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RACIAL DISPARITIES IN SPECIAL EDUCATION: PERSISTENCE, REMEDIES, AND IMPACTS

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ABSTRACT

RACIAL DISPARITIES IN SPECIAL EDUCATION:
PERSISTENCE, REMEDIES, AND IMPACTS

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Black males are disproportionately placed in special education throughout the United States. Yet, the degree to which such disparities are warranted has been subject to debate. Prior research suggests that special education is used too often in high-poverty schools partly due to limited resources available to support struggling students (Skiba et al., 2006). More recent studies, however, suggest that, when considering student background characteristics and peer racial and socioeconomic composition, Black students are *underrepresented* in special education, specifically in high-minority schools (Elder et al., 2021).

Given these varying findings and interpretations, in this dissertation I sought to bring further clarity to the issue of disproportionality as it relates to Black males. First, I replicated previous research using student-level data from two high-poverty school districts based in a Northeastern state to examine variation in special education placement by race and gender, before and after adjusting for background characteristics. To then understand whether special education placement was effective, I used student fixed effect models to estimate how academic achievement trajectories changed for students after placement and whether these findings differed by race and gender.

I found that Black males in the sample were placed in special education at higher rates than students of other race-by-gender groups, even after adjusting for background characteristics. Prior to placement, Black males experienced large declines in academic achievement, and this trend continued after receiving special education. Together, these findings support the notion that Black males are likely overrepresented in special education.

Provided these findings, in the second part of this dissertation, I tested the effectiveness of a potential policy mechanism in reducing disproportionality. Specifically, I asked whether providing teachers with additional resources to direct struggling students through a comprehensive student support program reduced the probability of special education placement for Black males. Using two distinct identification strategies, I found that this form of support reduced special education placement rates for Black students, nearly eliminating their disproportionate representation in the districts. I conclude with policy implications for both measuring and addressing disproportionality.

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CHAPTER 1. INTRODUCTION

Among the most contested topics within special education research concerns racial disparities in students identified with disabilities. This phenomenon, referred to as disproportionality in special education placement (henceforth referred to as simply "disproportionality'), is historically rooted in concerns surrounding the overrepresentation of Black students in special education across public schools in the United States (Donovan & Cross, 2002). Although racial disparities in the numbers of Black and non-Black students identified with disabilities are not definitive evidence of racial discrimination, regardless of the mechanism, the overrepresentation of Black students in special education is believed to be harmful for a number of reasons, including the exacerbation of within-school segregation (Skiba et al., 2006). Federal policy mandates thus now require states to track school-level statistics related to disproportionality in an effort to identify and resolve potential inequities (Kramarczuk Voulgarides et al., 2017).

More recently, however, this dominant narrative of disproportionality has been questioned by researchers suggesting that, when taking into account a number of student background characteristics and peer racial and socioeconomic composition, Black students may in fact be *underrepresented* in special education relative to their White peers, specifically in high-minority schools (Elder et al., 2021; Morgan et al., 2015). In other words, according to such researchers, overrepresentation is not only justified, but an even greater proportion of Black students should be placed in special education. Consequently, there have been calls to retract recent policy mandates that regard descriptive evidence of overrepresentation as a major concern to address, as these may deprive students of special education services they are entitled to and need to succeed.

These varying interpretations of disproportionality reflect the convoluted nature of the disability identification process (Büttner & Hasselhorn, 2011). Such issues are especially prominent across disability categories that are evaluated with less medical clarity, including high-incidence categories like specific learning disabilities and emotional disturbance. In stark contrast to other disability categories that can be diagnosed through more direct means, such as those caused by definitive biological traits (e.g., deafness and hearing impairments), these disabilities are largely diagnosed based upon what is considered "typical" among a student's peers in their respective schools. It is thus difficult to parse out whether a particular diagnosis is warranted or not.

Accordingly, traditional statistics of disproportionality are especially difficult to interpret, because using disparities in the proportions of students among demographic groups as evidence of over- or underrepresentation requires some reference group for which one must assume accurate identification (Collins et al., 2016). Disproportionality statistics used to present differences between racial groups, for example, generally use White students as a reference group, but there is no reason to believe such students are more appropriately identified. Thus, a defensible response to questions about racial disparities in special education becomes further complicated.

Despite growing research on disproportionality over the last several years, there is far from a consensus on what to conclude from racial disparities in special education placement and how best to address them. A few things are clear, however. Firstly, it is well-established that students with disabilities face far greater challenges in educational attainment and are thus much less likely to experience positive educational outcomes such as high school graduation and postsecondary degree attainment (Donovan & Cross, 2002). Secondly, while some disabilities are naturally occurring, others are caused by various socioeconomic mechanisms such as those brought about by poverty, and Black students in particular are disproportionately impacted by these factors (Grindal et al., 2019). Thirdly, special education supports are definitively warranted for students with disabilities who are otherwise unable to achieve at levels close to their peers, but some research suggests that such supports are not always effective and appropriate in improving student achievement (Schwartz et al., 2021; Hehir, 2016).

Taking these three points into consideration, more research is needed to understand how best to address the socioeconomic factors that explain *why* students need special education supports in the first place. While much of the policy response to disproportionality has focused on the identification process, far less attention has been paid to the socioeconomic mechanisms disproportionally impacting students of color that may affect neurological processes leading to disabilities or related issues that result in special education placement. Of course, focusing on factors brought about or enhanced by poverty does not negate the need to also address potential racial discrimination in the identification process, but it provides an avenue for addressing an immediate and agreed upon source of established disparities. Simply put, intervening with respect to socioeconomic factors may reduce racial disparities in special education placement. Limited research, however, has thoroughly explored the impact of such interventions and programs on special education placement, specifically through the lens of disproportionality.

In response to this research need, the purpose of this dissertation was to quantitatively explore how special education assignment intersects with race within two high poverty and racially diverse school-districts. I first sought to examine whether racial disparities among those receiving special education services were present, and if so, what factors may explain them. Next, to further uncover potential inequities, I explored the effectiveness of special education supports in improving academic achievement and whether this varies by race. Finally, I analyzed how access to high-quality early learning opportunities and integrated student support affect the probability of special education placement overall and by race. Together, these research objectives demonstrate how reducing the educational effects of poverty influence special education outcomes overall and for Black students in particular.

Background literature

Research on disproportionality has uncovered multiple mechanisms by which students of color may be referred to special education at higher rates relative to their representation in the student population. Early theories considered the mediating role of poverty (O'Connor & Fernandez, 2006). Because students from low socioeconomic status (SES) backgrounds are frequently deprived of high quality learning environments – be it in the home or in center-based care settings – limited learning opportunities at an early age may result in developmental delays, often leading to special education referrals (Skiba et al., 2005; Sullivan & Proctor, 2016). Alternatively, students from low SES backgrounds may be more exposed to mental trauma through the evident challenges presented by poverty, thereby resulting in more severe emotional disturbance (Walsh & Theodorakakis, 2017). Given that students of color are disproportionately represented in low-income communities, some researchers have argued that the overrepresentation of Black students in special education is expected and should not be necessarily perceived as misdiagnosis (Morgan et al., 2015).

While the overrepresentation of Black students in special education can be partly explained by factors related to poverty, racial biases have also been reported in the literature. Some studies have found that Black students are still more likely to be placed in special education within their respective schools even after accounting for various indicators of SES

(Grindal et al., 2019; R. J. Skiba et al., 2005). Some prior research indicates that the variance in special education placement accounted for by race is reduced with the inclusion of SES indicators, though race nonetheless remains a statistically significant predictor. Additional qualitative research has uncovered both explicit and implicit biases teachers hold that may trigger referrals and subsequently lead to diagnoses (Chin et al., 2020). These biases may be a result of cultural mismatches between White teachers and school administrators and low-income and high-minority student populations (Kramarczuk Voulgarides et al., 2017).

While no consensus among researchers exists on the extent to which disproportionality is a problem, scholars of disability studies have noted that, regardless of the mechanisms by which students of color are placed in education, it is nonetheless an issue (Collins et al., 2016; R. J. Skiba et al., 2016). Given the negative association between special education placement and various positive long-term academic and employment outcomes (Hanushek et al., 2002; Morgan, Frisco, et al., 2017; Suzanne M. Donovan, 2002), these scholars argue that such disparities in placement represent a modern form of tracking, by which minority students are placed into environments that limit their ability to succeed in the education system (Tyson, 2013). Given the large correlations among racial gaps in education – including special education placement, grade retention, discipline, advanced course-taking, and postsecondary enrollment – disproportionality may have severe consequences for future educational and employment attainment (Shores et al., 2020). Targeted efforts at the policy level to reduce disproportionality in special education placement have consequently become increasingly important.

Dating back to 1997, the Department of Education (U.S. ED) has required states to monitor disproportionality (Albrecht et al., 2012). Serious accountability measures that actually required states to publicly report schools with "significant" disproportionality were not put in place, however, until the reauthorization of ESEA in the form of the Every Student Succeeds Act (ESSA) in 2015 (Kramarczuk Voulgarides et al., 2017). As it currently stands, states have received limited guidance at the federal level concerning how best to decrease disproportionality. ESSA requires districts identified with significant disproportionality – a term that is open to interpretation by states – to review and present underlying factors, and then revise policies, procedures, and practices. Additionally, districts are required to direct the maximum amount of comprehensive coordinated early intervening services (CCEIS) funds to serve children in the overidentified groups. CCEIS activities include professional development and educational and behavioral evaluations, services, and supports such as Response to Intervention (RIT) and Multi-Tiered Systems of Support (MTSS). Evidence on the effect of approaches like RTI and MTSS have been mixed, with some studies finding small declines in the probability of special education placement after schools adopted RTI, whereas others have found modest increases in Learning Disabilities diagnoses in non-White students (Shea & Jenkins, 2022).

Alternative policy approaches have considered imposing quotas on special education placement and disproportionality (Ballis & Heath, 2019). Education policies that impose quotas on schools have histories of unintended consequences, however, such as the "teaching to the test" phenomenon that emerged following the No Child Left Behind Act (Jennings & Bearak, 2014). Recent evidence from Texas demonstrates that Black students experienced small gains in high school completion and college attainments after district-level caps were placed on Black and Hispanic disproportionality, perhaps bolstering the notion that some Black students in the state were misidentified (Ballis & Heath, 2019). District-level caps on special education enrollment as a whole, however, led to reductions in high school and college completions for Black and Hispanic students in special education and general education, conceivably due to the denial of services for students who actually needed them (Ballis & Heath, 2019). Similarly, simply requiring states to collect data in an effort to raise awareness on issues related to racial equity has not been successful in reducing disproportionality in other measures like disciplinary rates (McIntosh et al., 2020). In sum, as opposed to quotas, there is a need for more proactive policy solutions to reducing disproportionality that target root causes.

Additionally, recent policy mandates have presupposed that differences in special education placement by race are definitively reflective of discrimination. Yet, as previously mentioned, recent research suggests a more complicated picture, whereby Black students may actually be underrepresented in special education within high-minority districts after taking into account several background characteristics (Elder et al., 2021; Morgan et al., 2015, 2020). If this is indeed the case, caps on special education placement may be more harmful by depriving students of the supports that they need. There is thus a need for a more nuanced discussion and policy approach towards addressing disparities in special education.

Purpose and research questions

The purpose of this dissertation is twofold. Firstly, given varying and often contradictory research on the extent to which disproportionality exists and is problematic, I replicated previous research using data from two high-poverty school districts to examine variation in special education placement by race, before and after adjusting for covariates. Secondly, I estimated how academic achievement trajectories changed for students after being placed in special education and how that differed by race. These analyses contextualized the way special education intersects with race in high-poverty school districts. While disproportionality across various racial and ethnic lines have been reported in the literature, my specific focus here was on racial disparities as they relate to Black students. Given previous research demonstrating an overrepresentation of males in special education, I also analyzed disproportionality as it relates specifically to Black males (Coutinho & Oswald, 2005)

The second part of this dissertation explored how two models of integrated student support affected the probability of special education placement, with a similar focus on differential impacts by race. The first program is a form of high-quality Early Childhood Education (ECE), as offered through a city-wide universal public prekindergarten (preK) program, in which students and their families also receive support through the City Connects integrated student support program. The second program is City Connects at just the elementary and middle school level. Integrated student support, as explained later, is not specifically focused on altering special education referrals, but targets multiple risk factors that may contribute to placement.

The following research questions were addressed in this study:

1. To what extent do special education placement rates in high-poverty schools differ by race and gender, particularly for students identified after third grade? How do these relationships change after taking into account socioeconomic status, gender, English Learner status, prior achievement, and school attended?
2. Upon partialing out the variance between students, schools, grades, and years, what are the relationships between special education placement and mathematics and reading achievement in grades 4-8? To what extent do these relationships vary by race and gender?
3. What is the impact of enrolling in a City Connects public prekindergarten program on the probability of special education placement in elementary school, and are there differential impacts by race and gender?

4. To what extent do school-level rates of special education placement differ after the introduction of City Connects? To what extent do special education placement rates differ by race and gender before and after the introduction of City Connects?

I first examined how the probability of disability identification differs by race and gender, seeking to determine if there is disproportionality in special education placement in the districts studied and how it compares to what has been found in the previous studies. I then analyzed how the relationship between special education placement and race changes upon the inclusion of other background characteristics. The goal here was to see if observed variation in special education placement by race can be explained by other observable background factors.

The second research question builds on recent literature examining how placement into special education affects student achievement, with a particular focus on disentangling variation by race. This stems from prior research suggesting that special education does not meaningfully improve academic achievement outcomes for Black students, perhaps suggesting that some students are misidentified and thereby receiving inappropriate supports (Schwartz et al., 2021). The findings from these analyses provide further clarity on the extent to which differences in special education placement rates are warranted. For example, if Black students are overrepresented in special education compared to other racial groups, and academic achievement does not improve upon placement, then these findings together have important implications for the types of interventions supports that should be directed toward this student population and the associated desired outcomes (i.e., reduced placement).

Research Question 3 asks if enrollment in a City Connects public preK program compared to other district-run preK programs is associated with changes in the probability of special education placement at an individual level, and whether observed effects differ by race.

Research Question 4 similarly asks if implementing City Connects in elementary and middle school leads to school-level changes in the proportions of students placed in special education overall and for Black students. The early childhood and elementary/middle school models of the program differ in important ways, so it is equally important to look at the impacts of both separately.

I hypothesized the existence of some disparities in special education revealed through the findings of Research Question 1, with Black students – specifically males – overrepresented with and without controlling for other background characteristics. In line with previous research, I anticipated strong effects of special education placement on student achievement, but minimal impacts for Black students particularly. I hypothesized that participation in a City Connects public preK program reduced the probability of special education classification for all students, but even greater effects for Black students. Similarly, I hypothesized that the introduction of City Connects to schools reduced special education placement for all students, with greater effects for Black students.

Theory of change

High-quality early childhood education has been previously evidenced to reduce special education rates in high-poverty communities by providing students with early learning environments that they are too often deprived of, while also better preparing students for kindergarten. If students enter kindergarten more academically prepared and more accustomed to the general classroom environment, one can theorize that their achievement and behavior will also improve. Although racial biases may still put students of color at a disadvantage, the SES mediating factors can certainly be mitigated through high-quality ECE.

The impact of ECE on cognitive, non-cognitive, and long-term outcomes such as employment is well-established (McCoy et al., 2016). Early studies dating back to the 1960s and 1970s analyzing ECE models such as Head Start have demonstrated persistent positive effects throughout adolescence, but more recent research on state- and city-wide universal public preK programs – which have become nearly ubiquitous in urban locales across the country in the last two decades – have frequently displayed effects on academic achievement that fade out by the end of elementary school (Bailey et al., 2020). A key component of earlier successful ECE models were family engagement supports, which are notably absent in most public preK programs. Consequently, there is a need to continue studying public preK and other ECE programs today, thereby further elucidating the conditions under which students in such programs best thrive in the long-term. Analyzing the connection between high-quality ECE and special education placement is one meaningful way to gauge persistence.

In their meta-analysis of quasi-experimental and experimental studies exploring the impacts of ECE, McCoy and colleagues (2017) found that receiving ECE reduced the probability of ever being placed in special education by 8%. More recent evaluations of state-wide programs in places like North Carolina, Tennessee and Texas have found mixed effects on special education placement. While some studies have found that public preK participation decreases special education placement, null effects and even increases in diagnoses have also been reported (Andrews et al., 2012; Dodge et al., 2017; Lipsey et al., 2018).

Most pertinent to this study is a recent examination of the Boston Public Schools (BPS) public preK program, considered to be one of the best publicly-subsidized preK programs in the country. Conducted by Weiland and colleagues (2020), the study found that random student assignment to the most popular (i.e., highly desired) preK programs in Boston had no effects on special education placement by the end of third grade. Similarly, a more recent study of longer term effects of the BPS's public preK program prior to its expansion in 2005 also found no impacts on special education placement (Gray-Lobe et al., 2021). However, effects by race were not examined.

While improved access to ECE has been productive in improving child learning before kindergarten, support for mental and emotional well-being has proved a more difficult challenge (McCoy et al., 2017). Much previous research has illuminated the link between the trauma induced by poverty and childhood health, development, and learning (Walsh & Theodorakakis, 2017). Exposure to trauma within the home and neighborhood violence – both more common for children from low SES backgrounds – also affects mental and emotional well-being (Acri et al., 2017). When considering these experiences, it is not difficult to understand why achievement gaps between students from high and low-income backgrounds are already present *before* children start kindergarten (Garcia, 2015; Wang, 2008).

Given the myriad out-of-school factors affecting students social and emotional well-being, the key program of focus in this dissertation is an integrated student support (ISS) program that emerged from the Boston College Lynch School of Education in the late 1990s called City Connects. ISS programs like City Connects generally fall under the umbrella of "wraparound" services, which are systematic approaches to providing out-of-school supports targeted to students from low SES backgrounds (McShane, 2019). These students commonly lack access to basic resources necessary to ameliorate the various challenges brought about by poverty, ranging from food insecurity, to a lack of adequate medical and mental healthcare, and limited access to extracurricular activities and academic enrichment opportunities. ISS supports generally bring together teachers, families, school counselors, and local community partners to best target the strengths and needs of students so that they are better prepared to learn

Poverty-induced trauma, if neglected or inappropriately addressed, may cause greater emotional disturbance for students and further affects their ability to learn at the same level as their peers (Acri et al., 2017). Even absent trauma, the deprivation of basic necessities influences academic, social, and psychological development. Consequently, intervening on out-of-school factors is an important mechanism by which correct disability diagnoses can be made and appropriate services provided. Recent evaluations of City Connects at the elementary school level have already found large positive outcomes on elementary report card grades, middle school standardized test achievement, high school graduation, and college enrollment and completion (Lee-St. John et al., 2018; Pollack et al., 2020; Walsh et al., 2014). The relationship between City Connects and special education placement – while not previously explored very systematically – may be an important mediating factor in improving student outcomes.

Scholars of education policy have argued over the last several decades that many of the racial and socioeconomic disparities in academic achievement are difficult for schools to address alone (Beatty, 2013). While policymakers and reformers have historically perceived schools as the solution to various social problems, research has increasingly shown that schools are ill-equipped to handle the challenges in high-poverty communities alone (Raudenbush, 2009). By targeting the risk factors that lead to special education referrals, investments in high-quality ECE and well-coordinated ISS programs have the potential to mitigate the impacts of poverty.

Data and research methodology

The proposed study used a combination of student and school-level administrative, enrollment application, and assessment data from two urban school districts in Massachusetts spanning 2004 to 2019. Both districts have been operating public preK programs and City Connects in a number of schools over the last 15 years. Additionally, the districts serve racially, ethnically, and socioeconomically diverse student populations that are similar to several other large urban school districts in the country, offering the potential for more externally valid results. The districts also have among the highest rates of special education placement in the nation, so there is increased policy relevance in studying disproportionality.

The sample for Research Question 1 consisted of students in both districts enrolled in grades 3 to 8 between 2006 and 2019 who were not placed in special education by the end of third grade. Accordingly, third grade served as a baseline for achievement and other background characteristics to control for determining whether observed racial disparities in special education were present or persisted. The outcome measure for this analysis was therefore placement in special education by the last time point students were observed. While students are more often placed in special education in earlier grades, there are no standard measures of achievement prior to third grade to partial out the corresponding variance in special education placement when estimating the models. This restriction does have the benefit, however, of largely limiting the special education placement observed in these later grades to disabilities that are more "subjective" in identification, which were the focus of this study.

The Research Question 2 sample was further restricted from the prior question's sample to students who were eventually placed in special education between grades 4 and 8. Student fixed-effects models were estimated to measure within-student change in math and reading achievement (using standardized z-scores) following placement in special education. Again, because students are not administered standardized tests prior to third grade, these models were only be estimated for those placed in special education after third grade. Models were estimated with interactions by race and gender to examine the differential impact of special education placement on academic achievement for Black students and Black males.

Research Question 3 was limited to students in District 1 because the district operates a public preK enrollment process with an embedded lottery that can be used to simulate a natural experiment by which effects of preK programs that implemented City Connects can be better isolated. This is important because when families self-select into preK programs, simply including an indicator of whether a student attended that school to estimate its impact can be misleading due to selection bias. Families that enroll their children into such a program may differ in important ways from families that choose not to enroll. This level of bias can be removed, however, when using the district's centralized school assignment process at preK.

Four cohorts of students who were subject to school assignment in preK via the lottery in the assignment process were followed for up to six years, beginning with their preK year. Two-stage least square models using the offer to a City Connects preK program and the probability of receiving such an offer as instruments were used to estimate the impact of enrolling in the program on special education placement. These models were estimated separately for all Black students and Black males to examine the differential impact of enrolling in a City Connects public preK program on special education placement for these two subgroups.

Finally, in Research Question 4 I measured how the proportions of students placed in special education in schools overall changed following the implementation of City Connects. All schools in both districts spanning 2004 to 2019 were included in the analysis, with the exception of schools that were already operating City Connects prior to 2006. Using recent advancements in the econometrics literature, difference-in-differences models that permit variation in the timing of when treatment began were used to address this research question (Callaway & Sant'Anna, 2020). The proportions of Black students and Black males placed in special education were also examined as outcome measures to explore potential differential impacts by race and gender.

Significance of the study

This dissertation contributes to the intersection of the research on special education placement, disproportionality, public preK, and ISS. Firstly, this research provides replicated evidence in relation to previous research of the extent to which racial disparities in special education exist, specifically in high-poverty school districts. This responds to calls by researchers to examine disproportionality at a more local level given variation in special education placement policies across districts and states (Cruz & Rodl, 2018). Secondly, Research Question 2 provides replicated evidence concerning the effect of special education placement on academic achievement to offer more context surrounding the appropriateness of services and supports. Findings from these first two research questions together deepen our understanding of the ways special education intersects with race in high-poverty schools.

Thirdly, this study demonstrates the extent to which high-quality public preK and ISS can mitigate the mediating factors related to SES that may lead to eventual disability diagnoses. Such findings have implications for how state and local educational agencies may better serve the most at-risk students. While the findings may not be generalizable to all preK and ISS programs, further research may uncover the mechanisms by which such interventions impact special education outcomes. For example, ISS may provide an avenue for earlier intervention for struggling students prior to initiation of the special education referral process. Similarly, additional investments in family support within preK programs may better position students to be successful in kindergarten by providing a more conducive environment to learning within the home.

Concerning disproportionality, this study provides evidence on a potential policy lever for reducing differences in rates of special education placement. Through the study of City Connects, I show how targeting disability risk-factors induced by poverty affects the probability of special education placement, particularly for Black students. Existing policy solutions and prior research has assumed bias in the placement process as the primary cause of disproportionality. This study provides emerging evidence on potentially more effective and appropriate means by which equity in special education can be achieved.

Through Research Question 3, this study also bolsters the evidence on the relationship between ECE and special education placement. While many previous studies investigating the impact of ECE programs on special education placement demonstrated large and positive effects, there is a need to update the literature. Firstly, the intensive nature of some early ECE models make it difficult to isolate the program effects from other supports offered to families. Parenting education and home visits, for example, were a major feature of many early ECE programs. Observed effects may certainly be attributed to such additional supports as opposed to the instructional and curriculum aspects of ECE. Secondly, changes in context have certainly increased the need to study current programs. Families today now have greater access to ECE supports than in decades prior. As such, in many recent studies investigating the impacts of a specific ECE program, most students in the control group – even in high-poverty settings – receive some form of ECE through other means.

The question at hand is not necessarily whether ECE is effective, but rather, do publicly-subsidized programs embedded within public school districts provide added benefits over others. Studies of contemporary universal public preK programs have produced mixed findings of effects on special education placement (Muschkin et al., 2015; Andrews et al., 2012; Phillips et al., 2016, Weiland et al., 2020). Understanding the key features of successful programs is thus of great policy interest. Building upon the work of Weiland and colleagues (2020) – who found no effects of over-subscribed (i.e., high-demand) preK programs in Boston – this dissertation bolsters the evidence on the effect of ECE on special education placement by examining the impact of specific public preK programs that incorporate integrated student support.

More specific to the literature on integrated student support in general, this study supplements earlier evidence from the City Connects program suggesting that the intervention may indeed impact special education outcomes. In one study, researchers found that students in non-City Connects schools in Boston who were referred to special education were 22 percent more likely to be deemed ineligible than similar students in City Connect schools (Boston College Center for Child, 2009). Once these treated students entered middle school in non-City Connects schools, they were no more likely than comparison students to be later placed in special education. This suggests over-referral in the non-City Connects schools, whereby students who did not need special education were nevertheless being referred because no other options were available. Focused interviews with principals and teachers confirmed that the intervention added new systems and processes that changed the special education referral process, resulting in less referrals overall.

A limitation of the previous work on City Connects and special education is the inability to draw causal inferences. Most students attending the schools in the prior study examining the "accuracy" of referrals were not randomized to treatment and comparison conditions, and the resulting covariates for matching were limited to demographic characteristics and report card scores that may be confounded with eventual special education status. Taking advantage of recent developments in the difference-in-differences literature, the analytic approach employed here permits causal inferences to discern the impact of City Connects on school-level special education percentages overall and among Black students. Observed effects in either direction may serve as evidence of a foot-in-the-door mechanism by which City Connects impacts persist in the long-run.

The structure for the remainder of this dissertation is as follows. In Chapter 2, I provide additional background information regarding special education and the debates concerning disproportionality. I thereby discuss the gaps in the literature and offer potential policy solutions as well as a theory of change. In Chapter 3, I discuss the data and methodologies used to address the research questions. Findings are presented in Chapter 4. Finally, I conclude with interpretations of these findings in Chapter 5 while also discussing limitations, policy significance, and directions for future research.

CHAPTER 2. LITERATURE REVIEW

This chapter begins with a brief overview of special education in the US, beginning with its history, followed by some of the seminal research that has been done on its impacts. Next, I discuss the key equity issues surrounding special education. Then, I summarize some of the research on the two interventions that I theorize can improve equity in special education. In doing so, I provide a theoretical framework by which integrated student support and publicly subsidized and high-quality early childhood education (ECE) can reduce special education placement.

Overview of special education in the United States

Following federal legislation that granted students with disabilities (SWDs) a right to public education in the 1970s, special education has been a topic of increasing interest within the broader discourse on educational equity in the United States (Ford & Russo, 2016; Skiba et al., 2008). The Civil Rights movement throughout the mid-20th century paved the way for the Rehabilitation Act of 1973, which required schools and other institutions receiving federal aid to provide "reasonable accommodations" for individuals with disabilities (Smith & Kozleski, 2005). Section 504 of this law in particular defines disabilities as "any physical or mental condition which substantially limits at least one major life activity" (Rehabilitation Act, 1973). Prior to this law, SWDs – many of which were students of color – were often excluded from public schools or placed in completely separate environments (Dunn, 1968).

The Education for Handicapped Children Act was enacted in 1975 requiring schools to evaluate SWDs, create unique educational plans that would best emulate the experience of non-SWDs, and place them in the least restrictive environment (LRE). This act was reauthorized in 1990 under the Individuals with Disabilities Education Act (IDEA, 1990), which requires that schools develop individualized education programs (IEP) for all SWDs who would otherwise be unable to access the general curriculum. While all students in special education have some disability, not every SWD is placed in special education. IDEA also entitles SWDs to an appropriate evaluation with parent and teacher participation, maintain the LRE, and provide Free Appropriate Public Education (FAPE) (defined as special education related services that meet state standards, at no cost to the family).

Thirteen categories of disabilities are recognized under IDEA, although four of these categories comprise 80 percent of SWDs: specific learning disabilities, speech or language impairment, other health impairment, and autism (U.S. Department of Education, 2021). In recent years, the proportion of students with a learning disability (LD) has dropped from 50% to 33% following major changes to the identification process, but the share of students with autism has more than doubled in the last 10 years (U.S. Department of Education, 2021). IDEA was again reauthorized in 2004 to align with the requirements of No Child Left Behind (NCLB) Act, such as the specification of performance goals and achievement indicators SWDs. In the 1997 and 2004 reauthorizations of IDEA, equity became an evident focus, with local educational agencies being required to track the disproportionate representations of any demographic group in special education.

Disability identification and special education placement process

The disability identification process for students without an existing medical condition definitively warranting special education placement has been a source of constant debate over time. Most SWDs – particularly those in high-incident categories – are first identified in elementary school, whereas those with disabilities more easily identifiable through some biological criteria are generally identified immediately upon school entry.

While the disability identification process has evolved over time, many aspects of the referral process remain the same. Referrals most often starts with a teacher's recommendation to the family of a child, although parents or other school professional staff may also initiate the process (Harry & Anderson, 1994). For disabilities that are not definitively biologically based (henceforth referred to as "judgmental disabilities"), academic performance and behavior in and outside the classroom that deviate from what is expected of students in a particular grade (or age) are common reasons for a referral. Accordingly, not every student is subject to an evaluation. Depending on the specific issue, the referred child may then undergo a number of psychological assessments, followed by clinical evaluation.

