WHITE REPRESENTATION IN NEIGHBORHOOD SCHOOLS: SCHOOL FUNDING, NONPROFIT INVESTMENT, AND ACADEMIC OUTCOMES

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ABSTRACT

My dissertation examines the enrollment patterns of White children in traditional U.S. public schools in 2010. I link schools to their attendance boundaries to compare the percentage of White children living in a catchment area to the percentage of White children who attend the local neighborhood school. I find that just under a third of schools are roughly representative of their catchment area (29%), the plurality are underrepresented White (40%), and the remaining 31% are overrepresented White. Descriptive analyses determine that White underrepresentation is more common in urban schools. White underrepresented schools tend to be in poorer neighborhoods and have a higher-than-average share of students in poverty and students with limited English proficiency.

I investigate whether there is a connection between White representation and school quality outcomes. I focus on four facets of school quality that I hypothesize might be responsive to White representation: 1) school funding metrics, 2) school-supporting nonprofit presence, 3) standardized test scores, and 4) Gifted and Talented programming.

Overall, the findings here offer mixed support for the theory of “opportunity hoarding,” in which White underrepresented schools receive fewer resources. Taken together, descriptive analyses find that White underrepresentation is largely associated with negative outcomes. White underrepresented schools have less public and charitable funding than their peers. White underrepresented schools are lower performing academically than White overrepresented schools, although they are not clearly academically different from representative White schools. White underrepresented

schools are not necessarily less likely to have a GAT program, but when they do have a GAT program, it disproportionately targets White students.

Furthermore, multivariate analyses reveal that the bivariate relationships between White representation and school outcomes are not entirely explained by the percentage of White students in a school, nor other covariates. This suggests that there is a meaningful distinction between White representation and the percentage of White students in a school. In other words, White representation tells us something about a school, net of the presence of White students. However, this was not the case for every multivariate model in the study. I find a significant negative association between White representation and school funding. White underrepresented schools have significantly lower mean teacher salaries and per-pupil salary expenditures, net of the percentage of White students within the school. This could be evidence that disproportionately low White enrollment leads to diminished school resources or less experienced teachers. Alternately, it could be that White families are more adept than non-White families at avoiding under-resourced schools.

I find no evidence of a connection between White representation and whether a school has a school-supporting nonprofit. Instead, the economic composition of the school appears to be a more important driver of school nonprofit presence and nonprofit revenue. I also find no connection between White representation and test scores. However, White representation appears to influence the racial composition of GAT programs. Schools that are less White than their neighborhoods tend to have GAT programs that are significantly Whiter than the schools.

To my parents, Nancy LaParo and Aaron Watters, who told me I was good at math until it came true.

And to all my students: you definitely taught me more.

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CHAPTER 1

INTRODUCTION

White Representation in Neighborhood Schools

Neighborhood public schools are decreasing in popularity in the United States. The percentage of children who attend their assigned public school dropped from 80% in 1993 to 69% in 2016 as proportionally more students attended magnet schools, charter schools, non-religious private schools, out-of-district public schools, or engaged in homeschooling (Grady, Bielick, and Aud 2010; Murnane and Reardon 2018; Wang, Rathburn, and Musu 2019). The decoupling of school and neighborhood opens the door to racial disparities between a public school and its surrounding neighborhood (Bischoff and Tach 2018).

In this dissertation, I focus on a single facet of neighborhood schools: the representation of non-Hispanic White students in comparison to the neighborhood, which I define here as the school catchment area. I am particularly interested in those schools in which there are fewer White children than one would expect based on neighborhood composition, or what I term "White underrepresentation." White underrepresentation has garnered recent research attention because there is mounting evidence that the average traditional public school is less White than its surrounding neighborhood (Bischoff and Tach 2018; Candipan 2019; Sohoni and Saporito 2009). In other words, White underrepresentation is the norm in neighborhood schools.

In a country with increasing racial diversity (Colby and Ortman 2015), schools that are highly segregated by race (Reardon and Owens 2014), and severe economic inequality that is tightly linked to race (Shapiro 2017), the notion that White families are pulling away from neighborhood schools at a higher rate than other racial groups has caused some alarm. One overarching concern is that White underrepresentation might exacerbate school racial segregation (Monarrez, Kisida, and Chingos 2019; Sohoni and Saporito 2009).

Previous research has investigated the neighborhood characteristics that prompt the disproportionately low enrollment of White students in neighborhood schools. Researchers found that both neighborhood poverty and neighborhood inequality exacerbate White underrepresentation in neighborhood schools (Bischoff and Tach 2018; Candipan 2019; Sohoni and Saporito 2009).

In this dissertation, I turn the conversation about White underrepresentation in neighborhood schools from neighborhood characteristics to school characteristics. White underrepresentation has yet to be linked directly to school outcomes, in either a negative or positive direction. Therefore, in this study, I explore the relationship between White underrepresentation and school quality outcomes. I select a wide range of monetary and academic measures and dissect their relationship with White representation.

What I call "White representation" has many names, including the "neighborhood-school link" (Bischoff & Tach 2018) and the "neighborhood-school gap" (Candipan 2019) and the "racial imbalance score" (Whitehurst et al. 2017). I define White representation as the difference between the percentage of White elementary-age children in a neighborhood and the percentage of White students enrolled in a neighborhood elementary school. It follows that White *underrepresentation* occurs when there is a larger share of elementary-age Whites in the neighborhood than in the corresponding neighborhood school. White underrepresentation is not simply the percentage of White families that opt out of neighborhood schools, but rather whether White families opt out of neighborhood schools at a *higher rate* than other groups.

It is important to delineate the difference between 1) the percentage of White students at a school and 2) White representation at a school relative to the neighborhood. The two are related but conceptually distinct. White representation takes the neighborhood into account, whereas the percentage of White students does not. In a hypothetical example, a school that is 70% White in a 50% White neighborhood would demonstrate White *over*representation of 20 percentage points. On the other hand, a school that is 70% White in a 90% White neighborhood would demonstrate White *under*representation of 20 percentage points. In these two hypothetical cases, the percentage of White students in the school is the same, but the White representation values are vastly different.

Research Questions

In this dissertation, I combine eleven secondary datasets to paint a detailed picture of the neighborhood and school correlates of White representation. I ask the following research questions:

1. What does White representation in neighborhood schools look like in the U.S.?
2. Is White representation in neighborhood schools associated with school funding measures? Specifically, is it associated with:
    a. Mean teacher salary?

    b. Per pupil personnel expenditure?
    c. Student-teacher ratio?
3. Is White representation in neighborhood schools associated with school-supporting nonprofits?
4. Is White representation in neighborhood schools associated with standardized test scores?
5. Is White representation in neighborhood schools associated with Gifted and Talented programming?

In other words, I hope to learn whether underrepresented White neighborhood schools experience reduced (or perhaps improved) school quality by observing a wide range of school quality metrics.

Because school racial composition is not randomly assigned across neighborhood schools and is correlated with other neighborhood and school characteristics, it is impossible to draw a direct causal line between White representation and the school outcomes in this study and I do not attempt to do so. Instead, I spend time outlining both bivariate analyses and multivariate regression analyses in an effort to tease out the differences between White school composition and White representation. I consider this study to be a largely exploratory endeavor to understand how White representation might matter for public, neighborhood schools.

I now provide a brief overview of the chapters that follow. First, I review the literature on White representation in neighborhood schools and identify theories that might explain a connection between White representation and school outcomes. Next, I introduce the sample and provide a descriptive review of White representation in the U.S.

Much of what I find aligns with previous research, but I supply additional context about how school characteristics differ depending on the White representation level of the school.

The following three chapters comprise the substantive analytical chapters in this dissertation. Each addresses a subset of the research questions above. In Chapter 4, I examine the connection between White representation and school funding. I find that salary expenditures and student-teacher ratio vary based on White representation.

In Chapter 5, I match two datasets of tax-exempt organizations to my sample of neighborhood schools to provide a landscape of school-supporting nonprofits in public elementary schools. I do not find evidence that White representation affects nonprofit presence in schools, but I do find evidence that both the economic composition of the neighborhood and school impacts a school's chances of having a nonprofit.

In Chapter 6, I observe the relationship between White representation and two very different academic measures: standardized test scores and Gifted and Talented (GAT) programming. I find that both underrepresented White schools and schools with fewer White students tend to have overrepresented White GAT programs.

Statement on Racism in Quantitative Research and this Study

In light of the topic of my research, which addresses both racial composition and school outcomes, I would like to briefly address the ethical concerns that surfaced as I conducted this research.

Statistical measurement, and particularly the measurement of racial differences, is rooted in a racist history. The fields of statistics and sociology were advanced by those who called themselves scientists, like Francis Galton, in the pursuit of racist ends (Galton 1869; Zuberi 2001). As a White woman who calls myself a scientist and studies racial inequality in 2021, it is incumbent upon me to not unwittingly make a similar mistake. I state unequivocally that race is socially constructed and not based on genetic nor biological differences (Omi and Winant 2014). Any connection between race and school outcomes in this paper is the result of racist policies and practices and does not reflect an argument for inherent racial differences.

I am painfully aware that the concept “White underrepresentation” can come across as if fewer White children is a bad thing and therefore more White children is a good thing. While this is not my belief nor my intention, I understand that this notion can cause harm. I apologize in advance if a careless turn of phrase in the text that follows implies that Whiteness is somehow associated with goodness. While I do not believe that Whiteness is associated with goodness, I also understand that it is a pervasive stereotype that is easily activated.

I believe that there is a place for quantitative research in the eradication of racial disparities. I also believe that reframing racial disparities in the United States, when possible, in terms of White people and Whiteness is an antidote to the “racism without racists” phenomenon identified by Bonilla-Silva (2010). However, treating any racial group as a monolith, as I do for White people in this study, comes with a commensurate loss of texture and nuance and may serve to reinforce racial categories in potentially harmful ways.

There is an inherent risk in quantitative data analysis that the people within the study will get lost behind the numbers. This is especially true in the datasets I present here, in which the smallest unit is not a single person, but an entire school full of people, about whom I possess very little information. I feel an immense responsibility to do the people included in this study justice, no matter how aggregated and anonymous they may be. I take responsibility for the content presented here. All errors and opinions are mine alone, and I welcome critical feedback on them.

