-added	Reading value-added	0.000	1.000
Math value-added	Math value-added	0.000	1.000

Notes: High poverty reflects residence in a neighborhood with a poverty rate greater than or equal to 20%, while low poverty reflects residence in a neighborhood with a poverty rate less than 20%.

Source: U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Table C2. Descriptive Statistics for Baseline Confounders, Neighborhood Exposures, and Outcomes

Variable	Percent	Mean	SD
Outcomes (standardized to kindergarten test scores)			
Reading test scores, spring third grade		2.943	0.373
Reading test scores, spring fourth grade		3.155	0.368
Reading test scores, spring fifth grade		3.361	0.429
Math test scores, spring third grade		3.632	0.651
Math test scores, spring fourth grade		3.948	0.658
Math test scores, spring fifth grade		4.221	0.662
Neighborhood exposure			
Neighborhood poverty level			
High poverty	23.49		
Low poverty	76.51		
Neighborhood poverty rate		0.140	0.112
Neighborhood % less than HS		0.163	0.129
Neighborhood % HS grad		0.291	0.101
Neighborhood % college grad		0.260	0.170
Neighborhood % female-headed		0.273	0.166
Neighborhood unemployment rate		0.082	0.049
Neighborhood % Black		0.145	0.215
Neighborhood % Hispanic		0.185	0.707
Neighborhood % White		0.707	0.258
Baseline confounders			
Gender			
Male	48.79		
Female	51.21		
Race			
White (non-Hispanic)	47.41		
Black (non-Hispanic)	12.94		
Hispanic	25.58		
Asian	8.10		
Other	5.97		
Child age (months)		67.427	4.460
Birth weight (ounces)			
Parents married at birth	66.11		
English first language	82.18		
Household size		4.578	1.367

Table C2 (Continued)

Variable	Percent	Mean	SD
Parent 1 age		33.966	6.749
Parent 2 age		36.519	7.357
Parent 1 employment			
Not in the labor force	38.78		
Less than 35 hours per week	18.56		
35 or more hours per week	42.67		
Parent 2 employment			
Not in the labor force	8.53		
Less than 35 hours per week	4.57		
35 or more hours per week	86.90		
Family income		63,377.06	58,000.07
Parent education			
Less than high school diploma	9.62		
High school diploma	20.57		
Vocational/technical degree	32.01		
Bachelor’s degree	21.60		
Graduate degree	16.19		
Parent occupation		45.558	11.985
Family received WIC in past 6 months	50.90		
Family received food stamps in past year	27.42		
Family received TANF ever	4.81		
Parent currently married	74.19		
Two biological parents in household	71.19		
Parent practices numbers with child			
Not at all	0.51		
Once or twice a week	5.95		
3-6 times a week	28.10		
Everyday	65.44		
Parent reads books to child			
Not at all	1.07		
Once or twice a week	12.47		
3-6 times a week	32.51		
Everyday	53.95		
Parent expectations			
No postsecondary attendance	4.35		
Some postsecondary schooling	12.31		
Bachelor’s degree	47.05		
Graduate degree	36.29		

Table C2 (Continued)

Variable	Percent	Mean	SD
Teacher reported externalizing behaviors	58.59		
Teacher reported internalizing behaviors	45.02		
Observation – child motivation level		3.413	0.849
Observation – child cooperation level		3.934	0.791
Observation – child attention level		3.352	0.901
Parent report of child health scale		1.554	0.789
Reading test scores, fall kindergarten		0.000	1.000
Math test scores, fall kindergarten		0.000	1.000
Locale			
Large city	15.67		
Medium city	9.76		
Small city	7.27		
Suburb	36.20		
Rural	31.11		
Region			
Northeast	15.26		
Midwest	21.96		
South	37.07		
West	25.72		

Notes: High poverty reflects residence in a neighborhood with a poverty rate greater than or equal to 20%, while low poverty reflects residence in a neighborhood with a poverty rate less than 20%.

Source: U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Table C3. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps in Fifth Grade Test Scores

Estimands	Point Estimate	[2.5, 97.5] Percentile Bootstrap Interval
Reading Test Scores		
ObsGap	-0.483	[-0.548, -0.425]
ObsGap-CnfGap(All~tot)	-0.063	[-0.092, -0.032]
ObsGap-CnfGap(Comp~tot)	-0.054	[-0.086, -0.030]
ObsGap-CnfGap(Res~low)	-0.028	[-0.042, -0.013]
ObsGap-CnfGap(Prac~low)	-0.014	[-0.025, -0.005]
Math Test Scores		
ObsGap	-0.575	[-0.610, -0.460]
ObsGap-CnfGap(All~tot)	-0.048	[-0.080, -0.010]
ObsGap-CnfGap(Comp~tot)	-0.022	[-0.054, 0.002]
ObsGap-CnfGap(Res~low)	0.060	[0.029, 0.060]
ObsGap-CnfGap(Prac~low)	0.066	[0.044, 0.065]