In the case of LD, which is the highest incident category, students were historically identified using the discrepancy model, which looked for discrepancies between student performance on an IQ test and their academic achievement (Fuchs & Fuchs, 2006). The discrepancy model has since been largely abandoned following research demonstrating numerous pitfalls. Firstly, although the discrepancy model provides a simple and standardized method to identify students with LD, it often provides little information on how best to support students. Secondly, findings from the assessments do not always discriminate between disabilities and the results of inadequate teaching. Thirdly, students must first fail in order to qualify for a clinical examination, which may take a few years despite the fact that they would derive greater benefits from early intervention. Finally, the model may discriminate against underrepresented minorities through the use of assessments with racially biased components, thereby inflating concerns of disproportionality (Fuchs & Fuchs, 2006).

Today, most states have adopted more evidence-based processes to identify SWDs. Response to Intervention (RTI), for instance, is a multi-tiered approach to assisting struggling learners by exposing them to a number of intensive evidence-based interventions – first in groups and then individually – and tracking progress before subjecting students to special education placement. A similar approach to RTI – Multi-Tiered Systems of Support (MTSS) – has been developed for students with behavioral issues to support additional socio-emotional needs. If evidence-based interventions are unsuccessful in improving student academic or behavioral progress, then students will generally undergo further professional evaluation. In most school districts, a discussion among the teacher, school psychologist, professional evaluator, and parents takes places before a decision is reached. Research suggests that teacher referrals lead to special education placement between 50% and 85% of the time (Hibel et al., 2010).

If a child is found through this process to have a disability that limits their ability to succeed in a general education program, they become eligible for special education. Parents have the right to waive special education services for their children but, if they approve, an IEP team is created, consisting of the parents, a special education and general education teacher, a district representative, a person qualified to interpret the results, and the student themselves if they are over the age of 14. The IEP team designs the accommodations, modifications, and services that the student needs to help them make progress in the general curriculum. This also includes the percentage of time outside of the general classroom students need for additional support. Annual goals are established as a way to set a standard for what the student can realistically achieve within that timeframe. The IEP is reviewed annually, and students are generally reevaluated every three years to determine whether they still need special education support. Specific aspects of this referral process vary slightly across states and districts.

Research on special education

SWDs make up approximately 14% of the student population across public schools in the United States, an increase in 3% over the last 20 years (U.S. Department of Education, 2019). LD is the most common diagnosis, making up a third of all SWDs, followed by speech or language impairment (20%), health impairment (14.4%), autism (10.2%), development delay (6.6%), and emotional disturbance (5.1%.). The remaining categories make up approximately 3% (U.S. Department of Education, 2019). Massachusetts, which is the state of the school district studied in this research, has the fourth highest proportion of SWDS among all the states in the nation with 18% of the student population classified with a disability (U.S. Department of Education, 2018).

Although much progress has been made in granting SWDs increased access to general classroom settings, there remain strong negative associations between special education placement and various indicators of academic attainment (Donovan & Cross, 2002). SWDs are more likely to score lower on standardized assessments, repeat a grade, face school discipline, drop out of high school, earn less in the labor market, and less likely to enroll in and complete postsecondary education (Affleck et al., 1990; Hanushek et al., 2002; Morgan et al., 2017; Sullivan & Field, 2013). To some extent, these negative associations are to be expected, as IEP supports may not be able to fully mitigate the unique obstacles that SWDs face, specifically in the most serious cases (Eckes & Swando, 2009).

A more appropriate comparison, employing students who are similar on various academic and behavioral characteristics but are not placed in special education offers a more complete picture. Due to the non-random nature by which special education is assigned, it is difficult to discern the causal impact of being labeled with a disability. Accordingly, few studies using causal inference designs with student-level data have estimated the impact of special education placement. The findings from such studies have been mixed, which may be due to the methodology and the nature of the samples, thus painting an ambiguous picture concerning the utility of disability services.

To estimate the causal impact of receiving special education, one segment of the literature has employed matching procedures to construct virtually similar samples with the exception that one sample receives special education and the other does not. Matching on various background information that are predictive of special education placement such as student demographics, home, academic and behavioral characteristics, Morgan and colleagues (2017) found null overall impacts of special education services on various outcomes. They also reported negative impacts for students with the lowest probability of being placed in special education yet were still identified as a SWD (Morgan, Frisco, et al., 2017). Simply put, compared to students with otherwise similar academic and behavioral backgrounds, SWDs experience either the same or worse academic outcomes. Sullivan and Field (2013) also found large negative impacts of special education services received in preschool on math and reading achievement in kindergarten. In another study, a cohort of low-income kindergarten SWDs in Chicago tracked through sixth grade were found to have not improved in math and reading scores relative to a comparison group matched on various school and family characteristics (Reynolds & Wolfe, 1999). Students with LD performed notably worse than those with other disabilities.

Other studies using student fixed-effects models have demonstrated more positive results. These studies leverage repeated observations within students to control for time-invariant characteristics that may be correlated with special education placement and, thus, the estimates are less susceptible to omitted variable bias, as may be the case with the studies using matching.

Hanushek and colleagues (2002) found marginally positive effects of special education placement in fourth grade or beyond on math scores, with larger effects for students with learning disabilities (0.11 SDs) and emotional disturbances (0.15 SDs). In Kentucky, Hurwitz and colleagues (2020) also found that achievement for students improved relative to their prior trajectory after placement in special education as early as kindergarten, although their sample was very restricted. These results were closely replicated in a more recent and econometrically sound study in New York City by Schwartz and colleagues (2021), but they only examined effects for students identified with LD in fourth grade or after. Because most students are identified in earlier grades, the generalizability of these findings may be limited. More notably, the results were practically null for Black and White males and noticeably smaller for Hispanic students. Positive estimates of the effects of special education placement appeared to be driven by the outcomes for female and Asian students.

In summary, although the evidence is not entirely conclusive, it appears that special education placement results in positive impacts for students who undoubtedly need it based upon less subjective evaluations, but potentially neutral or even negative impacts in less clear-cut cases. This underscores the importance of properly identifying students. While the neutral effects of special education are potentially attributable to inadequacy or inefficiency of IEP supports (Sullivan & Field, 2013), the negative relationship between special education placement and academic outcomes paints a more troubling and paradoxical picture. Why would the provision of supports aimed at ameliorating the effects of a particular disability further reduce a student's probability of educational success? Even for students who may not necessarily require an IEP, why wouldn't additional support services improve achievement?

One answer appears to lie in the label (Becker, 1963). Sociologists often conceive of judgmental disabilities as socially constructed (Anyon, 2009; Asch, 1984; Hibel, 2019; Jones, 1996). Simply stated, students are labeled a certain way because they are socially “deviant” from what is considered the “norm” in society. For example, if a student is not able to read by the third grade, society perceives there to be something “wrong” with that student. The expectation that a student should read by third grade is socially constructed because society has deemed that to be a standard for what is considered “normal”. Teachers referrals for special education evaluation and subsequent clinical judgements reflect explicit and implicit societal expectations and biases based upon what they deem to be “normal” (Ahram et al., 2011). Additional qualitative research has uncovered both explicit and implicit biases teachers hold that may trigger referrals and subsequently lead to diagnoses (Chin et al., 2020). These biases may be a result of cultural mismatches between White teachers and school administrators on the one hand, and low-income and high-minority student populations on the other (Kramarczuk Voulgarides et al., 2017).

There is reason to believe that a disability diagnosis has a stigmatizing effect due to the student being seen as “deficient” from what is considered normal. Labeling Theory suggests that individuals who are labeled as part of a group based upon socially “deviant” behavior buy into a certain image of themselves. Howard Becker, who first coined the term within the context of criminal activity, argued that people often see themselves through the image others have of them (Becker, 1963). Consequently, being labelled as a deviant can lead to “deviance amplification” because the label becomes an important way in which a student identifies themselves.

Applications of Labeling Theory in education have backed this assertion. For instance, Rist (1977) found that randomly assigning students the label “spurter” increased performance on an IQ test. Alternatively, research on the label attached to high-achieving students has produced evidence of both positive reinforcement and negatives stigmatization (Rentzsch et al., 2011; Shoenberger et al., 2015). Researchers have thus theorized that students placed into lower academic tracks internalize lower expectations about themselves in the classroom, resulting in less effort in school and perhaps contributing to past and current Black-White and high-low SES status achievement gaps. Consequently, SWDs often hold negative beliefs about their own academic abilities, thereby neutralizing any potential impacts brought about through the additional supports they receive (Morgan, Frisco, et al., 2017; Valås, 2001). Research has also underscored how individuals doing the labelling (i.e., teachers, parents, and other school staff) are also guilty of buying into the labels by having lower expectations of SWDs (Shifrer et al., 2013; Smith et al., 1986).

Disproportionality in special education placement

Concerns about the ineffectiveness of special education are especially pronounced when factoring in equity issues. Even prior to the passing of the Education for Handicapped Children Act in 1975, concerns about the overrepresentation of Black students in special education were voiced: Dunn (1968) stated the following:

> A better education than special class placement is needed for socioculturally deprived children with mild learning problems who have been labeled educable mentally retarded. Over the years, the status of these pupils who come from poverty, broken and inadequate homes, and low status ethnic groups has been a checkered one. In the early days, these children were simply excluded from school. Then, as Hollingworth (1923) pointed out, with the advent of compulsory attendance laws, the schools and these children "were forced into a reluctant mutual recognition of each other." This resulted in the establishment of self-contained special schools and classes as a method of transferring these "misfits" out of the regular grades. This practice continues to this day and, unless counterforces are set in motion now, it will probably become even more prevalent in the immediate future due in large measure to increased racial integration and militant teacher organizations (p. 5).

More than 50 years ago, Lloyd Dunn foreshadowed the use of special education as a means for segregation in a post-Brown v. Board world. His concerns were not unwarranted considering the fact that tracking of students of color into lower academic tracks had been rampant since the end of the 19th century, when high school enrollment was beginning to increase (Tyack, 1974). To maintain social advantage, students of middle and upper classes were sorted into college preparation tracks while most of those from lower classes – many of whom were Black and immigrant – were exposed to vocational curriculums, diverting them from a path to college (Labaree, 2010).The tracking of students of color into special education is seemingly no different; by removing students from general classroom environments in K-12 settings, these students are often also diverted from the path to postsecondary achievement and success.

Several decades of research has illuminated disproportionately by race and ethnicity in special education throughout the United States (Ford & Russo, 2016; Harry & Anderson, 1994; Skiba et al., 2016; Sullivan & Bal, 2013; Sullivan, 2011). Given that this literature covers multiple racial and ethnic groups with regard to the mechanisms and driving factors leading to disproportionality, this dissertation is limited to racial disproportionality as it relates specifically to Black students. The factors leading to disproportionality faced by other racial and ethnic groups may be dissimilar and thus it is important to treat each group distinctly. As demonstrated here, there is a fairly robust literature on disproportionality relating to Black students, yet the contradictory nature of some of the research leaves much to explore further.

Disproportionality is particularly problematic with regard to the aforementioned judgmental disabilities in which diagnoses are based upon more subjective evaluations (Hibel et al., 2010). In the case of disproportionate overrepresentation, the concern is that students who do not actually have a disability are nonetheless being placed in special education, where their needs are not appropriately being met. On the contrary, disproportionate underrepresentation may result in students not receiving services that they are entitled to, and should be receiving, to meet their educational needs.

Early research on disproportionality in special education uncovered the overrepresentation of Black and male students in multiple disability categories (Coutinho & Oswald, 2005; Skiba et al., 2006). Given the decades of research demonstrating the negative association between disability diagnosis and various student outcomes, the overrepresentation of Black students – specifically those who are male – has serious equity ramifications with regard to the achievement gap (Harry & Klingner, 2014; Donovan & Cross, 2002). In both high- and low-minority schools, Black students are overrepresented across most judgmental disability categories. Within specific disability categories such as emotional disabilities and LD, Black students are more than twice as likely to be identified relative to their White peers (Sullivan, 2011). Once identified, Black students are also removed from traditional classrooms at higher rates, thereby increasing within-school segregation (Skiba et al., 2006).

While racial disparities in special education placement are not conclusive evidence of discrimination, disproportionality has been linked to multiple factors that may reflect inequities. Early research on disproportionality was predicated upon what some researchers call the Theory of Compromised Human Development (TCHD) (O'Connor & Fernandez, 2006). In short, the TCHD suggests that, because students from low SES backgrounds experience various challenges in the early years of development, they are more likely to be at risk for disabilities like LD and emotional disturbance. Since Black students are more likely to grow up in low SES households, they are also more likely to develop a disability. Simply stated, in the views of the TCHD, the overrepresentation of Black students in special education is largely mediated by poverty.

Disproportionality in such contexts, according to this theory, should thus be expected and not perceived as misidentification (Morgan et al., 2015).

The TCHD has been challenged by researchers who have found that Black students are still more likely to be placed in special education even after accounting for various indicators of SES (Grindal et al., 2019; Skiba et al., 2005). While the variance in special education placement accounted for by race is reduced upon the inclusion of SES indicators, race nonetheless remains a significant predictive factor. As mentioned earlier, the labelers (i.e., teachers) conceptualize a universalized definition of normal that situates White and middle-class children as the norm against which the development of minority children is evaluated. This definition punishes Black students regardless of their early development experiences (O'Connor & Fernandez, 2006).

Racial bias, along with factors related to poverty, in the special education placement process was evident in the findings of Skiba and colleagues, who conducted qualitative research in seven districts experiencing high levels of disproportionality in special education (Skiba et al., 2006). The researchers uncovered the following five factors that contributed to disproportionality: lack of early learning opportunities, neighborhood violence, pressure to assign students due to increased accountability from standardized tests, lack of resources for classroom teachers to effectively manage disruptive behavior, and cultural mismatches between students and teachers (and other school-staff).

Although the evaluation process is conducted by professionals, Harry and Klingner (2014) found that the psychological assessments conducted by psychologists are highly idiosyncratic and biased towards the results that they or the teacher making the referral wish to see. Thus, the biases teachers hold have major consequences for the special education placement of their students. Simply providing additional learning support once students are in school, then, may not be enough to overcome these racial barriers. Some researchers have thus advocated for teachers to receive increased training in the process of identifying students who may have a disability through a more social-justice oriented perspective (Sullivan & Proctor, 2016).

In more recent years, research on disproportionality has become more contested, with the TCHD has received renewed backing. In particular, Morgan and colleagues (2015) found that Black students are actually *underrepresented* in special education after accounting for indicators of SES. The researchers used survey data to match Black and White students on a number of variables that are predictive of disability identification (e.g., birth weight, behavior indexes prior to entering school, SES indicators, etc.) creating appropriate/ counterfactuals whereby race is the only differing factor. Additional studies using more detailed health records have found that the overrepresentation of Black students only exists in low-minority schools (Elder et al., 2021; Farkas et al., 2020). Peer effects drive these disparities because a low performing student in a high-performing school is more likely to be targeted as developmentally behind than a school in which the low performing student's achievement is considered closer to the average (Farkas et al., 2020).

These findings, while running contrary to earlier understandings of disproportionality, are not entirely surprising, however, and underscore the subjective nature of the special education placement process. As already established, teachers refer students to special education based upon what they perceive as typical, and that perception is largely driven by what the general population of students they deal with are like. In an affluent suburb where most students are White, a low-achieving Black student from a low SES household may be identified as potentially having a disability from a teacher not only because of their race, but also because of their performance. Such a student is more likely to blend in with the general population in a high-minority and high-poverty concentrated school. Overrepresentation of minority students in special education is an unwarranted perception, according to these researchers, and is potentially harmful if districts deliberately attempt to not place Black students in special education when they may actually be in need of such services (Morgan, Farkas, et al., 2017).

Still, the discrepancies between the studies claiming underrepresentation versus those insisting on overrepresentation of Black students in special education are difficult to reconcile. In their synthesis of the literature on disproportionality, Cruz and Rodl find that the way SES is operationalized matters (Cruz & Rodl, 2018). Overrepresentation is generally found when free and reduced-priced lunch is used as a proxy for SES status, whereas more specific variables like parental income and education have a suppressor effect by either removing or reversing the effect of race (Ludlow & Klein, 2014). Another source of discrepancy is in the type of data used. National or larger-scale datasets that incorporate various contexts are more likely to result in underrepresentation, whereas those that focus on local contexts (i.e., looking at just one district) often find overrepresentation. Because special education referrals are driven by perceptions of contextual norms, Cruz and Rodl recommend that researchers use local data as opposed to national datasets (Cruz & Rodl, 2018). Finally, the choice of covariates has important implications. Morgan and colleagues included academic and behavioral measures as controls in their models, despite the fact that these may be confounded with racial biases.

The assertion that Black students are actually underrepresented in special education has also been harshly criticized by scholars of disability studies for “logical and statistical flaws and dangerous assumptions about the reality of disability identification” (Collins et al., 2016; Skiba et al., 2016). For instance, critics have disputed the notion that Black and White students who are all but racially equal exist in reality given the racially-biased institutions persistent throughout society. Accordingly, adding all possible and relevant covariates into a model results in a misleading picture of the reality generally faced by Black versus White children.

Challenges to measuring disproportionality. An important factor complicating interpretations of disproportionality concern the way it is measured. Disproportionality is typically measured in two ways: the relative risk ratio and the composite index. While helpful, neither statistic alone provides insight into the underlying mechanisms that cause disproportionality.

The relative risk of disability diagnosis for a specific demographic group is measured in relation to the rest of the population. For example, if 20% of Black students in a given sample are identified with a disability, but only 10% of the rest of the students have a disability, then the relative risk for Black students is twice that much of non-Black students. The U.S. Department of Education has granted states flexibility to define thresholds of significant disproportionality based on relative risk ratios, but researchers have previously used benchmarks ranging from 1.5 to 3.0 (Programs & Education, 2017). The disadvantage to using relative risk ratios, however, is that it is impossible to discern whether the demographic group of interest is over- or underrepresented. In the aforementioned example, the case could also be that Black students are appropriately represented, and the reference group (non-Black students) are two times *underrepresented*.

The composition index, on the other hand, does not use a reference group and instead compares the proportion of students in special education from a given demographic group with the proportion of the group in the sample of interest. Nationally, for example, 18% of Black students are identified as having a disability, whereas the total Black student population is almost 15%, resulting in an index of 3%. There is little agreement on what constitutes significant disproportionality according to the composite index, although some have recommended a 10% benchmark (Skiba et al., 2008). In very homogenous populations, where one demographic group makes up a very large proportion of the sample, the composition index is less useful. If, for instance, Black students constitute 90% of students in a school, then significant disproportionality would impossibly require more than 100% of special education students to be Black.

Federal and State responses to disproportionality. The federal response to research on disproportionality in special education has been more receptive to the theory of minority overrepresentation, regardless of the underlying causes. Since the 1997 reauthorization of IDEA, states and districts have been required to collect and monitor data on disproportionality, but only since 2004 have any specific actions been required if significant disproportionality is found (Albrecht et al., 2012).

Although not defined until the reauthorization of ESSA in 2015, evidence of significant disproportionality requires that local educational agencies allocate 15% of their IDEA Part B funds on coordinated early intervention services or professional development to support students with high-needs that may later warrant a disability diagnosis. Significant disproportionality was previously defined as a particular demographic group having three times or larger relative risk for being placed in special education for three consecutive years, but states now have more flexibility in establishing thresholds (Individual with Disabilities Education Act, 2004). Identified districts are required to review and present the underlying factors leading to significant disproportionality, and then revise policies, procedures, and practices. Additionally, districts are required to direct the maximum amount of comprehensive coordinated early intervening services (CCEIS) funds to serve children in the overidentified groups. CCEIS activities include professional development and educational and behavioral evaluations, services, and supports such as RTI and MTSS. Implementation of these regulations began in March 2019 after multiple delays sparked by court challenges, so it is too early to estimate their impact.

Limited by insufficient guidance and inconsistent implementation, the federal response to disproportionality has had limited impacts (Albrecht et al., 2012). In response, some states have taken matters into their own hands. Recent evidence from Texas, for example, demonstrates that Black students experienced small gains in high school completion and college attainments after district-level caps were placed on Black and Hispanic disproportionality, perhaps bolstering the notion that some Black students in the state were misidentified (Ballis & Heath, 2019). District-level caps on special education enrollment as a whole, however, led to reductions in high school and college completions for Black and Hispanic students in special education and general education (Ballis & Heath, 2019). Alternative approaches like RTI and MTSS have also become more common, although there is limited evidence of their effectiveness in the context of disproportionality (Sullivan & Proctor, 2016).

The lack of success to date in reducing disproportionality to date warrants attention to other potential interventions. The focus of the proposed research is on the disproportionality that potentially occurs due to the disadvantages that students from low SES background face, namely in the lack of access to high quality early learning environments and the out-of-school supports that mitigate some of the impacts of poverty. By providing students with access to higher quality ECE and coordinated out-of-school supports, students from low SES backgrounds will potentially be in a better position to grow from both an academic and a behavioral perspective, thereby leading to lower special education referrals. Because Black students are more likely to live in low SES households, I hypothesize that they will be differentially impacted by such supports. Still, the threat of racial bias exists and, thus, I do not theorize that racial gaps in special education placement will completely be erased.

Education and inequity in the United States

Understanding the scope and need for integrated student support and high-quality ECE as approaches to combat disproportionality requires an in-depth understanding of how poverty impacts educational achievement and attainment. Accordingly, I proceed in this section with an overview of how schools are placed in difficult positions to mitigate the impacts of growing up in a low SES household.

Arguably the most salient obstacle blocking the path to narrowing the achievement gap in the United States is the high level of economic inequality (Owens, 2018). Inequality, as defined by Reardon and Bischoff (2011), pertains to both inequality in opportunity and outcomes across the following domains: socioeconomic, health, political, and sociocultural. Each plays a role in the inequalities pervasive and persistent in the US education system. However, socioeconomic inequality is of specific interest here. Defined by Carter and Reardon (2014), socioeconomic inequality refers to "the unequal distribution of economic resources (e.g., money, usually measured by income or wealth, and access to credit), opportunities to build human capital (e.g., from schooling, technology, and job training), and social resources (e.g., access to social capital and information)" (p. 4)

Despite having the highest gross domestic product (GDP) overall in the world, the US is also a leader among advanced countries in socioeconomic inequality (Stiglitz, 2016). The 2015 report *School Performance in Context* found that, in comparison to eight major countries, the US ranked among the worst with regard to economic inequity, social stress, and support for young families (Harvey et al., 2015). Lack of affordable healthcare, childcare, and overall community support exacerbate the impact of poverty, which in turn directly affects children growing up in low socioeconomic conditions (Holliday et al., 2014).

Education has long been theorized as the "equalizer" to these disparate economic conditions (Bernardi & Ballarino, 2016). This notion idealizes education as a meritocracy, whereby individuals will be rewarded with economic gain and upward class movement as long as they work hard and perform well in school (Brown & Tannock, 2009). The reality, however, is that access to a high quality, effective, and equitable education is also directly impacted by economic conditions (Owens, 2018). Low quality education is a strong factor in perpetuating this cycle, as individuals who grow up in low SES households struggle to escape such conditions throughout their lives, thereby passing on the cycle to the subsequent generation. Recent research, in support of this notion, has found that the fraction of children who earn more than their parents has fallen from 90% for children born in the 1940s to 50% for children born in the 1980s (Chetty et al., 2014).

Income inequality is also directly connected to racial inequality (Reardon & Bischoff, 2011). Following a successful period of integration after the Supreme Court's ruling in Brown vs. the Board of Education, urban locales throughout the US have experienced *increasing* levels of segregation through both the removal of court-ordered desegregation efforts (e.g., busing) and the relocation of wealthier and White families to suburban towns (Reardon & Bischoff, 2011; Schneider, 2008). The resultant urban communities – highly characterized as mostly minority and economically depressed due to various factors such as structural racism over the course of previous decades – have been left depleted of resources at both the school and individual level (Owens, 2016). In turn, while the Black-White achievement gap narrowed considerably between 1960 and 1990, progress since has largely stalled (Ferguson, 2020; Raudenbush, 2009).

Due to a myriad of reasons stemming from such neighborhood poverty, schools in low-income communities have struggled in their pursuit to educate their students, many of whom face severe trauma outside of the classroom. The major role that SES factors play in the disability identification process is thus not surprising (Grindal et al., 2019). Additionally, it is perhaps no surprise that the achievement gap between students of low and high SES, as measured by the National Assessment of Education Progress (NAEP), has not significantly narrowed through the last two decades (Ferguson, 2020). The most recent NAEP results arrive on the heels of two decades characterized by educational reform, whereby billions of dollars were invested into schools to increase achievement. This bleak outlook on public schooling has subsequently led to increased efforts at both the federal and state level to provide students, especially in urban communities, with alternative school options in the form of private vouchers and charter schools, both of which have had mixed success in improving student outcomes (Mitchell et al., 2017).

Following several decades of research, the answer to the following underlying question is seemingly still beyond reach: What can schools do, if anything, to improve student well-being, academic achievement, and ultimately, economic outcomes for those students with greatest disadvantage?

The role of schools

A longstanding debate in education policy, dating back several decades, revolves around the question of whether schools actually serve as an exacerbator of inequality or as a class equalizer. Dumont and Ready (2020) argue that the answer depends on what researchers consider the counterfactual in such an analysis. Those pointing to schools as drivers of inequality focus on the lack of equal access to high-quality schooling, whereas the proponents of schools as equalizers focus on the positive effects resulting from increases in exposure to schooling.

Evidence of the former stance includes decades of research findings related to the negative association between high SES school composition and academic growth (Duncan & Murnane, 2011). These findings appear to be moderated by factors such as poor curriculum and instruction, peer contagion effects, and disparities in economic, social, and cultural capital (Dumont & Ready, 2020). Due to students from low SES backgrounds having limited options for quality schooling, the evident societal and structural mechanisms that create such inequalities place them in a very difficult position to succeed academically and economically. Without a quality schooling experience, students from low SES backgrounds fall and stay behind their more affluent peers (Downey et al., 2004). The additional tracking of minority students into special education further exacerbates these effects.

Those arguing in favor of the school equalizer role point to research depicting increases in academic achievement of students from low SES backgrounds following greater investments in human capital through additional days of schooling and the introduction of various program interventions (Jackson et al., 2020; Raudenbush, 2009). Contrary to the conclusions drawn by many in the education community from the seminal Coleman Report (1966) that found little variation in student achievement *levels* between schools, more recent evidence has found that up to three-quarters of the variation in student *growth* occurs between schools (Atteberry & McEachin, 2020). As an example, consider the Chicago Public School (CPS) system, which, despite pervasive poverty, ranks among the top school districts in the nation – regardless of SES composition – with regards to achievement *growth* between third and eighth grade (Reardon & Hinze-Pifer, 2017). The reasons why are unclear, however, especially considering that the district has faced enrollment declines, school closings, and funding issues over the last several years. The success of CPS in contributing to student growth does prove that schools have *some* agency in closing achievement gaps.

Recent research has also indicated that, at least at the high school level, enrolling in schools with high social-emotional learning and test-score value-added leads to improvements in student achievement, attendance, and behavior (Jackson et al., 2020). Additionally, the once accepted notion of summer learning loss as a significant driver of inequality has drawn increased skepticism following a replication effort with new data from the same researchers (von Hippel et al., 2018). The researchers illustrate that previous evidence of summer learning loss is largely a function of measurement artifacts. Their own analyses using the Early Childhood Longitudinal Study (ECLS) 1999 cohort finds contradictory evidence of summer learning loss for students from low SES backgrounds, and argue that the achievement gap narrows, if anything, during early schooling years.

Schmidt and Burroughs (2015) further argue that, at least for mathematics, one of the key factors driving inequality in schools is unequal opportunity to learn (OTL). Although not a panacea for reducing inequality in outcomes, simply providing students with more challenging coursework and exposing them to algebraic concepts at an earlier age is correlated with improved student outcomes, thereby demonstrating that schools can do more than previously thought. I now turn attention to one way in which investments in schooling can improve student outcomes: high quality ECE.

Early childhood education

The provision of high-quality and publicly-subsidized ECE is among the most significant ways that investments in schooling can help close the achievement gap (Yoshikawa et al., 2016). Few findings in education research have reached such broad consensus from policymakers and researchers alike. As previously established, the pre-existing achievement gaps between high- and low-SES and Black and White students at the start of kindergarten largely reflect inequalities in access to high-quality early childhood learning opportunities. Teachers making special education referrals may very well assume such achievement gaps to be a product of developmental delays, thereby contributing to potential disability misidentification. Consequently, providing such high-quality experiences through public prekindergarten (preK) programs and other forms of center-based care have become forefront policy priorities across the education sector (Friedman-Krause et al., 2020).

Dating back to President Lyndon B. Johnson's "War on Poverty" initiatives in the mid-1960s, by which the Head Start program was enacted, state-funded public preK programs for students from low SES backgrounds have become nearly universal, with 43 states now offering some form of public preK, five of which are "universal" (Friedman-Krause et al., 2020). Nearly half of the 69% of all 4-year-olds enrolled in preK across the country are in publicly-funded programs. Due to limited funding, however, seats are generally limited in most states and school districts, leaving many three- and four-year-old children without guaranteed access. Additionally, the quality of state-funded ECE differs across and within states, with some programs more effective than others. Still, the impacts of various forms of ECE on academic achievement, as well as numerous other outcomes, are well-documented across various settings, including large scale implementations through state-wide programs (Campbell et al., 2002; Ludwig & Miller, 2007; Muschkin et al., 2015; Nores et al., 2005; Phillips et al., 2016).

The earliest study investigating the causal impact of ECE was conducted on a sample of 123 at-risk students through the High/Scope Perry Preschool program in 1962. The two treated cohorts received either one or two years of ECE prior to kindergarten. The program's 0.75 standard deviation impact on IQ by age 5 was instrumental in obtaining federal support for Head Start (Nores et al., 2005). A decade later, the Carolina Abecedarian project, which also randomized a descriptively similar sample of students through a more intensive ECE intervention, resulted in even larger effects (Campbell et al., 2002). Most notably, the achievement effects from the Abecedarian study persisted through high school, whereas the effects of Perry Preschool faded out by the time students were eight years old (Bailey et al., 2017). Reemergence of positive effects into adulthood for the Perry Preschool program were discovered in later studies, however, whereby program participants had higher educational attainment and employment earnings, and lower rates of criminal activity and welfare receipt than the control group (Nores et al., 2005). Similarly, some studies of Head Start have also generally found a pattern of early fadeout, followed by reemergence of effects into adulthood (Deming, 2009).