CHAPTER 2

LITERATURE REVIEW

White Representation in Neighborhood Schools

Most children in the U.S. attend traditional public schools, which means neighborhood schools typically mirror the racial composition of their neighborhoods (Bischoff and Tach 2018; Wang, Rathburn, and Musu 2019). However, the share of students who attend neighborhood schools has decreased in the last two decades (Wang, Rathburn, and Musu 2019). Increased enrollment in non-neighborhood schools increases the possibility of neighborhood schools that do not reflect the racial makeup of the neighborhoods which they serve, or what researchers have referred to as “weakening the link” or “loosening the tie” between a school and its neighborhood (Bischoff and Tach 2018; Burdick-Will 2017; Candipan 2019).

There is a complex relationship between neighborhood composition and school composition. Public schools in the U.S. are less White than their neighborhoods in part because of racial differences in age, birth rates, and immigration (Orfield and Lee 2006). Whites are on average older than other racial groups and have lower average birth rates. White immigrants also make up a smaller share of incoming immigrants than other racial groups. Taken together, these trends culminate in a majority-White nation in which the youngest residents are majority-non-White (Lichter 2013). In 2011, this applied only to one-year-olds (Lichter 2013), but by 2018, less than half of all children under fifteen were White in a nation that was 60% White overall (Frey 2019; U.S. Census 2018).

Even when considering only the school-age population, the relationship between neighborhood composition and school composition is not straightforward. A neighborhood's school age residents typically define a school's composition. However, the relationship is bidirectional; schools can also influence neighborhood composition (Goyette 2008; Goyette, Iceland, and Weininger 2014; Lareau and Goyette 2014; Owens 2017). We know, for example, that property values are responsive to public school and district test scores, meaning that schools can exert a pulling force on families moving into a neighborhood (Dhar and Ross 2012; Nguyen-Hoang and Yinger 2011). Families seek out neighborhoods that come with high-performing public schools and will pay a premium for it. White and middle-class families in particular are more likely to select into a neighborhood because of its corresponding public school, in no small part because they have the financial means to do so (Goyette 2008). Because families consider school racial composition when choosing schools (Houston and Henig 2019; Schneider and Buckley 2002) and families select into neighborhoods because of the local assigned school, the racial composition of a school can drive the racial composition of a neighborhood, which, in turn, affects the composition of the school.

Recent research has used White representation in neighborhood schools as one way to capture how loosely or tightly neighborhood and school demographics are linked. This research unearthed a pattern of White underrepresentation in neighborhood schools. In a study of 3,874 elementary schools within the nation's 22 largest school districts (all urban) using data from the year 2000, Sohoni and Saporito (2009) find a lower percentage of White students in neighborhood schools than in their corresponding catchment areas. Bischoff and Tach (2018) replicate this result with a larger sample of

8,173 urban schools using 2010 data. Bischoff and Tach (2018) find that urban catchment areas (or neighborhoods) are on average about three percentage points Whiter than their local elementary school. In a longitudinal study of 4,255 urban elementary schools, also using 2010 data, Candipan (2019) found a similar difference of four percentage points in urban schools. Candipan's longitudinal study also reveals that average White underrepresentation may be relatively stable over time in urban schools; White underrepresentation in neighborhood schools went from a three-percentage-point difference in 2000 to a four-percentage-point difference in 2010. Because this is a relatively small change over the course of a decade within the same set of urban districts, is unclear whether the increase indicates a meaningful change in behavior patterns for White families.

Suburban schools demonstrate a tighter link between school and neighborhood than urban schools. In the same 2018 study, Bischoff and Tach examine 6,115 suburban schools and their corresponding neighborhoods and find that suburban school areas are just barely Whiter than their catchment areas, by two-tenths of a percentage point. In other words, suburban schools are slightly overrepresented White while their urban counterparts are underrepresented White.

Researchers have looked to neighborhood characteristics to explain the White underrepresentation in urban schools and the difference in White representation by urbanicity. Previous research gives us several clues about which neighborhood characteristics are the most important in determining White representation. One important factor is the racial makeup of the neighborhood. There is a curvilinear relationship between the percentage of White students in a neighborhood and the percentage of White children in a neighborhood school (Bischoff and Tach 2018; Sohoni and Saporito 2009). White underrepresentation is most pronounced in neighborhoods that are around half White, and less pronounced at the extremes, in either neighborhoods that have a small White presence or neighborhoods that have a large White presence. In other words, the most racially balanced neighborhoods for White children, where their share of a neighborhood closely matches their presence in the country (52% in 2016), show the biggest average difference between the percentage of White residents and the percentage of White students attending the local school.

White representation is also responsive to the share of Black and Latino children living in the neighborhood. Sohoni and Saporito (2009) find that the share of Black and Latino children in the neighborhood (measured separately) have a similar, negative effect on the presence of White students in their residentially zoned schools. Additionally, Bischoff and Tach (2018) find that, in urban schools, White children are the least likely to enroll in their neighborhood school in majority-Black neighborhoods. They find this is not the case in suburban schools, where instead White children are the least likely to enroll in their neighborhood school in majority-Hispanic neighborhoods. The researchers attribute this difference to "new suburban Hispanic destinations;" as Hispanic families increasingly move to the suburbs, there appears to be a trend in White flight away from increasingly Hispanic school districts, and White underrepresentation may play a part in this story (Bischoff and Tach 2018; Hall and Hibel 2017).

Socioeconomic diversity also plays a role in White representation in neighborhood schools. Neighborhoods with educational and financial inequality, or what Bischoff and Tach (2018) term "social distance," tend to have mismatched neighborhoods and schools. Neighborhoods with higher income inequality demonstrate a weaker correlation between neighborhood and school composition, even after accounting for racial makeup (Bischoff and Tach 2018). Similarly, neighborhoods with a wider White-Black education gap are also associated with White underrepresentation (Bischoff and Tach 2018). Heightened racial and socioeconomic diversity in a neighborhood both lead to disproportionately low White participation in neighborhood schools.

Neighborhood change over time may also be important in the story of White representation in neighborhood schools. Candipan (2019) evaluates neighborhoods that are experiencing socioeconomic change and finds that neighborhoods experiencing "socioeconomic ascent" (defined as a 10-percentage point or higher rise in neighborhood SES percentile rank over the course of a decade) are more likely to see White underrepresentation in the local neighborhood school. This is in comparison to socioeconomically stable neighborhoods (those with little or no change in SES percentile rank) and declining neighborhoods (those with at least a 10-percentage point decrease in SES percentile rank), both of which are more likely to demonstrate representative White neighborhood school participation.

The availability of nearby "school choice" options (non-neighborhood schools) also contributes to White underrepresentation in neighborhood schools. Home schooling is relatively rare (Wang, Rathburn, and Musu 2019), so for White underrepresentation to occur, there must also exist alternative school options for White families to disproportionately select into, such as magnet, charter, and private schools. However, the expansion of school choice does not by definition contribute to White underrepresentation, so long as "choice" schools are used similarly by all racial groups.

School choice only contributes to racial imbalance in a neighborhood school when enrollment in choice schools is racially disproportionate.

Nearby private schools are consistently linked to lower White representation (Saporito & Sohoni 2009, Bischoff & Tach 2018, Candipan 2019). This is at least in part because White children are overrepresented in private schools. In 2016, White children made up 52% of school-age youths, but 69% of private school attendees (Kids Count Data Center 2019; Wang, Rathburn, and Musu 2019).

Charter schools and magnet schools are less consistently linked to White underrepresentation. Bischoff and Tach (2018) use Census transportation data to assess whether the number of magnet and charter schools within the average commuting distance of a neighborhood is connected to White representation. They find that the presence of magnet schools disproportionately decreases White participation in urban neighborhood schools, but not suburban ones. They further find that the presence of charter schools has no significant effect on White enrollment in either urban or suburban schools. Candipan (2019), however, offers a conflicting result using a different method to measure the school choice landscape. When nearby charter and magnet schools are captured within a fixed proximity (within a 2-mile radius) rather than by commuting patterns, charter school presence predicts a disproportionate decrease in the share of White students in nearby neighborhood schools, whereas nearby magnet schools do not. Candipan further finds that the socioeconomic stability of the neighborhood may mitigate the relationship between charter school presence and White representation. Namely, charter schools predict a larger gap between the neighborhood and school in ascending neighborhoods, as opposed to stable and declining neighborhoods. Candipan's conclusions about charter schools may differ from that of Bischoff and Tach's for many reasons, including measurement and sample differences, but it is possible that Candipan's inclusion of neighborhood stability is the decisive factor. In the face of mixed evidence for the relative importance of magnet and charter schools in their contribution to White representation, further research is warranted.

Overall, it is clear that school choice factors into White representation. In the absence of an intra-district transfer program, the availability of non-neighborhood schools is somewhat of a pre-requisite for either White underrepresentation or White overrepresentation to manifest. While it is true that White demand for school choice may prompt the creation of new schools, the schools must be open and ready to enroll students for families to enact their desire to send their child to a non-neighborhood school. Research so far suggests that private schools may be more important than magnet or charter schools in the story of White representation.

Neighborhood safety may also influence White representation in neighborhood schools, particularly in areas where alternatives to the neighborhood school are plentiful. In a study of Chicago Public Schools, an urban district with a robust school choice landscape, Burdick-Will (2017) finds that neighborhoods with high violent crime rates disperse students to a larger number of schools across the city than safer neighborhoods do. Although Burdick-Will does not examine this effect for White students in isolation, we know that a looser connection between neighborhood and school tends to exacerbate White underrepresentation. If neighborhood crime rates contribute to a decoupling of neighborhood and school, as Burdick-Will finds, then they may also contribute to White underrepresentation.

White Representation and School Segregation

White representation requires study because of its potential connection to school inequality. There is a clear connection between White representation and racial segregation in schools. The connection is both intuitive and empirical (Monarrez, Kisida, and Chingos 2019; Sohoni and Saporito 2009). However, White representation itself is neither a measure of residential segregation nor a measure of school segregation. In what follows, I explain how White representation relates to school segregation measures, first in theory, and then in the existing literature.

There are many ways to measure racial segregation in schools, but comparing a school to its neighborhood is *not* typically one of them. Instead, the most well-regarded and widely-used segregation measures compare a larger organizing unit (such as a school district) to many smaller units nested within the larger unit (such as schools) (Iceland, Weinberg, and Steinmetz 2002; Massey and Denton 1988; Reardon and Owens 2014). White representation, in contrast, is not calculated using an aggregate racial composition as a benchmark. Instead, White representation only tells us something about the smallest unit, the school. Unlike measures of school segregation, White representation is a one-to-one comparison of the school to its neighborhood, rather than a one-to-many comparison of the school to all other schools in its district.