Notes: Estimates are reported in standard deviation units and are computed using g-computation, combining results from linear modeling, recursive partitioning, random forests, and gradient boosting using a stacking algorithm super learner; they are combined across 5 imputations; confidence intervals are based on the [2.5, 97.5] percentiles simulated via the repeated half-sample bootstrap with 200 replications per imputation and bootstrap bias correction. “ObsGap” stands for the observed gap, which contrasts residence in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20%. “ConfGap” stands for the counterfactual gap. Different vectors of school characteristics are represented, where “All” stands for all dimensions of school context, “Comp” stands for school composition; “Res” stands for school resources; and “Prac” stands for instructional practices.

Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), “School District Finance Survey (F-33),” fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), “Local Education Agency Universe Survey,” “Public Elementary/Secondary School Survey,” 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Table C4. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps Between Neighborhood Poverty Greater than or Equal to 30% vs. Less than 30%

Estimands	Point Estimate	[2.5, 97.5] Percentile Bootstrap Interval
Reading Test Scores		
ObsGap	-0.504	[-0.573, -0.427]
ObsGap-CnfGap(All~tot)	-0.053	[-0.099, 0.001]
ObsGap-CnfGap(Comp~tot)	-0.030	[-0.069, 0.009]
ObsGap-CnfGap(Res~low)	-0.039	[-0.066, -0.011]
ObsGap-CnfGap(Prac~low)	-0.026	[-0.045, -0.004]
Math Test Scores		
ObsGap	-0.545	[-0.618, -0.435]
ObsGap-CnfGap(All~tot)	-0.014	[-0.084, 0.022]
ObsGap-CnfGap(Comp~tot)	0.014	[-0.035, 0.035]
ObsGap-CnfGap(Res~low)	0.034	[-0.024, 0.051]
ObsGap-CnfGap(Prac~low)	0.031	[-0.018, 0.053]

Notes: Estimates are reported in standard deviation units and are computed using g-computation, combining results from linear modeling, recursive partitioning, random forests, and gradient boosting using a stacking algorithm super learner; they are combined across 5 imputations; confidence intervals are based on the [2.5, 97.5] percentiles simulated via the repeated half-sample bootstrap with 200 replications per imputation and bootstrap bias correction. "ObsGap" stands for the observed gap, which contrasts residence in a neighborhood with a poverty rate greater than or equal to 30% versus less than 30%. "ConfGap" stands for the counterfactual gap. Different vectors of school characteristics are represented, where "All" stands for all dimensions of school context, "Comp" for school composition; "Res" stands for school resources; and "Prac" for instructional practices.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Table C5. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps Between those in vs. Outside of Top Quintile on Neighborhood Disadvantage Index

Estimands	Point Estimate	[2.5, 97.5] Percentile Bootstrap Interval
Reading Test Scores		
ObsGap	-0.578	[-0.629, -0.527]
ObsGap-CnfGap(All~tot)	-0.055	[-0.086, -0.023]
ObsGap-CnfGap(Comp~tot)	-0.039	[-0.066, -0.014]
ObsGap-CnfGap(Res~low)	-0.026	[-0.043, -0.008]
ObsGap-CnfGap(Prac~low)	-0.029	[-0.041, -0.014]
Math Test Scores		
ObsGap	-0.683	[-0.691, -0.552]
ObsGap-CnfGap(All~tot)	-0.036	[-0.054, 0.012]
ObsGap-CnfGap(Comp~tot)	-0.003	[-0.021, 0.036]
ObsGap-CnfGap(Res~low)	0.092	[0.067, 0.114]
ObsGap-CnfGap(Prac~low)	0.065	[0.056, 0.079]

Notes: Estimates are reported in standard deviation units and are computed using g-computation, combining results from linear modeling, recursive partitioning, random forests, and gradient boosting using a stacking algorithm super learner; they are combined across 5 imputations; confidence intervals are based on the [2.5, 97.5] percentiles simulated via the repeated half-sample bootstrap with 200 replications per imputation and bootstrap bias correction. “ObsGap” stands for the observed gap, which contrasts residence in a neighborhood in the top quintile of the neighborhood disadvantage index vs. outside of the top quintile. “ConfGap” stands for the counterfactual gap. Different vectors of school characteristics are represented, where “All” for all dimensions of school context, “Comp” for school composition; “Res” for school resources; and “Prac” for instructional practices.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), “School District Finance Survey (F-33),” fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), “Local Education Agency Universe Survey,” “Public Elementary/Secondary School Survey,” 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Table C6. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps Using ECLS-K Sampling Weights