While research on the long-term outcomes of state-funded public preK programs are limited due to the recency of their implementation, short-term effects have been mixed, with some studies demonstrating evidence of early fade-out. In Boston for instance, students randomly assigned a seat to high-demand public preK programs did not score statistically significantly higher on standardized math and reading assessments through third grade compared to students attending other ECE programs across the city (Weiland et al., 2020). In North

Carolina, however, the effects of two universal preK programs compared to other ECE programs on reading and math achievement were found to have persisted through third grade (Dodge et al., 2017).

The mixed findings of the effects of ECE programs on outcomes has stimulated questions concerning what exactly contributes to the persistence or fadeout of effects (Bailey et al., 2017; Bailey et al., 2020). Bailey and colleagues have described three mechanisms that may explain why some intervention effects fadeout, whereas others persist or even reemerge: skill-building, sustaining environments, and foot-in-the-door interventions. Skill-building interventions target "malleable" and fundamental skills that would not eventually develop in the absence of an intervention, such as emotional self-regulation, certain academic skills, and academic motivation. Because many ECE programs target skills that most students eventually develop, there is reason to believe that students not exposed to such programs ultimately "catch up" to the treated group, thereby resulting in fadeout.

Sustained environments refer to contexts where the skills gained from an intervention are built upon, thereby sustaining normative growth. Among the most salient impediments to skill building following receiving high-quality ECE is placement in a school where most students did not receive similar experiences. Peer effects may thereby impede normative growth following an initial jolt in achievement. For example, while the impacts of receiving an enrollment offer in a high-demand public preK program in Boston as a whole did not result in overall significant impacts on academic achievement by third grade, positive effects were found among students who subsequently enrolled in high-quality elementary schools (Unterman & Weiland, 2020). Johnson and Jackson (2019) similarly found larger and sustained effects of Head Start when students subsequently enrolled in better-funded schools, representing an example of what they and other researchers have termed “dynamic complementarity” (Cunha & Heckman, 2007).

The foot-in-the-door mechanism refers to interventions that occur at key time periods of high opportunity or vulnerability. A fundamental aspect of foot-in-the-door interventions is that the direct effects of the interventions are not as important as the period in which they occur. Thus, effects of such interventions are mediated through other mechanisms based upon these key time periods that carry longer into the future. Consider interventions that aim for students to gain mastery in algebra early in high school (e.g., Double Dose Algebra). Although the algebraic skills attained through such an intervention may not be long-lasting, there may still be persistent, auxiliary effects on other outcomes because completing algebra by ninth grade increases the likelihood that students are on track to graduate high school on time and complete a sufficient number of math courses necessary to enroll in a four-year college (Cortes et al., 2015). In other words, foot-in-the-door interventions have a domino effect of sorts, whereby the initial intervention gives the first push. Because studying the long-term effects of interventions is often difficult, Bailey and colleagues have consequently advised researchers to study these “front doors”, whereby future effects of interventions can potentially be understood through their mediating effects (Bailey et al., 2017)

Early childhood education and special education placement

While the persistent effects of some ECE programs have been considered across all three mechanisms, the potential effects of ECE on avoidance of placement in special education as a potential foot-in-the-door mechanism is most relevant here. As already established, students from low-income backgrounds who are less-ready for kindergarten due to lower quality early childhood learning environments may persistently remain academically behind their higher SES counterparts. The inability to "catch-up" may then later result in a disability diagnosis. This may be due to a misdiagnosis or simply a reflection of the disadvantaged circumstances from which they grew up. If ECE programs cause students to avoid special education placement, then persisting or reemerging effects evident from long-term outcomes may certainly be a product of that mediating mechanism, even if effects on shorter-term outcomes like academic achievement do not persist. Considering the aforementioned literature on the potential negative impacts of student placement in special education, the mediating role that disability identifications plays in the long-term impacts of ECE programs has warranted further research.

Several studies have investigated the impact of ECE programs on special education placement. A recent meta-analysis of 18 studies across nine interventions (e.g., Perry Preschool, Abecedarian, Head Start, etc.) from 1962 to 2003 found average reductions of 0.33 standard deviations or 12.5 percentage points for special education placement (McCoy et al., 2017). Investigations into more recent state-wide programs have been more mixed, however. In North Carolina, the state's two ECE programs provided to high-risk and low-income children successfully reduced the probability of special education placement in later grades by almost 40%, most of which was attributed to declines in diagnoses of specific learning disabilities (Muschkin et al., 2015). Similarly, in Texas, the state's public pre-K program reduced the probability of special education placement by 13 percent (Andrews et al., 2012). In Tulsa, however, the Community Action Project Head Start program did not significantly reduce special education placement through middle school (Phillips et al., 2016).

Most relevant to the proposed study is an analysis of high-demand public preK programs in Boston, whereby the researchers leveraged the district's Deferred Acceptance (DA) lottery enrollment system to investigate the impact of the program on various outcomes, including special education placement (Weiland et al., 2020). The researchers found no impacts on special education placement by the third grade for a subset sample of first-choice lottery winners versus first-choice lottery losers who never enrolled (more on this later), but there were impacts when using an inverse probability weighting approach that utilized a larger but nonrandom sample. Specifically, they found a 7% reduction in probability of being assigned to special education for students who enrolled in public preK versus those who did not enroll.

Limitations of past ECE research on special education outcomes

While many previous studies investigating the impact of ECE programs on special education placement demonstrate large and positive effects, there is a need to update the literature. Firstly, the intensive nature of some early ECE models make it difficult to entangle the school-level effects. Parenting education was a major feature of many early ECE programs. In the Abecedarian study, for example, half of the treatment group also received a three-year home and school resource program. Observed effects may certainly be attributed to such additional supports as opposed to the instructional and curriculum aspects of ECE.

Secondly, changes in context have certainly increased the need to study modern day programs. Families today now have greater access to ECE supports than in decades prior. As such, in many recent studies investigating the impacts of a specific ECE program, most students in the control group – even in high-poverty settings – receive some form of ECE through other means. The question at hand now is not necessarily whether ECE is effective, but rather, does a specific program provide added benefits over others.

Thirdly, the research on effects of ECE enrollment on special education placement for specific subpopulations has been much more limited. Muschkin and colleagues (2015) conducted subgroup analyses in their study analyzing the impact of two North Carolina ECE programs, and found that “More at Four” (i.e., the public preK program) had positive effects on reducing special education placements across all subgroups. The effects were smaller, however, for Black students, perhaps demonstrating evidence of persistent racial biases.

Fourthly, several studies – both more recent and older – fall short of establishing strong causal evidence. While randomization was a key feature in some of the older and outdated ECE models, more recent studies have relied on less internally or externally valid designs due to the lack of random assignment. For instance, age cutoffs for enrollment are commonly leveraged to employ regression discontinuity (RD) designs, as was done in the Tulsa study (Gormley et al., 2005; Ludwig & Miller, 2007). While RD designs have been established by many researchers as the strongest research design to make causal inferences after RCTs (William R. Shadish, Thomas D. Cook, 2002), Lipsey and colleagues (2015) have outlined several threats to internal validity in RD designs that specifically leverage such age cut-offs. Other studies have relied on matching nonrandom samples on a limited set of student characteristics that do not fully account for differences in the families that enroll their children in one program versus another (Andrews et al., 2012).

Building upon the work of Weiland and colleagues (2020), this dissertation bolsters the evidence on the impact of ECE on special education placement by examining the impact of specific public preK programs that incorporate integrated student support (explained further in the ensuing section). These analyses test whether pairing high-quality early learning with supports aimed at mitigating the effects of poverty provide a greater impact. Such programs – which more closely resemble the Abecedarian and Perry Preschool models through increased family engagement – are hypothesized to provide improved sustained environments within the home to help parents support their children during and after completion of public preK.

Poverty and emotional well-being

The provision of ECE in modern-day programs is perceived as a form of human capital investment by which the achievement gap can be closed, or at least substantially reduced. As mentioned previously, older models generally incorporated a wide array of other services aimed at parents, likely contributing to sustained environments. Few models with such comprehensive services, however, exist today. The average preK program thus is limited in its ability to tackle some of the "out-of-school" factors that may inhibit childhood development and lead to special education placement.

An additional body of literature has concentrated on the impacts of out-of-school factors – namely poverty – on educational attainment independent of the school attended. While out-of-school and in-school factors are certainly intertwined in the sense that growing up in a low SES household in a low SES community is predictive of attending a lower quality school, there are certainly specific out-of-school characteristics that affect a child's ability to succeed, regardless of where they attend school and the instructional resources invested in their learning.

Poverty itself directly impacts children's health, development, and learning (Walsh & Theodorakakis, 2017). Exposure to trauma within the home and neighborhood violence – both more common for children from low SES backgrounds – also affects mental and emotional well-being (Acri et al., 2017). When considering these experiences, it is not difficult to understand why SES-related achievement gaps are already present before children start kindergarten. While access to universal ECE has been productive in improving child learning before kindergarten, support for mental and emotional well-being has proved to be a more difficult challenge (McCoy et al., 2017). Recent research has illuminated the link between poverty-associated trauma and academic learning (Walsh & Theodorakakis, 2017).

Poverty negatively impacts the development of the stress response system, directly compromising child development, learning, and health (Walsh & Theodorakakis, 2017). When students are facing significant difficulties related to issues like hunger, homelessness, mental and physical trauma, among other challenges, school becomes an afterthought. The extent to which instruction-based interventions are capable of mitigating these learning challenges are likely limited. Consider curriculums that require students to work in groups or engage in discussions based upon assigned reading. Students with behavioral issues developed as a result of their childhood contexts often find it difficult, regardless of the classroom material, to participate effectively in such learning environments. Consequently, even with instructional and academic investments, emotional disturbance may still elicit special education referrals. The question to consider then is, what can schools do to support the mental well-being of students from disadvantaged contexts?

Integrated student support

The idea of schools serving as mediators between students and community supports to alleviate out-of-school factors affecting childhood development dates back to the 1970s with the founding of Communities in Schools (McShane, 2019). This introduced the concept known as integrated student support, or "wraparound" services, whereby trained coordinators work directly with schools – most often in low SES and urban communities –to connect students with community resources. These community supports include medical and dental care, mental health services, basic needs like food or shelter, academic enrichment programs, tutoring, and mentoring (McShane, 2019). The integrated student support model relies on five essential elements to support service delivery: community partnerships, student support coordination, integration into the school setting, needs assessments, and data tracking (Moore et al., 2017).

Thousands of students nationwide are served through a Communities in School affiliated partner (McShane, 2019). More informally, multiple school districts such as Oakland, CA and Cincinnati, OH have labeled all of their schools as “community schools”.

Evaluations of the community schools’ model on academic achievement specifically have shown more promising results in recent years. Earlier evidence of these models were underwhelming with regard to academic achievement, but a recent study of a well-implemented model in New York City schools found positive impacts on high school graduation, attendance, disciplinary rates, and math achievement after three years of implementation (Johnston et al., 2020).

A related, but perhaps more successful approach based upon the research evidence has been the City Connects integrated student support model, which began over 20 years ago in Boston but has since expanded to over 100 schools across several additional school districts (Walsh et al., 2014). Recent evaluations of City Connects at the elementary school level have found large positive outcomes on elementary report card grades, middle school standardized test achievement, high school graduation, and college enrollment and completion (Lee-St. John et al., 2018; Pollack et al., 2020; Walsh et al., 2014).

Like Communities in Schools, the City Connects model involves the pairing of schools with a coordinator, who is typically a certified social worker with a Masters in Social Work graduate degree. The coordinator meets with teachers at the beginning of each year to place student into tiers of need, in a process known as “the whole class review”. The coordinators then work with individual students, their families, and teachers to develop a plan of support for that student through community partners. Supports may range from enrichment activities in the arts and sports, to learning-based activities like tutoring, as well as clinical support for those with medical, emotional, and psychological needs. The individualized whole class review process ensures that each student receives appropriate supports targeted towards their specific needs. Additional individual student reviews are provided to students with the highest needs.

At the heart of the City Connects model are the community partnerships and family connections. Coordination with community partners and families ensures that the supports are accessible and appropriate. While it is difficult to pinpoint exactly what uniquely makes the City Connects model more successful than other forms of integrated student support, high-quality data collection and subsequent use has resulted in high levels of fidelity of implementation. This high fidelity of implementation, along with strong community and family partnerships delivering coordinated supports, are theorized as the most crucial elements linking the implementation of City Connects to student overall well-being, which in turn has impacted academic achievement.

Integrated student support and special education. While limited research has investigated the relationship between the implementation of integrated student support programs like City Connects and special education outcomes, researchers have long theorized that school-based wraparound approaches to positive behavioral interventions and supports better serve high-risk students (Eber et al., 2002; Furman & Jackson, 2002). As alluded to earlier, special education referral is often a tool used by teachers when they deem a student unfit for the traditional classroom experience. Rarely do teachers have other supports and services at their disposal to refer at-risk students. On the other hand, the wraparound model is more proactive and targeted in nature, allowing for intervention earlier on with potentially more effective means.

Evidence from City Connects indicates that the intervention may indeed impact special education outcomes. In one study, researchers found that students in non-City Connects schools in Boston who were referred to special education were 22 percent more likely to be deemed ineligible than similar students in City Connect schools (Center for Optimized Student Support, 2009). Once these treated students entered middle school in non-City Connects schools, they were no more likely than comparison students to be later placed in special education. This suggests over-referral in the non-City Connects schools, whereby students who did not need special education were nevertheless being referred because no other options were available. Focused interviews with principals and teachers confirmed that the intervention added new systems and processes that changed the special education referral process, resulting in less referrals overall.

A limitation of the previous work on City Connects and special education is the inability to draw causal inferences. Most students attending the schools in the previous analysis were not randomized to treatment and comparison conditions, and the resulting covariates for matching were limited to demographic characteristics and report card scores that may be confounded with eventual special education status. Leveraging recent developments within the difference-in-differences literature, the analytic approach employed in this study supports more defensible causal inferences regarding the impact of City Connects on school-level special education percentages overall, and among Black students in particular. Observed effects in either direction may serve as potential evidence of a foot-in-the-door mechanism by which City Connects impacts persist over time.

Chapter Summary

Although well-intentioned, the Civil Rights-based origins of increased special education access in the US have ironically produced additional equity issues in the form of disproportionality. Although students from low SES background face a heightened risk of developmental delays and emotional disturbance, the subjective nature of the referral process still often results in the disproportionate placement of Black students. Inappropriate supports, combined with potential stigmatization that occurs from being labeled with a disability, may further exacerbate the difficulties such students face. It is therefore unsurprising that many studies have found limited effects of being placed in special education for Black students. Simply placing quotas on the proportion of students in special education does not appear to be an effective solution, as was done in Texas, because this may deprive students of supports they actually need (Ballis & Heath, 2019). Instead, special education supports should be preceded or replaced by other interventions that target the risk factors leading to heightened risk of disability diagnosis.

In this dissertation, I sought to examine the impact of integrated student support in both the early childhood and elementary context. High-quality ECE offers at-risk students an opportunity to gain the academic and behavioral skills necessary for kindergarten readiness. As previously mentioned, several studies – although not without methodological flaws – already suggest that high-quality ECE can reduce the likelihood of special education placement. Yet, ECE may not completely address the out-of-school factors at-risk students face that may cause emotional trauma. Integrated student support interventions like City Connects have the capability to enhance the supports students receive in schools before special education referral. Consequently, providing both high-quality ECE and integrated student support may be among the most successful and cost-effective approaches schools can take to reduce the risk of students being placed in special education.

Through this dissertation, I addressed the methodological and substantive gaps in the literature by studying the impact of both public preK and integrated student support on special education placement within the context of disproportionality, using strong quasi-experimental designs with high internal validity. This work contributes to the increased research on disproportionality in disability identification by shedding light on whether early learning opportunities and out-of-school supports can improve special education placement outcomes with a specific focus on equity. The results will be of policy interest given recent federal legislation requiring states to more rigorously track and address racial disparities in special education placement (Kramarczuk Voulgarides et al., 2017).

CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY

In this chapter, I present a detailed description of the data and methodology used to address the research questions. I begin with an overview of the research questions, followed by a description of the data and variables. Next, I identify and explain the statistical models used to answer each research question. Finally, I identify potential threats to internal and external validity, along with descriptions of sensitivity analyses to check for the robustness of the findings.

Study purpose and research questions

The purpose of this dissertation is twofold. Firstly, given mixed research findings on the extent to which disproportionality exists and is problematic, I sought to replicate previous research using data from two high-poverty school districts to examine variation in special education placement by race, along with the effects of being placed in special education on academic achievement and how that differs, if at all, by race. These analyses contextualize the way special education intersects with race in two high minority school districts. While disproportionality across various racial and ethnic lines have been reported in the literature, the focus here is on racial disparities as they relate to Black students. Given previous research demonstrating an overrepresentation of males in special education, I also analyzed disproportionality as it relates specifically to Black boys (Coutinho & Oswald, 2005)

The second part of this dissertation explores how two integrated student support programs operationalized through the City Connects intervention impact the probability of special education placement, with a similar focus on differential impacts by race. The first program is the City Connects prekindergarten (preK) program. The second program is City Connects at just the elementary school level. While not specifically focused on altering special education referrals, City Connects in both contexts targets multiple risk factors that may contribute to the probability of placement.

The following research questions are addressed in this study:

1. To what extent do special education placement rates in high-poverty schools differ by race and gender, particularly for students identified after third grade? How do these relationships change after taking into account socioeconomic status, gender, English Learner status, prior achievement, and school attended?
2. Upon partialing out variance between students, schools, grades, and years, what is the relationship between special education placement and mathematics and reading achievement in grades 4-8? To what extent does this relationship vary by race and gender?
3. What is the impact of enrolling in a City Connects public prekindergarten program on the probability of special education placement in elementary school, and are there differential impacts by race and gender?
4. To what extent do school-level rates of special education placement differ after the introduction of City Connects? To what extent do special education placement rates differ by race and gender before and after the introduction of City Connects?

I first examined how the probability of disability identification differs by race. This constitutes a starting point for determining if there is disproportionality in special education placement and how it compares to what has been found in the previous studies. I then examined how the relationship between special education placement and race changes upon the inclusion of other background characteristics. The goal here is to see the extent to which the observed variation in special education placement by race can be explained by other background factors observed prior to placement.

The second research question builds on more recent literature examining how placement into special education affects student achievement, with a particular focus on possible differences by race. This stems from prior research suggesting that special education does not meaningfully improve academic achievement outcomes for Black students, perhaps suggesting that some students are misidentified and thereby receiving inappropriate supports (Schwartz et al., 2021).

The findings from these analyses aid in the interpretation of the findings from the previous research question. For example, if Black students are found through Research Question 1 to be overrepresented in special education compared to other racial groups, and there are no differences in achievement upon being identified as such through Research Question 2, then these findings have important implications for the types of interventions supports that should be directed toward this student population, along with whether reduced or increased placement is warranted.

Research Question 3 asks if enrollment in a City Connects public preK program – compared to a non-City Connects public preK program – impacts the probability of special education placement at an individual level, and whether the observed impacts differ by race. Research Question 4 similarly asks if implementing City Connects in elementary and middle school impacts special education placement overall, and for Black students in particular, at the school-level. The early childhood and elementary/middle school models of the program differ in important ways, so it is important to look at the impacts of each separately. As I argue later in this chapter, the methodologies employed to address research questions 2 – 4 permit strong correlational inferences about the relationship between the predictors and outcomes, but causal inferences are more problematic.

Data and sample description

The studies comprising this dissertation use a combination of student and school-level administrative, enrollment application, and assessment data from two urban school districts in Massachusetts spanning 2004 to 2019. Both districts have been operating public preK programs and City Connects across a number of schools over the last 15 years. District characteristics as of December 2021 are presented in Table 3.1.

Table 3.1

Student demographics in districts of study, December 2021

Student characteristic	Percent for District 1	Percent for District 2
Black	29%	18%
Hispanic	43%	68%
White	15%	9%
Asian	9%	2%
English Learner	30%	16%
First language not English	48%	30%
Economically disadvantaged*	71%	87%
Special education	22%	25%

Note. *student participates in one or more of these state-administered programs: SNAP, TAFDC, DCF foster care, and MassHealth

Both school districts also serve racially, ethnically, and socioeconomically diverse student populations that are similar to several other large urban school districts in the country, yielding results with greater external validity. The districts also have among the highest rates of special education placement across the nation, so there is increased policy relevance in studying disproportionality.

Special education in districts of study

As of 2021, approximately 22% of all students in District 1 and 25% of students in District 2 are identified as having a disability, which is somewhat larger than the state average at 18.4% (Department of Elementary and Secondary Education, 2021). Most SWDs fall under the judgmental category, with nearly half classified with a specific learning disability (SLD). The other SWDs are mostly designated as having communication disorders, emotional disturbance (ED), intellectual disability, and developmental delays. Students with autism and physical disabilities make up less than 10% of the SWD population.

The graduation and dropout rates for SWDs in both districts is about 54% and 5%, respectively, compared to 74% and 4.0%, respectively, throughout the state. Approximately 37% of SWDs receive instruction in a substantially separate classroom setting compared to 20% throughout the state. Academic achievement levels of SWDs in these districts are similar to SWDs in other large cities across the United States.

Historically, the state from which these two districts reside provided individualized education plans (IEPs) to non-SPED students in the 1990s, but the state adopted the federal policy in 2000 that provided IEPs to only SWDs. Despite this change in policy, the rates have largely remained stable across the last two decades. The Council of the Great City Schools (Council of the Great City Schools, 2009) issued a report on behalf of District 1, concluding that special education services were relied upon far too often for struggling learners, which was a symptom of "lack of a systemic core literacy program, weak interventions and progress monitoring, undefined positive behavior intervention and supports (PBIS) programming, inadequate differentiated instruction and technology" (p.13).

The report found no evidence of “severe disproportionality”, but reported subgroup differences depict some overrepresentation for Black students, specifically boys. Due to the lack of publicly available data on disproportionality prior to recent years, it is unclear whether this raised awareness has impacted rates of classification for Black students. The concerns raised in the report regarding why special education referrals are high also underscore much of what was mentioned in Chapter 2. Additionally, these concerns support the theory of change suggested in this dissertation about the ways in which preK and City Connects can reduce special education placement.

Sample description

The data and sample for each research question differ. In particular, analyses for Research Questions 1 and 2 use student-level data from both districts, but Research Question 3 employs only District 1 data. For Research Question 4, the analysis is at the school level and encompass both school districts.

Analytic Sample for Research Questions 1 and 2. The data for Research Questions 1 and 2 comprise student-level records in Districts 1 and 2 spanning the 2001/02 and 2015/16 academic years. The sample was restricted to students who were enrolled in either district during third grade and not placed in special education prior to fourth grade. Students must also have non-missing third-grade achievement data and one subsequent year of achievement data to be included in the sample. Accordingly, 14 cohorts of third-graders (fall entry from 2001 to 2014) were followed. As such, both of these research questions focus on students not placed in special education prior to fourth grade. The total sample – 75% of which comes from District 1 – includes approximately 85,700 students, 8% of which were eventually placed in special education

These sample restrictions were placed so that third grade achievement on the state's standardized test can serve as a baseline by which to determine if race is predictive of special education placement among otherwise similarly achieving students. Because state tests are only administered between third and eighth grades, such analyses cannot be conducted on students identified in special education in earlier grades. This restriction does have the benefit of limiting the special education placement observed in these later grades to disabilities that are more "subjective" in identification. As explained in the previous chapter, these high-incident disabilities tend to be diagnosed at later grades, so many of these placements – which are the focus of study – are still captured by the data.

Analytic Sample for Research Question 3. As explained in the ensuing sections, a randomized lottery that occurs as part of the preK program assignment process in District 1 was leveraged to make causal inferences about the impact of assignment to City Connects preK program on special education placement. Because such an assignment mechanism does not exist in District 2's, data for Research Question 3 was limited to District 1.

The sample was further restricted to students whose families applied for a public preK spot and had a probability of placement into a City Connects program between 0 and 1 (i.e., a non-deterministic chance of being awarded a seat). Four cohorts of students were followed through the 2015/16 school year, beginning with the year they could have first possibly enrolled in District 1's public preK program. The 2010/11 year is the first in which City Connect entered public preK programs. The eldest cohort was in fourth grade at the time of data collection and the youngest cohort reached first grade. A depiction of the cohorts and years of data available is presented in Table 3.2. Students who were identified with an IEP prior to preK entrance via District 1's ECE offerings for three-year old students are excluded.

Table 3.2

Depiction of cohorts and years of data available

Cohort (preK year)	KG year	1st grade year	2nd grade year	3rd grade year	4th grade year
2010/11	2011/12	2012/13	2013/14	2014/15	2015/16
2011/12	2012/13	2013/14	2014/15	2015/16	-
2012/13	2013/14	2014/15	2015/16	-	-
2013/14	2014/15	2015/16	-	-	-

In total, 11,079 students attended a District 1 preK program between 2010 and 2013, of which 84% (n=9,300) had not previously attended District 1's offering for three-year-old children with special education needs (K0). Upon excluding the K0 students, approximately 19% of students in the four cohorts (n=1,737) attended one of 16 City Connects preK programs, and nearly half of these students (n=851) were assigned to such programs via the lottery. The comparison sample consists of 2,561 students who had a probability between 0 and 1 of being assigned to a City Connects preK program but were offered a seat in another District 1 preK program. Almost all of these students enrolled in another District 1 preK program, although a small proportion (4%) still found their way into a City Connects program. Contrary to previous work on the subject (e.g., Weiland et al., 2020), where only first-choice and oversubscribed schools were considered, I was able to use the maximum number of students subject to lottery placement to a City Connects program, amounting to a sample of 3,412 students.

Analytic Sample for Research Question 4. While the prior research questions are designed to make inferences at the student level, in Research Question 4, the focus is on the *school level*. Data for this analysis comprises data from 140 elementary and middle schools in both districts between 2004/05 and 2015/16. Approximately 40% of these schools (n=57) received City Connects for at least one year during this time span.

An important limitation to making causal inferences about City Connects in Research Question 3 is that the intervention was not randomly assigned to the schools. While selection bias stemming from non-random student assignment to schools is removed through the lottery mechanism, bias from self-selection of schools to the intervention remains. Consequently, if treatment and comparison schools differed in observed and/or unobserved ways that are correlated with special education placement, then any observed relationship cannot be defensibly interpreted as causal. In other words, Research Question 3 asks about the impact of *being assigned to schools implementing City Connects* on special education placement as opposed to the impact of the intervention itself. Research Question 4, accordingly, asks what happens to special education placement rates in schools in the immediate years following the implementation of City Connects. As explained below, the methodology used here limits selection bias stemming from schools self-selecting into the intervention.

Power analyses

Across all research questions, it is necessary to establish whether there is sufficient statistical power to detect substantively meaningful differences in the outcome between the various treatment and control conditions. Given that this research uses observational longitudinal data, there is no control over the sample sizes available. Consequently, it is necessary to determine the minimum detectable effect size based upon the expected sample sizes. For research questions 1 – 3, the software PowerUp! was used to estimate the minimum detectable effect size given the study conditions (Dong & Maynard, 2013). For research question 4, I used the "Power Panel" R Shiny application, which was developed by Schochet (2022) specifically for event-study designs like difference-in-differences models. All baseline power analyses assume a power of 0.80, a two-tailed test with an alpha of 0.05, and no cluster or blocked assignment. Minimum detectable effect sizes at greater levels of power are also presented. Where relevant, I also calculated how much power is present to detect effect sizes found in prior studies.

Power analysis for Research Question 1

Given that there is no "treatment" condition in Research Question 1, the power analysis here simply concerns the minimum detectable effect size in terms of probability of special education placement for Black students compared to other racial groups. With a sample size of 85,600 – 33% of whom are reported Black – effect sizes as low as 0.03 can be detected. Similar effect sizes can also be detected when power is set to greater than 0.90.

Power analysis for Research Question 2

The "treatment" condition in this research question is special education placement, with 8% of students in the sample of 85,700 experiencing the event. As explained in the methodology section, because the analytic approach here captures within-student change in achievement following special education placement, over 80% of the variance in achievement can be explained by the model, drastically increasing power. Given these sample characteristics, effect sizes as low as 0.01 can be detected. Subgroup analyses for Black students (33% of the sample) and Black boys (16% of the sample) can detect effect sizes of 0.02 and 0.03, respectively. Effect sizes found in similar prior studies have been as low as 0.05 standard deviations, and this study has greater than 0.95 power to detect such effect sizes.

Power analysis for Research Question 3

While treatment students are clustered across several public preK programs in the district, treatment assignment is determined at the individual level. The sample includes 3,400 students across six cohorts of students applying to public preK, and nearly half were offered a seat. With a sample size of 3,400, 23% of whom are in the treatment group, effect sizes as low as 0.11 can be detected. As stated earlier, across prior studies, ECE reduced the likeliness of special education placement by an average of 0.33 standard deviations (12.5 percentage points) (McCoy et al., 2016). So, there is more than sufficient power (>0.99) to detect important effect sizes, including smaller than those identified in previous research. For subgroup analyses, however, the sample was first restricted to Black students (n=700) and then Black male students (n=336). In the analysis with just Black students, there is power to detect effect sizes as large as 0.22, and for the analysis with just Black and male students, there is power to detect effect sizes as large as 0.29.