If every neighborhood school in the United States perfectly matched its neighborhood racial composition, schools would still be racially segregated within their district due to neighborhood segregation. In the United States, both neighborhoods and schools are racially segregated (Owens 2020). Because neighborhoods are often racially segregated, a school that is representative of its neighborhood does not necessarily decrease racial segregation within a district. In some cases, a school that represents its neighborhood will lower the racial segregation within a district, whereas in other cases, a school that represents its neighborhood will increase racial segregation within a district (Monarrez, Kisida, and Chingos 2019). It depends on the racial composition of the district and the amount of residential segregation within its neighborhoods.

However, it is also clear that White representation has the potential to exacerbate school segregation. Previous research has studied the relationship between White representation and school segregation and found that both White underrepresentation and overrepresentation in neighborhood schools (in other words, an imbalance in either direction) can contribute to school segregation (Monarrez, Kisida, and Chingos 2019; Sohoni and Saporito 2009; Whitehurst et al. 2017). In a study of large, urban districts, Sohoni and Saporito (2009) compare neighborhood segregation to school segregation and find that the average school is more racially segregated than its corresponding neighborhood. This suggests that racially disproportionate enrollment in neighborhood schools exacerbates, rather than mitigates, the school segregation caused by residential segregation.

Theoretical Framework Connecting White Representation and School Characteristics

Does White representation, net of the share of White students in a school, matter for school outcomes? We know that White representation differs by neighborhood and dovetails with school segregation, but it does not necessarily follow that White underrepresentation harms traditional neighborhood schools.

Taken at face value, White representation should not matter for neighborhood schools. Schools are complex systems in which complex humans converge to complete the complex work of educating children. A small demographic difference between the school and neighborhood should not make much of a difference. Moreover, a small *racial* discrepancy between the school and neighborhood should not make much of a difference. However, school outcomes are consistently linked to demographic and neighborhood influences far outside of the purview of the school (Chetty, Hendren, and Katz 2016; Downey and Condron 2016), so it is worthwhile to interrogate the connection.

In the following section, I outline three ways that White representation might affect neighborhood schools. I describe the three theoretical pathways and, where possible, summarize the empirical support for each. The three pathways are: 1) White underrepresentation draws resources from neighborhood schools, 2) White underrepresentation has no effect on neighborhood schools, and 3) White underrepresentation draws resources *to* neighborhood schools. The pathways are, of course, an oversimplification, but they provide a useful lens for which to think through the hypothetical relationship between White representation and school outcomes. I focus on White underrepresentation (in comparison to parity and overrepresentation) because of its prevalence in previous literature (Bischoff and Tach 2018; Candipan 2019; Sohoni and Saporito 2009). I conclude with thoughts about reverse causality and the effect that school characteristics might have on White representation.

Pathway 1 – Opportunity Hoarding: White Underrepresentation Draws Resources from Neighborhood Schools

Every school has a set of resources that benefit students. These resources are broadly defined and range from monetary resources to physical resources (such as facilities and materials) to intangible resources (such as teacher experience and family social capital). Some resources affect student academic outcomes and others may not. Some resources may also be unevenly distributed between students within the same school.

In a theoretical model in which White underrepresentation draws resources from neighborhood schools, the White neighbors who disproportionately avoid the local school must be in possession of something that would otherwise benefit the school if they were to send their children there. Moreover, it must be a benefit beyond any benefit associated with the addition of another White child to the school's roster, should there be such a benefit (recall that the aim is to isolate the effects of White underrepresentation, net of any effects of the proportion of White students). Examples of such beneficial possessions could be money to donate to the school, extra time to spend volunteering, a propensity for fundraising, or a political connection.

I call this pathway the *opportunity hoarding* pathway, a term I adapt from Charles Tilly (1998). Tilly identifies opportunity hoarding as one of the many structures that supports inequality. Opportunity hoarding occurs when a socially constructed group (such as those who identify as racially White) create a pathway for resources that is restricted to in-group members. This can occur at any scale, from the smallest social circle, to a category as large as that of White people in America. Importantly, opportunity hoarding need not be organized nor intentional to occur (Reeves 2018; Tilly 1998).

Why might two schools with the same composition of White students have different outcomes depending on the composition of the neighborhood? How could this result in opportunity hoarding? Consider two hypothetical schools with the same percentage of White students. One school exactly matches its neighborhood in terms of the percentage of White children and the other has a far larger share of White children in the neighborhood than attend the school. Why might the two schools differ? It may be that the White underrepresented school has a poorer reputation among White families. The school is, for some reason, less desirable to White families than it is to other groups. If opportunity hoarding were occurring, we would expect the schools that are less desirable to White families to receive fewer resources. This could mean that White underrepresentation prompts disinvestment or that White families are more skilled at avoiding under-resourced schools. Either way, if opportunity hoarding were occurring, we would expect White underrepresented schools to be less well off than their counterparts.

School desirability is not objective and may be racially segregated. There is evidence that families choose schools based on information from their networks. Because personal networks are often racially and socioeconomically homogenous, so might be school reputation. In the U.S., Whites hold a disproportionate amount of political capital (Omi and Winant 2014), social capital (Dika and Singh 2002) and financial capital (Chmielewski and Reardon 2016; Omi and Winant 2014) Because White families in the U.S. have on average greater access to wealth and power, White underrepresentation in a neighborhood school (rather than the underrepresentation of any other race) may reflect a school with a poor reputation, or no reputation, among the wealthier or more powerful residents in the neighborhood. This in turn could prompt political, social, or financial disinvestment in the school.

In a study of families' choice of school district, Lareau (2014) found that families typically use personal experience and their social network to select a school district. The districts that families consider, and therefore their ultimate selections, are largely limited to the districts that someone in their personal network has vouched for, rather than a systematic review of all school districts in the area. This leads to a stratification of the pool of districts a family might consider; middle class families considered one set of districts while working class families considered a different set, with very little overlap. For upper- and middle-class families, their personal networks provide a roadmap to the highest performing school districts in the area. Because personal networks tend to be racially segregated, it is possible that the networked nature of school selection contributes to White underrepresentation in neighborhood schools.

Lareau found that personal networks drive selection into neighborhood schools. There is also evidence that personal networks drive selection out of neighborhood schools (Lacireno-Paquet and Brantley 2008, Stein et al. 2010, Altenhofen et al. 2016). For example, in a qualitative study of over 500 families applying to enroll their children in charter schools, Altenhofen et al. (2016) found that more than half of applicants learned about the charter schools they were applying to through their social networks. It was the primary pathway that families found their way to applying to charter schools. In other words, personal networks determined if and how families considered exiting their zoned neighborhood school. While personal networks were not the only factor considered in the decision-making process, personal networks were the most commonly cited factor.

For both the selection into and the selection out of neighborhood schools, the racially segregated nature of personal networks may play a part in racially imbalanced schools. White underrepresentation in neighborhood schools indicates that a school is less desirable to White families, and therefore White networks, than it is to other racial groups and their respective networks. If White underrepresentation is associated with diminished school resources or school outcomes, this suggests that resources and educational opportunities are clustered in schools that are more desirable to White families and their networks. This would indicate opportunity hoarding on the part of White families. Either schools that are more reputable among White families are receiving more resources and opportunities or White families are more adept at selecting into schools with additional resources and opportunities.

There is a direct link between race and attitudes towards public spending. People tend to take a more generous stance on public spending when it benefits their in-group, and a less generous stance if it benefits an out-group (Alesina, Baqir, and Easterly 1999). For example, White Americans are on average less likely to support progressive tax policies if they believe their neighborhood is becoming increasingly Latino. State tax policies bear such attitudes out; states with a larger proportion of Latino residents are less likely to have progressive tax policies (O'Brien, 2017). It is therefore possible that White residents' support of public-school funding will decrease in cases of White underrepresentation in the local school. Furthermore, White residents who are not taking advantage of public schools of any type, and instead home school their children or enroll them in private school, might leverage their political resources to tap the brakes on local investment in public schools (Alesina, Baqir, and Easterly 1999; O'Brien 2017; Sosina and Weathers 2019).

Public funds are not the only source of money for public schools. It is also common practice for public schools to accept private donations (Brown, Sargrad, and Benner 2017; Nelson and Gazley 2014). It is reasonable to expect that a resident who uses a neighborhood school is more likely to donate money to the school than someone who opts for an alternate institution. In the U.S., where White Americans hold the highest average wealth of any racial group, to the tune of one dollar in wealth for every eight cents owned by Black Americans and ten cents owned by Hispanic Americans (Shapiro 2017), it may be that White underrepresentation in a school depletes the pool of potential charitable donations.

In a national study of school-supporting nonprofits, Nelson and Gazley (2014) find that having a larger share of White residents in a district significantly increases the amount of money donated to school-supporting nonprofits, even after controlling for socio-economic characteristics (Nelson and Gazley 2014). The school supporting nonprofits with the most revenue, perhaps predictably, are in districts with very few low-poverty students (Brown, Sargrad, and Benner 2017). Unfortunately, this means that the most private contributions often go to schools that need them the least.

If White underrepresentation diminishes school resources, it might be due to White opportunity hoarding. Opportunity hoarding occurs when the average White family, wittingly or unwittingly, possesses resources that would benefit the neighborhood school, but disproportionately enrolls elsewhere. All the hypotheses in this study are written to reflect an opportunity hoarding lens. In other words, I predict that White underrepresentation predicts poorer school outcomes than White parity and White overrepresentation. However, there is evidence for other theoretical pathways.

Pathway 2 – Covariates Explain Differences: White Underrepresentation Has No Effect on Neighborhood Schools

In the next theoretical pathway, White underrepresentation does not matter for schools. Any differences between White underrepresented schools and other schools are explained by other school characteristics. Previous literature shows that White underrepresentation is correlated with lower neighborhood income, a larger share of Black students, and the presence of nearby private, magnet, and charter schools. Each of these correlates are readily connected to school outcomes. Low-income neighborhoods tend to see diminished outcomes for local neighborhood schools (Downey and Condron 2016). The proportion of Black students in a school is also associated with lower average funding (Sosina and Weathers 2019) and lower average academic performance (Chmielewski and Reardon 2016; Downey and Condron 2016; Mendoza-Denton 2014).