Estimands	Point Estimate	[2.5, 97.5] Percentile Bootstrap Interval
Reading Test Scores		
ObsGap	-0.481	[-0.521, -0.439]
ObsGap-CnfGap(All~tot)	-0.045	[-0.085, -0.003]
ObsGap-CnfGap(Comp~tot)	-0.017	[-0.058, 0.024]
ObsGap-CnfGap(Res~low)	-0.010	[-0.056, 0.027]
ObsGap-CnfGap(Prac~low)	-0.010	[-0.055, 0.027]
Math Test Scores		
ObsGap	-0.538	[-0.541, -0.485]
ObsGap-CnfGap(All~tot)	-0.083	[-0.095, -0.040]
ObsGap-CnfGap(Comp~tot)	-0.046	[-0.063, -0.008]
ObsGap-CnfGap(Res~low)	0.069	[-0.016, 0.066]
ObsGap-CnfGap(Prac~low)	0.054	[-0.023, 0.059]

Notes: Estimates are reported in standard deviation units and are computed using g-computation, combining results from linear modeling, recursive partitioning, random forests, and gradient boosting using a stacking algorithm super learner; they are combined across 5 imputations; confidence intervals are based on the [2.5, 97.5] percentiles simulated via the repeated half-sample bootstrap with 200 replications per imputation and bootstrap bias correction. "ObsGap" stands for the observed gap, which contrasts residence in a neighborhood with a poverty rate greater than or equal to 20% versus less than 20%. "ConfGap" stands for the counterfactual gap. Different vectors of school characteristics are represented, where "All" stands for all dimensions of school context, "Comp" stands for school composition; "Res" stands for school resources; and "Prac" stands for instructional practices.

Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

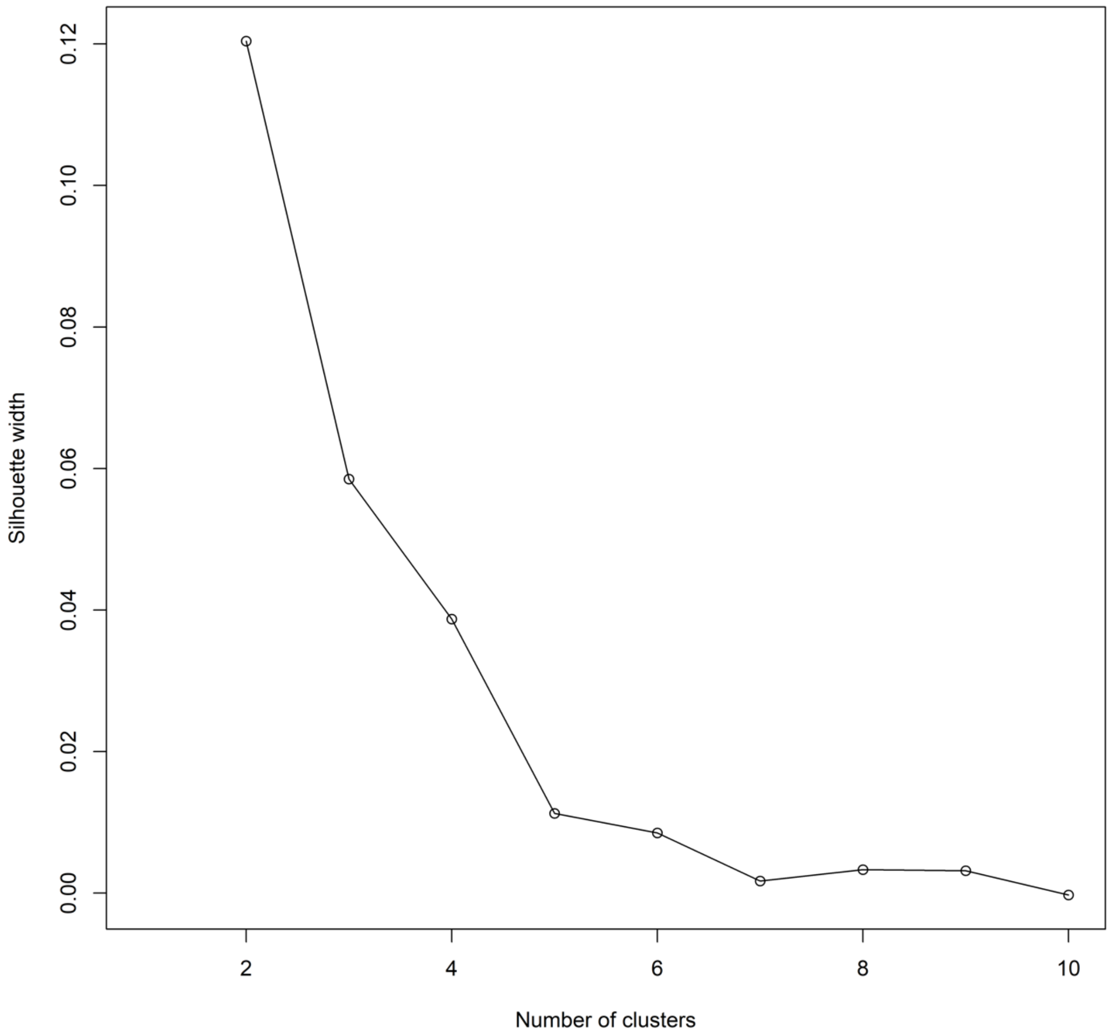
Table C7. Estimated Differences between Observed Gaps and Post-intervention Counterfactual Gaps and Model Weight for Each Model in Super Learner