Power analysis for Research Question 4

Using the "Power Panel" R Shiny application recently developed by Schochet (2022) specifically for event-study designs like difference-in-differences models, I used available sample statistics to calculate the minimum detectable effect size. In addition to typical sample inputs used for power analyses, the Power Panel software also considers the number of time periods, treatment timing groups (i.e., the number of cohorts that started receiving City Connects in the same year), the start period for each timing group, and cluster size. Importantly, the software does not assume random assignment to treatment, as is done in many classical power tools, allowing for more precise estimation in this context. For these analyses, in which I estimated treatment effects at the *school level*, I used 11 time periods total with eight treatment timing groups. The sample includes 40 treatment and 100 comparison schools. Given these study characteristics, and a two-tailed test with an alpha of 0.05, effect sizes as small as 0.10 standard deviations can be detected with 0.80 power. Effect sizes greater than 0.11 SDs can be estimated with greater than 0.90 power.

Description of variables

The full list of predictor and outcome variables, by research question, are provided in Table 3.3 below. A discussion of the rationale for each variable's inclusion in the analyses follows.

Outcome variables

For Research Question 1, the outcome is a binary indicator of whether or not a student was placed in special education by the end of eighth grade at the latest. Several students, however, do not have data up to eighth grade because the data for more recent cohorts are not available that far out. Given the aforementioned sample restrictions, the outcome variable in Research Question 1 concerns special education placement between fourth and eighth grade, effectively measuring the probability of being identified through a more subjective referral and evaluation process.

For Research Question 2, student achievement is measured using standardized state achievement tests in math and reading, which Massachusetts has required public schools to administer to all students in grades 3 to 8 since the No Child Left Behind (NCLB) Act passed in 2004. In the period of this study, the Massachusetts Comprehensive Assessment System (MCAS) in math and English Language Arts (ELA) was used prior to 2015. This assessment was scored using a Rasch measurement model. In the 2015/16 school year, all schools administered the Partnership for Assessment of Readiness for College and Careers (PARCC), although some piloted this assessment in the prior year as well. Since 2016/17, the state has administered a new version of the MCAS. Both PARCC and the Next Generation MCAS use 3-parameter IRT models.

Given these changes in the assessment over time, the Massachusetts Department of Elementary and Secondary Education (DESE) recommends using raw scores for the original MCAS, mode-adjusted theta values for the PARCC, and standard theta values for the Next Generation MCAS when combining assessment results for longitudinal analyses. Based upon DESE's recommendation, these retrieved scores were standardized by grade, subject, and year.

I note, however, that these transformations do not completely mitigate the challenges brought forth by changes to assessments and is thus a limitation of this dissertation. For example, the PARCC assessment, while intended to measure the same constructs as the MCAS, has been widely perceived as more difficult than the MCAS (Nichols-Barrer et al., 2015). Consequently, while I interpret assessment outcomes for students and schools as repeated measures over time, there may be more measurement error for students who took different assessments due to potentially shifting constructs.

In Research Question 3, the outcome is a binary indicator of whether students were placed in special education by the last grade students were observed. For the eldest cohort, this meant fourth grade, and for the youngest cohort, this was first grade. To test for potential differences in regression treatment effects, I also used special education placement by each grade level (from first to fourth).

Finally, for Research Question 4, given that the analysis is at the school-level, the proportion of special education students in a school, along with the proportions of Black students and Black males in special education, were used as the primary outcome variables.

Student-level predictor variables

All student-level analyses (i.e., Research Questions 1 – 3) incorporated standard student characteristics that have previously been found in the literature as predictors of the respective outcomes. These variables included gender, race, socioeconomic status (SES), and English Learner (EL) status. Baseline student achievement was also included as a predictor in Research Question 1.

It is important to note that the operationalization of the race variable is undoubtedly limited in this study. District practices for classifying students within a racial group are unknown, but it is clear that the small number of categories are unable to capture within-race variation. For example, the schooling experiences of African Americans who trace their lineage back to slaves in the US may differ in important ways from Black individuals whose families more recently immigrated to the nation (e.g., children of Somali, Eritrean, Haitian, etc. descent). As it relates to special education placement, prior literature has not seriously considered these differences and, unfortunately this was the case for this dissertation.

The key predictors of interest varied by research question. For Research Question 1, race was of focal interest. Special education placement, while an outcome for Research Questions 1 and 3, was the main predictor of interest for Research Question 2. Due to district changes in data privacy protocols, information on the exact disability a student is classified with was not available for most years. For Research Question 3, a number of variables pertaining to the preK program assignment mechanism were used, namely, the receipt of an offer to enroll in a City Connects preK program, an indicator of whether the student ultimately enrolled in such a program, and the probability of being assigned to such a program (i.e., the Deferred Acceptance propensity score – see below).

School predictor variables

Baseline measures of the proportions of minority and economically disadvantaged students, as well as school achievement, served as covariates for Research Question 4. As explained in the ensuing sections on analytic strategies, I employed a weighting procedure to "match" City Connects schools to comparison schools using these characteristics.

Table 3.3

Variable descriptions

Variable	Research question	Definition	Operationalization
		Outcome variables	
Special education placement	1 + 3	Whether or not student was identified by eighth grade at the latest.	Binary indicator with never placed in special education as reference group
Academic achievement	2	Student scores between grades 4 and 8 on state standardized math and reading assessment	Standardized raw or theta score (depending on assessment administered – see explanation below) by grade, subject, and year
Proportion of students identified as special needs	4	School-level percent of students with special needs, overall and for just Black students, by year	Ratio ranging from 0 to 1
		Student-level predictor variables	
Race	1-3	White, Black, Hispanic, Asian, Other	Categorical variable with Black as reference category
Economic disadvantage	1-3	Ever had eligibility for free and/or reduced-price lunch	Binary with paid lunch as reference
Gender	1-3	Male/female	Binary with female as reference

English Learner	1-3	Current EL, former EL, or not EL	Categorical with not EL as reference category
Academic achievement	3	Student performance between grades 3 and 7 on state standardized math and reading assessment	Z-score standardized by grade, subject, and year
Received offer at CCNX preK	3	Received offer to enroll in CCNX school at preK via lottery	Binary indicator with never received CCNX offer as reference group
DA propensity score for offer to CCNX preK	3	Probability of randomly being assigned to a CCNX school via public preK enrollment lottery	Ratio ranging from 0 to 1
Enrolled in CCNX preK	3	Enrolled in CCNX preK school upon receiving offer via lottery	Binary indicator with never enrolled in CCNX as reference group
		School-level predictor variables	
Proportion of minority students	4	Proportion of students in a school identified as Black or Hispanic	Ratio ranging from 0 to 1
School performance quality	4	Average student performance on math and ELA standardized tests	Standardized z-score
Proportion of economically disadvantaged students	4	Proportion of students in a school eligible for free or reduced-price lunch	Ratio ranging from 0 to 1

Public preK lottery in District 1

On average in a given year, about half of students enrolled in District 1 kindergarten will have previously attended one of the district's 60-plus public preK programs, representing approximately a third of 4-year-olds in the city (Shapiro et al., 2019). While District 1 only maintains seats for half the number of students (n=3,000) who subsequently enroll in kindergarten the following year, due to limited demand overall, most students who apply are offered a seat in some program. Schools vary in the number of seats available, however, so while a student eventually gets a seat somewhere, it may not be their top choice. The district operates a lottery system that uses the Deferred Acceptance (DA) algorithm to assign students to public preK programs when there is "oversubscription" (i.e., more applicants than available slots), which allows one to study the program's impacts with high internal validity.

In short, the enrollment process at preK allows families to make a list of up to 10 preferred schools. Schools for which the demand for enrollment is higher than the seats available rank students based upon variables such as walking distance and whether they have siblings attending that particular school. When there is a tie on the priorities, the available enrollment seats are randomized based upon a lottery draw, whereby students with the lowest of lottery numbers are assigned to the preferred school. For those who miss out on their first preferred choice, the process repeats at the next preferred school on their list, assuming that school is also oversubscribed. If the student's second preferred school is undersubscribed, then they "win" a seat there.

In recent years, education researchers have capitalized on the adoption of these choice-based enrollment systems– which include a randomized lottery component – to study the impact of attending particular types of schools or school-level interventions that have not been randomly assigned (Chabrier et al., 2016). Such a method has been popular in the school choice literature to study the impact of charter and private schools (Zimmer & Engberg, 2016). When families self-select into preK programs, simply including an indicator of whether a student attended that school to estimate its impact can be misleading due to selection bias. Families that enroll their children in such a program may differ in important ways from families that choose not to enroll. Lotteries that occur through urban enrollment systems can be used to develop instruments that partition out this endogeneity.

To make causal inferences taking advantage of this lottery system, researchers have historically focused primarily on students that are randomized to *oversubscribed* schools that are their *first* priority, as this is the most intuitive and least computationally intensive method. Simply put, consider students with equal priorities who applied to the same oversubscribed public preK program as their first choice. Some will randomly be assigned to that high priority program, whereas the others will be assigned elsewhere. The assignment of students to another program (i.e., their second or subsequent options) is not as straightforward, because that assignment may not actually be random, and instead based upon their priority ranking. Untangling who is randomized in these second and subsequent lotteries has been a challenge for researchers. One popular method for dealing with this issue has been to condition on the priority ranking and the full list of schools student apply to, which is referred to as a “risk set”. Due to the high dimensionality by which risk sets occur (i.e., the various ordering of schools students applied to), this method leads to smaller sample sizes, neglects randomized enrollment into undersubscribed schools, and increases degrees of freedom (Abdulkadiroğlu et al., 2017).

Abdulkadiroğlu and colleagues (2017) recently introduced a method to improve the generalizability of previous studies using DA-based assignment systems. In short, the method calls for simulating a large number of draws from the lottery mechanism, keeping all information about priority rankings and preference variables the same, but changing the random lottery number that was drawn by the school district. In other words, the process is repeated *n* number of times, resulting in known probabilities of assignment to any program, regardless of whether it was the student's first preferred choice or not.

A probability of assignment – referred to as the DA propensity score – between 0 and 1 indicates students who were subject to randomization. A student with a DA propensity score of 0 is never assigned to a particular program, so they are not subject to randomization; their assignment is not dependent on the lottery number they are assigned. Similarly, students with a propensity score of 1 are always assigned to a specific program, regardless of their lottery number, meaning that their assignment is also not subject to randomization. This process maximizes the number of students subject to randomization, in contrast to simply focusing on just oversubscribed schools and that of a student's first choice. Additionally, the use of the DA propensity score removes the high dimensionality of using risk sets by summarizing all that information into the form of one probability. As explained later in section 3.6, this methodology was used to estimate the impact of being assigned to City Connects preK programs.

Analytic plan by research question

In the ensuing sections, I present and explain the specific analytic models used to answer each research question. Beforehand, there are three points to be made that are applicable to all research questions.

First, I estimated all regression models within an Ordinary Least Squares (OLS) framework. In the case of Research Questions 1 and 3, for which the outcome variable is dichotomous, instead of using logistic regression, OLS was still used so as to interpret the regression coefficients as linear probabilities. Coefficients of categorical predictors can be interpreted as the difference in the probability of being placed in special education compared to the reference group. Prior research has indicated that a linear probability model (LPM) can be used when the relationship between probability and the corresponding log odds is approximately linear over the range of modeled probabilities (Huang, 2019; von Hippel, 2015). While this generally holds true for probabilities between 0.2 and 0.8, for categorical variables – which are the primary predictors in this study – discrete probabilities perform just as well in LPMs as logistic models (von Hippel, 2015). LPMs are thus often preferred in the social sciences due to the less intuitive and often misunderstood interpretation of odds ratios (Niu, 2020).

Secondly, to account for the nesting of observations within schools, I used cluster robust standard errors at the school level across all models. In the case of Research Questions 1 through 3, students are clustered within schools. For Research Question 4, time points are clustered within schools. Clustering of standard errors is necessary because, when observations are nested within groups, they are no longer independent and thus violate the basic assumptions of the standard OLS regression model (Raudenbush & Bryk, 2002). A potential consequence is the underestimation of standard errors, increasing the risk of a Type I error. Cluster robust standard errors are an established methodology to correct for the correlation of observations within clusters (Abadie et al., 2017).

Finally, subgroup analyses by race and gender are an important feature of all research questions. It is well-established, however, that multiple hypothesis testing can inflate the probability of a Type I error. While several statistical adjustments have been recommended in the literature, these approaches are generally overconservative and reduce power (Bloom & Michalopoulos, 2013). Bloom and Michalopoulos (2013) offer an alternative lens through which subgroup analyses can be interpreted without having to make statistical adjustments. They distinguish between confirmatory and exploratory findings. The former provides definitive evidence of a subgroup effect and is a result of a strong causal design, a well-supported existing theory, and statistically significant findings of large magnitude (based on previously reported literature). Exploratory findings are considered suggestive only and may result when subgroup findings are not statistically significant and/or differ from the full-sample results.

As argued in Chapter 2, there is theoretical support for the subgroup analyses proposed in the ensuing section. I stop short, however, of making causal inferences based upon the methodological approaches used for research questions 2 – 4. Results based upon subgroup analyses were therefore interpreted as exploratory in nature.

Research Question 1

In the first research question I explored potential differences in special education classification rates by race, before and after controlling for other background characteristics. The research question is as follows: *To what extent do special education placement rates in high-poverty schools differ by race and gender? How does the relationship between race and special education placement change after taking into account socioeconomic status, gender, English Learner status, and prior achievement?*

Differences in special education classification rates by race were first descriptively examined through a basic cross-tabulation with a chi-square test of association. Because the chi-square test is sensitive to sample size, to improve statistical inference, I used the following OLS model:

$$Y_i = \beta_0 + \beta_1 Race_i + \varepsilon_i \tag{3.1}$$

Here, Y_i represents a binary indicator of whether or not student *i* was ever placed in special education by the last period observed up until eighth grade. The coefficient for *Race* is the predictor of interest, for which Black is the reference group. The purpose here is to simply see if Black students are differentially likely to be placed in special education than other racial groups.

To examine differences in special education placement probability by gender, I repeated Equation 3.1 but replaced the indicator for race with gender. Next, additional covariates were added to Equation 3.1 to produce the following equation:

$$Y_{its} = \beta_0 + \beta_1 Race_i + \alpha_t + \delta_s + X_{its} + \varepsilon_{its} \tag{3.2}$$

Here, Y_i is the outcome for student *i* in cohort *t* in school *s*, α_t is a third-grade cohort fixed-effect to partial out the variance posed by potential differences across years, δ_s is a school fixed-effect, and *X* is a vector of background characteristics including gender, bilingual and free or reduced-priced lunch, foreign-born, and third-grade baseline achievement in math and reading.

Finally, interactions between race and gender were examined to see how the probabilities differed specifically for Black males compared to other groups defined by race and gender. Given the complexity in interpreting three-way interaction terms, I estimated marginal probabilities for all race and gender terms across every model in Research Question 1.

Conclusions about over- and under-identification cannot be deduced through these models because it is unclear whether any racial group has an “optimal” special education classification rate. The purpose is simply to see how the groups vary on special education placement, before and after controlling for background characteristics.

Research Question 2

The next research question is: *Upon partialing out the variance between students, schools, grade, and year, is there a relationship between special education placement and mathematics and reading achievement in grades 4-8? Does this relationship vary by race and gender?*

This research question provides additional context to the prior question by examining the effectiveness of special education supports in improving student achievement. Here, I adapted the approach of Schwartz and colleagues (2021) by leveraging idiosyncratic variation in the timing of special education within students. Specifically, I used the following model:

$$Y_{igst} = \beta_0 + \beta_1 SpecialEd_{igst} + \vartheta_i + \theta_g + \delta_s + \alpha_t + X_{igst} + \varepsilon_{igst} \quad (3.3)$$

Here, Y_{igst} is the academic outcome (i.e., math or reading achievement, standardized by grade, subject, and year) for student *i*, in grade *g*, in school *s*, and year *t*, and θ_g, α_t, δ_s, and ϑ_i are grade, year, school, and student-fixed effects. Common grade and year differences are captured by the corresponding fixed-effects. The student and school-fixed effects partial out variance from time-invariant characteristics that may be related to the outcome. Time-variant student characteristics (FRL, bilingual status, school mobility, and grade retention) are captured by X_{igst}.

The effect of the main predictor of interest is captured by β_1. The predictor is a binary indicator taking a value of 1 for the years in which the student is placed in special education and all subsequent years, even if the student is later reclassified, and a 0 for all years before special education placement.

Special education placement here refers to the timing in which students were assigned an individualized educational program (IEP), which for most students coincides with a disability diagnosis. Because this event may result in various family, student, and school shifts in educational attitudes and involvement, this coefficient captures more than just the effect of what students receive academically as part of their IEP. Accordingly, while the various fixed effects included in the model account for 90% of the variance in student achievement, I cannot completely rule out the possibility that special education placement is confounded with other time-varying characteristics that may correlate with future achievement. I do argue, however, that the effect captured by this coefficient remains of key interest because special education placement is about more than just the academic supports students receive. For instance, some families may react to a disability diagnosis by providing their children with more academic support outside of school. On the opposite end, special education placement may also isolate students and introduce a negative stigma about their abilities and thereby affecting their motivation to do well in school.

To account for dynamic treatment effects (i.e., differences in effects of special education placement by post-placement year), I reformulated Equation 3.3 using an event-study specification:

$$Y_{igst} = \beta_0 + \sum_{r=-4}^{3} \beta_r SpecialEd(t - t_t^{treat} = r) + \vartheta_i + \theta_g + \delta_s + \alpha_t + X_{igst} + \varepsilon_{igst} \quad (3.4)$$

The only change in this equation from 3.3 is the operationalization of the treatment effect as a vector of regression coefficients ($\sum_{r=-4}^{3} \beta_1$) capturing within-student change in achievement for each year prior to and after special education placement, relative to the year before students were placed in special education $(t - t_t^{treat} = r)$.

Finally, heterogeneity in treatment effects by race and gender combinations were examined by interacting these variables with the special education indicator. Given prior research on the ineffectiveness of special education supports in improving achievement for Black boys, this population served as the reference group (Schwartz et al., 2021). Combined with the results from Research Question 1, the findings here provide more context for potential policy solutions by addressing the role of identification. This information can then be used to interpret the findings from the subsequent research questions on the relationship between integrated student support and special education placement.

Research Question 3

The next research question is stated as follows: *What is the impact of enrolling in a City Connects public prekindergarten program on the probability of special education placement in elementary school, and are there differential impacts by race and gender?*

For this research question, I analyzed differences in the probability of special education placement by the last time students were observed in the data between students who were randomly assigned to City Connects preK programs versus those who were assigned to other District 1 preK programs.

The analytic process for Research Question 3 begins with successfully simulating the DA lottery mechanism conducted by District 1 so that the results converge with 95 percent accuracy to the observed lottery results. In other words, using school application data provided by District 1, one should be able to simulate the actual assignment results with almost perfect accuracy so that students are assigned to the preK program they were actually assigned to.

Upon successfully replicating the original assignment mechanism, the simulation was then run 500 times for each lottery conducted, with the lottery number for each student randomized following each cycle. The probability that a student was assigned to a City Connects preK program (i.e., "the DA propensity score") was then obtained by tabulating the proportion of times they were assigned across the 500 simulations. Only treated students who have similar DA propensity scores to at least one comparison student were retained for the analysis, as this signifies pairs with approximately equal probabilities of being assigned to treatment. This DA propensity score, along with a binary indicator of whether a student was assigned to a City Connects preK program (and an indicator of if they enrolled), was operationalized using a two-stage least squares framework to estimate the impact of being assigned and enrolled in a City Connects preK program on special education placement.

The final sample of randomized students was examined for balance on observed demographic characteristics. In particular, the specific student characteristics of interest were regressed on treatment assignment, DA propensity score, and lottery year. This effectively measures whether student characteristics differ by treatment status. Statistical significance at $p < 0.05$ was used to assess the degree to which the sample was balanced on a given characteristic.

To analyze the treatment effect of City Connects public preK enrollment, I first consider a naïve regression model that simply includes a dichotomous indicator of whether a student was enrolled in such a school or not:

$$Y_{ist} = \beta_0 + \beta_1 Enroll\_CCNX_{ist} + \alpha_t + {}'X_{igst} + \varepsilon_{ist} \tag{3.5}$$

Here, Y_{ist} indicates ever special education placement for student *i,* in school *s,* in cohort *t.* $Enroll\_CCNX_{ist}$ is the primary predictor of interest, indicating whether or not a student enrolled in a City Connects preK program. Cohort-fixed effects and a vector of baseline covariates are also included in the model. The sample for this model includes all District 1 preK students in the study timeframe, with the exception of those previously enrolled in the K0 program.

As alluded to earlier, $Enroll\_CCNX_{ist}$ is endogenous to self-selection; not every family applies to public preK in District 1, and not every student that eventually enrolls in a City Connects program was randomized into that school. To account for student self-selection into a City Connects program, the school assignment mechanism was used to estimate the impact of receiving an offer to a City Connects preK program on special education placement by including a set of binary indicators for each value of the DA propensity score ($\sum_p \delta_p 1\{P_i = p\}$) in the model:

$$Y_{ist} = \beta_0 + \beta_1 Offer\_CCNX_{ist} + \sum_p \delta_p 1\{P_i = p\} + \alpha_t + {}'X_{igst} + \varepsilon_{ist} \quad (3.6)$$

In Equation 3.6, rather than use an indicator of enrollment in a City Connects preK program, I included a binary indicator of receiving an offer, as not every student who received an offer went on to enroll. Approximately 92 percent of students offered to a City Connects preK program eventually enrolled. Non-compliance with the lottery offer was resolved in the subsequent model.

Only students who applied for public preK in District 1 and were subject to randomization to a City Connects preK program (i.e., an assignment probability between 0 and 1) were included in the analysis for Equation 3.6. By conditioning on the propensity score, the non-random endogeneity in enrolling in a City Connects preK program is approximately partitioned out so as to provide an unbiased estimate. The estimate of the coefficient for $Offer\_CCNX_{ist}$ estimates an intent-to-treat (ITT) effect, as it underestimates the impact of actually complying with the offer received. The ITT effect is still of important policy relevance given the reality that not all parents enroll their families if offered a seat.

To provide a direct estimate of actually complying with the offer to enroll in a City Connects preK program – the Local Average Treatment Effect (LATE) – I estimated a two-stage least squares model, whereby the enrollment offer was used as an instrument (conditioned on the DA propensity score) to partition out the endogeneity in accepting the offer for enrollment. The intuition behind the LATE is that the effect of receiving an offer to a City Connects preK program is only realized through actually attending the program.

The first stage is depicted in Equation 3.7 below:

$$Enroll\_CCNX_{ist} = \beta_0 + \beta_1 Offer\_CCNX_{ist} + \sum_p \delta_p 1\{P_i = p\} + \alpha_t + {}'X_{igst} + \varepsilon_{ist} \qquad (3.7)$$

Here, enrollment in a City Connects preK program is a function of receiving an offer to enroll, the DA propensity score, cohort-level fixed effects, and student-level characteristics. The predicted value of $Enroll\_CCNX_{ist}$ is then used in the second-stage equation below:

$$Y_{ist} = \beta_0 + \beta_1 \widehat{Enroll\_CCNX_{ist}} + \sum_p \delta_p 1\{P_i = p\} + \alpha_t + {}'X_{igst} + \varepsilon_{ist} \qquad (3.8)$$

Equation 3.8 mimics Equation 3.6, with the exception that the offer for City Connects is replaced by the predicted value of $Enroll\_CCNX_{ist}$ from the first stage equation (Equation 3.7). This model provides the LATE for attending a City Connects preK program in District 1.

To specifically address the impact of City Connects preK on special education placement for Black students overall and for Black males, I res-estimated Equations 3.6-3.8 while restricting the sample to these subgroups of interest. While subgroup analyses are typically conducted through interactions, in the context of instrumental variables, these models can become quite complex. Namely, all predictor variables in the outcome model of a two-stage least-squares model must also be in the first-stage, otherwise the model becomes a “forbidden regression”, producing biased and imprecise estimates (see Wooldridge, 2010). Interaction terms must therefore also be instrumented, leading to multiple instrumental variables.

Restricting the sample of the analysis to just the subgroups of interest mitigates this issue. A consequence of this approach, however, is a reduction in sample size. There are approximately 700 Black students in the sample, half of whom are male, so the power to estimate meaningful effect sizes was considerably lower. Accordingly, effect sizes were of greater importance than statistical significance here, and the benchmarks produced by Kraft (2020) were referenced for interpretation. Given the aforementioned discussion regarding the interpretation of subgroup effects, the results here will likely be exploratory in nature, at best.

Research Question 4

The fourth research question is: *To what extent do school-level rates of special education placement differ before and after the introduction of City Connects? To what extent do special education placement rates vary by race and gender before and after the introduction of City Connects?*

While District 1's kindergarten school assignment mechanism can be leveraged similarly to estimate the impact of being assigned to a City Connects elementary program on special education placement, I did not use this approach for a school-level analysis for two reasons.

Firstly, although some students in these school assignment lotteries were randomly assigned in kindergarten to City Connects schools, the schools themselves were not randomly assigned to the intervention. Consequently, if schools that opt into the intervention differ in important ways from schools that do not, then the estimated effects may be attributed to these unobserved factors. It is difficult to pinpoint these differences beyond basic demographic characteristics, however, which say little about how schools differ in their effectiveness. This is because differences in achievement or other outcomes might be a result of the intervention itself rather than baseline measures. This concern is also present in Research Question 3, but a school-level analysis is not practical given that the focus is on treatment assignment at an individual grade-level.

The school-level analyses used generalized difference-in-differences models with two-way fixed effects (TWFE) regressions, whereby I estimated changes in the proportion of students placed in special education for City Connects schools in the years following the first few years of implementation, relative to the last pretreatment period. Such an analysis is robust to pre-existing differences in schools and only requires that the treatment and comparison schools demonstrated parallel trends in the outcome measure in the pretreatment period. Parallel trends offer strong evidence that comparison schools provide an appropriate counterfactual for what would have occurred in as treatment schools in the posttreatment period had they not received treatment.

Simply stated, this analysis answers whether or not the introduction of City Connects to schools affected their overall special education classification rates. The TWFE model is presented in Equation 3.9:

$$Y_{st} = \beta_0 + \beta_1(Post_t * CCNX_{st}) + \lambda_t + \delta_s + \varepsilon_{st} \tag{3.9}$$

Here, the outcome, Y_{st}, is now the proportion of students in school *s,* in year *t,* that have been placed in special education. The main coefficient of interest is β_1, which is the differential impact of being a City Connects school (i.e., $CCNX_{st}$) in the post-treatment period (i.e., $Post_t$). School fixed-effects, δ_s, remove all time-invariant heterogeneity between schools. Similarly, year fixed-effects, λ_t, remove heterogeneity between years, thereby estimating the "natural" change in special education rates over time for non-City Connects schools. The TWFE model allows for variation in the time at which schools started receiving the intervention by the inclusion of school and year fixed-effects (Lee, 2016). Equation 3.9 was also estimated for the proportions of Black and Black male students in special education.

More recently, economists have discovered a myriad of issues brought forth by TWFE models, particularly in contexts where treatment implementation is staggered and most units adopt treatment by the last period in the panel (Goodman-Bacon, 2018). Briefly stated, the TWFE estimator has traditionally been understood as a combination of average effects between treated and never-treated units, and treated and not-yet-treated units. In reality, as Goodman-

Bacon (2018) demonstrates, decomposing the TWFE shows that, when a large number of units eventually adopt treatment, comparisons between later-treated and already-treated units often negatively weight the average treatment effect. In other words, units that adopted treatment earlier will inappropriately become comparison units for units that later receive treatment. Also concerning is that, in calculating treatment effects, disproportionate weight is assigned to units that receive treatment in the middle of the panel, which lacks any theoretical backing.

Among other issues with TWFE estimators, parallel trends are often not realized in practice due to inherent differences between units that take up treatment and those that do not, meaning that the resultant comparison group offers a poor counterfactual. Also problematic, but more easily resolved through an event-study framework, TWFE estimators assume treatment effects are constant over time through the use of a simple post versus pre-treatment period binary indicator.

To resolve the inherent limitations of TWFE estimators, a number of alternative approaches have been developed and tested by economists in recent years (see De Chaisemartin & D'haultfoeuille (2021) for a full survey of recently proposed estimators). While there is far from a consensus regarding which estimator is most adequate for given scenarios, I focused on the estimator developed by Callaway and Sant'Anna (2020) due to its ability to include not-yet-treated units as controls, which is important given that several units in this analysis eventually adopted treatment. Additionally, this estimator, as described below, accommodates conditional parallel trends (i.e., parallel trends only holds when conditioning on baseline covariates) and places less assumptions on the functional form of the outcome model.

The Callaway-Sant'Anna estimator (CS for short) is a non-parametric (as opposed to regression-based) estimator of the Average Treatment Effect on the Treated (ATT). In short, the

CS estimator calculates treatment effects by post-treatment period for each group, which is defined as units that receive treatment at the same time point. For example, schools that receive City Connects in 2011 are considered one group. The comparison units for a given group are units that either never receive treatment or have not yet been treated. Average treatment effects by group and year can be estimated, leading to a large number of ATT estimates. These estimates may then be averaged across all groups for each post-treatment period, with group estimates weighted by size (i.e., the number of treated schools in a given group), to calculate treatment effects by each year relative to the last pretreatment period.

The CS estimator resolves the fundamental issues of TWFE by making only the appropriate comparisons, assigning theoretically supported weights, and permitting easy to interpret dynamic treatment effects. To resolve issues related to nonparallel trends in the pre-treatment period, propensity score weights using baseline covariates can be introduced into the model, allowing for a comparison group with more similar baseline equivalence to the treatment group. While this does not guarantee pre-treatment parallel trends, it certainly increases its likelihood.

Prior to applying the CS estimator for this research question, I analyzed the extent to which the TWFE estimator from Equation 3.9 was biased by decomposing the TWFE estimator using Goodman-Bacon's decomposition formula to assess how negative weighting may factor into the ATT estimate. Next, I estimated Equation 3.9 using an event-study framework:

$$Y_{st} = \beta_0 + \sum_{r=-5}^{5} \beta_r I(t - t_t^{treat} = r) + \delta_s + \varepsilon_{st} \tag{3.10}$$

The only distinction with Equation 3.9 here is the replacement of the binary post-treatment coefficient with β_r, which is a vector of regression coefficients capturing within-school changes in special education placement rates for each year before and after receiving treatment (up to five years), relative to the immediate pre-treatment year (i.e. β_{-1}). To test for parallel trends, the coefficients for each pre-treatment year (i.e., lags) were inspected for statistical significance. Lag coefficients not statistically distinct from 0 suggest that treatment and comparison schools were trending similarly in the pre-treatment period.