White underrepresentation is more likely to occur in settings with a larger set of school choice offerings, which may or may not affect neighborhood school outcomes. The research on the effects of school choice availability on traditional public schools is mixed (Belfield and Levin 2002; Cordes 2018; Epple, Romano, and Zimmer 2016; Goldhaber and Eide 2003; Usher and Kober 2011). Studies typically examine school funding, student test scores, racial integration, or a combination of the three to determine whether an increase in non-neighborhood school enrollment has any effect on traditional neighborhood schools. Many such studies indicate that increased competition from choice schools increases the academic performance of nearby public schools. For example, Cordes (2018) assesses the impact of charter school exposure on nearby traditional public school students in New York City and finds a small but significant boost in math and ELA test scores for students who attend a traditional public school that is within a mile of a charter school. Cordes (2018) further finds that the distance between schools matters; the closer the charter school, the more pronounced the academic boost is at traditional public schools. Because the school choice landscape is an established covariate of White representation, it may be that any connection between White representation and school outcomes is explained by other factors, such as the school choice landscape, that are already related to school outcomes in the literature.

White underrepresentation may be correlated with, but not connected to, school outcomes. If this were the case, I would expect the bivariate associations between White representation and school outcomes to reveal noticeable differences in school resources and test scores for White underrepresented schools, but I would expect the association to diminish after controlling for other school and neighborhood characteristics.

Pathway 3 – Crowding Out: White Underrepresentation Draws Resources to Neighborhood Schools

In the third pathway, White underrepresentation predicts a benefit to neighborhood schools. I call this pathway *crowding out*. In this model, White underrepresentation is the result of a neighborhood school serving a non-White population particularly well and thereby drawing both more of that group to the school and drawing additional resources to the school. Instead of White underrepresentation reflecting increased White aversion to the neighborhood school, White underrepresentation reflects an overrepresentation of another group.

There is limited empirical evidence that this occurs, suggesting that it is not a widespread phenomenon. In one ethnographic account, for example, a neighborhood high school decided to specialize in serving Asian LEP students and began to intentionally enroll out-of-catchment students who met the criteria of both being an Asian and an LEP student (McWilliams 2019). According to McWilliams (2019), this approach also attracted resources, targeting the specialized ELL program, to the school.

In the case of "crowding out," focusing on White representation might be missing the more important story: an overrepresentation of a different group that reflects increased selection into the school for one or more groups that are non-White.

Reverse Causality: How Neighborhood Schools Might Affect White Representation

I have discussed how White representation might affect traditional neighborhood schools, but I will now briefly outline why the reverse is also plausible. When considering school options, families often think first about school location and the student body demographics (Schneider and Buckley 2002). However, other characteristics of traditional neighborhood schools also affect families' school selection (Houston and Henig 2019). Families who are on the fence about public school education may be won over by a high-performing school with state-of-the-art amenities that only a generous education budget could purchase, or they may be repelled by low test scores and inadequate facilities. In other words, the quality of traditional public schools very likely pushes White families toward, or pulls them from, other school sectors, including private schools, magnet schools, and charter schools.

Poor academic achievement in assigned, neighborhood schools may generate demand for alternative school options (Glomm, Harris, and Lo 2005; Saultz, Fitzpatrick, and Jacobsen 2015). The relatively recent proliferation of charter schools in the last three decades offers an opportunity to study this claim. In a study of charter school openings in Michigan and California, Glomm, Harris, and Lo (2005) find that there is a negative relationship between the number of charter schools that open within a district and the district's pre-charter test scores. In other words, the worse a district's average test scores, the more likely that a charter school will open within a district to provide the opportunity for families to exit their neighborhood school. Low performing neighborhood schools generate demand for school choice, which then may result in more White students exiting from neighborhood schools. In a case like this, the school characteristics determine the White representation, not the other way around. However, the effect is still interesting because it suggests that White families avoid low performing neighborhood schools at a higher rate than other groups. The causal direction is reversed, but the disproportionality remains.

This study will not attempt to untangle the causal direction in the relationship between White participation in neighborhood schools and school quality. School participation is not exogenous to school and neighborhood characteristics and there is every reason to believe that there is a feedback loop between a school and its composition. School choice may affect neighborhood school characteristics and neighborhood school characteristics may affect school choice. This likely applies to

White families as much as, or, considering their higher average wealth and power, perhaps even more than, other racial groups.

While recent studies (Bischoff & Tach 2018, Candipan 2019) present White representation as a meaningful construct, and I agree, I also believe it could use more pressure-testing. One way to stress-test a metric that represents White-driven racial imbalance is to hold it up against school quality metrics. This is because the main reason to be concerned about racial imbalance in schools is the resulting disparate funding and opportunities for segregated schools. In other words, White representation is important to study if it can be linked to school quality, even if it is difficult to untangle correlation and causation.

CHAPTER 3

DESCRIPTIVE SUMMARY OF WHITE REPRESENTATION IN U.S. NEIGHBORHOOD SCHOOLS

Some schools match their neighborhoods' racial compositions and others do not. In this chapter, I summarize White representation in neighborhood elementary schools. Like researchers before me, I explore neighborhood characteristics correlated with White representation. This exploration includes the school choice landscape. I add an additional layer by exploring select school characteristics that are correlated with White representation. The descriptive portrait of White representation in this chapter lays the groundwork for connecting White representation to school quality metrics in the following chapters.

Data

The unit of analysis in this study is the school-neighborhood pair. "Neighborhood" refers to the school attendance boundary (SAB), or the catchment area from which a school draws students. In districts where there is more than one elementary school, district leaders typically carve up the district into residential zones and assign one or more residential zones to each school. In this way, every child living in the district is guaranteed a seat at their assigned school. Even in districts with intra-district school choice policies, each residence in the sample has a default assigned school in which a child living at that residence is ensured a seat. Using the school attendance boundary as the "neighborhood" offers more precision than using the Census block or tract, as some studies do (Monarrez, Kisida, and Chingos 2019; Whitehurst et al. 2017). This is because

Census units do not perfectly overlap with the way districts apportion students to schools, so the Census-defined area around a school building does not necessarily reflect the pool of students from which a school draws. The tradeoff of using school attendance boundaries as “neighborhoods” is a reduction in sample size; school attendance boundary data are not yet available for every school in the country in the way that Census tract and block data are.

Data Sources

The 2010 SAB data used in this study was collected and published for public use by the Minnesota Population Center and is called the School Attendance Boundary Information System (SABINS). The present study is limited to schools included in SABINS that serve 4th graders. I focus on elementary schools because they typically draw from a smaller geographic area than middle and high schools and are less likely to be subject to intra-district school choice policies, which decouple the public school from the neighborhood (Bischoff and Tach 2018). My analysis is limited to standard schools (excluding alternative, special education, and vocational schools).

The SAB-to-school relationship is many-to-many, meaning that some schools serve multiple, non-contiguous attendance boundaries and some attendance boundaries distribute 4th graders across more than one school (College of William and Mary and the Minnesota Population Center 2011). Just over 94% of schools in SABINS have a one-to-one SAB relationship, but the remaining six percent of schools draw from between two and ten SABs. To study school-level outcomes, I created dataset with one observation per school. In cases where schools serve multiple attendance boundaries, I calculate a population-weighted average of all the SABs which send students to a given school. In cases where multiple schools draw students from the same attendance boundary, each school appears only once in the dataset, but the shared SAB information appears more than once, for each corresponding school.

The measurement of the racial composition of schoolchildren within a school catchment area is made possible by SABINS, which links SABs to U.S. Census and American Communities Survey (ACS) data to provide population estimates broken down by age and race for those living within each SAB, in addition to the aggregate total population within a SAB.

I obtain median household income data from the ACS 2008-2012 at the level of the Census block group (U.S. Census Bureau 2014). Block groups do not perfectly map to SABs and therefore require spatial matching to be assigned to their corresponding SAB(s). Block groups are typically smaller than SABs and so more than one block group may sit, completely or partially, within a SAB. Just over half the block groups that overlapped with any SAB in the sample fell completely within a school attendance boundary. The remainder partially overlapped one or more SABs in the sample. To calculate an estimate of SAB median household income, I weigh the median household income of each block group that intersects with a SAB by the area of its overlap with the SAB. This areal weighting technique has been found to be comparable to population weighting techniques in studies similar to this one (Saporito et al. 2007).

School data is provided by the 2009-10 Common Core of Data (CCD) and the 2009-10 Civil Rights Data Collection (CRDC), both of which are publicly available administrative datasets (National Center for Education Statistics 2011a; Office of Civil Rights 2011). The CCD provides the school region, the total number of students, the total number of K-4th graders, the racial composition of K-4th grade students, and the percentage of students who are eligible for free or reduced lunch (FRL). The CRDC provides the percentage of students with disabilities (students with IEPs) and the percentage of students with limited English proficiency (LEP). In general, I found the CCD data to be more reliable and deferred to the CCD where possible and used the CRDC data to supplement any gaps in the CCD.

Many of the analyses conducted here differentiate between urban and non-urban (namely, suburban and rural) schools. For the purposes of this study, urbanicity is defined at the district level, which means all schools within one district are placed in the same urbanicity category. I use district-level urbanicity designations from the 2009-10 Local Education Agency (School District) Universe Survey (LEAUS) (National Center for Education Statistics 2011b). In reality, according to CCD school-level designations, school urbanicity sometimes varies within districts. For example, North Kansas City School District has 20 elementary schools, 14 of which are listed in the CCD as urban, four of which are suburban, and two of which are rural. The entire district of North Kansas City is designated "urban" in the LEAUS, so all schools within the district are also urban for the purposes of this study. This means that within-district variation in urbanicity is not reflected here. Throughout, I define urbanicity at the district level to capture within-district patterns and to ensure that no single district is distributed across analyses when urban districts are analyzed separately from suburban and rural ones. Hereafter, any mention of urbanicity, whether it refer to the school or district, is referring to the district's urbanicity.