Estimands	Linear Model (Weight)	Regression Tree (Weight)	Random Forest (Weight)	Boosted Tree (Weight)
Reading Test Scores				
ObsGap-CnfGap(All~tot)	-0.043	-0.182	-0.097	-0.097
	(0.550)	(0.082)	(0.108)	(0.260)
ObsGap-CnfGap(Comp~tot)	-0.019	-0.182	-0.046	-0.033
	(0.693)	(0.026)	(0.102)	(0.178)
ObsGap-CnfGap(Res~low)	-0.050	0.000	0.001	-0.024
	(0.556)	(0.146)	(0.131)	(0.167)
ObsGap-CnfGap(Prac~low)	-0.023	0.000	-0.002	-0.005
	(0.352)	(0.242)	(0.199)	(0.206)
Math Test Scores				
ObsGap-CnfGap(All~tot)	-0.037	-0.227	-0.093	-0.093
	(0.496)	(0.090)	(0.081)	(0.333)
ObsGap-CnfGap(Comp~tot)	-0.001	-0.227	-0.048	-0.025
	(0.624)	(0.042)	(0.076)	(0.257)
ObsGap-CnfGap(Res~low)	0.029	0.036	0.025	0.015
	(0.625)	(0.148)	(0.132)	(0.095)
ObsGap-CnfGap(Prac~low)	0.010	0.036	0.038	0.022
	(0.459)	(0.237)	(0.181)	(0.123)

Notes: Estimates are reported in standard deviation units and show point estimates and the weighting applied in the Super Learner, computed using g-computation, from linear modeling, recursive partitioning, random forests, and gradient boosting; they are combined across 5 imputations; confidence intervals are based on the [2.5, 97.5] percentiles simulated via the repeated half-sample bootstrap with 200 replications per imputation and bootstrap bias correction.

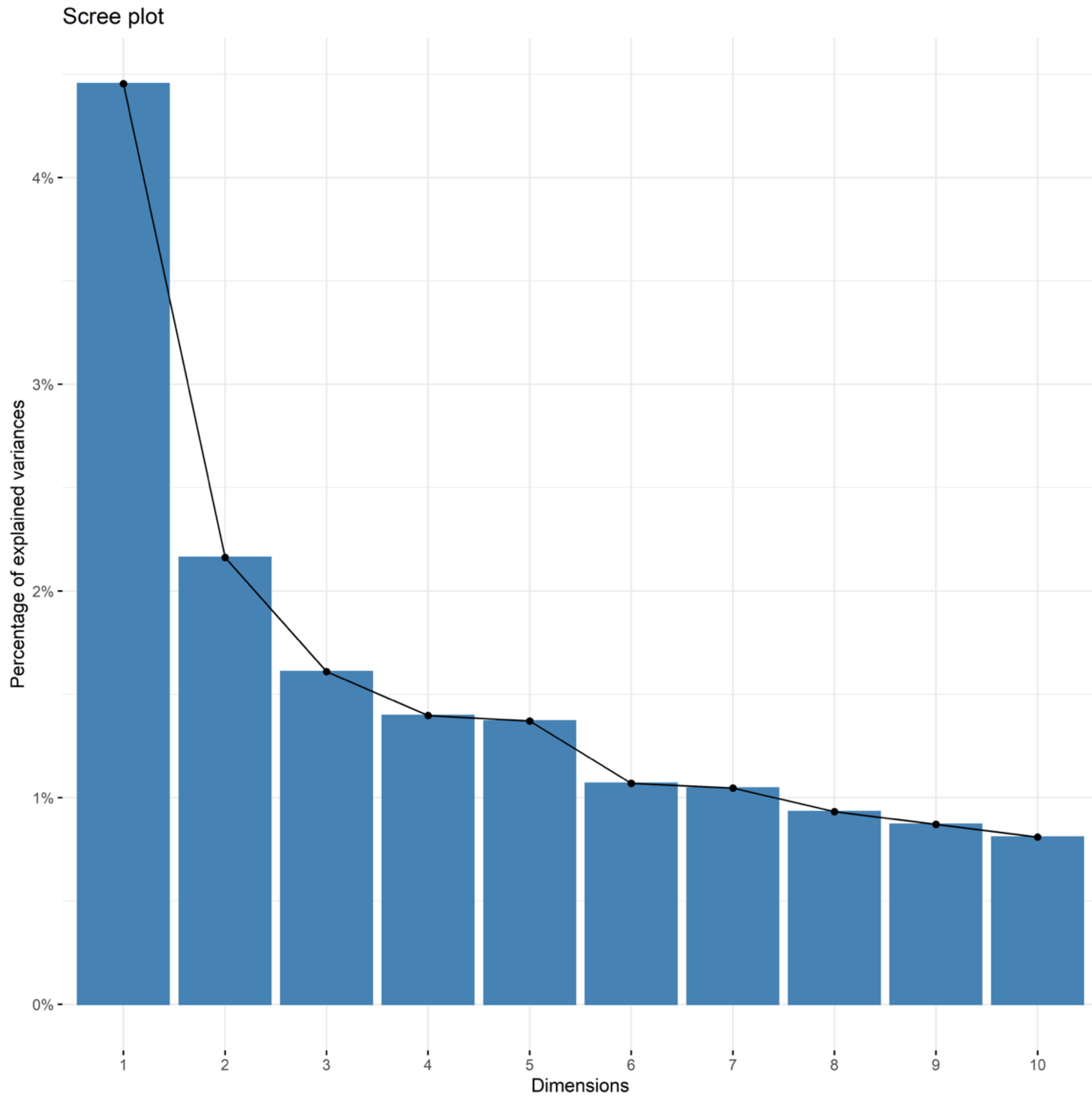
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Figure C1. Optimal Clusters for Partitioning Around Medoids using School Context Measures