For the final model, I used the CS method to calculate the ATT for each pre and post-treatment period. Similar to the event-study model, the pre-treatment period estimates (i.e., lags) provide a test for pre-treatment parallel trends. The estimator incorporated propensity score weights that account for basic school demographic information at baseline (proportions of economically disadvantaged, Black, Hispanic, Asian, White, and EL students, as well as baseline achievement and accountability level such as turnaround status). Dynamic treatment effects up to five years post-treatment are presented. Standard errors are clustered by school and presented alongside confidence intervals and tests for statistical significance.

Robustness of findings

In this section, I review the potential threats to internal and external validity across the analyses for all research questions and discuss the degree to which these are likely to be mitigated in the proposed study. Sensitivity analyses are discussed as necessary. Finally, the chapter concludes with noteworthy limitations.

Threats to internal validity

Shadish and colleagues (2002) cite eight threats to internal validity. Simply stated, internal validity relates to the ability to make strong causal claims about treatment efficacy, given the research design (especially the sample of units employed in the study). Given that the research designs employed here are quasi-experimental, a number of robustness checks are necessary to ensure the internal validity of the results. Here, I discuss only those threats that are most relevant while providing tests for robustness.

While Research Question 1 is not a causal question and is used purely for descriptive purposes, omitted variable bias still factors into the interpretation of the findings. Prior studies estimating the likelihood of special education placement by race have leveraged more detailed datasets that include potential mediating factors involved in disability diagnoses, such as health records and behavioral assessment scores prior to entering school. These types of data were not available for this analysis, so understanding the sources of variation in special education by race was limited to the few observed student characteristics in the dataset.

The validity of estimates from Research Question 2 rests on the assumption that no unobserved time-varying covariates are confounded with special education placement. Controlling for student and school time-invariant characteristics, along with observed time-varying covariates, and grade and year fixed effects account for a large proportion of variance in student achievement. As previously explained, the remaining unexplained variance may be attributed to various factors that are confounded with special education placement and achievement. Beyond IEP supports, parents may invest more in their child, both financially (e.g., by pairing special education supports with out-of-school services like tutoring) and through general involvement. Additionally, other members in the school community, including teachers, may provide more attention to students. Consequently, the models for Research Question 2 capture the effects of all that students experience after being placed in special education as opposed to just the IEP, which I argue is of even greater interest in the context of this dissertation.

Threats to internal validity Research Question 3 relate to attrition, sample selection bias, and post-preK treatment. Attrition is a notable threat given that students in District 1 have access to other school options outside the district (e.g., charter schools) and thus their records may not appear in the dataset after their preK year. While almost all students subject to randomization enrolled in District 1 at preK, it is established that many depart the district by kindergarten (Weiland et al., 2020). Because I am restricted to data from District 1, the future special education status of students who leave the district will not be known. Results may still be valid, however, if treatment and control students do not differ in attrition rates. Accordingly, differential attrition was investigated and the validity of the estimates based on these findings were interpreted based upon WhatWorks Clearinghouse standards (2020).

Concerning selection bias, I have previously noted that leveraging the lottery component of the school assignment mechanism only resolves randomization at the student level. It is plausible that schools implementing City Connects differ from comparison schools in ways that are related to special education placement. Special education placement rates at treatment and comparison schools will be compared using data from the 2009 school year, which is the last year before City Connects entered the preK programs to serve as a baseline comparison. Still, treatment schools could have also implemented other reforms at the time City Connects was established. The inability to partial out such a confound will remain a limitation of this study.

Finally, it is noteworthy that many City Connects preK programs operate in schools that also implement the intervention at elementary grades. Observed treatment effects may not be able to distinguish between receipt of treatment at preK versus the later grades. Such a confound is also present in other studies evaluating the efficacy of district-wide preK programs on outcomes measured at later grades, whereby the effect of preK cannot be disentangled from the effects of being assigned to the schools operating such programs. Restricting the sample of treated students to those who only received the intervention in preK will drastically reduce the sample size, making for a far less robust comparison. Consequently, this issue will be an important limitation.

For Research Question 4, most pertinent to the validity of the model estimates is satisfaction of the previously defined parallel trends assumption. In the absence of parallel trends, the comparison group cannot be used as an appropriate counterfactual for the treatment group in the posttreatment period. If trends are found to not be parallel (using the statistical significance of the lag indicators in the model), then alternative specifications can be employed like the augmented Synthetic Control Model (SCM) (Ben-Michael et al., 2019). This model assigns weights to comparison units to exactly match the pretreatment outcome trend of the treatment group. Treatment effects with statistical significance, by each lead and lag year, can be reported in the same way as the CS estimator to offer a comparison between the findings from these two methodologies.

Given that Research Question 4 is a school-level analysis, there is further concern that student composition within schools may change over time in ways that are correlated with special education placement. If, for example, students from traditionally lower achieving backgrounds entered City Connects schools around the same time as the intervention was implemented, this may artificially inflate special education placement rates. Accordingly, I tested for changes to the racial, socioeconomic, and English Learner makeup of the student population following the implementation of City Connects. This entailed replacing special education placement with these other demographic characteristics as the outcome variable in the main analytic models. I also tested for year-to-year mobility rates of special education students to see if there is differential change in the level of student movement in and out of treatment schools. This is particularly important to test because changes in special education rates in schools may be a function of movement in and out of the schools instead of changes to the placement process.

As previously noted, some of the schools that received City Connects were also labeled turnaround at the same time and received aid from the state to implement various improvement strategies. Within District 2, all turnaround schools also received City Connects. To correct for this confound, I restricted the sample to just schools in District 1 to see if the results replicated with non-turnaround schools.

Lastly, an outstanding limitation concerns the fact that not every grade in a City Connects school necessarily receives the intervention. As such, estimated effect sizes will likely underestimate the true effect (if it exists) of the intervention on special education placement rates.

Threats to external validity

External validity refers to the extent to which results replicate from the population in which the units were drawn. For Research Questions 1 and 2, as previously stated, the samples are restricted to students placed in special education after third grade. These are generally students diagnosed within the more subjective disability categories (e.g., specific learning disabilities). Accordingly, these findings generalize to only such students, which is not an essential difficulty since they are the focus of this dissertation.

Similarly, the findings may not necessarily generalize to all public preK and integrated student support programs across the nation. District 1's public preK program differs from similar programs across the country in curriculum rigor and teacher training (Weiland et al., 2020). Similarly, the City Connects intervention has been identified by the federal government as an exemplary form of integrated student support, in view of its higher fidelity of implementation and more targeted support (Department of Education, 2021).

In terms of external validity across District 1, because Research Question 3 focuses only on students who were subject to lottery randomization and not the total sample of District 1 students in the timeframe of analysis, there may be differences between the analytic sample and the full population of preK attendees. For example, students subject to randomization to a City Connects preK program may have been more likely to list certain high-demand programs as their top choices in their applications. Previous research suggests these students are more likely to be White and less economically disadvantaged (Shapiro et al., 2019). Accordingly, it is plausible that the analytic sample may not generalize to both all District 1 preK attendees and those who went on to attend City Connect preK programs. Tests for balance on covariates across the analytic sample and all of District 1 preK will be conducted in a similar manner as depicted in Table 3.4. Observed differences will limit the generalizability of the findings from this research question.

CHAPTER 4. RESULTS

In this chapter, findings from each research question are presented, along with accompanying tables and figures. Generally, I begin with descriptive statistics displaying the characteristics of the analytic sample, after which main results are presented. For brevity and to maintain focus, I only present and discuss model parameters for predictors of specific interest, while noting whether and what covariates were included. Notably, as a standard, I present standard errors and indicators of statistical significance, but note that these tests rely upon random sampling assumptions that do not apply in these analyses. In other words, the sample *is* the population of interest. Accordingly, while statistical significance is discussed, I focus mostly on the practical significance of the effect sizes. Where relevant, sensitivity analyses follow the summary of the main findings. Interpretations of these findings are expanded upon in Chapter 5.

RQ1. Relationship between special education and student characteristics

As detailed in the previous chapter, the purpose of this research question is to understand the relationship between special education placement and race and gender, before and after partialing out the variance from other covariates. A description of the analytic sample is provided in Table 4.1.

The analytic sample of 85,673 largely resembles the demographic makeup of the population from which it was drawn (see Table 3.1), with the exception of special education. Only 8% of the analytic sample was ever placed in special education, whereas more than 20% of students across both districts are in special education every year. The reason for this discrepancy is the exclusionary criteria for this analysis; students placed in special education prior to fourth grade, along with those who were placed prior to ever taking the state standardized assessment in

English language arts (ELA), were excluded. These criteria exclude more than two-thirds of all students in both districts ever placed in special education by eighth grade.

Descriptive statistics of ever-special education placement by student characteristics are also displayed in Table 4.1. Based upon basic chi-square tests of association, there were statistically significant differences at $p < 0.01$ in the proportion of students placed in special education by race, gender, free-and-reduced price lunch (FRL) status, and bilingual/limited English proficiency (LEP) status. Black, FRL, male, non-bilingual, and ever-LEP students were more likely to be placed in special education than their counterparts. About 10% of Black students were placed in special education compared to 8% of non-Black students. Approximately 9% of FRL, male, and bilingual students were placed in special education compared to 4% of non-FRL, 7% of female, and 10% of non-bilingual students, respectively. Students who were ever classified as LEP were placed in special education at higher rates (5%) than non-LEP students (3%).

Table 4.1

Differences in special education placement, by student characteristics

Characteristic		Percent of total sample	Percent ever placed in special education	Chi-square statistic
Special education		8%	-	
Race				
	Black	33%	10%	
	White	14%	7%	251***
	Asian	7%	4%	
	Hispanic	44%	8%	
	Other race	2%	9%	
Free/reduced price lunch (FRL)				280***
	FRL	91%	9%	
	Not FRL	9%	4%	
Gender				
	Male	47%	9%	124***
	Female	53%	7%	
Bilingual				
	Bilingual	25%	9%	12***
	Not Bilingual	75%	10%	
LEP				
	LEP	21%	5%	23***
	Not LEP	79%	3%	
Sample size		85,673	7,142	

Note. ***p < 0.01, **p<0.05, *p<0.10

Bilingual sample includes only students from District 1. LEP sample only includes students in District 2.

In Table 4.2 I compare the average ELA achievement score at baseline for students never placed in special education with those eventually placed. Before placement, students ever placed in special education scored almost a half of a standard deviation (SD) lower than the grade-year mean on their first state standardized ELA assessment recorded in the dataset. Students never placed in special education scored significantly better, averaging about a tenth of a SD greater than the grade-year mean on their first ELA assessment recorded in the data.

Table 4.2

Differences in English Language Arts achievement at first administration

Sample	Mean ELA achievement (SDs)	Standard deviation	Sample size
Total sample	0.11	1.00	85,673
Ever special education sample	-0.42	0.97	7,142
Never special education sample	0.16	1.03	78,530

Note. For the ever-special education sample, ELA score at first administration represents achievement prior to being placed in special education. Difference in ELA achievement between ever and never special education sample is statistically significant at $p < 0.01$ using a two-sample t-test.

Probability of special education placement by race and gender

Next, I present parameter estimates from linear probability models demonstrating differences in the probability of special education placement by race and gender. I started with two bivariate models using just race (Model 1) and gender (Model 2) separately, as these are the main predictors of interest. These results reflect those from the chi-square tests; among the analytic sample, the special education placement rate for Black students was 3 percentage points greater than that of White students, 5 percentage points greater than that of Asian students, and 1 percentage point greater than that of Hispanic students. The placement rate for males was 2 percentage points greater than the rate for females. All differences were statistically significant at $p < 0.05$. Both models explain a very small amount of variance in special education placement; the R^2 for the race and gender models is 0.03 and 0.001, respectively.

In the following model (Model 3), I added FRL and fixed effects for school, grade, and year, which increased the R^2 to 0.06. Notably, the relationships between the outcome and race and gender do not significantly change from the bivariate models. Then, I added to this model student ELA scores as a baseline achievement measure (Model 4), and this increased the variance accounted for in the outcome to 8%. Importantly, I find that Black and White students no longer differed in their probability of special education placement after accounting for all of these covariates. Black students still had placement rates 4 and 1 percentage points higher than the rates for Asians and Hispanics, respectively. The placement rate for male students remained 1 percentage point greater than that of female students.

Because English language proficiency was operationalized differently by the two districts (bilingual in District 1 and LEP in District 2), I did not include these in the main models. In Appendix A Table A1, I present the results for Model 4 for each district separately while including the English proficiency indicator from each dataset. The only difference from the main findings is that there was no longer a significant difference between Black and Hispanic students in special education placement, meaning the differences found in the full sample models are likely attributable to bilingualism.

Table 4.3

Coefficients from linear probability models estimating relationship between student characteristics and probability of special education placement

Variable	Model 1	Model 2	Model 3	Model 4
White	**-0.03***** (0.003)	-	**-0.01**** (0.004)	0.00 (0.003)
Asian	**-0.05***** (0.003)	-	**-0.05***** (0.01)	**-0.04***** (0.01)
Hispanic	**-0.01***** (0.002)	-	**-0.01*** (0.003)	**-0.01***** (0.003)
Other race	-0.01 (0.01)	-	0.01 (0.01)	**0.01**** (0.01)
Male	-	**0.02***** (0.002)	**0.02***** (0.002)	**0.01***** (0.002)
FRL	-	-	**0.05***** (0.01)	**0.03***** (0.01)
ELA achievement	-	-	-	**-0.05***** (0.003)
School fixed effects	No	No	Yes	Yes
Year/grade fixed effects	No	No	Yes	Yes
R^2	0.03	0.001	0.06	0.08
Sample size	85,672	85,644	85,644	85,644

Note. ***p < 0.01, **p<0.05, *p<0.10

Parameter estimates calculated using OLS linear probability models. Coefficients can be interpreted as difference in probability of special education placement for a student of a given characteristic and the reference group. Black, female, and paid lunch are the reference categories for race, gender, and FRL, respectively. Robust standard errors, in parentheses, are clustered at the school level.

Probability of special education placement by race-gender interaction

Finally, I expanded Model 4 by including the interaction between race and gender. This model includes all covariates from Model 4, but for brevity, only predictors pertaining to race and gender are displayed in Table 4.4. To aid in interpretation, I also include marginal probabilities, which indicate the probability of special education placement for each race-by-gender group after controlling for other characteristics.

For Black males versus males of other races, the differences in probabilities resemble the main results for race from Model 4 in Table 4.3. Black males had a 10% probability of being placed in special education after controlling for the set of covariates, and this probability is no different than White males. The placement rate for Black males was only 1 percentage point greater, however, than that of White females (9% probability). Black male placement rates were 5 percentage points higher compared to Asians, regardless of gender. Compared to the rates of Hispanic males and females, Black male placement rates were 1 and 3 percentage points greater, respectively. Upon running separate models for each school district using their distinct variables for English learner (see Appendix A Table A2), I found that Black and Hispanic males had similar probabilities of special education placement. Compared to Black females (8% probability), the placement rates for Black males were 2 percentage points greater. Accordingly, Black females had special education placement rates 1 percentage point *lower* compared to that of White females and Hispanic males.

Table 4.4

Results from linear probability model with interaction between race and gender on probability of special education placement

Variable	Coefficient (linear probability)	Marginal probability
Black male	Omitted (reference)	10%
White male	0.00 (0.004)	10%
Asian male	**-0.05***** (0.01)	5%
Hispanic male	**-0.01***** (0.004)	9%
Other race male	0.01 (0.01)	11%
Black Female	**-0.02***** (0.004)	8%
White female	**0.01*** (0.01)	9%
Asian female	**0.02***** (0.01)	5%
Hispanic female	0.00 (0.004)	7%
Other race female	0.00 (0.00)	10%
R^2	0.08	-
Sample size	85,644	-

Note. ***p < 0.01, **p<0.05, *p<0.10

Parameter estimates calculated using OLS linear probability models. Coefficients can be interpreted as difference in probability of special education placement for Black males compared to the mentioned student characteristics. Covariates include ELA achievement, FRL, and school, grade, and year fixed effects. Robust standard errors, in parentheses are clustered at the school level.

RQ2. Relationship between special education and student achievement

To address Research Question 2, I used student fixed effects models to examine how within-student achievement changes after special education placement. The analytic sample included students in the Research Question 1 sample with at least two years of achievement data, leading to 242,480 observations nested within 70,585 students. Approximately 10% of these students were placed in special education after third grade, a slightly larger percentage compared to the Research Question 1 sample. The treatment effect estimate, however, only leveraged students for whom achievement was observed at least once before and after special education placement. Note that the effects described across this section should not be interpreted as causal impacts.

Main and interaction effects by race and gender using TWFE

In Tables 4.5 and 4.6, coefficients for main and interaction effects from the two-way fixed effects (TWFE) models are presented, showing the average within-student change in math and ELA academic achievement following special education placement. For brevity, only estimates for predictors of interest are displayed and interpreted. While the treatment effects for the "other" race category is presented in the tables, because it includes a wide array of racial backgrounds, I chose not to directly interpret those findings. Due to the various other racial backgrounds represented in the "other" category within that group, little can be said about the aggregated estimates.

As described in the last chapter, all models included indicators for mobility and retention, along with fixed effects for grade, year, school, and student. EL status could not be included as a covariate in the models because it was operationalized differently in the two districts. In Appendix A Table A3 I present estimates by district for the main TWFE models with and without the EL variable for each district, showing that the regression effect associated with special education does not change when the variable is included.

As shown in Table 4.5, I found that student achievement in ELA decreased by an average of 0.03 SDs following placement in special education, and this estimate is statistically significant at $p < 0.05$. Conversely, I find that math achievement increased by 0.03 SDs, although this estimate is less precise, being only statistically significant at $p < 0.10$.

Columns 4 and 5 in Table 4.5 demonstrate considerable heterogeneity in regression effects by race, with Black students as the reference group. Namely, Black and White students both experienced declines of 0.06 SDs in ELA achievement following special education placement. The interaction effect for Hispanic students was 0.06 SDs, suggesting no change in ELA achievement following special education placement. The interaction effect for Asian students was statistically significant at 0.25 SDs, translating to an overall regression effect of 0.19 SDs in ELA. Asian students were the only group for which statistically significant positive regression effects in ELA following special education placement were observed.

For math achievement, the regression effect associated with the special education indicator for Black students was 0.04 SDs (statistically significant at $p < 0.05$). The interaction regression effect for White students was statistically significant at -0.14 SDs, meaning that such students experienced declines of approximately 0.10 SDs in math following special education placement. No other interaction effects were statistically significant, suggesting that similar regression effects of 0.04 SDs in math were observed across other racial groups. Although not statistically significant (perhaps due to a low sample size), the interaction regression effect for Asian students was 0.09 SDs.

Table 4.5

Relationship between special education placement by race and gender for math and ELA achievement

	ELA	Math	ELA x Race	Math x Race	ELA x Gender	Math x Gender
Special Ed	**-0.03****	**0.03***	**-0.06*****	**0.04****	**-0.09*****	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
White*Special Ed			-0.06	**-0.14*****		
			(0.04)	(0.03)		
Asian*Special Ed			**0.25*****	0.09		
			(0.04)	(0.06)		
Hispanic*Special Ed			**0.06****	-0.02		
			(0.02)	(0.02)		
Other*Special Ed			0.06	0.03		
			(0.07)	(0.06)		
Female*Special Ed					**0.12*****	**0.09*****
					(0.02)	(0.02)
Adjusted R^2	0.73	0.77	0.73	0.77	0.73	0.77
Observations	242,480	235,112	242,480	235,112	242,480	235,112

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All models include indicators for mobility and retention, along with fixed effects for grade, year, school, and student. Robust standard errors, clustered at the school level, are in parentheses. In the race interaction models, Black students are the reference group. In the gender interaction models, males are the reference group.

The coefficients for the interaction of special education with gender are presented in the final two columns of Table 4.5, with males as the reference category. I found that males experienced declines of 0.09 SDs in ELA and 0.02 SDs in math following special education placement, although the coefficient associated with math achievement was not statistically significant. Female students appear to have benefited academically, however, following special education placement. The interaction regression effect in ELA was 0.12 SDs, translating to an overall change in 0.03 SDs following placement. In math, the regression effect was 0.09 SDs, translating to an overall change in 0.07 SDs.

Three-way interaction effects with race and gender using TWFE

To examine how achievement changed for students following special education placement by race for each gender, I expanded the models in Tables 4.5 to include three-way interactions with special education placement, race, and gender. Importantly, there was limited power in this analysis due to smaller sample sizes within special education-by-race-by-gender groups, so few regression coefficients were statistically significant. Model estimates are presented in Table 4.6, with Black males before special education placement serving as the reference group. Given the convoluted nature of three-way interactions, I focus here on marginal effects.

As an example, given the reference group, the coefficient for the main effect of special education refers to that of Black males following placement (-0.13 SDs). The coefficient for the interaction between female and special education is thus specific to Black females after placement compared to Black males (0.14 SDs). The marginal effect for Black females is thus 0.14 – 0.13, resulting in 0.01 SDs.

For ELA, the negative coefficient associated with special education placement was largely concentrated among boys of all races except Asians. Notably, Black and White males experienced a drop of about 0.13 and 0.16 SDs, respectively, in ELA after special education placement. ELA achievement for Hispanic males decreased by 0.06 SDs, while Asian males *increased* by 0.11 SDs.

Most females experienced gains in ELA achievement after special education placement. For Black females, the increase was only 0.01 SDs, whereas for Hispanics, the increase was 0.04 SDs. Asian females experienced the largest gain among all race-by-gender subgroups with a regression coefficient corresponding to 0.27 SDs. White females, who from Research Question 1 were found to have the highest probability of special education placement compared to females of other races, were found to experience declines of approximately 0.07 SDs.

For math, I found no changes in achievement following special education placement for Black and Hispanic males, and a large negative regression coefficient corresponding to 0.14 SDs for White males. For Asian males, I observed a positive regression coefficient associated with special education placement with a magnitude of 0.07 SDs, although this was not statistically significant. Similar to ELA achievement, females largely benefited from special education placement in math. Black, Hispanic, and Asian females experienced increases of 0.09, 0.07, and 0.21 SDs, respectively. White females were the exception, experiencing a 0.05 SD decline.

Table 4.6

Relationship between special education placement-by-race-by-gender for math and ELA achievement

	ELA	Marginal effect	Math	Marginal effect
Special Ed (Black Male)	**-0.13*** **	-0.13	-0.00	0.00
	(0.02)		(0.02)	
Female*Special Ed (Black)	**0.14*** **	0.01	**0.09*** **	0.09
	(0.03)		(0.03)	
White*Special Ed (Male)	-0.03	-0.16	**-0.14*** **	-0.14
	(0.05)		(0.05)	
Asian*Special Ed (Male)	**0.24*** **	0.11	0.07	0.07
	(0.05)		(0.05)	
Hispanic*Special Ed (Male)	**0.07** **	-0.06	-0.02	-0.02
	(0.03)		(0.03)	
Other*Special Ed (Male)	0.05	-0.08	0.12	0.12
	(0.09)		(0.08)	
White*Special Ed*Female	-0.05	-0.07	0.00	-0.05
	(0.06)		(0.06)	
Asian*Special Ed*Female	0.02	0.27	0.05	0.21
	(0.10)		(0.09)	
Hispanic*Special Ed*Female	-0.04	0.04	0.00	0.07
	(0.04)		(0.04)	
Other*Special Ed*Female	0.05	0.11	-0.18	0.03
	(0.11)		(0.13)	
Adjusted R^2	0.73		0.77	
Observations	242480		235112	

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Models include indicators for mobility, retention, and fixed effects for grade, year, school, and student. Three-way interaction between special education placement, race, and gender is tested. Robust standard errors, clustered at the school level, are in parentheses. Black male students pre-special education placement are the reference group.

Event-study model estimates

Finally, I present in Table 4.7, model estimates using an event-study representation, which tracks academic achievement for each year before and after special education placement relative to the last year before placement. This framework is useful for interpreting the estimates from the TWFE model. Specifically, one can discern the extent to which observed effects are an artifact of regression to the mean or a continuation of a prior trend, as opposed to the causal effect of special education placement (Daw & Hatfield, 2018). Because the TWFE model pools all estimates from the pre-special education period against the post, whereas the event-study specifically compares each pre and post year against the immediate pre-special education year, these estimates are not entirely comparable.

Due to the complexity of interpreting interactions with a large number of coefficients, I complemented the main effect analyses with subgroup analyses where the treatment sample (i.e., ever-special education students) was first restricted to Black students, and then just Black males. Given the large sample size, this restriction did not significantly reduce power; 2,700 Black students and 1,492 Black males were placed in special education during the study timeframe.

As shown in the column titled "All", students placed special education experienced significant declines in ELA and math achievement in the years preceding placement. In ELA, achievement largely remained stable from the last pre-special education year. In math, achievement improved by 0.04 SDs following the first year of placement, and the coefficient increased to 0.08 SDs by the third year. Yet, these coefficients remained smaller than those observed three years before placement (0.12 SDs higher than the pre-placement year). In other words, while math achievement increased following special education placement, student performance had not recovered from the decreases observed in the years before placement.

For Black students, the decline in ELA achievement observed in Table 4.5 (0.06 SDs) appears to simply be a continuation of the decline in the pre-special education period. Following the first year of placement, ELA achievement declined by 0.03 SDs relative to the last pre-special education period. This regression effect corresponded to -0.07 SDs by the fourth year. I observed similar trends among just Black males, although the declines appeared even steeper and more apparent as soon as the first year following placement.

In math, Black students also experienced modest declines in achievement for each year before special education placement, but their scores nearly recovered by the third year following placement. The decline for Black males was greater in the pre-special education period, but three years after placement, achievement largely recovered to where students were two years before placement.

Table 4.7

Event-study Relationship between special education placement by race and gender for math and ELA achievement

	ELA			Math		
	All	Black students	Black Males	All	Black students	Black Males
5 years Pre	**0.18*****	**0.23*****	**0.31*****	**0.17*****	**0.19*****	**0.31*****
	(0.03)	(0.05)	(0.07)	(0.04)	(0.06)	(0.09)
4 years Pre	**0.16*****	**0.18*****	**0.26*****	**0.15*****	**0.13*****	**0.24*****
	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)
3 years Pre	**0.09*****	**0.09*****	**0.18*****	**0.12*****	**0.10*****	**0.17*****
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
2 years Pre	**0.04*****	0.03	**0.08*****	**0.03****	0.03	**0.09*****
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
1 years Post	-0.00	-0.03	**-0.06***	**0.04*****	**0.05****	0.04
	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)
2 years Post	0.00	-0.04	**-0.09*****	**0.07*****	**0.09*****	**0.07****
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
3 years Post	0.03	-0.01	-0.07	**0.08*****	**0.11*****	**0.11****
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
4 years Post	-0.00	**-0.07****	**-0.10****	**0.07*****	**0.06***	0.04
	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.04)
5 years Post	-0.01	-0.07	-0.12**	0.04	0.03	-0.03
	(0.03)	(0.04)	(0.06)	(0.03)	(0.04)	(0.06)
Adjusted R^2	0.73	0.72	0.72	0.77	0.77	0.77
Observations	242,480	226,731	222,084	235,112	219,773	215,263

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All models include indicators for mobility and retention, along with fixed effects for grade, year, school, and student. Year prior to special education placement is the reference group (i.e., Pre − 1). Robust standard errors, clustered at the school level, are in parentheses.

RQ3. The impact of City Connects preK on probability of special education placement

To address Research Question 3, I first used the centralized assignment mechanism at preK in District 1 between 2010 and 2013 to approximate student probabilities of receiving an offer to a City Connects preK program. Because student assignment among individuals with the same preference priorities is determined via lottery, Abdulkadiroğlu and colleagues (2017) showed that simulating the assignment mechanism a large number of times while altering the lottery number following each run can be used to determine the probability of assignment to a given school or set of schools. The accuracy of such probabilities and their validity for model estimation rests upon the assumption that the assignment mechanism has been appropriately simulated. Accordingly, I first attempted to simulate the actual assignment results using student preference application data and the actual lottery number assigned to students. Table 4.8 shows that, on average, I was able to replicate the results with 95% accuracy, meaning that the simulation correctly predicted 95% of students' actual school assignments.

Table 4.8

Lottery assignment simulation results, 2010-2013

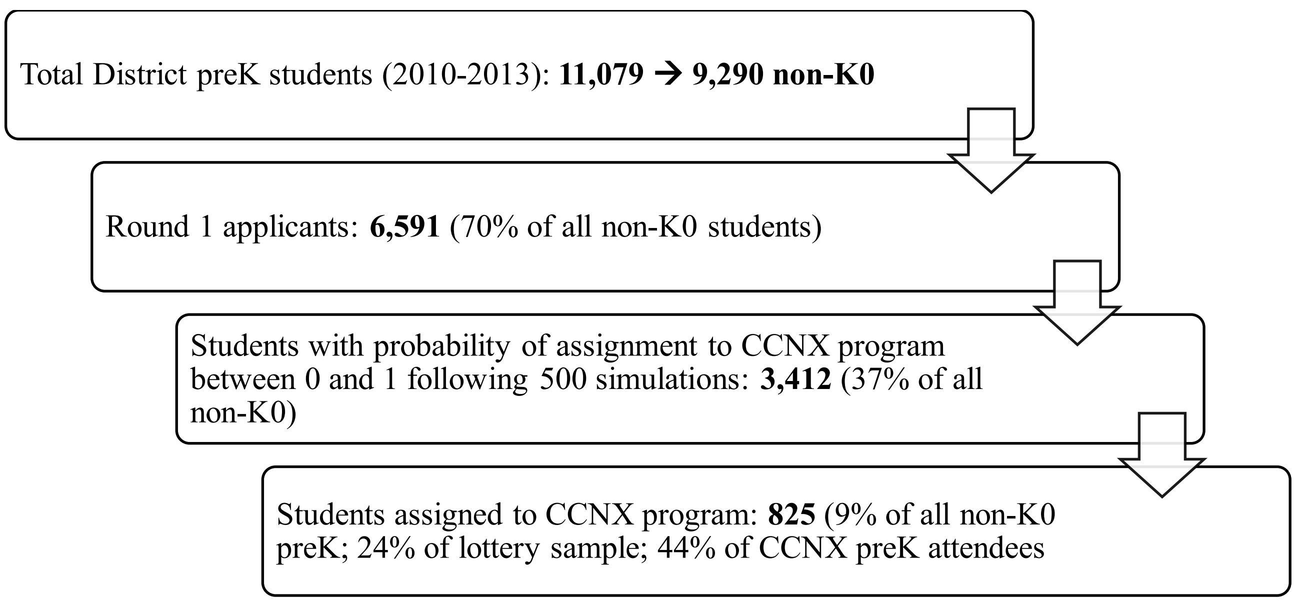
Lottery year (fall)	Correct assignment	Incorrect assignment	Percent match
2010	1,491	60	96%
2011	1,500	57	96%
2012	1,669	91	95%
2013	1,615	108	94%

Note. Correct assignment means that the simulation of the assignment mechanism matched the actual assignment the district provided to the student. Incorrect assignments may result from exceptions and special circumstances.