Because the focus of the study is White representation, I include only SAB-school pairs in which it is mathematically possible to attain both underrepresentation and overrepresentation for White students. Limiting the sample in this way enhances the logic of the analyses that follow, which make comparisons across levels of White representation. I exclude schools that are forced into one of two categories of White representation by nature of their neighborhood composition. For example, it is mathematically impossible for a neighborhood that is 100% White to have an overrepresented White school. The enrollment of 500 additional White students at such a school would not tip the scale to White overrepresentation; the school can either be representative of its neighborhood with 100% White schoolchildren, or underrepresented White, if there are less than 100% White schoolchildren. It can never be overrepresented White. Similarly, on the other end of the spectrum, a SAB that is 0% White does not have the potential to be underrepresented White. The way to ensure that all schools in the sample have the potential to experience the full range of White representation, from underrepresentation to overrepresentation, is to exclude neighborhoods that are extreme outliers in terms of the percentage of White children living in the neighborhood. Therefore, I eliminate SABs in which less than 3% or more than 97% of elementary-aged children are White. This step eliminates 1,946 SABs, 1,298 of which are urban SABs with a composition of less than three percent White. Eliminating neighborhoods that are nearly all non-White slightly biases the sample to neighborhoods that are Whiter and wealthier than the full available sample of SABs because there are more all-non-White neighborhoods than there are all-White neighborhoods. This step ensures that every school in the sample could in theory, based on the racial makeup of its neighborhood, be overrepresented White, representative White, or overrepresented White. The sample is therefore not intended to represent all neighborhood elementary schools, but only those far enough away from the tails of the distribution of the percentage of White children in a neighborhood to have the potential to be in any category of White representation.

The final sample consists of 17,507 public elementary schools in 5,165 districts. The schools serve 10.1 million students, 7.6 million of whom are K-4th graders. This represents 27% of the elementary schools (65,874) and 38% of the districts (13,588) at the time (Wang, Rathburn, and Musu 2019). The biggest restriction on sample size was the availability of school attendance boundary data. The sample size varies in subsequent analytical chapters due to data availability of variables not included in this descriptive review of White representation. All sample size changes are noted along with an explanation of the changes.

Representativeness of the Sample

The sample is not perfectly representative of all neighborhoods and schools at the time. As I mentioned earlier, the sample of SABs included here are slightly Whiter and wealthier than the average SAB available in the SABINS data, due to the removal of neighborhoods that are the least White. The sample also differs from the national population of school-SAB pairs in 2010 in a few other notable ways. The sample includes a larger share of suburban schools (42%) and a smaller share of rural schools (24%) than the full CCD dataset of comparable schools (29% and 45%, respectively). The sample is also a slight overrepresentation in terms of the proportion of urban schools (36% of the sample versus 26% of similar schools in the CCD). The sample is largely representative of the regions of the country, except for Northeastern schools, which are underrepresented. Northeast schools make up only 7% of the sample compared to 16% of the comparable elementary schools included in CCD data. The sample mean school size is slightly larger than that of the potential pool of elementary schools, an average of 523 students compared to 462 students, which may be related to the smaller share of rural schools included in the sample. The sample is nearly identical to all available schools in terms of the percentage of students receiving FRL (52% in both cases). The sample also closely matches the average racial makeup of comparable schools in the CCD data; the sample schools average 55% White, 23% Hispanic, 15% Black, and 5% Asian, whereas CCD schools average 55% White, 22% Hispanic, 15% Black, and 4% Asian. The sample has a comparable share of students with disabilities in comparison to similar elementary schools in the CRDC (for both, the average school is made up of 13% students with IEPs). The sample has a slight overrepresentation of students with LEP (schools in the sample are 14% LEP compared to 12% in the full set of comparable CRDC schools). Any differences noted here are largely due to the availability of the 2010 SABINS data, which presented the largest restriction on available schools for the sample. Schools were also removed from the sample if they had missing data on any of the baseline school or neighborhood characteristics included in Table 3-1. Table 3-1 displays a descriptive overview of school and neighborhood characteristics.

Descriptive Statistics

White Representation in Neighborhood Schools

For each SAB, I divide the number of White 5-9-year-olds living in the SAB by the total number of 5-9-year-olds. The result is percentage of White elementary age

Table 3-1. Descriptive Statistics of School and Neighborhood Characteristics by Urbanicity

	Total				Urban	Suburban and rural
	Mean	SD	Minimum	Maximum	Mean	Mean
Neighborhood % White 5-9-year-olds	54.99	29.29	3.00	97.00	39.32	63.24
School % White K-4th graders	53.21	31.90	0	100	35.07	62.76
White representation (continuous)	-1.78	8.39	-76.62	68.13	-4.26	-0.48
White representation (categorical, share)						
Underrepresented White	0.40				0.56	0.32
Representative White	0.29				0.25	0.34
Overrepresented White	0.31				0.20	0.37
District urbanicity (share)						
Urban	0.34				1.0	
Suburban	0.42					0.63
Rural	0.24					0.37
Region (share)						
Northeast	0.07				0.04	0.09
Midwest	0.21				0.16	0.24
South	0.44				0.42	0.44
West	0.27				0.38	0.22
Median household income (in 1000s)	62.96	27.19	9.49	235.93	60.01	64.51
Population	8285.79	12052.13	91	261851	8988.96	7915.70
Neighborhood # 5-9-year-olds	539.60	663.63	11	11291	574.46	521.25
School total # students	522.73	238.27	13	2837	548.98	504.58
School # K-4th graders	391.42	191.60	6	1532	414.72	379.15
School % Asian K-4th graders	4.71	7.76	0	91.33	5.97	4.05
Asian representation (continuous)	0.42	2.49	-24.10	45.79	0.42	0.40
School % Black K-4th graders	14.82	21.27	0	100	22.09	10.99
Black representation (continuous)	2.56	6.55	-69.00	73.10	4.26	1.66
School % Hispanic K-4th graders	23.40	26.44	0	100	33.37	18.16
Hispanic representation (continuous)	-0.17	6.70	-77.78	66.63	0.95	-0.76
% Students with FRL	52.30	27.19	0	99.84	61.12	47.65
% Students with disabilities	12.60	5.33	0	54.37	12.14	12.85
% Students with LEP	13.90	16.43	0	100	19.47	10.96
# Private schools within 2 miles	1.53	2.48	0	24	2.66	0.94
# Charter schools within 2 miles	0.38	1.21	0	27	0.79	0.16
# Magnet schools within 2 miles	0.43	1.72	0	34	0.95	0.15
N	17,507				6,037	11,470

children living in the SAB. I then calculate the percentage of White kindergarten through 4th grade students at each school. I select kindergarten through 4th graders to match the 5-9-year-old age range measured in the SAB as closely as possible. The aim is to capture students in the neighborhood and the school within the same age group. It is probable that some K-4th graders do not fall in this age range, particularly in the highest and lowest grades.

Previous research has shown, and I confirm here, that American neighborhood schools are less White than their surrounding neighborhoods. However, the difference is relatively small and differs across contexts. At 55.0%, White children make up the majority of 5-9-year-olds in the average neighborhood (Table 3-1). In neighborhood schools, White elementary students also make up the majority of K-4th grade students, at 53.2%. The small difference between these two percentages indicates that the average neighborhood elementary school in 2010 had a -1.8 percentage point White representation rate compared to its surrounding neighborhood. In other words, the average difference between the percent of White 5-9-year-olds living in a neighborhood and the percent of White K-4th graders attending a corresponding neighborhood school is -1.8 percentage points. This closely matches the difference of -1.6 percentage points found by Bischoff and Tach (2018) in their study of 14,288 neighborhood elementary schools in the same year and is slightly smaller than the difference of -2.6 percentage points found by Whitehurst, et al. in their study of 86,109 neighborhood, charter, and magnet schools (elementary through high school) using data from 2013.

Like Bischoff and Tach (2018), I also find that White representation varies by urbanicity. In urban schools in the sample, White representation dips to a difference of -

4.3 percentage points (Table 3-1). Suburban and rural schools are slightly underrepresented White, but hover near exact representation, at -0.5 percentage points. This difference, though small, suggests that White representation may work differently depending on the urbanicity of the school. This is one of the reasons that urban and non-urban schools are analyzed separately throughout the remainder of the study. It should be noted, however, that although *suburban and rural* schools are analyzed together here, they do differ slightly in terms of White representation. Rural schools taken alone are nearly one percentage point overrepresented White and suburban schools taken alone are about one percentage point underrepresented White. I analyze suburban and rural schools together both because this did not seem a compelling enough difference to justify separating them and to avoid adding unnecessary complexity to the study. However, there may be key differences between suburban and rural schools that go unexplored here because of the choice to combine the two categories.

As I outline in the introduction, White representation is linked to, but distinct from, the percentage of White children in a neighborhood. The two metrics are positively correlated (r=.182), but the correlation is perhaps not as strong as one might assume going by intuition alone.

To better capture the construct I wish to evaluate, I divide the continuous measure of White representation into three mutually exclusive and collectively exhaustive categories: White *over*representation, White *under*representation, and *equal* White representation (hereafter called “White parity” or “representative White”). The purpose of these groupings is to establish: 1) whether there is an imbalance between the school and the neighborhood and 2) in which direction the imbalance lies. For the purposes of this study, I am more interested in the distinction between an underrepresented White school and a representative White school than I am in, say, the distinction between a school is underrepresented White at -8 percentage points and a school that is *less* underrepresented, but still underrepresented, White at -6 percentage points. Like any justifiable transformation from a continuous measure to a categorical measure, the choice increases the clarity of the construct, but the tradeoff is an overall loss of information about the underlying structure of White representation.

I define White parity, or an equal representation of White children in the school and neighborhood, as ranging between a representation of -2 and +2 percentage points (inclusive of both values), or within a quarter of a standard deviation in either direction from "perfect" representation at zero. White overrepresentation applies to schools with White representation above two percentage points and White underrepresentation applies to schools with White representation below negative two percentage points. Schools with White parity closely match their neighborhoods in terms of White student makeup. This racial balance suggests that Whites are neither selecting-in nor selecting-out of the neighborhood school at a higher rate than other racial groups. When Whites are overrepresented or underrepresented, on the other hand, it represents a racial imbalance, at least for White children, at the neighborhood school.

The remainder of the chapter explores the differences between the three levels of White representation at neighborhood schools: White underrepresentation, White parity, and White overrepresentation. Schools are roughly evenly divided between the three categories, although the plurality of schools are underrepresented White. Forty percent of schools are underrepresented White, 29% of schools are representative White, and 31% of schools are overrepresented White.

Like the continuous measure of White representation, underrepresentation is most common in urban areas. Fifty-six percent of urban schools are underrepresented White. White underrepresentation is less common in suburban and rural areas, where only 32% of schools are underrepresented White.

White Representation and Neighborhood Characteristics

Table 3-2 presents the bivariate relationships between White representation and neighborhood and school characteristics. Urban and non-urban schools are presented separately.

Neighborhoods with underrepresented White schools tend to have a high population. In urban areas, underrepresented White schools are in neighborhoods with an average of over 1,000 more residents than the neighborhoods of schools with White parity or White overrepresentation. In suburban and rural areas, the contrast is even larger and the difference in population is over 2,000 more residents for neighborhoods with underrepresented White schools.