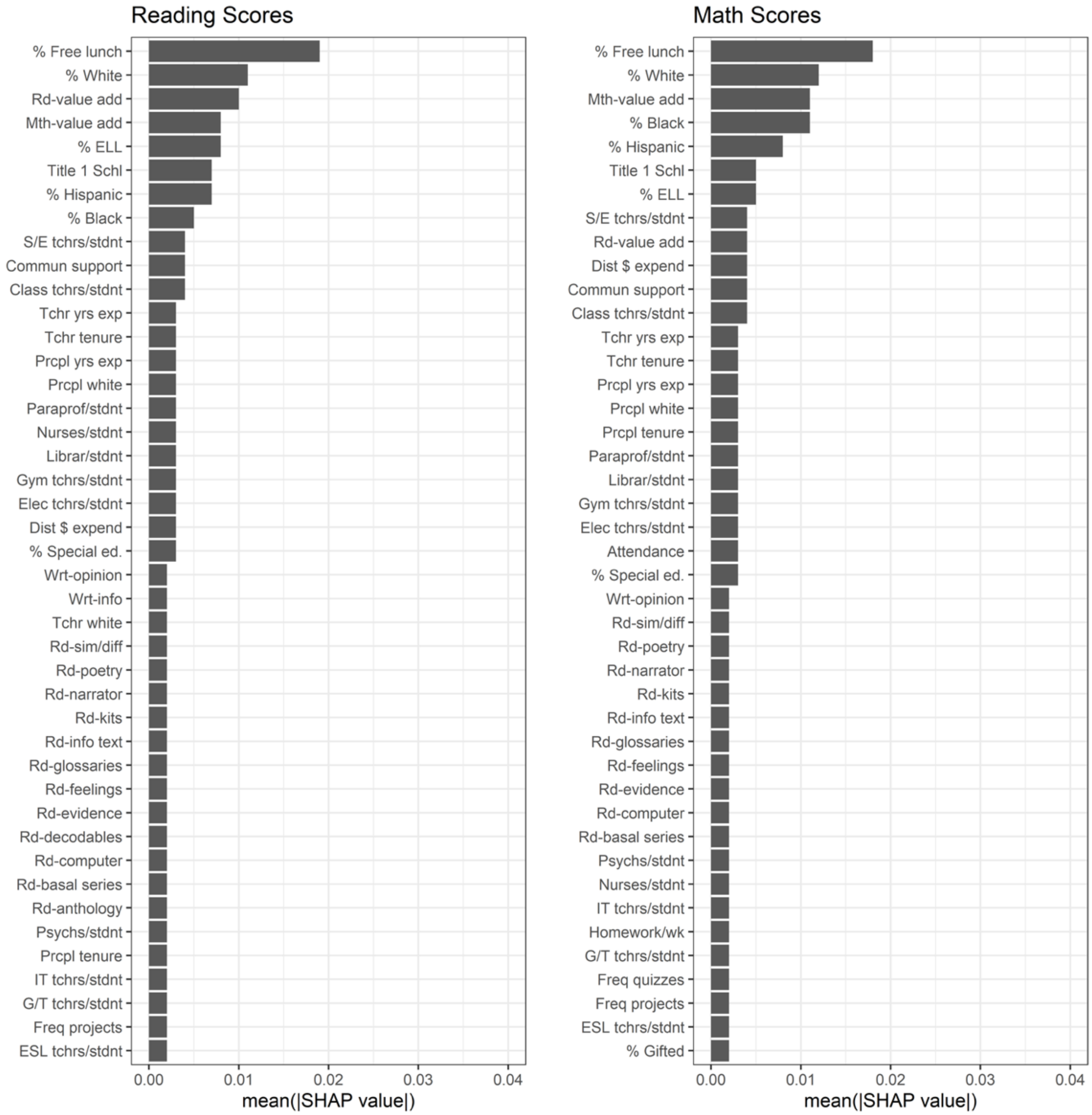
Notes: This figure depicts the optimal number of clusters for partitioning using Partitioning Around Medoids (PAM) method based on all school characteristics, for clusters ranging from 2 to 10. The silhouette width evaluates the quality of the clusters formed.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Figure C2. Percentage of Explained Variance Across Dimensions for Factor Analysis of Mixed Data Using School Context Measures