The high accuracy of the simulation results provides strong evidence that, upon rerunning the assignment mechanism a large number of times while randomizing individual-assigned lottery numbers for each draw, one should be able to approximate the probability of assignment to a City Connects preK program (i.e., the DA propensity score). This is done by calculating the proportion of times a student was assigned to a City Connects preK program relative to the number of simulations. Following the approach of Winters and Shanks (2021), I simulated the lottery 500 times, changing the lottery number at each draw. Students who had a probability of assignment to a City Connects program between 0 and 1 – meaning there was a non-determinant probability of assignment – were retained for the analyses. Upon excluding students already classified with a disability when submitting their preferences, the total sample size was 3,412. The flowchart in Figure 4.1 shows how the analytic sample was derived.

Figure 4.1

Analytic sample derivation from total applicants to District 1 *preK programs, 2010-2013*



Note. K-0 refers to students in the district's preschool offering for three-year-old children with special needs. These students were excluded from the sample because they were already identified with a disability by the time they started preK. There are four rounds of application cycles in the district, but only applicants to the first round were retained because it is difficult to develop probabilities for students applying in later rounds due to dependency on what occurs after the first round. Weiland and colleagues (2020) show that most students subject to assignment via lottery were first round applicants. CCNX is an abbreviation for City Connects.

Characteristics of the analytic sample, disaggregated by treatment status, are provided in Table 4.9. The treatment sample comprised the 24% of students among the lottery sample who were randomly assigned to a City Connects preK program. While there are unadjusted differences between the samples on several characteristics, assignment is only random within DA propensity score strata. In other words, for randomization to be successful, within these strata, there should be no differences on observed characteristics between the samples. Therefore, to estimate covariate balance, I ran linear probability models where the dependent variable was the student characteristic of interest and the independent variable was a binary indicator of assignment to a treatment program, conditional on DA propensity score and lottery year. This effectively resembles Equation 3.6, with the outcome variable now being each student characteristic.

The results in Column 4 demonstrate no statistically significant differences between the treatment and comparison samples at $p < 0.05$, conditional on DA propensity score. Treatment students were about 5% less likely to be male, but this is only statistically significant at $p < 0.10$. Accordingly, I conclude that the simulation was successful in approximating random assignment of students to treatment and comparison groups.

Table 4.9

Differences between students assigned to and not assigned to City Connects preK program, 2010-2013

Characteristic	Comparison	Treatment	Linear probability
Bilingual	8%	5%	-0.06
Male	52%	48%	-0.05*
Special ed	6%	8%	0.00
FRL	48%	55%	0.01
Foreign born	3%	5%	0.00
Black	19%	25%	0.00
White	31%	26%	0.02
Hispanic	38%	33%	0.01
Asian	8%	13%	-0.03
Stayed in district[a]	74%	72%	0.03
Complied	92%	89%	0.01
Sample size	2,587	825	

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[a] Stayed in district means the student was observed in the district during the last year in which data was available (2015/16). This variable was used to measure attrition.

Because randomization only occurs within DA propensity score strata, Linear probability provides difference in the probability of a student being of particular demographic group by treatment status, conditional on lottery year and DA propensity score. Treatment refers to students among the lottery sample who were assigned to a City Connects preK program. Time-variant characteristics (special education, bilingual, and FRL) are measured at preK.

Approximately 18% of the students in the sample were no longer in the district after preK, and 26% of the sample were no longer in the district by the last year in the study period (2015/16). More importantly, there was no differential attrition by treatment condition (24% for comparison and 26% for treatment); in other words, assignment to a preK program implementing City Connects did not predict attrition. According to What Works Clearinghouse standards, this level of overall and differential attrition is expected to produce minimal bias, defined as the difference between the impact estimated using data from the sample experiencing attrition and the impact that would have been estimated had there been no attrition.

Notably, students across both treatment and comparison groups were more than 90% likely to comply with their lottery offer. Strong compliance was likely due to high demand and the dearth of alternative options within the district if families were not awarded their top program choice. Only 4% of comparison students eventually enrolled in a City Connects preK program compared to 92% of treatment students. The difference in treatment take-up was therefore 88%, which is substantially larger than prior studies using school enrollment lotteries. As a comparison, the difference in treatment take-up in the District 1 preK study by Weiland and colleagues (2020) was only 29%.

Intent-to-treat estimates

Intent-to-treat analyses conducted with the lottery data demonstrated the effect of *being assigned* to a City Connects preK program (compared to a non-City Connects program) on the probability of special education placement by the last time students were observed in the data. These results, for the full sample and the two subgroups of interest (Black and Black males) are presented in Table 4.10. As explained further in the next chapter, the adjusted R^2 in these models are low (< 0.10), so the regression coefficients should be interpreted with caution.

Table 4.10

ITT estimates of placement in special education by end of last grade available

	Full sample	Black	Black males
Assigned to CCNX preK	-0.02	-0.05	-0.04
	(0.03)	(0.03)	(0.09)
Constant	0.13^{***}	0.15^{***}	0.26^{***}
	(0.03)	(0.05)	(0.08)
Adjusted R^2	0.04	0.05	0.04
Observations	3323	720	345

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As shown in Table 4.10, across all samples, there were no statistically significant effects of being assigned to preK programs implementing City Connects compared to non-City Connects programs on the probability of special education placement by the last time students were observed in the data. Assigned to programs implementing City Connects was associated with a 2-percentage point decrease in the probability of being placed in special education. For Black students and Black males, assignment to programs implementing City Connects reduced the probability of special education placement by 5 and 4-percentage points, respectively.

Because data beyond the 2015/16 school year was not available, students could be tracked at most until fourth grade for the eldest cohort (2010/11 preK entrance), and first grade for the youngest cohort (2013/14 preK entrance). Given these differences, I supplemented the analyses from Table 4.10 using ever-special education placement by first, second, and third grade as the outcomes separately. The effect of being assigned to a City Connects preK program compared to a non-City Connects program on ever-special education placement for first and second grade were virtually the same, and the effects for third grade were identical to the main results (and thus not presented). Accordingly, for brevity, I reproduced Table 4.10 with just special education placement by first grade as the outcome, shown in Table 4.11. When using special education placement by the end of first grade as the outcome variable, as shown in Table 4.11, there was no effect associated with City Connects preK assignment.

Table 4.11

ITT estimates by end of first grade

	Full sample	Black	Black males
Assigned to CCNX preK	-0.01	-0.01	0.01
	(0.02)	(0.02)	(0.07)
Constant	0.03^{*}	0.05	0.21^{***}
	(0.02)	(0.04)	(0.07)
Adjusted R^2	0.04	0.05	0.03
Observations	3323	720	345

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Seeing that there appears to be different treatment effect estimates based upon grade level, I conducted a subgroup analysis looking just at those students who had reached at least third grade by the time their outcomes were observed. Among this sample of 976 students, I found larger but still statistically non-significant effects. As shown in Appendix A Table A4, the ITT estimate was -0.04 for all students, and -0.18 for Black students, although the sample size for the latter was small for the number of variables used (n = 197). Due to low power, standard errors were particularly large. I thus conclude that assignment to preK programs implementing City Connects was not associated with the probability that students were placed in special education at earlier grades, but may have decreased placement for students who would have otherwise been identified after second grade, with effects greater for Black students.

Local average treatment effect estimates

While most students attended the preK program to which they were assigned , the lack of 100% compliance means the ITT effects underestimate the actual impact of attending preK programs implementing City Connects on the probability of special education placement. To capture the treatment effect estimates for compliers, meaning students whose treatment status was solely dependent on lottery assignment, the local average treatment effect (LATE) was calculated by using assignment to treatment as an instrument within a two-stage least squares framework. First-stage statistics (F-statistic and R^2) and LATE estimates, for the full sample and both subsamples, are presented in Table 4.12. LATE estimates using special education placement by first grade as the outcome are presented in Table 4.13. Similar to the ITT estimates, the adjusted R^2 in these models are similarly low and should thus also be interpreted with caution.

First-stage estimates across all models in both tables demonstrate that lottery assignment to preK programs implementing City Connects was indeed a strong instrument. The F-statistics were all statistically significant at $p < 0.01$, and the adjusted R^2 shows that the first-stage model accounts for at least 70% of the variance in treatment compliance. For the full sample, this corresponds to 75% of the sample being "compliers". These students enroll in City Connects programs when assigned and are highly unlikely to attend a preK programs implementing City Connects when not assigned.

Table 4.12

LATE estimates of placement in special education by end of last grade available

	Full sample	Black	Black males
Attended CCNX preK	-0.03	-0.08	-0.06
	(0.04)	(0.05)	(0.12)
Constant	0.09^{***}	0.08	0.21^{***}
	(0.03)	(0.06)	(0.08)
First-stage R^2	0.75	0.70	0.80
First-stage F-statistic	335.1	108.7	50.3
Adjusted R^2	0.04	0.05	0.04
Observations	3323	720	345

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As expected, the LATE estimates are slightly larger than the ITT estimates, but none are statistically significant. Compliance with assignment to programs implementing City Connects was associated with a 3-percentage point decrease in the probability of being placed in special education. For Black students and Black males, compliance with assignment to programs implementing City Connects reduced the probability of special education placement by 8 and 6-percentage points, respectively (see table 4.12). When using special education placement by the end of first grade as the outcome variable, as shown in Table 4.13, the effects were again nearly 0.

Table 4.13

LATE estimates by end of first grade

	Full sample	Black	Black males
Attended CCNX preK	-0.02	-0.01	0.01
	(0.03)	(0.04)	(0.09)
Constant	0.01	0.01	0.16**
	(0.02)	(0.04)	(0.07)
First-stage R^2	0.75	0.70	0.79
First-stage F-statistic	335.1	108.7	50.3
Adjusted R^2	0.04	0.05	0.04
Observations	3323	720	345

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For students who had reached at least third grade, as shown in Table A5 in Appendix A, the LATE estimates were -0.06 for the full sample and -0.21 for Black students. Neither effect was statistically significant, again due to low power, but demonstrate that effects of the intervention may not emerge until at least third grade.

External validity

While the use of the centralized assignment mechanism provides strong internal validity by focusing only on students randomized to treatment conditions, there is concern for external validity. In prior research, Shapiro and colleagues (2019) show that students applying to public preK in District 1 tend to come from more advantaged backgrounds than those who do not. Accordingly, these findings cannot be generalized to the population of students in the district. Whether these findings generalize to all preK students in the district is an additional concern.

To explore this further, I examined the differences between students whose preK program assignment was subject to randomization and those who did not have to compete for a spot via the lottery. As shown in Table 4.14, there were important differences between the groups. Namely, students subject to the lottery were significantly less likely to be bilingual, low-income, and Black. This is unsurprising, however, given that all students subject to the lottery applied to an oversubscribed program, which tend to be housed in the most desirable schools. Families from advantaged backgrounds are more likely to have knowledge about the quality of programs, and accordingly more likely to compete for spots in such schools.

Table 4.14

Differences between lottery and non-lottery sample

Characteristic	Lottery sample	Non-lottery preK	Effect size
Bilingual	13%	25%	0.31
Male	50%	50%	0.00
Special ed	6%	9%	0.11
FRL	49%	68%	0.39
Foreign born	4%	8%	0.17
Black	20%	33%	0.28
White	30%	12%	0.50
Hispanic	37%	46%	0.18
Asian	9%	7%	0.07
Sample size	3,412	5,878	

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Consequently, the findings from this research question cannot be generalized to the population of preK attendees in the district. Alternative analytic approaches that use the full sample of preK attendees (e.g., matching-based methods) are unable to effectively mitigate the threat to internal validity stemming from self-selection into assignment to the treatment condition. The tradeoff between internal and external validity is vividly illustrated through these analyses.

I argue, however, that because the analytic sample includes students less likely to benefit from an intervention like City Connects, observed treatment effects are likely underestimated. In other words, because City Connects is an intervention designed to improve outcomes for students with difficult circumstances outside of school, students from more advantaged backgrounds are less likely to benefit as much from such supports and services. Consequently, special education outcomes are also less likely to be affected by the intervention for a subset of students in the sample. If the sample were to have a larger proportion of students from higher poverty backgrounds, then it is likely that treatment effects would be larger, as suggested through subgroup analyses with Black students (most of whom received free/reduced price lunch).

Sensitivity analyses for internal validity

Although the impact of student self-selection into treatment on the estimated treatment effect is ameliorated through the use of the centralized assignment mechanism, school self-selection into the intervention is still a threat to internal validity. In other words, causal inference of the treatment effect rests on the assumption that the outcome variable is only affected through receipt of the intervention via lottery assignment and not inherent differences among the schools. If schools implementing City Connects differed from those that did not in ways related to special education placement, then theoretically, there could be some other mechanism through which the outcome is impacted via assignment to a City Connects program. Consequently, this would violate the exclusion restriction assumption that is foundational to the validity of IV designs.

The exclusion restriction assumption cannot be formally tested, but evidence in its support can be gathered here by testing for whether assignment to a City Connects preK program resulted in students experiencing different levels of educational inputs that may be correlated with special education placement. In Appendix A Table A6, I present model estimates separately regressing a lottery offer to a City Connects preK program on three inputs that may be related to special education placement: class size, teacher credentials, and student-teacher ratio. The justification for using these variables is provided in the previous chapter. I found no significant regression effect for a lottery offer to a City Connects preK program on these outcomes. While this does not rule out the possibility of unobserved differences between treatment and comparison schools, it does reduce this threat to validity.

Finally, to test whether a cohort effect may be driving the estimate for students who had reached at least third grade at the time the outcome was observed, I re-estimated the ITT and LATE models using special education placement by first grade as the outcome variable. Similar to the full sample analysis, as shown in Appendix A Tables A7 and A8, I found coefficients for assignment to programs implementing City Connects close to 0. This suggests the lack of a meaningful cohort effect driving estimates.

RQ4: School-level changes to special education rates following City Connects

To address Research Question 4, I used difference-in-differences models to estimate how the proportion of special education students changed in schools after they began implementing City Connects, relative to their expected change given trends in comparison schools. In this section, I begin by presenting results using overall special education rates as the outcome, followed by subgroup analyses.

Main effects

As shown in Table 4.15, at baseline, treatment and comparison schools had similar rates of special education placement, but despite being in the same districts, differed significantly in academic achievement and student demographics. In general, treatment schools were more likely to serve underrepresented minorities. Yet, inferences from difference-in-differences are generally robust to pre-existing differences between groups on observable characteristics, as long as treatment and comparison groups followed parallel trends in the outcome measure prior to treatment (Murnane & Willett, 2010).

Table 4.15

Differences between treatment and comparison schools at baseline (2005/06)

Characteristic	Comparison	Treatment	Effect size difference
Special education	20%	20%	0.03
Low income	78%	82%	0.40
English Learner	14%	20%	0.47
Black	35%	35%	0.08
White	17%	10%	0.51
Hispanic	37%	44%	0.35
ELA z-score	-0.57	-0.88	0.70
Math z-score	-0.49	-0.76	0.60
Number of schools	100	39	

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Effect size here is a standardized difference in means calculated using Cohen's D.

Evidence of pre-treatment parallel trends is depicted in Table 4.16 through the event study pre-treatment lag indicator coefficients. In the three years prior to implementation, schools that adopted City Connects had stable special education rates relative to changes in comparison schools. This can be illustrated by regression estimates close to 0 percentage points in each pre-treatment period, which are all relative to the year before City Connects was implemented. Estimates close to 0 indicate that treatment schools were not experiencing differential changes in the outcome relative to comparison schools. For example, two years before implementation, schools that eventually adopted City Connects had experienced a slight increase in 0.46 percentage points in the proportion of students placed in special education relative to what had occurred in comparison schools, but this was imprecisely estimated.

Table 4.16

Two-way fixed effects and Event Study estimates of City Connects implementation on percentage of special education students

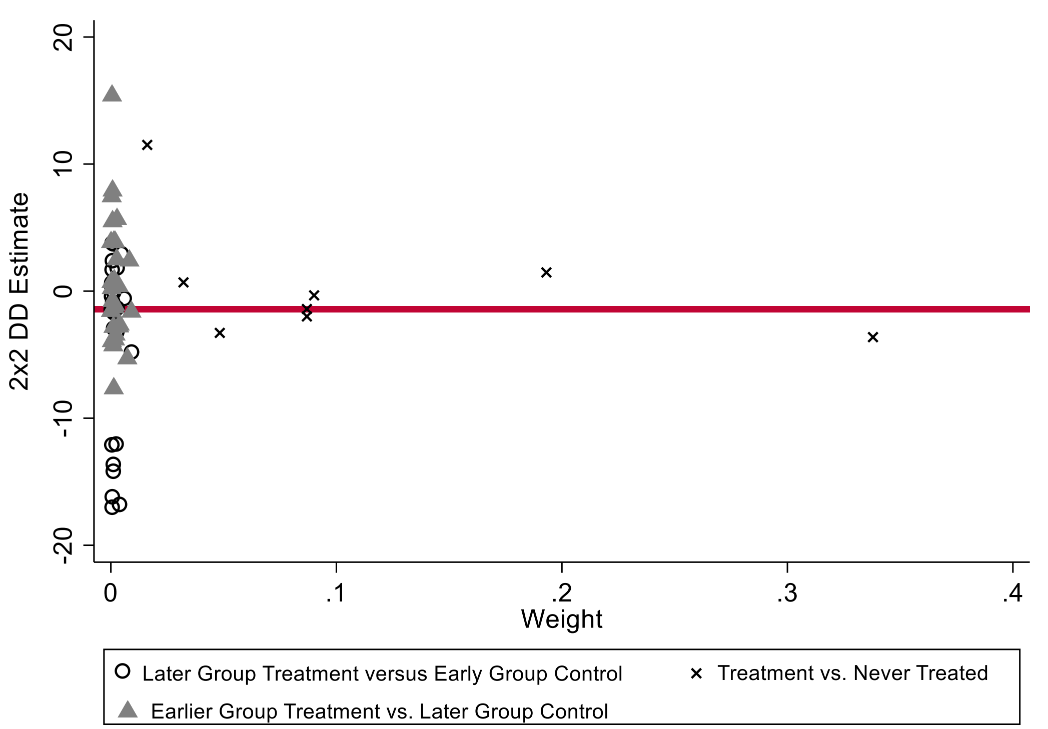
	TWFE	Event Study
Treatment	-1.28*	
	(0.67)	
5 years Pre		0.93
		(0.72)
4 years Pre		1.24*
		(0.67)
3 years Pre		0.31
		(0.61)
2 years Pre		0.46
		(0.42)
1 years Post		-0.44
		(0.33)
2 years Post		-0.88
		(0.69)
3 years Post		-0.98
		(0.86)
4 years Post		-1.01
		(0.85)
5 years Post		-0.52
		(1.39)
Constant	19.89***	19.54***
	(0.36)	(0.46)
Adjusted R^2	0.94	0.94
Observations	1429	1429

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The reference group for the TWFE estimate are all pre-treatment years, whereas for the event-study, the reference group is the last pre-treatment year (Pre-1). Regression coefficients can be interpreted as percentage point differences in the proportion of students placed in special education.

Additionally, as described in the previous chapter, models using two-way fixed effects (TWFE) – which are by school and year – may be negatively biased due to the use of earlier treated units as controls for later treated units. Figure 4.2 provides the Bacon decomposition for this set of analyses, showing that most of the treatment effect stems from appropriate comparisons between treated units and never-treated units. The appropriate weights are indicated by the "x" (treatment versus never treated) and triangle (early treated versus later treated) marks in Figure 4.2, and these collectively make up over 95% of the weight in the TWFE estimate. This indicates that the treatment effects largely stem from comparisons between treatment versus never treated schools. Negative weights due to comparisons between later and earlier treated units, indicated by the circles in Figure 4.2, are largely clustered around a weight of 0, accounting for less than 5% of the treatment effect, and thereby indicating limited bias.

Figure 4.2

Bacon Decomposition of two-way fixed effects



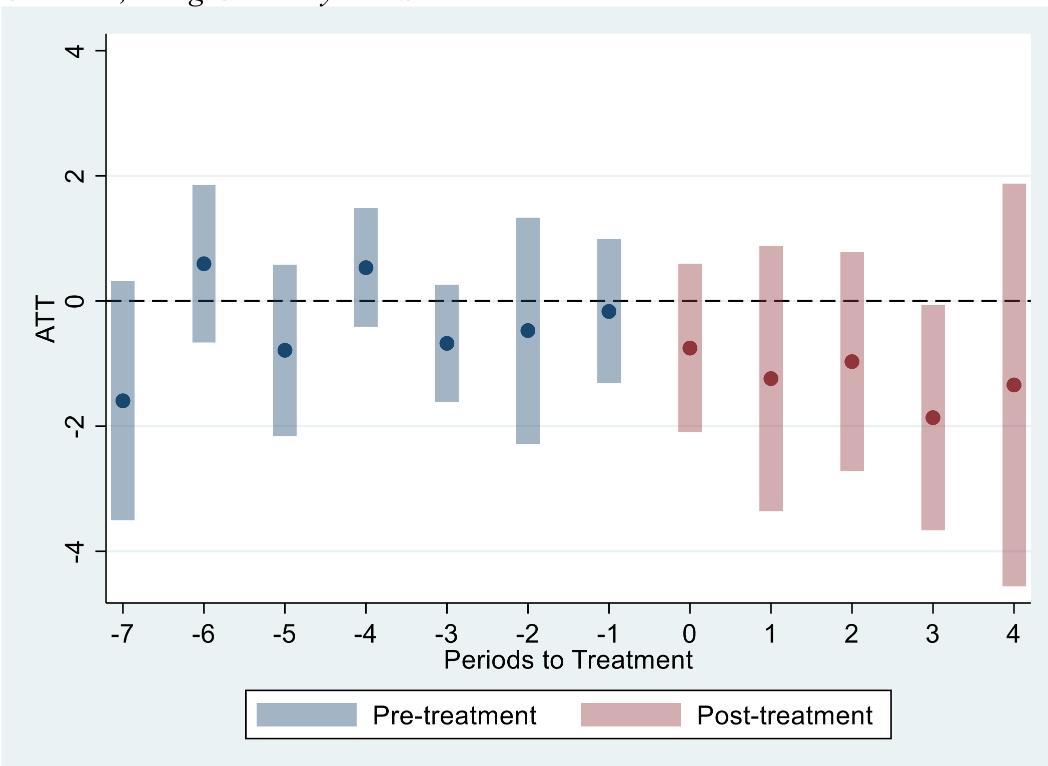
The TWFE estimate from Table 4.16 indicates that, on average, special education placement rates at schools that adopted City Connects decreased by an average of 1.30 percentage points (statistically significant at $p < 0.10$) relative to changes in comparison schools in the years following implementation. In other words, in the absence of City Connects, treatment schools would have been expected to have a special education placement rate 1.30 percentage points greater than the observed rate in the post implementation period. This represents an approximately 6.5% drop in special education following five years of implementation from the prior rate of 20%. Event study post-treatment estimates, which are relative to the immediate pre-treatment year, were not statistically significant and suggest that the effect relative to the year before treatment were closer to 1 percentage point. Generally, TWFE estimates have greater power because the estimates are pooled across all post-treatment years and compare outcome values that are pooled across all pre-treatment years.

The presence of pre-treatment parallel trends, coupled with the limited level of negative weighting, and the generally stable post-implementation treatment effects all provide supporting evidence that the TWFE estimate does not suffer from the largest sources of bias reported in the recent econometrics literature (Goodman-Bacon, 2021). Importantly, however, the TWFE treatment effect takes most weight from units that receive treatment in the middle of the panel. In the study data, schools take up treatment at nine different points, which would thereby imply uneven weighting across treatment groups (i.e., schools that receive treatment at the same time). Additionally, when treatment and comparison units differ on important baseline observables, as is the case here, the parallel trends assumption may not be sufficient to deem comparison units as adequate counterfactuals (Rambachan & Roth, 2019).

Figure 3 depicts the results for the Callaway and Sant'Anna estimator, the most appropriate model given the considerations discussed in Chapter 3, which ameliorates the outstanding issues pertaining the to the validity of the TWFE estimate (also described in Chapter 3). The pre-treatment coefficients, depicted in blue, represent year-to-year changes in special education placement rates for City Connects schools relative to comparison schools, which were weighted based upon baseline math and ELA achievement. The post-treatment coefficients, depicted in red, demonstrate change in special education placement rates for treatment schools from *T-1*, the year before schools adopted City Connects. The 95% confidence intervals are represented by the rectangles, signifying statistical significance at $p < 0.05$ when 0 is not in the interval.

Figure 4.3

Changes in proportion of special education students over time for schools implementing City Connects, using Callaway and Sant'Anna estimator



Note. Model estimates are based upon the Callaway & Sant'Anna Estimator (2020). Baseline covariates include math and ELA achievement. The reference category in the pre-treatment period is the immediate prior year. For example, the reference category for T-2 is T-3, and for T-3 it is T-4, etc. In the post-treatment period, the reference category is the year prior to City Connects implementation (T-1).

The findings in Figure 3 also provide supporting evidence of parallel trends as indicated by the lack of statistically significant coefficients in the pre-treatment period, which are also small in magnitude. Like the event-study, all estimates in the post-treatment period were negative, representing declines in special education placement rates following City Connects implementation. Only the post-fourth year estimate, however, is statistically significant, suggesting a two-percentage point decline in special education placement. This translates to a 10% drop in special education placement rates from the baseline level of 20%. For perspective, this amounts to approximately 400 less students in special education across treatment schools by the fourth year of implementation. By the fifth year, the regression effect associated with the treatment indicator slightly decreased as the confidence interval widened, which likely stems from lost power due to less schools that had received five years of treatment.

Subgroup analyses

Through subgroup analyses, I sought to understand whether all Black students' and Black males' placement in special education was associated with being in a City Connects school. As shown in Table 4.17, at baseline, Black students made up 35% of all students, but 37% of the special education population. More concerning, Black males made up 19% of all students, but 25% of the special education population. This means that there were two and six percentage points more Black students and Black males, respectively, in special education than expected given their representation in the population. These disparities were larger in the comparison schools.

Table 4.17

Special education characteristics of sample at baseline (2005/06)

Characteristic	Percent of student population	Percent of comparison schools	Percent of treatment schools	Effect size difference
Special education	20%	20%	20%	0.03
Black	35%	35%	35%	0.08
Black male	19%	19%	18%	0.10
Black in special education	24%	24%	22%	0.14
Black male in special education	30%	31%	28%	0.16
Proportion of Black in special education	37%	38%	35%	0.17
Proportion of Black male in special education	25%	26%	23%	0.18
Number of schools	139	100	39	

Note. Effect size based upon Cohen's D. Baseline is the 2005/06 school year.
Black and Black male in special education refer to the proportion of students in special education from these groups. These statistics can be compared with the overall special education rate to gauge potential disparities. The proportions of Black and Black males in special education can similarly be compared to the overall percentage of Black and Black males in special education to gauge potential disparities.

While the findings from Research Question 1 show that this disproportionality can be explained by prior achievement and other student characteristics, the findings from Research Question 2 demonstrate that Black students – and Black males in particular – do not experience increases in academic achievement following special education placement. This lack of efficacy suggests that Black males may not be appropriately served through special education, but instead through alternative supports such as those provided through City Connects.

To conduct subgroup analyses, the main analyses were re-run using both the proportions of Black students and Black males in special education as outcome variables. As an additional outcome, I also used a simple measure of disproportionality, which is the difference between the proportion of Black students (males) in the sample and the proportion of Black students (males) in special education. TWFE model estimates are presented in Table 4.18.

Table 4.18

Coefficients of City Connects Regression Effect from TWFE subgroup analysis

	Percent Black Sped	Percent Black Male Sped	Disproportionality – Black	Disproportionality - Black Male
City Connects implemented	-1.57	-1.51	-0.54	-0.99
	(1.27)	(2.04)	(0.98)	(0.83)
Constant	21.99***	27.83***	2.37**	6.71***
	(0.89)	(1.07)	(0.92)	(0.74)
Adjusted R^2	0.73	0.59	0.58	0.44
Observations	1294	1294	1294	1294

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I found a 1.57 percentage point drop in the percentage of Black students in special education, on average, in the years after schools implemented City Connects compared to the years prior. The results are similar for Black males, although neither estimate is statistically significant. The gap between the "expected" and observed proportions of students in special education decreased by half a percentage point for all Black students and one-percentage point for Black males. Neither of these estimates were statistically significant. Next, I produced event-study estimates for this analysis, shown in Table 4.19.