Bischoff and Tach (2018) find a positive relationship between median household income and White representation and my descriptive results support this finding. The relationship is more evident in urban schools, where underrepresented White schools are in neighborhoods with an average median income that is nearly $9,000 lower than neighborhoods with overrepresented White schools. However, representative White

Table 3-2. Bivariate Relationships Between White Representation and School and Neighborhood Characteristics by Urbanicity

	Urban				Suburban and Rural			
	Under-represented White (<-2%)	Representative White (-2% to 2%)	Over-represented White (>2%)	ANOVA	Under-represented White (<-2%)	Representative White (-2% to 2%)	Over-represented White (>2%)	ANOVA
	Mean (SD)	Mean (SD)	Mean (SD)	R^2 p-value	Mean (SD)	Mean (SD)	Mean (SD)	R^2 (p-value)
Neighborhood % White 5-9-year-olds	36.69 (24.45)	35.08 (27.00)	51.64 (24.69)	R^2=.057 p<.00005	49.79 (26.764)	65.30 (29.02)	73.28 (20.91)	R^2=0.128 p<.00005
School % White K-4th graders	26.62 (23.13)	34.94 (28.41)	57.88 (24.42)	R^2=.190 p<.00005	41.82 (27.12)	65.47 (29.30)	78.82 (19.97)	R^2=0.267 p<.00005
Median household income (1000s)	58.10 (25.28)	58.74 (29.02)	66.74 (29.78)	R^2=.015 p<.00005	62.18 (25.82)	65.88 (27.20)	65.39 (27.55)	R^2=0.004 p<.00005
Neighborhood population	9549.66 (8919.63)	8310.52 (6326.25)	8321.97 (9055.37)	R^2=.005 p<.00005	9558.51 (18682.30)	7290.67 (5754.31)	7009.52 (12666.99)	R^2=0.007 p<.00005
Neighborhood # 5-9-year-olds	570.39 (512.37)	596.24 (508.10)	558.48 (565.66)	R^2=.001 *not significant*	606.79 (993.16)	501.94 (374.29)	462.72 (668.53)	R^2=0.007 p<.00005
School total # students	530.20 (197.15)	593.12 (210.24)	544.86 (201.71)	R^2=.017 p<.00005	543.16 (258.06)	524.69 (241.72)	453.47 (239.93)	R^2=0.025 p<.00005
School # K-4th graders	399.43 (152.82)	451.25 (161.62)	410.66 (153.96)	R^2=.019 p<.00005	408.48 (209.03)	400.26 (203.60)	335.27 (199.40)	R^2=0.026 p<.00005
School % Asian K-4th graders	5.34 (8.06)	6.86 (11.10)	6.32 (8.66)	R^2=.005 p<.00005	4.26 (6.73)	4.68 (8.06)	3.33 (5.78)	R^2=.007 p<.00005
School % Black K-4th graders	27.92 (28.97)	17.03 (21.70)	12.66 (16.07)	R^2=.064 p<.00005	19.23 (23.27)	9.31 (13.84)	5.21 (8.46)	R^2=.118 p<.00005

Table 3-2 (Continued)								
School % Hispanic K-4th graders	36.21 (31.06)	37.95 (32.42)	20.11 (20.64)	R^2=.049 p<.00005	28.16 (26.07)	17.29 (22.47)	10.12 (13.80)	R^2=.112 p<.00005
% Students with FRL	68.13 (25.35)	59.10 (30.54)	44.82 (27.73)	R^2=.100 p<.00005	59.11 (24.54)	44.36 (24.42)	40.42 (22.69)	R^2=.102 p<.00005
% Students with disabilities	12.46 (5.08)	11.68 (4.87)	11.85 (4.74)	R^2=.005 p<.00005	13.03 (5.53)	12.79 (5.24)	12.74 (5.68)	R^2=0.001 *not significant*
% Students with LEP	21.68 (19.09)	20.95 (18.79)	11.69 (13.15)	R^2=.046 p<.00005	17.52 (16.97)	10.48 (14.26)	5.63 (8.92)	R^2=0.116 p<.00005
# Private schools within 2 miles	3.24 (3.49)	2.18 (2.63)	1.71 (2.29)	R^2=.043 p<.00005	1.45 (2.18)	0.86 (1.73)	0.55 (1.24)	R^2=0.045 p<.00005
# Charter schools within 2 miles	1.00 (2.16)	0.58 (1.37)	0.46 (1.18)	R^2=.017 p<.00005	0.26 (0.73)	0.11 (0.49)	0.11 (0.47)	R^2=0.016 p<.00005
# Magnet schools within 2 miles	1.29 (3.38)	0.56 (1.57)	0.52 (1.41)	R^2=.019 p<.00005	0.31 (0.91)	0.10 (0.46)	0.07 (0.42)	R^2=.027 p<.00005
N	6,037				11,470			

schools are in neighborhoods that are only marginally wealthier on average than underrepresented White schools. In suburban and rural contexts, neighborhoods with White underrepresented schools are also the poorest, but the difference is only $3,200 in comparison to neighborhoods with White overrepresented schools. Also, in suburban and rural areas, representative White and overrepresented White schools are in neighborhoods that on average have nearly identical median household incomes.

White Representation and School Characteristics

I now observe a select number of school characteristics and describe how they vary by White representation (Table 3-2). School size appears to be associated with White representation, but the association looks different in urban and non-urban contexts. Underrepresented White schools in urban areas tend to have the fewest students whereas underrepresented White schools in suburban and rural settings tend to have the highest number of students. Perhaps unsurprisingly, this pattern holds steady for the number of K-4th graders in the school (recall that all schools in the sample serve 4th grade but may also serve higher grades).

White representation is related to, but distinct from, the percentage of White students at a school. Intuitively, the percentage of White K-4th grade students is strongly and positively correlated with the continuous measure of White representation (ranging from -100 to +100) (r=0.430). In urban areas, the average White underrepresented school has only 26.6% White K-4th graders, whereas schools with White parity are 34.9% White in the same grade span. As might be expected, overrepresented White schools in urban areas have by far the highest percentage of K-4th grade White students, at 57.9% of K-4th graders. In suburban and rural schools, the average school has a larger share of White students than the average urban school, but the pattern stays the same. Underrepresented White schools are only 41.82% White, whereas representative White schools are 65.5% White and overrepresented White schools are 78.8% White.

An underrepresentation of White students comes with a commensurate overrepresentation of at least one other racial group. Regardless of urbanicity, both Black and Hispanic students are overrepresented in the average White underrepresented school. The percentage of Asian students remains relatively steady across White representation categories for both urban and non-urban schools.

Similarly, White overrepresented schools must, by definition, have an underrepresentation of at least one other racial group. For both urban and non-urban schools, Black and Hispanic students are severely underrepresented in White overrepresented schools. The contrast is perhaps sharpest for Hispanic students in urban areas and Black students in suburban and rural areas. An average urban school is 33% Hispanic, but a White overrepresented urban school is only 20% Hispanic. Similarly, an average non-urban school is 11% Black, whereas a White overrepresented non-urban school is 5% Black.

Differences in student poverty offer perhaps the starkest contrast between White underrepresentation and White overrepresentation. Schools with White underrepresentation have the highest percentage of students who use FRL, which is a rough indicator of student financial need. In urban areas, 68.1% of students in White underrepresented schools qualify for FRL, which is nine percentage points higher than that of representative White schools (59.1% FRL) and over 23% percentage points higher than White overrepresented schools (44.8%). In suburban and rural schools, there also appears to be a strong, negative relationship between White representation and student poverty. In rural and suburban schools, just over 59% of students in White underrepresented elementary schools qualify for free or reduced lunch. This is nearly fifteen percentage points higher than schools with White parity (44.4% FRL) and nearly twenty percentage points higher than schools with White overrepresentation (40.4% FRL). In these areas, 68.1% of students in White underrepresented schools qualify for FRL.

There is also a large difference in the percentage of students with limited English proficiency (LEP) depending on White representation. Schools that are underrepresented White are made up of nearly 20% students with LEP. Schools with White parity are made up of an average of 16.7% students with LEP. Schools that are overrepresented White have a stunningly low percentage of students with LEP, at only 7.1%.

The percentage of students with IEPs remains relatively the same across White representation levels, regardless of urbanicity.

White Representation and the School Choice Context

White representation is linked to the school choice context of a neighborhood. I define “choice” or non-neighborhood schools as magnet schools, charter schools, private schools, and parochial schools. It should be noted that in this study I only consider voluntary alternatives to neighborhood schools. I do not directly address compulsory removal from neighborhood schools in cases of expulsion to an alternative school or incarceration in a juvenile justice center. Although rare, such removals could theoretically affect the White representation rate at neighborhood schools.

Children between the ages of six and sixteen are legally required to be in school in all U.S. states. There are therefore two primary ways that White underrepresentation can exist in a neighborhood school: 1) White students assigned to the school are siphoned off to other schools at a higher rate than other racial groups or 2) students from other racial groups and who live outside the catchment area enroll in the school at a higher rate than out-of-catchment White students. The first method (White students attending other schools at higher rates) is easier to accomplish with a robust offering of non-neighborhood "choice" schools. As I have already noted, however, a wide variety of nearby school choice options does not necessarily lead to White underrepresentation. If all racial groups attend non-neighborhood choice schools at the same rate, then White parity at the neighborhood school would be expected, regardless of the number of nearby choice schools.

School Choice Landscape Data Sources

To understand the school choice landscape of neighborhood schools, I capture the number of non-neighborhood schools that serve 4th grade students within a two-mile radius of the centroid of each neighborhood in 2010. I designate a two-mile radius because proximity is a primary consideration for families selecting schools (Schneider and Buckley 2002) and previous research has found two miles to be a reasonable radius for families considering school choices (Candipan 2019; Denice and Gross 2016). However, it should be noted that this cutoff is not universally agreed upon and at least one other study expands the radius to ten miles (Frankenberg et al. 2017). I require that the choice schools serve fourth grade students to ensure that they represent viable alternatives for my sample of elementary schools.