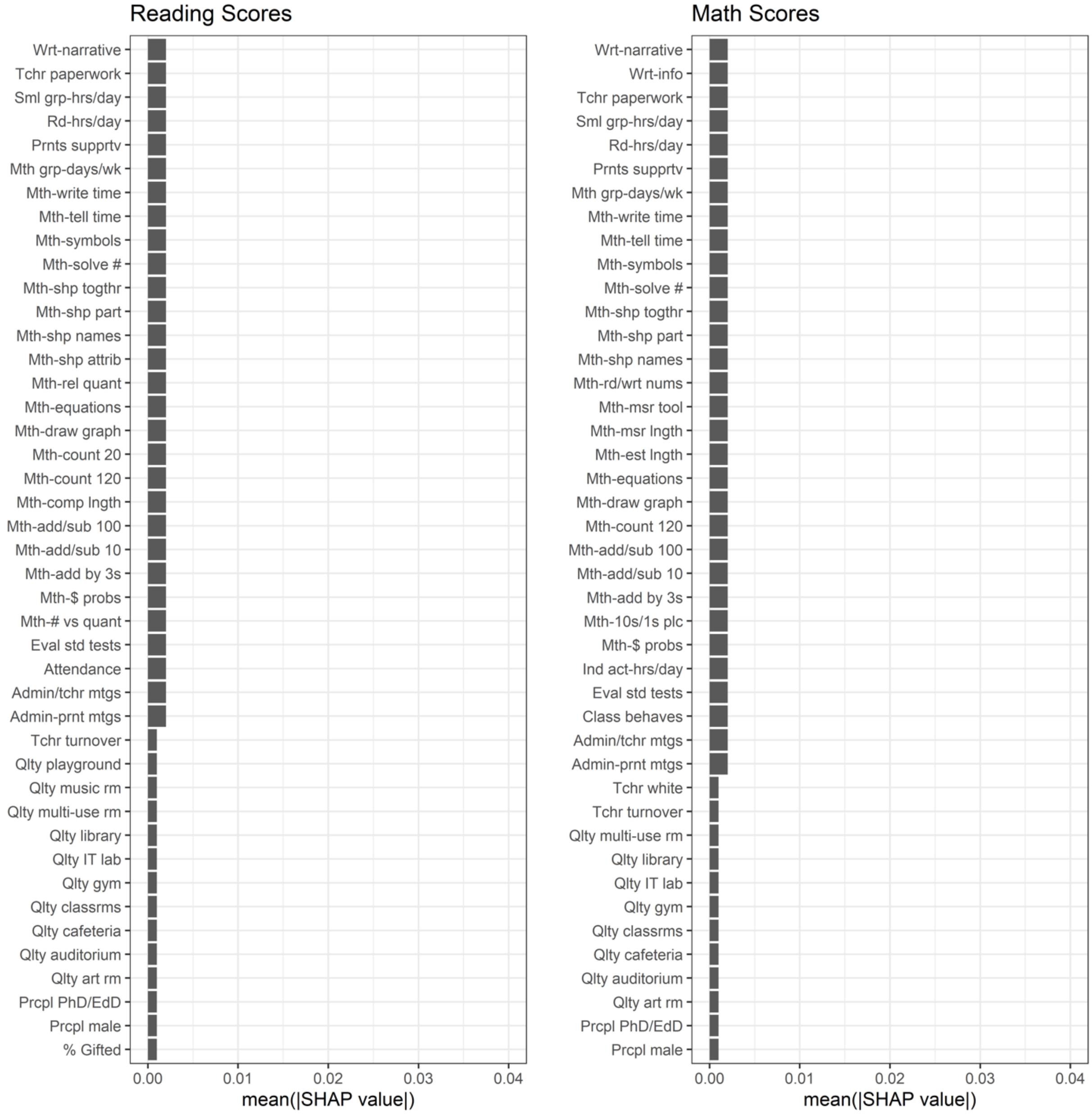
Notes: This figure presents a bar chart displaying the percentage of explained variance across ten dimensions based on Factor Analysis of Mixed Data (FAMD) including all school characteristics.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Figure C3. SHAP Values for First Quarter of School Characteristics