Table 4.19

Event-study subgroup analysis

	Percent Black Sped	Percent Black Male Sped	Disproportionality - Black	Disproportionality - Black Male
5 years Pre	0.94	0.18	-0.43	-0.70
	(1.37)	(2.37)	(1.57)	(1.53)
4 years Pre	2.02	1.00	0.12	-0.33
	(1.29)	(1.90)	(1.26)	(1.02)
3 years Pre	1.51	0.47	1.65	0.45
	(1.04)	(1.45)	(1.16)	(1.09)
2 years Pre	1.13	0.06	0.21	-0.35
	(0.70)	(1.13)	(0.57)	(0.60)
1 years Post	0.10	-0.26	-0.23	-0.93
	(1.00)	(1.63)	(0.94)	(0.84)
2 years Post	-2.11	-2.89	-1.21	-1.43
	(1.49)	(2.21)	(1.08)	(0.97)
3 years Post	0.99	1.89	1.21	-0.20
	(1.93)	(3.08)	(1.38)	(1.10)
4 years Post	-1.66	-3.71	-0.34	-2.11
	(1.74)	(2.70)	(1.77)	(1.55)
5 years Post	-0.61	-5.21	-0.76	-2.90
	(2.40)	(3.69)	(2.63)	(1.79)
Constant	21.69***	28.11***	3.11***	7.54***
	(1.09)	(1.43)	(1.03)	(0.82)
Adjusted R^2	0.74	0.60	0.59	0.46
Observations	1294	1294	1294	1294

Note. Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regression coefficients can be interpreted as percentage point differences in the proportions of students placed in special education.

The pre- and post-treatment coefficients for all Black students are not statistically significant, but in similar magnitude to the TWFE estimate. The pre-treatment lag coefficients ("Percent Black Sped" column) demonstrate a potential violation of the parallel trends assumption, showing that treatment schools were already experiencing about a two percentage-point decline in the proportion of Black students in special education before City Connects implementation (4-year pre estimate). In the first year of the intervention, there was no significant treatment effect, after which schools experienced a two-percentage point decline in special education placement that sustained through the fourth year of implementation. The gap in expected and observed special education placement for Black males (Column 3 estimates) narrowed by about one percentage point in the post-treatment period.

For Black males, the post-treatment effect estimates were also not statistically significant, but the observed trends suggest that there was in fact a change in special education placement following City Connects implementation. The pre-treatment estimates were close to 0 – meaning trends in comparison and treatment schools were parallel before City Connects implementation – but the post-treatment estimates demonstrate a considerable break from this trend. After no change in the proportion of Black males in special education after the first year of implementation, there was a three-percentage point decline by the second year, which increased to five percentage points by the fifth year. There was notably an *increase* in the percentage of Black males in special education in the third year, but this appears to be an outlier that may be an artifact of regression to the mean. Accordingly, the pre-existing five percentage point gap in expected and observed special education placement for Black males narrowed by three-percentage points, equivalent to about 100 fewer Black males in special education on average for a given year in the post-treatment period. Therefore, the drop in special education placement for

Black students is largely driven by changes in placement for Black males as opposed to Black females.

As for the main effects analysis, I also conducted these subgroup group analyses using the Callaway and Sant'Anna estimator. These results can be found in Figures A1-A4 in Appendix A, demonstrating similar results as the event-study estimates. The exception is that parallel trends was established for Black students, and the size of the post-treatment estimates were larger, albeit still not statistically significant.

Finally, to remove confounding of the City Connects treatment effect estimate with turnaround status, subgroup analyses were completed using just the District 1 sample, where no treatment schools experienced a turnaround intervention. For brevity, only the main effects and Black student subgroup estimates from the Callaway and Sant'Anna model are presented here (Figures A5 and A6 in Appendix A). These estimates largely replicate the main findings, showing that observed effects were not likely driven by turnaround schools.

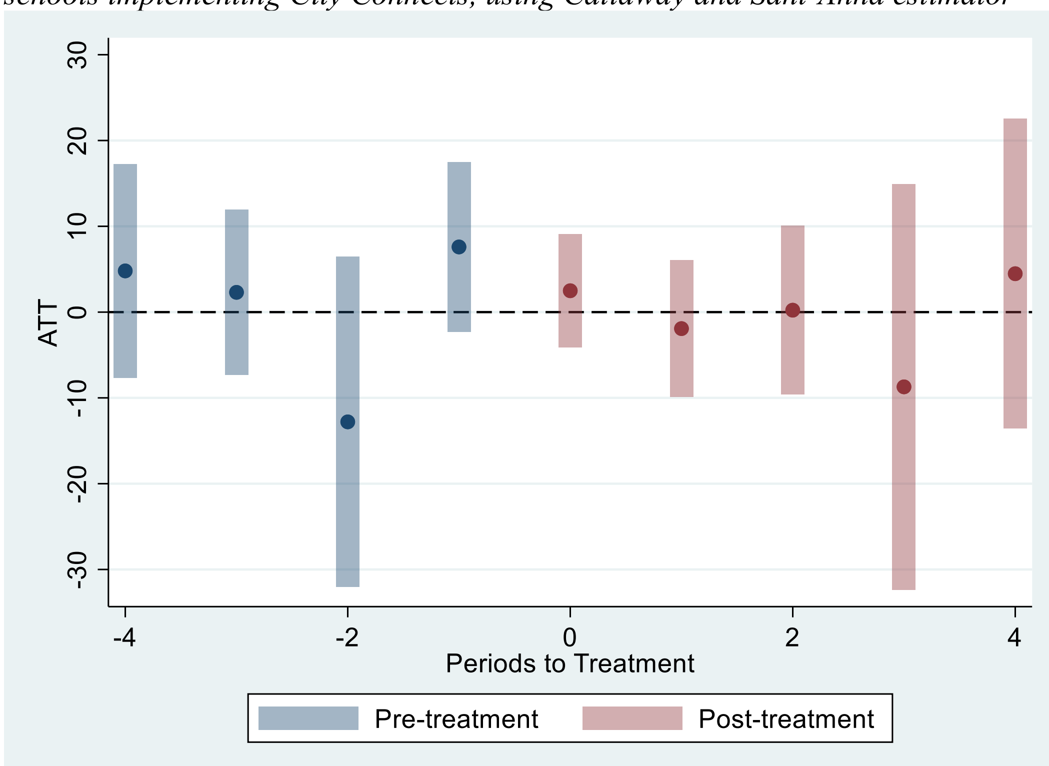
Sensitivity analyses to address mobility

To test if the observed City Connects treatment effect estimates simply reflect special education students leaving treatment schools, I created a new variable that represents the change in special education students from one year to the next through mobility. In other words, while some special education students may leave schools year-to-year, they may be replaced by other special education students. This new variable represents the difference between *replacers* (i.e., the number of special education students who entered a given school divided by the total number of special education students in that school in the previous year) and *movers* (i.e., the proportion of special education students who left from the previous year). A positive estimate indicates more students entered than left.

I re-estimated the Callaway and Sant'Anna model from the previous analyses using this new variable as the outcome. The results, shown in Figure 4, demonstrate that the average proportion of special education in treatment schools did not significantly change due to mobility from year-to-year following the implementation of City Connects. This suggests that the observed treatment effect is not simply driven by the mobility of special education students out of treatment schools.

Figure 4.4

Percentage point difference between special education replacers and movers over time for schools implementing City Connects, using Callaway and Sant'Anna estimator



Note. Replacers are the number of special education students who entered a given school divided by the total number of special education students in that school in the previous year. Movers are the proportion of special education students who left from the previous year. A positive percentage indicates more students entered City Connects schools than left, whereas a negative percentage means more students left than entered.

Declines in special education may also potentially reflect demographic changes in enrollment over time in treatment schools. Specifically, if treatment schools began enrolling students from backgrounds less likely to be placed in special education, then declines in placement would certainly follow. To test for such changes, I re-estimated the Callaway and Sant'Anna model from the previous analyses using the proportions of low-income, Black, Hispanic, White, and EL students as the outcome variables in separate models. These findings are presented in Figures A7-A11 in Appendix A. The results demonstrate modest declines in the proportion of low-income students and slight gains in the proportions of EL and White students in treatment schools following implementation of City Connects. Nonetheless, most of these estimates are not large enough in magnitude to explain declines in in the proportion of students placed in special education.

Summary of findings

Summary of Research Questions 1 findings

The models for Research Question 1 all explained a limited amount of variance in special education placement, which is unsurprising given that they are certainly limited in scope and do not capture the socio-emotional elements that may also lead to a disability diagnosis and subsequent placement. It is noteworthy, however, that differences in rates among Black, Hispanic, and White students did not persist upon controlling for the other variables in the models. When looking at comparisons between race-by-gender groups, there remained limited differences among Black, Hispanic, and White students by race. There were, however, significant differences between these three racial groups and Asian students in probability of special education placement. Asians are far less likely to be placed in special education, regardless of gender. Although these findings do not suggest evidence of racial bias against

Black students – male or female – in the special education placement process, it is important to further contextualize these findings to better discern potential inequities.

Summary of Research Question 2 findings

Using longitudinal data, the findings for Research Question 2 demonstrate considerable heterogeneity in student achievement across race and gender following special education placement. Across racial groups, Asian students – both male and female – appeared to benefit the most following special education placement in ELA and math achievement, demonstrating noteworthy gains in both subjects. On the other hand, the relationship between special education placement and academic achievement was most negative for White students, regardless of gender.

For Black and Hispanic students, effects varied by gender. Males from these groups experienced declines in ELA and no changes in math following special education placement. Event-study estimates showed that, at least for Black students, the drop in ELA achievement was likely a continuation of a negative trend from the pre-treatment period as opposed to a negative impact from special education. For math, however, student scores improved after special education placement, but the drop from where students were prior to placement was so large that students remained significantly behind from where they once were. Black and Hispanic females appeared to benefit modestly from special education placement, although these estimates likely reflect mean reversion. In sum, it appears that – with exception to Asian students – few students across these school districts positively and meaningfully benefited from special education placement as reflected by their academic achievement. Special education may have prevented further declines, however, as achievement stabilized for most subgroups after placement.

Summary of Research Question 3 findings

Descriptive statistics demonstrated that the lottery did indeed produce a random subset of students assigned to preK programs implementing City Connects and those with similar probabilities who were assigned comparison preK programs. Students assigned to preK programs with City Connects were slightly less likely to be placed in special education, particularly by third grade, but these estimates were imprecise. The sizes of the regression coefficients suggest that the City Connects effect was greater for Black students, though these were not statistically significant. The size of the regression coefficients were substantially larger, however, when restricting the sample to students who had reached at least third grade by the time their outcomes were observed, but again, no effects were statistically significant. This may, however, be due to low power stemming from a small sample size and the large standard errors typically produced through two-stage IV models.

Importantly, the analytic sample consists of students from less marginalized backgrounds, meaning they may have less to gain from an intervention targeting out-of-school factors. This suggests that model estimates may be more conservative than if the full sample of preK students was used. While these findings are far from confirmatory, they are somewhat suggestive that preK programs with comprehensive student support may reduce the need for special education for Black students when they reach third grade.

Summary of Research Question 4 findings

Analyses from Research Question 4 show that special education placement rates dropped by 10% at schools following four years of implementation of City Connects, translating to a decrease in special ed placement of about 400 students across treatment schools in a given year across the post-treatment period. With 39 treated schools in the sample, this amounts to approximately 10 fewer students in special education per school. These effects were mostly driven by declines in Black males served in special education, leading to a narrowing of the gap between expected and observed proportions of Black students in special education. Model estimates are robust to demographic changes in schools over time, turnaround status, and student mobility.

CHAPTER 5. DISCUSSION

In this final chapter, I begin by revisiting the goals of this study. Then, I connect the findings from Chapter 4 so as to provide a coherent interpretation of the results, followed by the implications for policy and practice. Next, I revisit the gaps in the literature discussed in Chapter 2 to position the overall contribution of this dissertation to the fields of special education, early childhood education, and integrated student support. Then, I discuss the limitations of the studies in terms of internal and external validity. Finally, I conclude with directions for future research.

Study goals

Throughout this dissertation, I sought to bring clarity to the discussion surrounding disproportionality in special education placement, focusing on two, high-poverty school districts in the Northeast. The motivation for this work stemmed from contradictory research suggesting both over- and underrepresentation of Black students in special education (Cruz & Rodl, 2018). Given that more than one in every five students in urban school districts are placed in special education, disentangling potential sources of inequities has important implications for policy and practice.[1]

Accordingly, I first sought to replicate prior research by estimating whether race predicted special education placement in urban schools and if that relationship changed after accounting for student background characteristics and school attended. To further demonstrate the degree to which differences in special education placement rates by race were warranted, I then sought to estimate changes in student achievement, by race and gender, after placement.

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[1] Based upon author's analysis using Stanford Education Data Archive

The intuition here is that, assuming special education supports are effective, and if placement is in fact warranted, then student achievement would likely improve following placement.

Upon finding evidence of different outcomes in special education by race and gender, I explored the effectiveness of two approaches to reducing the need for placement. Motivated by limited research on the effect of contemporary universal preK programs on reducing the probability of special education placement, I analyzed whether such programs with an integrated student support component were effective in reducing the proportions of students placed in special education. Then, I examined whether the introduction of an integrated support program – independent of preK – affected school levels of special education placement. Both studies here ask similar questions with minor nuances, but importantly, each mitigates important methodological limitations of the other.

Interpretation of findings

Taken together, the findings from the first two research questions suggest that special education is likely overused in these two school districts. The race-by-gender groups with the highest adjusted probabilities of special education placement – Black males, White males and females, and Hispanic males – experienced continued declines in ELA achievement following placement, and no changes in math achievement. On the other hand, the groups with the lowest probabilities of special education placement – in particular Asian males and females – experienced academic gains in both subjects following placement.

One way of interpreting these findings is that students who are more likely to need special education – proxied by low incidences of placement within race-by-gender groups – are more likely to benefit from its supports. For example, given the low rate of placement among Asian students, those placed in special education are likely in high need. Due to unobserved confounding, however, the special education regression effect may also reflect additional investments in education families make after their child is designated an IEP, such as after-school tutoring. Therefore, another possibility is that special education in the district is simply ineffective as a whole, and students who experience achievement gains after placement may simply be benefiting from other investments received at the time.

While this unobserved confounding may certainly drive part of the observed effects, given that there is heterogeneity in regression effect estimates by gender – such as Black females improving in math achievement but Black males experiencing no change – there is reason to believe that special education supports alone are effective for some students but not for others, and this may be tied to misidentification. If supports are not adequately aligned to student needs, then not only will they not be effective – as evidenced here – but there may be negative consequences stemming from how students perceive their own academic abilities after being identified with a disability.

The findings from Research Questions 3 provide suggestive evidence that some special education placement is avoidable. I found preliminary evidence that providing students with this ~~one~~ particular model of integrated student support starting in preK may reduce the probability of special education for Black students after second grade. While these effects were not statistically significant due to low power, the magnitude of the effect size – a 20% decrease in probability of placement – is practically meaningful.

Importantly, the effects do not emerge until students reach third grade, which is perhaps not surprising, given that this is when diagnoses for more subjective disabilities tend to increase. This suggests that receiving preK and City Connects together reduces special education placement in circumstances where students may be subject to less-medically defined disabilities.

Theoretically, such a connection makes sense given that increased early childhood experiences and intervening on out-of-school factors should only impact disability diagnoses that have a nurture element, like Specific Learning Disabilities.

Research Question 4 provides supporting evidence of the findings in Research Question 3. While answering a slightly different question about how the proportion of special education students changes in schools after the introduction of City Connects, I ameliorated concerns over school self-selection into the intervention by showing that there was no distinct pre-treatment trends in the outcome variable between treatment and comparison schools. Then, I examined whether there was a break in that trend in the post-treatment period. Following City Connects implementation, the proportion of special education students overall dropped by 10%, and the proportion of Black students in special education dropped by approximately 20%. When alternative options to provide students with additional support are available, teachers appear to be taking that opportunity, indicating that special education may not always be necessary for these students. Paired with prior research about the positive effect of City Connects, the reducing student placement in special education does not appear to be detrimental to student outcomes.

Implications

The findings from this dissertation do not support recent research implying that *more* under-represented minorities should be placed in special education in high-minority school districts (Elder et al., 2021). In the time period of this study, I showed through the first two research questions that placement rates in these two school districts were already highest among Black males, yet they experienced declines in ELA achievement and no meaningful improvement in math achievement after placement. Consequently, placing more Black students into special education would likely lead to unintended and inequitable consequences. Certainly, there is a need to improve special education supports as a whole, but this study provides preliminary evidence that it cannot be a panacea for all learning and socio-emotional needs, particularly those that are correlates of poverty and general disadvantage.

A second implication is to consider heterogeneity in special education experiences by race *and* gender. Prior research has largely treated special education experiences as homogenous within race. Here, I show important differences. For example, the Black females in this study had rates of identification lower than that of White males *and* females. Black females were are also more likely to benefit from special education supports compared to all White students. It is thus unclear whether Black females should be the target of potential policy levers aimed at reducing disproportionality among all Black students. Policy solutions aimed at decreasing disproportionality that ignore this nuance may target groups that are not in need of such intervention, resulting in negative consequences.

Third, it is clear that some special education placement is not completely inevitable due to nature. Rather, nurture plays an important role. I show that, when students are provided with high-quality early learning experiences combined with a particular model of integrated student support, they are less likely to require to experience learning challenges that result in special education placement. Providing such experiences and supports are both more cost-effective and conducive to improving student long-term academic outcomes.

Fourth, the findings from the latter two research questions show that poverty has an important role to play in whether students "develop" a disability. While prior literature has shown that socioeconomic status predicts special education status, few studies have attempted to study whether intervening against factors related to poverty reduces the probability that students are diagnosed with a disability leading to subsequent special education placement (Kincaid &

Sullivan, 2017). These results suggest that special education may not be the most appropriate way to ameliorate the academic challenges brought about as a result of poverty, but rather, a more proactive approach that centers the whole child needs starting at preK can be effective at reducing the need for special education at all, while also ensuring that students continue to thrive.

Finally, there are a number of implications regarding the way disproportionality is measured and interpreted. Based upon these findings, I argue that a more nuanced and localized approach is necessary in policy discussions surrounding disproportionality, but to do so requires better data than has previously been available.

Here, I offer three recommendations to bolster data collection efforts. First, statistics measuring disproportionality should be calculated within schools as opposed to across districts and states to control for differences in policies and peer composition. Furthermore, research on disproportionality cannot ignore within-school effects, as has been the case with studies using nationally representative survey data. In particular, accounting for school effects can show if students within the same school – subject to the same policies and procedures – are treated differently in the special education placement process by race.

Second, traditional statistics used to identify disproportionality like relative risk ratios should be adjusted for background characteristics like socioeconomic status and existing measures of baseline achievement to reflect potential sources of disparities. By adjusting for these variables, a clearer picture on potential mechanisms can be understood, with subsequent policy solutions developed. For instance, if Black students are found to be overrepresented in special education even after "controlling" for socioeconomic background and prior achievement, there is reason to believe that racial bias is a potential mediating factor. If racial disparities become nonexistent after controlling for other characteristics, then the sources of disproportionality become more evident, and policy solutions can accordingly target these risk factors.

Third, to provide more context with regard to whether disparities suggest over- or underrepresentation, disproportionality data should be combined with additional information demonstrating how student achievement changes after special education placement, disaggregated by race. Even after adjusting for background characteristics, traditional statistics measuring disproportionality are still difficult to interpret, because assuming such disparities are evidence of over- or underrepresentation requires some reference group for which one must assume accurate identification (Collins et al., 2016). Unfortunately it is thus unclear which groups are over- or underrepresented.

Disproportionality statistics clearly require additional context, and one strategy is to pair this data with evidence of the effectiveness of special education supports. Such evidence is one way to gauge whether placement is warranted or not, and I show here that the correlation between high-identification and effectiveness is not always consistent. The ineffectiveness of special education as a whole may certainly reflect deficiencies in the supports themselves, but heterogeneity in regression effect estimates by race bolster the evidence that some students are inappropriately identified. Such an analysis is difficult when sample sizes within particular racial groups are small, but the same challenge arises with traditional statistics of disproportionality as well.

Contributions

This study makes a number of contributions to the field of special education, early childhood education, and integrated student support. In the area of special education, this dissertation provides more clarity in the debate surrounding whether disabilities have a dimension of nurture. Although the lack of special education placement does not necessarily mean a student was not identified with a disability (I am unable to distinguish between the two here), the large drop in special education placement that took place following City Connects implementation implies at least some drops in disability diagnoses. I therefore find supporting evidence that some placement may be due to lack of learning and socio-emotional support. This is particularly the case for disabilities that do not necessarily warrant placement at later elementary grades.

Additionally, this study offers evidence on alternative ways through which schools can improve equity in special education placement. Evidence on the effect of approaches like RTI and MTSS have been mixed, with some studies finding small declines in the probability of special education placement after schools adopted RTI, whereas others have found modest increases in Learning Disabilities diagnoses in non-White students (Shea & Jenkins, 2022). Here, I show much larger regression effect estimates with an intervention that is not directly aimed at reducing special education placement. Accordingly, there is much to be learned about the supports teachers feel students need when they refer them for disability evaluations, and how existing approaches like RTI and MTSS respond to such needs.

For early childhood education, I show that preK programs can be much more effective in reducing future need for special education when combined with a particular model of integrated student support. As previously documented, prior research has demonstrated mixed evidence regarding the efficacy of preK in reducing the probability of future special education placement. Specifically, in District 1, there have been no documented effects of receiving public preK on special education placement (Gray-Lobe et al., 2021; Weiland et al., 2020). Given these preK programs tend to be heavily focused on academic training, my findings underscore the need to focus on students' socio-emotional needs as well in order to be most effective.

In the field of integrated student support, I have provided the most rigorous evidence to date showing the effects of such interventions on the probability of special education placement. Given the negative association between special education placement and academic achievement in the districts studied, these findings offer supporting evidence of a potential mechanism by which an intervention like City Connects improves and sustains increased academic achievement. This study also complements prior qualitative research showing that principals altered the special education referral process upon implementing City Connects (City Connects, 2009).

Limitations

Due to the use of imperfect and incomplete secondary data, this study is limited in a number of ways. Firstly, data is coarsened for a number of variables, limiting the level of inference across all research questions. For example, race is restricted to five categories for which there may be considerable heterogeneity. The experiences of African Americans, for example, may differ considerably from those of first and second-generation immigrants from African or Caribbean countries. More importantly, special education is treated as a unitary category in this study, when in reality, there may be significant heterogeneity in outcomes and observed relationships by disability type. I am also unable to distinguish between disability diagnoses and special education placement. For instance, in Research Questions 3 and 4 where I show drops in special education placement following exposure to City Connects, this may or may not coincide with drops in diagnoses of specific disabilities.

Secondly, while the data for these analyses comes from school districts with similar demographics to other urban school districts across the country, there may be important differences across a variety of factors in ways that make the findings less generalizable. For instance, District 1's public preK program differs from similar programs across the country in curriculum rigor and teacher training (Weiland et al., 2020). Similarly, the City Connects intervention has been identified by the federal government as an exemplary form of integrated student support, in view of its higher fidelity of implementation and more targeted support (Department of Education, 2021). Consequently, the findings likely do not generalize to all public preK and integrated student support programs across the nation.

With regard to Research Question 2, as previously noted in Chapter 3, we are able to make causal inferences about the effect of special education placement on student outcomes, but not the IEP supports themselves. Beyond IEP supports, parents may invest more in their child, both financially (e.g., by pairing special education supports with out-of-school services like tutoring) and through general involvement. Knowing whether IEP supports are effective is of greater policy relevance here and is pertinent to understanding whether students are appropriately served in special education. I rely on differences in treatment effect estimates by gender in attempt to disentangle these estimates but note that the results are somewhat ambiguous. Consequently, I cannot say definitively that Black males are over-placed in special education due to not benefiting academically following placement. I thus note the findings are at best suggestive.

Research Question 3 is limited in both generalizability and statistical power. Concerning the former, I present important differences between the analytic sample of students for whom preK assignment is due to the lottery and the full population of preK attendees. Students subject to randomization to a City Connects preK program were much more likely to be White and less economically disadvantaged (Shapiro et al., 2019). Focusing on just Black students and Black males in the subgroup analyses allows me to look at individuals who have among the most to benefit from preK and City Connects with regard to special education placement, there may still be unobserved differences between these students and the full population of preK attendees. Furthermore, these analyses are limited by small sample sizes. While I found substantively large effect sizes, they are paired with large standard errors, lending some ambiguity to the findings.

Directions for future research

Similar to prior studies, through this dissertation, I have showed that – at least in the two school districts studied – special education placement is particularly high for Black males. While differences in placement by race can be explained by background characteristics, special education supports for most students – particularly Black and White males – do not appear to be well-aligned to academic needs given poor achievement outcomes following placement. This leaves two potential areas for reform: either in the special education supports themselves, or improvement in the identification process. I find supporting evidence of the latter, and through the study of City Connects, show that providing comprehensive and whole-child supports can reduce special education placement rates, specifically for Black students.

These findings raise several follow-up questions on how integrated student support programs intersect with special education. First, follow-up studies with larger sample sizes to disaggregate data by disability category could uncover important sources of heterogeneity. For example, special education supports may be more effective for students with certain types of disabilities. Additionally, City Connects may help forestall special education placements by reducing disability diagnoses for certain categories. Low statistical power limited the ability to explore these questions in this study.

Second, the quantitative findings from Research Questions 3 and 4 can be complemented by qualitative research that elucidates the mechanisms by which City Connects reduces special education placement. Such research could seek the perspectives of teachers to understand how the presence of a City Connects coordinator and the system of supports changes how they identify students for special needs evaluations. Interviews with special education specialists and individuals generally part of IEP teams can shed light on the level of involvement of coordinators and how their presence affects the identification and placement process. Taken together with the quantitative evidence provided here, such qualitative research will provide a clearer picture on the extent to which the relationship between City Connects and special education placement here is truly causal.

Third, assuming the presence of City Connects does in fact change the special education placement process, it is important to know the types of services high-risk students are provided with that forestall eventual placement. Researchers could request teachers to identify students who they would have directly referred to special education evaluation in the absence of City Connects. Using propriety data collected by the program on student strengths, needs, and services, researchers could then document the profiles of services received by such high-risk students. Such information could be used by school districts that do not have support systems like City Connects in place to help reduce special education placement.

A fourth area of future research concerns students who are eventually placed in special education while attending a school implementing City Connects. If the intervention is indeed better at providing students with the appropriate necessary supports, this would translate to more "accurate" identification for those ultimately placed in special education. In other words, these should be students who are most likely to benefit from special education supports. To test such an assumption, researchers could track the academic trajectory of students placed in special education while in a school implementing City Connects. Evidence of improved achievement may indicate more accurate identification and better alignment of supports through City Connects.

An additional area of concern not explored in this dissertation is the amount of time spent outside of general classroom settings. Among the many concerns around disproportionality – even in cases where overrepresentation is warranted for a particular race – is that students of color may be placed in more restricted classroom settings (i.e., self-contained) more often than their White and Asian peers, exacerbating within-school segregation (Cartledge, 2005). Improving access to and time in general education settings has thus been an established point of policy concern (Bolourian et al., 2020). Among the challenges to creating more inclusivity is that many general classroom teachers do not have adequate training to support SWDs (Gilmour et al., 2022). Given research showing that City Connects improves teachers whole-child understandings of students, it would be useful to know if that translates to increased ability to support SWDs and ultimately more inclusion in general classroom settings (Sibley et al., 2017).

Finally, this dissertation adds to the mixed findings regarding disproportionality in special education, underscoring the importance of replication. Consequently, future research in other school districts and different contexts may provide some clarity concerning where special education is more or less effective and for what groups of students. For example, there might be differences in special education effectiveness by the level of poverty in school districts. Furthermore, the effect of City Connects on special education may differ in districts with more socioeconomic diversity.

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APPENDIX A. SUPPLEMENTARY RESULTS

Table A1

Coefficients from linear probability models estimating relationship between student characteristics and probability of special education placement, by district

Variable	District 1	District 2
White	0.01	**0.01****
	(0.004)	(0.003)
Asian	**-0.02*****	**-0.02*****
	(0.01)	(0.01)
Hispanic	-0.004	-0.01
	(0.004)	(0.003)
Other race	**0.02***	0.002
	(0.01)	(0.01)
Male	**0.01*****	**0.01*****
	(0.002)	(0.002)
FRL	**0.04*****	0.002
	(0.01)	(0.01)
ELA achievement	**-0.07*****	**-0.04****
	(0.003)	(0.004)
Bilingual	**-0.05*****	**-0.01****
	(0.01)	(0.01)
School fixed effects	Yes	Yes
Year/grade fixed effects	Yes	Yes
R^2	0.09	0.05
Sample size	62,911	22,733

Note. ***p < 0.01, **p<0.05, *p<0.10
Parameter estimates calculated using OLS linear probability models. Coefficients can be interpreted as difference in probability of special education placement for a student of a given characteristic and the reference group. Black, female, and paid lunch are the reference categories for race, gender, and FRL, respectively. Robust standard errors, in parentheses, are clustered at the school level.

Table A2

Marginal probabilities from linear probability model with interaction between race and gender on probability of special education placement, by district

Variable	Marginal probability (District 1)	Marginal probability (District 2)
Black male	11%	4%
White male	11%	5%
Asian male	8%	1%
Hispanic male	11%	4%
Other race male	12%	5%
Black Female	9%	3%
White female	11%	4%
Asian female	8%	1%
Hispanic female	9%	3%
Other race female	12%	2%
R^2	0.09	0.05
Sample size	62,911	22,733

Note. ***p < 0.01, **p<0.05, *p<0.10
Marginal probabilities extracted from OLS linear probability models with ever special education as the outcome. Models run separately by district to accommodate different bilingual variables. Covariates include ELA achievement, FRL, and school, grade, and year fixed effects. District 1 uses an indicator for bilingual status, whereas District 2 uses Limited English Proficiency.