The location of magnet and charter schools as well as grade-level information about the schools come from the CCD. I supplement missing magnet school data in several states (including California, Massachusetts, and New York) in the CCD data with magnet school data from the 2009-10 CRDC. The CRDC provides an additional 1,267 magnet schools once duplicates were removed. I use the CCD and CRDC designations for charter and magnet school, but both school types may be defined slightly differently by their local education agency. The definitions and regulations for charter and magnet schools differ depending on state and local regulations, which means a charter school in one city may not be perfectly analogous to a charter school in a different city (Bischoff and Tach 2018). Finally, the private school location and grade level data comes from the 2010 Private School Universe Survey, a national survey of private schools conducted every two years (National Center of Education Statistics 2012).

In the six percent of cases where a school is associated with more than one SAB, I include all choice schools within two miles of *any* centroid of *any* SAB that sends students to an individual school, removing any duplicate schools that are within two miles of two or more SABs associated with the same school.

School Choice Descriptive Statistics

On average, neighborhood schools are within two miles of 1.53 private schools, 0.4 magnet schools, and 0.4 charter schools (Table 3-1). Unsurprisingly, urban settings provide more nearby school choice options. In urban settings, the average neighborhood school is within two miles of 2.7 private schools, 1.0 magnet school, and 0.8 charter schools. The average suburban and rural neighborhood school is within two miles of 0.9

private schools, 0.2 magnet schools, and 0.2 charter schools. In practice this means that more than half of sampled suburban and rural schools are near no choice schools at all.

Descriptive analyses provide support for the theory that there is a relationship between school choice availability and White underrepresentation (Table 3-2). On average, schools with White overrepresentation have far fewer non-neighborhood elementary schools within a two-mile radius than their counterparts with lower White representation. This holds true in both urban and non-urban settings and applies to all three types of choice school (private, magnet, and charter). In urban areas, underrepresented White schools are near 3.24 private schools, 1.29 magnet schools, and 1.00 charter schools, whereas overrepresented White schools are near only 1.71 private schools, 0.52 magnet schools, and 0.46 charter schools. In suburban and rural areas, underrepresented White schools are near 1.45 private schools, 0.31 magnet schools, and 0.26 charter schools, whereas overrepresented White schools are near only 0.55 private schools, 0.11 magnet schools, and only 0.07 charter schools.

Conclusion

This chapter documents clear differences between schools and neighborhoods based on the level of White representation in the school. My findings replicate those of other researchers who have found a connection between neighborhood characteristics and White representation. White underrepresented schools tend to be in poorer and more populous neighborhoods. White underrepresented schools also tend to be surrounded with a larger variety of school choice options.

I also examine school characteristics through the lens of White representation. White underrepresented schools have a larger share of students in poverty and students with LEP. However, an association with school characteristics does not necessarily indicate that White representation matters for school outcomes. In the following three chapters, I explore the potential link between White representation to school outcomes. I begin with financial measures in Chapters 4 and 5 and move to academic measures in Chapter 6.

CHAPTER 4

WHITE REPRESENTATION AND SCHOOL EXPENDITURES

Introduction

One way to ascertain a community's investment in its local public schools is to measure its literal monetary investment in public schools. Well-funded schools are more likely to boast safe facilities, high quality materials, up-to-date curricula, and fairly-compensated teachers. Per pupil expenditure is only one of many ways to measure school quality, but it is a metric that has been connected to the long-term academic and employment success of students (Jackson, Johnson, and Persico 2016).

This chapter explores the relationship between White representation in neighborhood schools and public-school funding. I select three distinct but related measures of school funding: 1) per pupil personnel expenditure, 2) mean teacher salary, and 3) student-teacher ratio. Student-teacher ratio is not a direct monetary measure and instead captures a school's ability to fund more teachers per child, irrespective of teacher compensation.

Following the theory of opportunity hoarding, I hypothesize the following:

Hypothesis 1 Neighborhood schools with White overrepresentation and White parity will have higher per pupil expenditures than schools with White underrepresentation.

Hypothesis 2 Neighborhood schools with White overrepresentation and White parity will have higher mean teacher salaries than schools with White underrepresentation.

Hypothesis 3 Neighborhood schools with White overrepresentation and White parity will have lower student-teacher ratios than schools with White underrepresentation.

It bears repeating that there is a distinction between White representation and the percentage of White students. We saw in the preceding chapter that overrepresented White schools are also likely to be in majority-White neighborhoods. All hypotheses listed here are expected to hold true after controlling for the percentage of White school age children living in the SAB. In other words, I predict that the representation of White students at a school will matter regardless of the White population in a neighborhood. Any differences in school funding will not merely be due to a large percentage of White students, but a difference between the White presence in a neighborhood and its local school.

Data

The CRDC supplies school finance data. School funding outcomes are lead five years to the 2015-16 school year[1]. The CRDC distinguishes between funds from federal

[1] The original conception of this research proposed a two-year lead for outcome variables, or outcome variables for the 2011-12 school year. The Office of Civil Rights temporarily closed its offices in 2020 due to COVID-19 and consequently could not provide 2011-2012 data at the time of this research. However, I had already obtained the 2009-10 CRDC data from the Office of Civil Rights prior the office closure and I obtained the 2015-16 data from the Office of Civil Rights website. The 2015-16 school year is currently the only year available online. Therefore, the CRDC data here is limited to the 2009-10 and 2015-16 school years.

sources and funds from state and/or local sources (Office of Civil Rights 2017). The funding outcomes in this study exclude federal funding to better observe local differences in funding.

School-level finance data are typically less reliable than district-level finance data and the CRDC data are no exception (Atchison et al. 2017; Denison et al. 2011; Shores and Ejdemyr 2017). In an assessment of CRDC data quality, Atchison et al. (2017) find major discrepancies between non-personnel expenditures as reported on the CRDC and those reported directly by the school. However, CRDC personnel expenditure data were on average consistent with school-reported data. I therefore analyze per pupil salary expenditures and mean teacher salaries because both are school outcomes that consist exclusively of personnel expenditures. Atchison et al. (2017) also find that CRDC personnel expenditure data reflect real differences between schools, rather than consisting of formula-based sums. A formula-based sum is a value derived from district-level aggregate that is divided evenly across schools using a formula. If CRDC school expenditure data merely reflected a formula (such as the district average teacher salary multiplied by the number of teachers at each school), then school level data would not show meaningful differences between schools within a district.

To weed out data errors while maximizing the sample of schools, I follow a school finance data cleaning procedure first applied to the CRDC school finance data by Shores and Ejdemyr (2017). Beginning with the per pupil expenditure measure, I remove outliers that are less than half the 5th percentile and greater than 1.5 the 95th percentile.[2]

[2] Cases with $0 per pupil salary expenditure or no data were removed prior to this calculation. After missing data was removed, the minimum value was less than $0.01 and the maximum value was $298,904.

Next, I aggregate the CRDC school-level funding data to the district level. I compare the CRDC district aggregate data with the district funding data in the NCES Common Core of Data School District Finance Survey (F-33) for the 2015-16 school year (National Center of Education Statistics 2019). The F-33 provides only district-level funding data, not school-level data. The purpose of this comparison is to validate near-matches and eliminate cases where the CRDC and F-33 are divergent enough to cast doubt on the value of one or more schools in the CRDC data within a given district.

I construct a variable for per pupil salary expenditure in the NCES F-33 data by dividing total district salary expenditures by the total number of students within the district. The correlation between per pupil salary expenditures in the F-33 and per pupil state and local salary expenditures in the CRDC is initially very low (r=0.34). I confirmed that the low correlation was not due to the exclusion of federal salary expenditures; the correlation between the F-33 per pupil salary expenditures and the CRDC per pupil salary expenditures *including* federal funding was also very low (r=0.36). A scatterplot comparing the CRDC to the F-33 indicates that removing district outliers for the F-33 per pupil salary expenditure measure would likely correct this problem. Following the example of Shores and Ejdemyr (2017), I construct a ratio of per pupil salary expenditures in the F-33 to that of the CRDC and keep only the districts that fall between the 5th and 95th percentiles. This step increases the correlation between the F-33 and CRDC salary expenditure data to r=0.86 for both the CRDC per pupil salary expenditure metrics (including and excluding federal funds). This correlation is similar to the

Half of the 5th percentile was $1,201 and 1.5 the 95th percentile was $16,094. Only values within this range were retained.

correlations found by Shores and Ejdemyr (2017) for the years 2012-2014 (r >=.85 for all years). The removal of both school and district outliers in the CRDC data preserves 93% of schools and 86% of students in the original analytical sample described in Chapter 3.

I repeat the same outlier removal process for mean teacher salary. First, I calculate mean teacher salary by dividing the total state and local teacher salary expenditures by the total number of teachers. I remove outliers that are less than half the 5th percentile or more than 1.5 times the 95th percentile of mean teacher salary.[3] I then aggregate mean teacher salary to the district level and construct a comparable mean teacher salary variable using F-33 data. Initially, the correlation between mean teacher salary in the CRDC and the F-33 is 0.17. After restricting the sample to those between the 5th and 95th percentile of the ratio between CRDC and F-33 mean teacher salary, the correlation improves to 0.85, demonstrating much higher consistency between the two datasets. The deletion of both school and district outliers for mean teacher salary preserves 91% of schools and 91% of students in the remaining analytical sample (after the removal of the per pupil salary expenditure outliers described above).

I then adjust both personnel per pupil expenditure and mean teacher salary to account for regional differences in compensation using the 2015 Comparable Wage Index for Teachers (National Center of Education Statistics 2016). For the nineteen districts missing a comparable wage index estimate, I use the county-level comparable wage index, which is available for all nineteen districts.

[3] There was no missing data for this measure. However, before cleaning, the minimum value was \$0.01 and the maximum value was \$1,000,000. Half of the 5th percentile was \$17,899 and 1.5 the 95th percentile was \$132,022. Only values within this range were retained.

Student-teacher ratio is calculated by dividing the total number of students at a school by the total number of full-time equivalent (FTE) teachers. Because the number of FTE teachers is not disaggregated by grade level, the student-teacher ratio refers to the entire school, rather than just K-4th grades. This means the student-teacher ratio includes grade levels above 4th grade when a school serves such grades. The student-teacher ratio excludes pre-kindergarten students and teachers. Note that student-teacher ratio is not an indicator of class size; the ratio accounts for all FTE teachers in the building, including those who are not classroom teachers.

The sample consists of 14,815 schools in 4,029 districts.

Descriptive Analysis

Summary statistics for the three school funding outcomes are presented in Table 4-1. Teacher salaries averaged $59,677 per year in the 2015-16 school year, after adjusting for regional compensation differences. The average per pupil expenditure on personnel was $4,760. Student-teacher ratio averaged 16 students per teacher. A lower student-teacher ratio is more desirable as it represents fewer students per teacher.