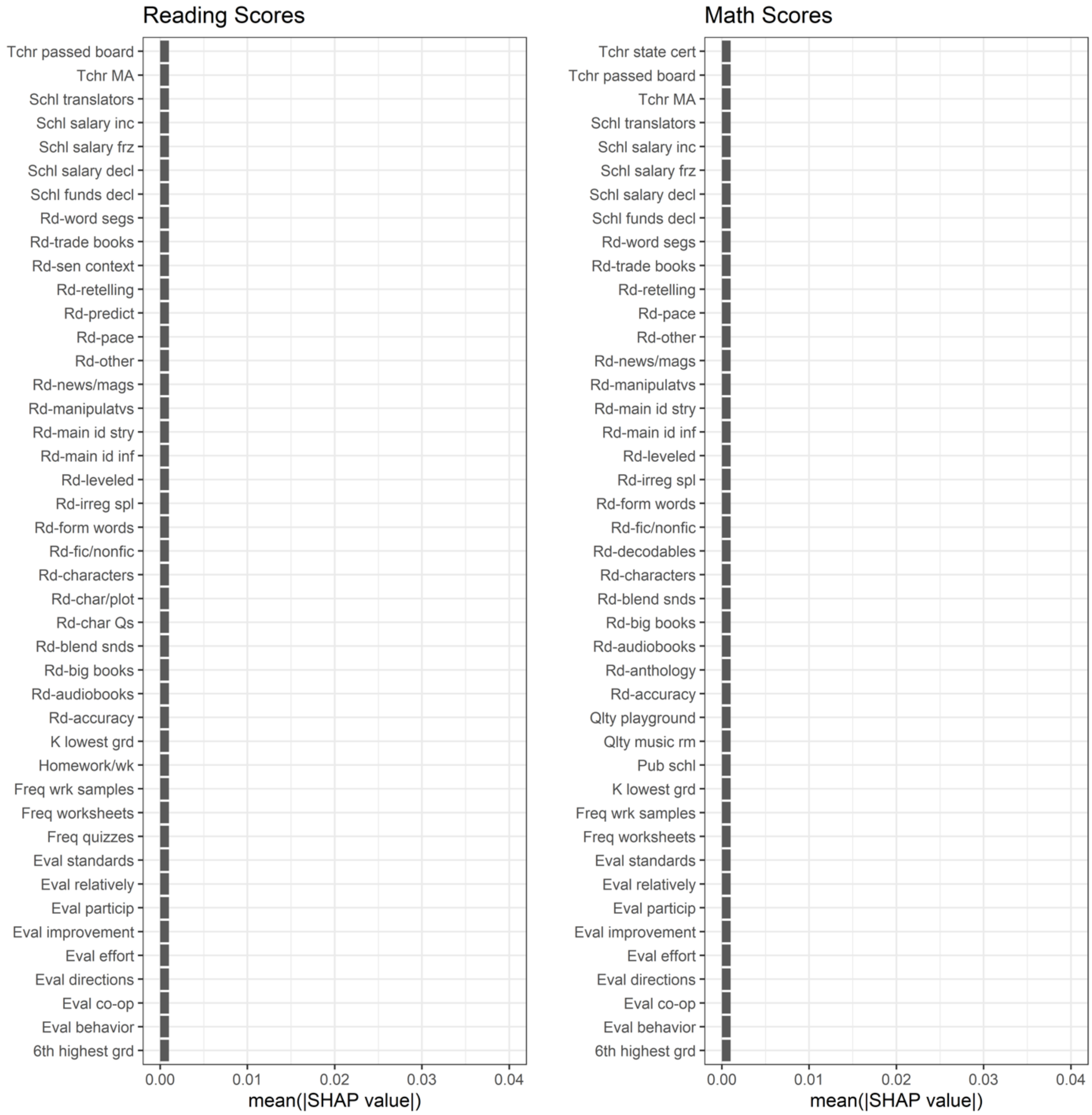
Notes: This figure reports mean absolute SHAP values computed from random forests. Each random forest includes neighborhood poverty, the full set of controls, and the full set of school characteristics as predictors. Results are combined across 5 multiply imputed datasets.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Figure C4. SHAP Values for Second Quarter of School Characteristics