Table A3

Relationship between special education placement and ELA and math achievement by district, with and without English Learner variable

	Special education coefficient	Standard error	Adjusted R-squared	Observations
District 1				
ELA	**0.08****	(0.04)	0.71	55585
ELA w/Bilingual	**0.08****	(0.04)	0.71	55585
Math	**0.10*****	(0.04)	0.75	55403
Math Bilingual	**0.10*****	(0.04)	0.75	55403
District 2				
ELA	**-0.04*****	(0.01)	0.73	186895
ELA w/LEP	**-0.04*****	(0.01)	0.73	186895
Math	0.02	(0.01)	0.78	179709
Math w/LEP	**0.02***	(0.01)	0.78	179707

Note. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Table presents special education effect using district samples separately, with and without use of each district's unique English Learner indicator. All models include indicators for mobility and retention, along with fixed effects for grade, year, school, and student. Robust standard errors, clustered at the school level, are in parentheses.

Table A4

ITT estimates for effect of assignment to City Connects preK on ever special education placement for students who had at least reached third grade

	Full sample	Black	Black males
Assigned CCNX preK	-0.04	-0.18	-0.14
	(0.08)	(0.14)	(0.11)
Constant	0.23***	0.14	0.06
	(0.05)	(0.12)	(0.17)
Adjusted R^2	0.05	0.10	0.02
Observations	976	197	93

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5

LATE estimates for effect of enrollment in City Connects preK program on ever special education placement for students who had at least reached third grade

	Full sample	Black	Black males
Attended CCNX preK	-0.06	-0.21	-0.19
	(0.11)	(0.14)	(0.13)
Constant	0.22***	0.05	0.09
	(0.06)	(0.11)	(0.15)
Adjusted R^2	0.05	0.09	0.01
Observations	976	197	93

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6

ITT estimates for effect of assignment to City Connects preK on percent of teachers licensed and highly qualified, average class size, and student-teacher ratio by last grade observed

	Percent Teachers Licensed	Percent Teachers Highly Qualified	Average Class Size	Student-Teacher Ratio
Assigned CCNX preK	0.26	-0.63	0.13	-0.17
	(0.46)	(1.83)	(0.32)	(0.24)
Constant	96.51	75.64	19.13	13.23
	(0.56)	(1.50)	(0.44)	(0.29)
Adjusted R^2	0.03	0.11	0.02	0.02
Observations	3141	3141	3141	3141

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7

ITT estimates for effect of assignment to City Connects preK on special education placement by first grade for students who had at least reached third grade

	Full sample	Black	Black males
Assigned CCNX preK	-0.02	0.04	-0.10
	(0.04)	(0.05)	(0.09)
Constant	0.04	-0.08	0.10
	(0.03)	(0.07)	(0.16)
Adjusted R^2	0.08	0.25	-0.05
Observations	976	197	93

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8

LATE estimates for effect of enrollment in City Connects preK program on special education placement by first grade for students who had at least reached third grade

	Full sample	Black	Black males
Attended CCNX preK	-0.02	0.05	-0.13
	(0.06)	(0.05)	(0.10)
Constant	0.06^{*}	-0.06	0.13
	(0.03)	(0.05)	(0.11)
Adjusted R^2	0.07	0.25	-0.06
Observations	976	197	93

Note. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A1

Callaway and Sant'Anna estimates of changes in proportion of Black students in special education over time, before and after implementation of City Connects

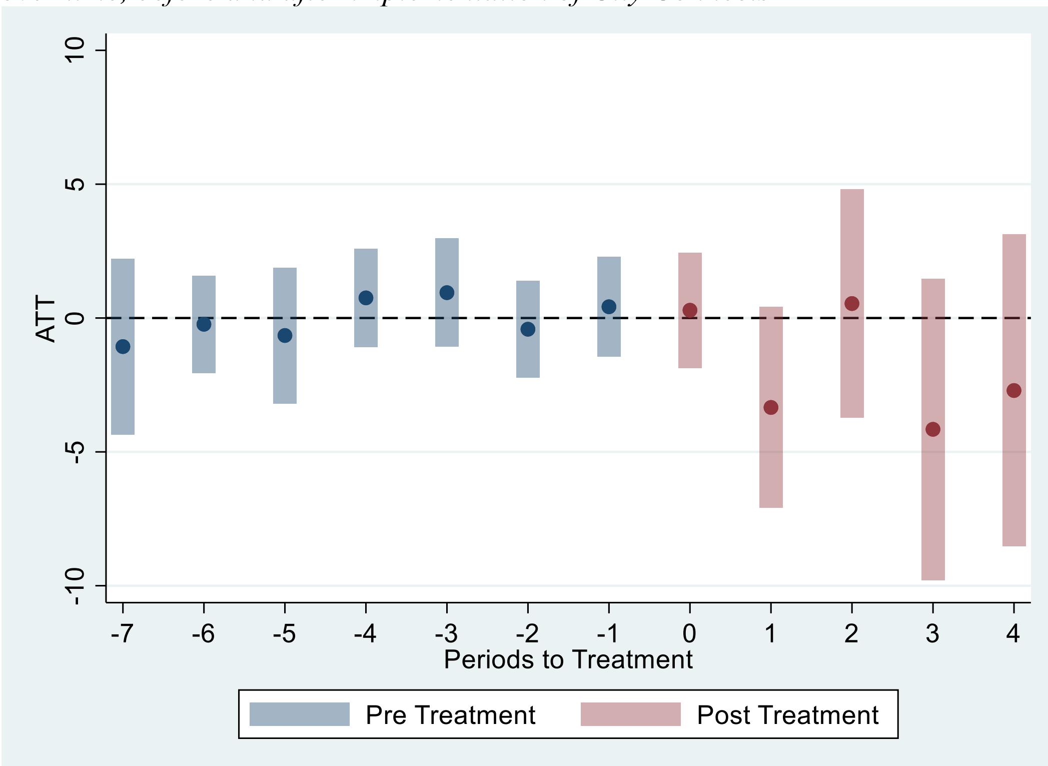

Figure A2

Callaway and Sant'Anna estimates of changes in proportion of Black male students in special education over time, before and after implementation of City Connects

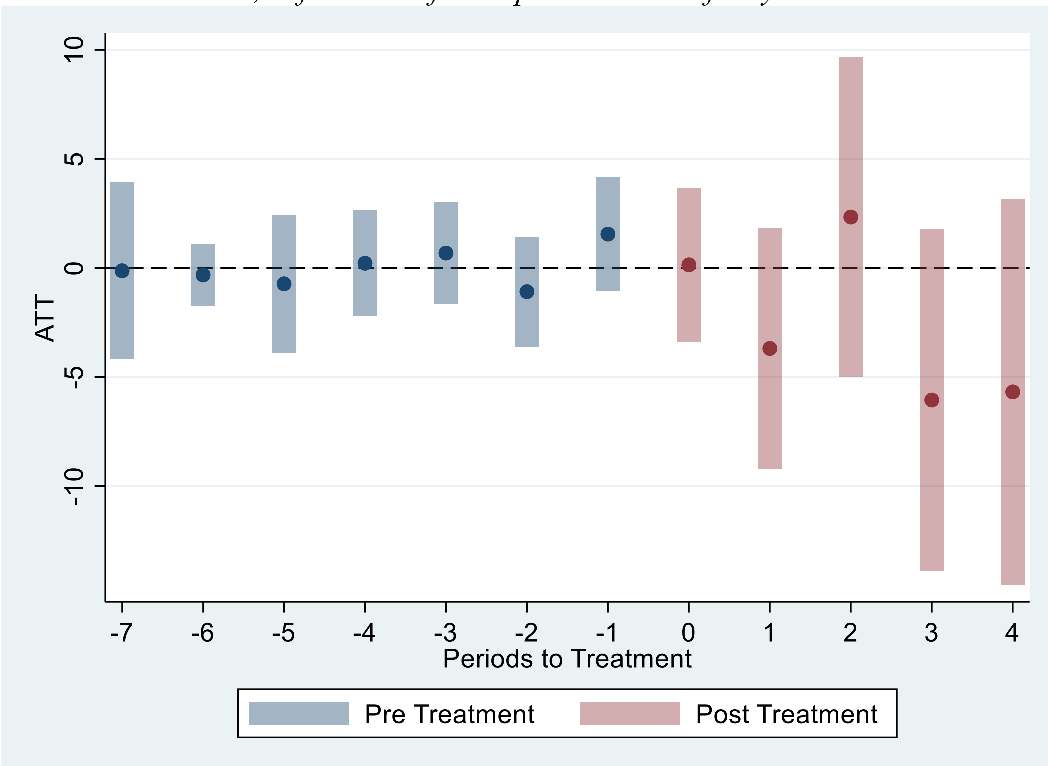

Figure A3

Callaway and Sant'Anna estimates of changes to level of disproportionality of Black students in special education over time, before and after implementation of City Connects

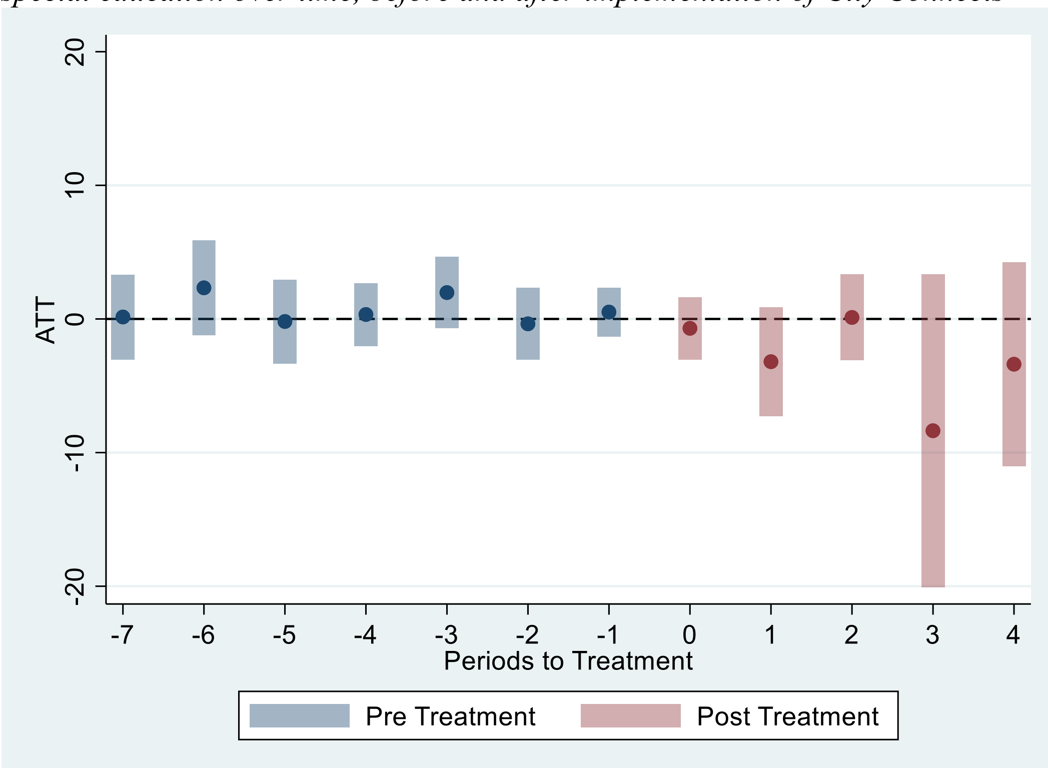

Figure A4

Callaway and Sant'Anna estimates of changes to level of disproportionality of Black male students in special education over time, before and after implementation of City Connects

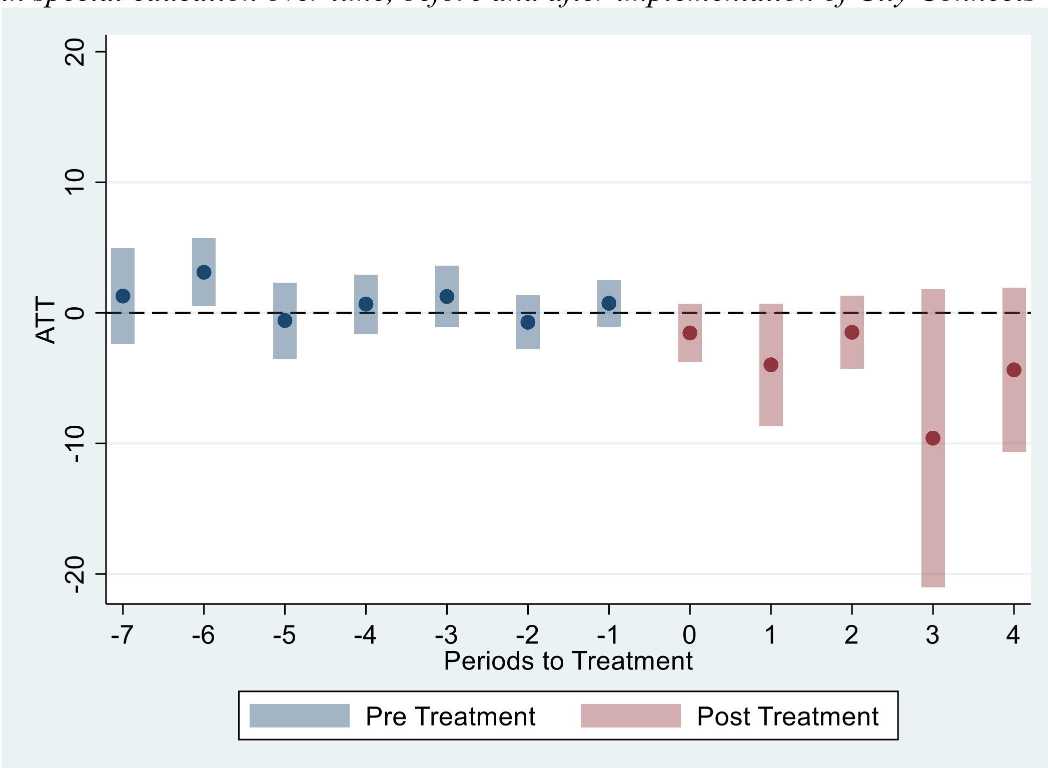

Figure A5

Callaway and Sant'Anna estimates of changes in proportion of students in special education over time, before and after implementation of City Connects, without turnaround schools

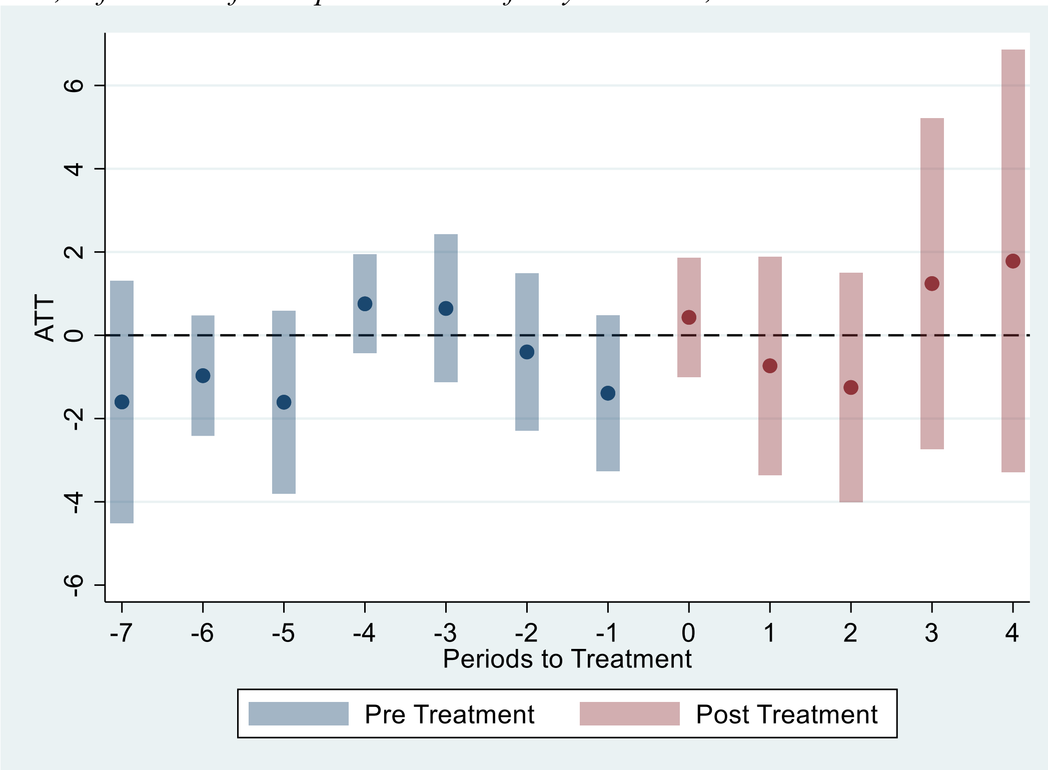

Figure A6

Callaway and Sant'Anna estimates of changes in proportion of Black students in special education over time, before and after implementation of City Connects, without turnaround schools

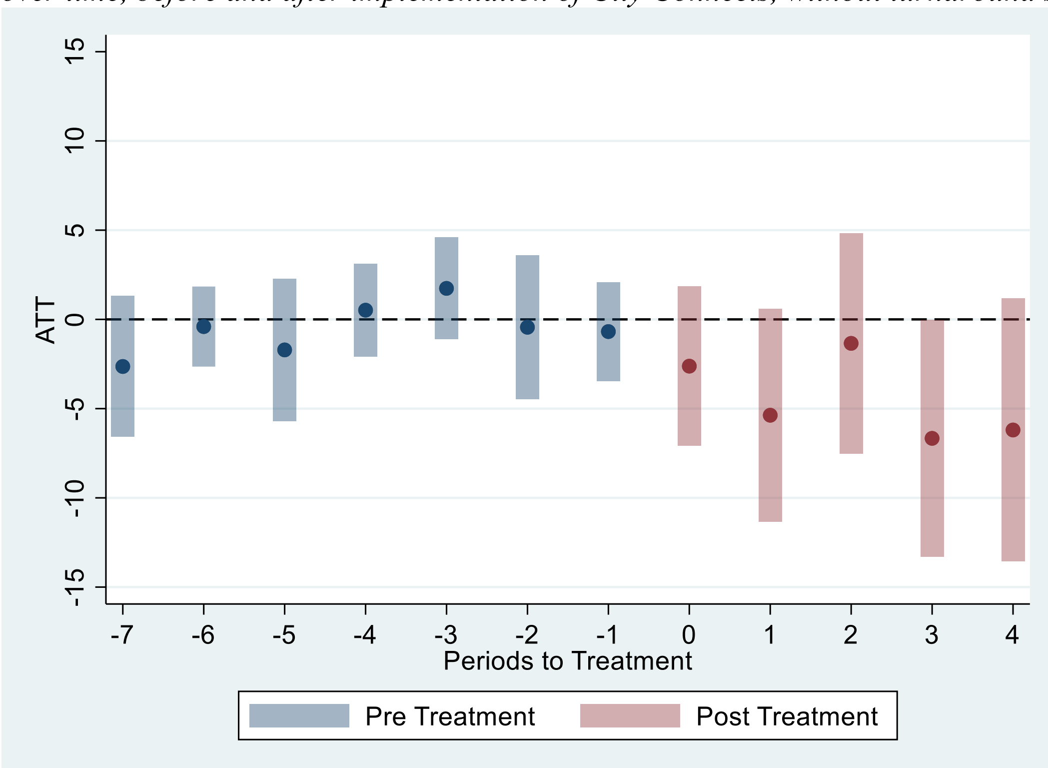

Figure A7

Callaway and Sant'Anna estimates of changes in proportion of low-income students over time, before and after implementation of City Connects

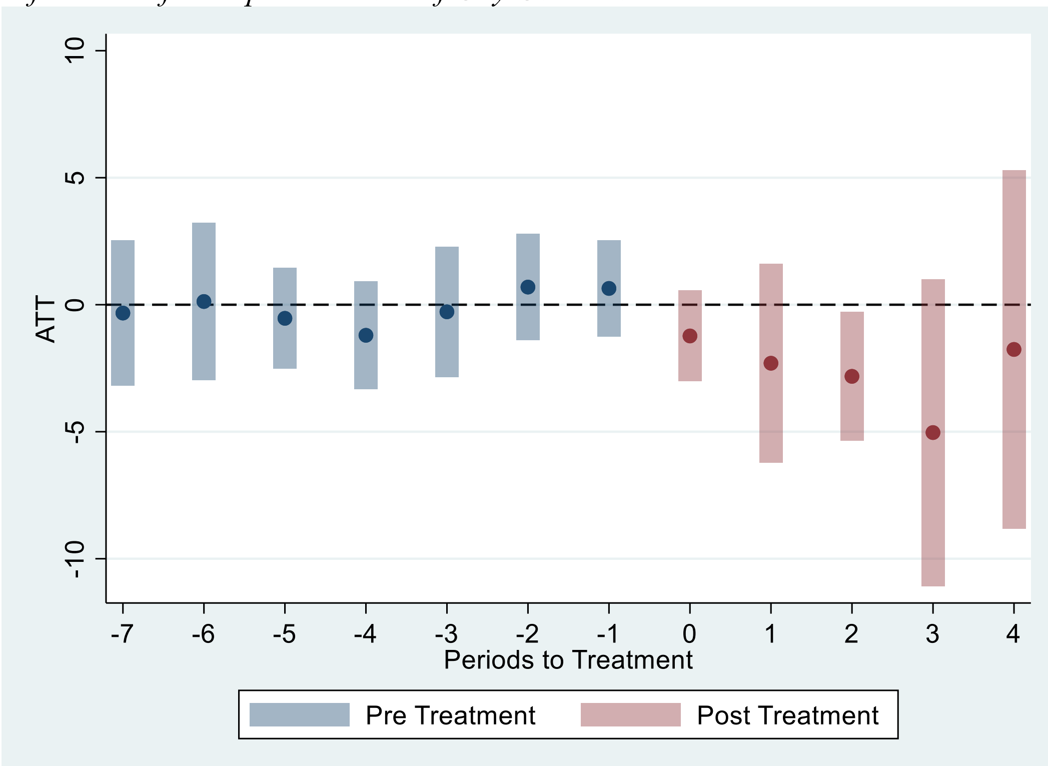

Figure A8

Callaway and Sant'Anna estimates of changes in proportion of Black students over time, before and after implementation of City Connects

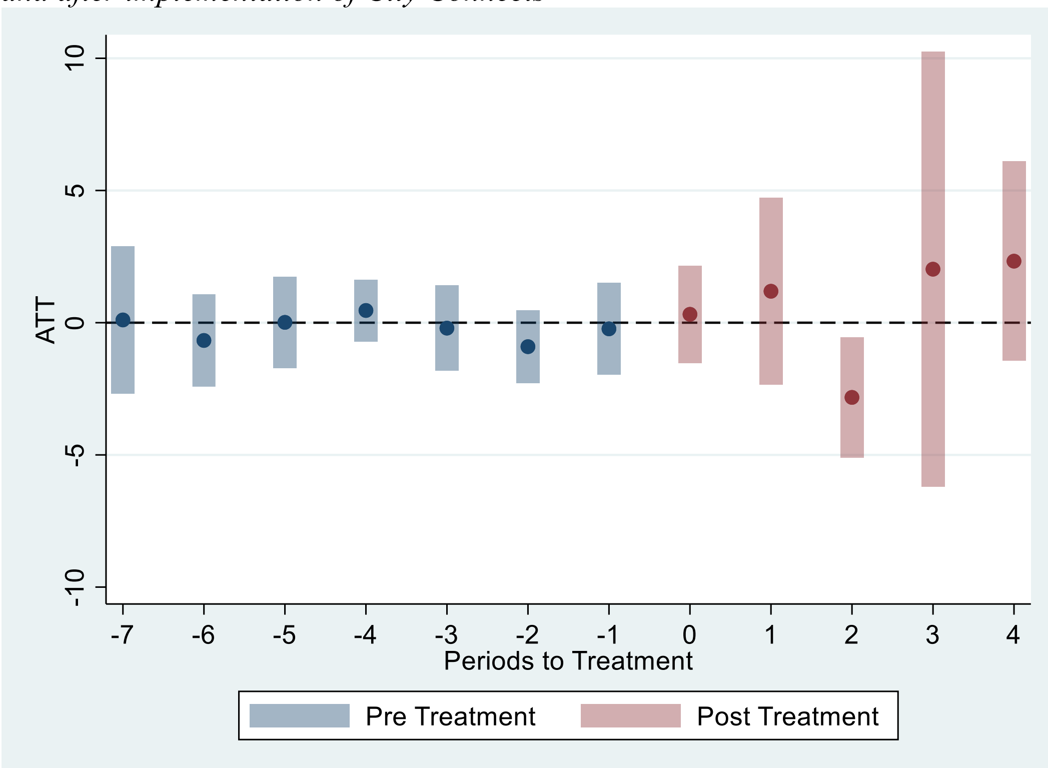

Figure A9

Callaway and Sant'Anna estimates of changes in proportion of Hispanic students over time, before and after implementation of City Connects

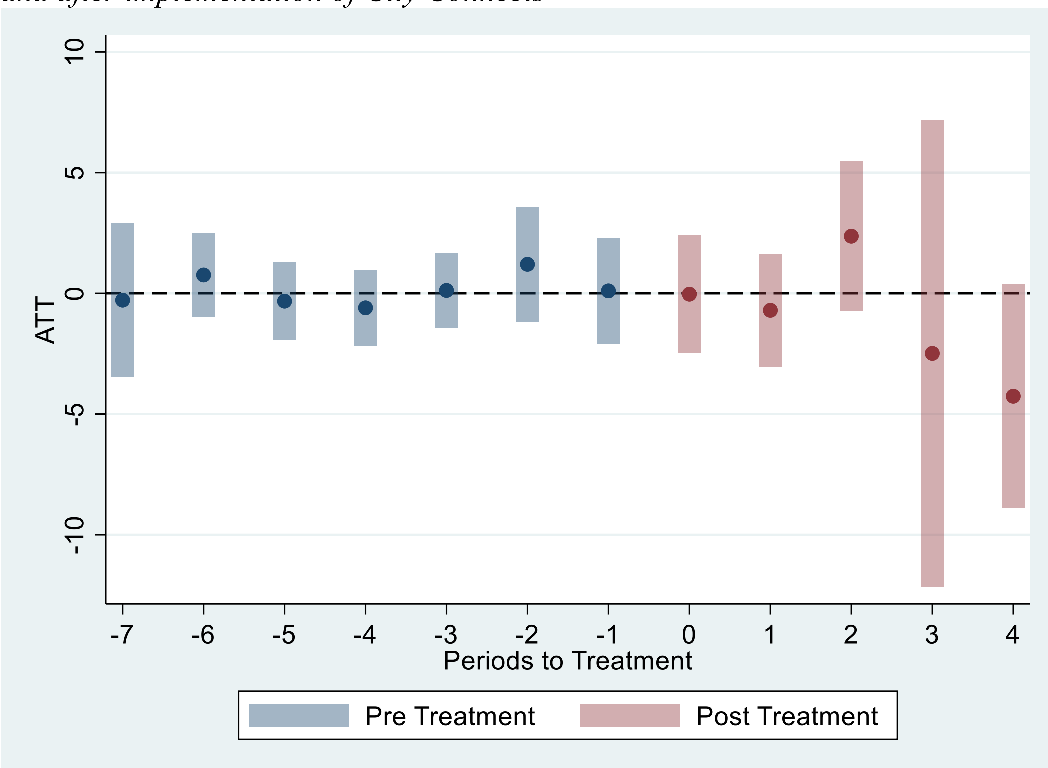

Figure A10

Callaway and Sant'Anna estimates of changes in proportion of White students over time, before and after implementation of City Connects

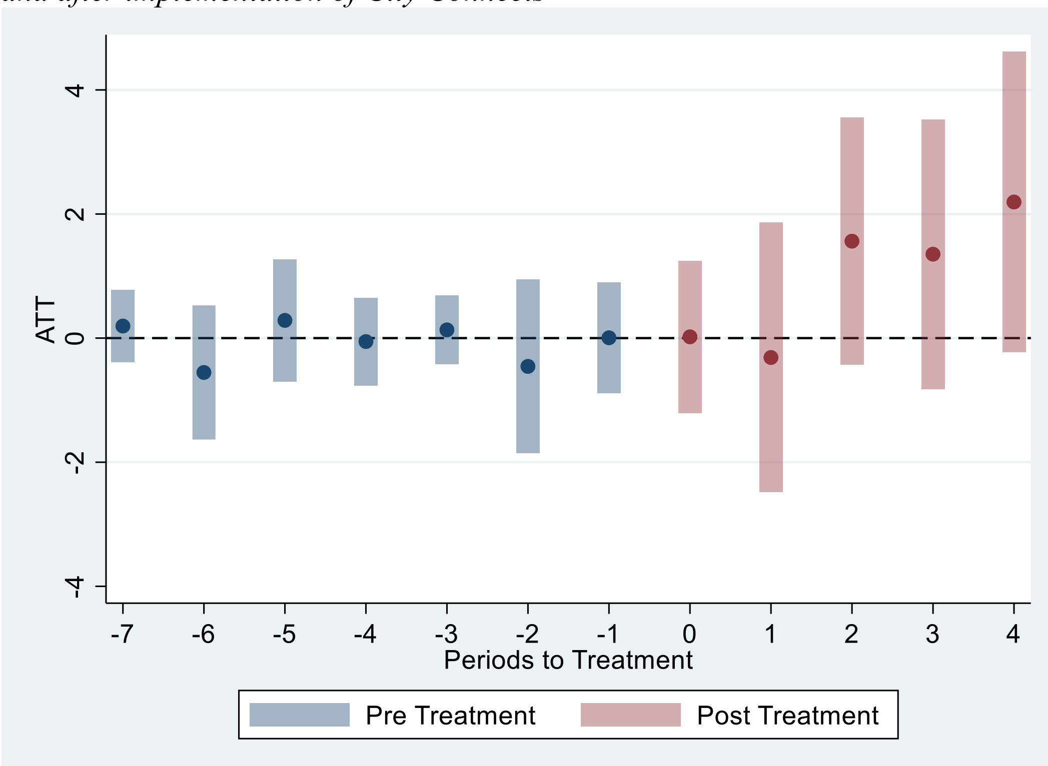

Figure A11

Callaway and Sant'Anna estimates of changes in proportion of English Learner students over time, before and after implementation of City Connects