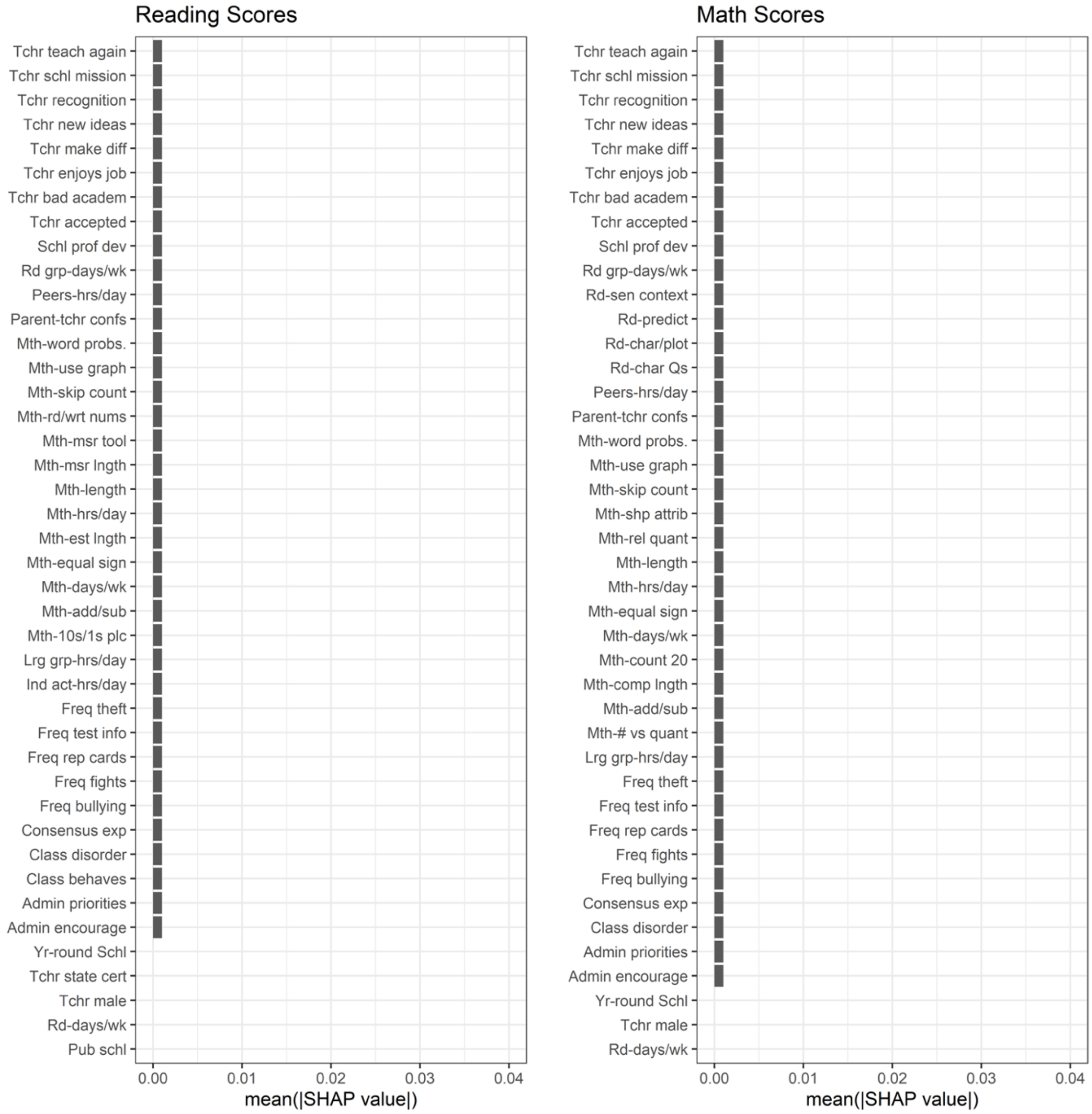
Notes: This figure reports mean absolute SHAP values computed from random forests. Each random forest includes neighborhood poverty, the full set of controls, and the full set of school characteristics as predictors. Results are combined across 5 multiply imputed datasets.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Figure C5. SHAP Values for Third Quarter of School Characteristics



Notes: This figure reports mean absolute SHAP values computed from random forests. Each random forest includes neighborhood poverty, the full set of controls, and the full set of school characteristics as predictors. Results are combined across 5 multiply imputed datasets.
Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.

Figure C6. SHAP Values for Fourth Quarter of School Characteristics



Notes: This figure reports mean absolute SHAP values computed from random forests. Each random forest includes neighborhood poverty, the full set of controls, and the full set of school characteristics as predictors. Results are combined across 5 multiply imputed datasets.

Source: Geolytics (2012); U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), Restricted-Use Data File; U.S. Department of Education, National Center for Education Statistics, Common Core of Data (CCD), "School District Finance Survey (F-33)," fiscal year 2012, Provisional Version 1a; U.S. Department of Education, National Center of Education Statistics, Common Core of Data (CCD), "Local Education Agency Universe Survey," "Public Elementary/Secondary School Survey," 2011-12, Version Provisional 1a; U.S. Department of Education, National Center for Education Statistics, Private School Universe Survey (PSS), 2011-12.