Mean teacher salaries are similar in urban and non-urban schools. Suburban and rural schools spend about $600 more on salaries per pupil than urban schools. Urban schools have a slightly higher student teacher ratio than suburban and rural schools (17.1 and 15.3, respectively).

To form a complete picture of the relationship between White presence and school funding measures, I first examine the bivariate relationships between the percentage of White K-4th graders and school spending outcomes (Table 4-2). The

Table 4-1. Descriptive Statistics of School Funding Measures by Urbanicity

	Total				Urban	Suburban and Rural
	Mean	SD	Minimum	Maximum	Mean	Mean
School mean teacher salary (1000s)	59.68	11.54	29.73	122.02	59.63	59.70
Per pupil salary expenditure	4759.63	1574.25	2200.53	20569.59	4366.91	4976.13
Student-teacher ratio	15.92	4.04	0.89	39.71	17.06	15.29
N	14,815				5,265	9,550

4-2. Bivariate Relationship Between % White K-4th Graders and School Funding Measures

	Urban % White K-4th graders	Suburban and Rural % White K-4th graders
	Pearson's r	Pearson's r
Mean teacher salary	0.081	0.059
Per pupil salary expenditure	0.125	0.320
Student-teacher ratio	-0.027	-0.202
N	5,265	9,550

Note: All correlations significant at $p<.0005$ level percentage of White students in a school is weakly, positively correlated with both mean teacher salaries and per pupil salary expenditures. The correlation is strongest for per pupil salary expenditures in suburban and rural schools (r=.32). In both urban and non-urban contexts, the percentage of White students is weakly, negatively correlated with student-teacher ratio. In suburban and rural schools, the correlation is stronger (r= -.20) than in urban schools (r= -.03).

I now examine the bivariate relationship between White representation and school funding (Table 4-3). I begin with urban settings. Before controlling for other common factors known to be associated with school funding, bivariate comparisons indicate that underrepresented White schools pay teachers less and spend less on personnel per pupil, yet also have the lowest student-teacher ratios (recall that a lower student-teacher ratio is preferable). This partially supports the opportunity hoarding hypothesis, in which resources are scarcer in White underrepresented schools. However, the average differences between White underrepresented schools and overrepresented White schools are small in magnitude for all three metrics. Namely, there is a negligible difference of seven dollars of salary expenditure per pupil between White underrepresented and White parity schools and a small difference of only $119 per pupil between White underrepresented and White overrepresented schools. Suburban and rural schools are similar to urban schools in that underrepresented White schools have the lowest mean teacher salaries and the lowest per-pupil salary expenditure. However, the differences for per pupil salary expenditure are larger and therefore more concerning. Average per pupil salary spending for underrepresented White schools is $4,685 compared to $4,944 in

Table 4-3. Bivariate Relationships Between White Representation and School Funding Measures by Urbanicity

	Urban				Suburban and Rural			
	Under-represented White	Representative White	Over-represented White	ANOVA	Under-represented White	Representative White	Over-represented White	ANOVA
	Mean (SD)	Mean (SD)	Mean (SD)	R^2 p-value	Mean (SD)	Mean (SD)	Mean (SD)	R^2 p-value
School mean teacher salary (in 1000s)	58.94 (11.26)	59.98 (11.80)	60.92 (11.39)	R^2=.005 p<.00005	58.25 (10.80)	60.60 (12.08)	60.12 (11.67)	R^2=.007 p<.00005
Per pupil salary expenditure	4340.00 (1047.74)	4347.16 (991.01)	4459.04 (994.28)	R^2=.002 p<.01	4684.84 (1553.31)	4944.24 (1617.83)	5244.19 (2027.77)	R^2=.017 p<.00005
Student-teacher ratio	16.80 (4.19)	17.37 (4.23)	17.35 (4.15)	R^2=.005 p<.00005	15.15 (3.69)	15.62 (3.89)	15.11 (3.82)	R^2=.004 p<.00005
N	5,265				9,950			

representative White schools, a difference of $259 per pupil, and $5244 in overrepresented White schools, a difference of $559 per pupil. For suburban and rural schools, the student-teacher ratio is relatively flat across the three White representation categories, but it is the lowest for overrepresented White schools (15.1) and the highest for representative White schools (15.6), with underrepresented White schools in the middle at 15.2.

The relatively small bivariate differences in per pupil personnel expenditure by White representation level in urban schools is somewhat surprising considering the strong positive relationship between White representation and the percentage of White students in a school. Previous research has demonstrated an average financial advantage to schools with more White students, particularly when it comes to local and state spending (Sosina and Weathers 2019). The personnel PPE measure presented here includes only state and local expenditures, excluding federal funds, which tend to compensate for state and local funding differences.

Multivariate Analysis

Mean Teacher Salary

I now address my hypotheses, beginning with the relationship between White representation and mean teacher salary. I hypothesize that mean teacher salary increases with White representation. I regress logged mean teacher salary, lead to 2015, on school and neighborhood independent variables captured in 2010. Outcomes are led a few years later to partially address causality and to account for the slow pace of change in school funding. In both models, I apply standard errors clustered at the district level, which prevents downwardly biased standard errors caused by the clustering of schools within districts. Because per pupil personnel expenditure largely varied between districts rather than within districts, I did not apply district fixed effects for these models. Estimates from OLS regression of logged mean teacher salary on White representation and other school and neighborhood characteristics are presented in Table 4-4.

I control for two neighborhood characteristics: the logged neighborhood median household income and the logged population of the neighborhood (regardless of age). In previous research, median household income is positively associated with White representation in neighborhood schools and logged total population is associated with significantly lower White representation in neighborhood schools (Bischoff & Tach 2018). I also control for the number of magnet, charter, and private schools within a two-mile radius of the centroid of the neighborhood. All models further control for the following school characteristics: the percentage of White students, the percentage of Black students, the percentage of students with LEP, the percentage of students with disabilities (defined as students with IEPs), the percentage of students with FRL, and the total number of students in the school. The suburban and rural model controls for whether a school is rural. For the White representation variable, White parity (between a negative two percentage point difference and positive two percentage point difference) serves as the reference category.

I construct separate models for urban schools and non-urban schools (suburban and rural schools). Previous research suggests that White representation may operate in different ways depending on urbanicity and, as we have already seen, White

4-4. Estimates from Ordinary Least Squares Regression of Logged Mean Teacher Salary on White Representation in Neighborhood School and Other School and Neighborhood Characteristics, by Urbanicity

	Urban	Suburban and Rural
	b (SE)	b (SE)
White representation in neighborhood school (vs. representative of neighborhood)		
Underrepresented	-0.028**	-0.025*
	(0.011)	(0.010)
Overrepresented	0.008	-0.009
	(0.011)	(0.007)
% White K-4th graders (school)	0.000	0.000
	(0.001)	(0.000)
% Black K-4th graders (school)	-0.002*	-0.002***
	(0.001)	(0.001)
Median household income (ln) (neighborhood)	0.062*	0.012
	(0.025)	(0.022)
Population (ln) (neighborhood)	0.010	0.023*
	(0.015)	(0.009)
# Private schools within 2 miles (neighborhood centroid)	0.012***	0.013**
	(0.003)	(0.004)
# Magnet schools within 2 miles (neighborhood centroid)	0.008	-0.006
	(0.008)	(0.013)
# Charter schools within 2 miles (neighborhood centroid)	-0.005	-0.023*
	(0.005)	(0.010)
Total # students (in 100s) (school)	-0.012**	-0.013***
	(0.004)	(0.003)
% Students with FRL (school)	0.001	-0.001*
	(0.001)	(0.000)
% Students with disabilities (school)	0.003	0.001
	(0.002)	(0.001)
% Students with LEP (school)	-0.001	0.000
	(0.001)	(0.001)
Rural (school)		-0.039**
		(0.014)
Constant	10.23	10.807
N	5,265	9,550
Adjusted R^2	0.108	0.083

*p<.05; **p<.01; ***p<.001

Note: Robust standard errors are clustered at the district level.

representation looks descriptively different in urban settings (Bischoff and Tach 2018; Candipan 2019; Sosina and Weathers 2019). However, a comparison between the urban model and the suburban/rural model of mean teacher salary does not overwhelmingly support the hypothesis that White representation may be more conceptually meaningful in an urban context. Instead, the models closely resemble one another.

In support of the opportunity hoarding hypothesis, White underrepresentation has a negative and significant coefficient in both the urban and suburban/rural models. Because the outcome variable is log-transformed, I convert coefficients to a percentage increase in mean teacher salary so that effects are more interpretable. Controlling for other variables in the model, teachers in White underrepresented schools in urban areas can expect an average salary that is 2.8% lower than that of their peers in schools with White parity between neighborhood and school ($p<.01$). For teachers in suburban and rural schools, White underrepresentation comes with a similar average penalty of 2.5% less in mean teacher salary than schools with White parity ($p<.05$).

White overrepresentation does not significantly differ from White parity in its prediction of mean teacher salary in either model. In neither model was the coefficient for White overrepresentation significant.

One overarching aim of this research is to tease out the difference between the percentage of White students in a neighborhood school and their relative representation compared to the neighborhood. Interestingly, the percentage of White students is not significant predictor of mean teacher salary in either model. This suggests that when it comes to mean teacher salary, White representation at a school may be more important than the percentage of White children attending the school. However, the percentage of

Black K-4th graders, another measure of school racial composition, was significant in both models. In both urbanicity categories, a ten-percentage point increase in Black K-4th graders predicts a decrease in mean teacher salary of 2.0% ($p<.05$ for urban schools, $p<.001$ for suburban and rural schools).

Per Pupil Personnel Expenditure

I now address the relationship between White representation and personnel PPE. Personnel expenditure differs from mean teacher salary in that it includes the salary of all staff, including administrators and instructional support staff, and it is divided across the total number of students at the school. I also hypothesized that personnel PPE would increase with White representation, particularly in urban schools.

I regress logged per-pupil personnel expenditure, lead to 2015, on school and neighborhood independent variables captured in 2010. Other than the dependent variables, the model is identical to the model construction for mean teacher salary.

I once again present separate models for urban schools and non-urban schools (Table 4-5). In line with my expectations, the two models differ when it comes to White representation. The opportunity hoarding hypothesis is supported in urban schools, but not suburban and rural ones. Underrepresented White schools in urban areas can expect an average of 2.6% *less* personnel PPE than schools with White parity ($p<.05$). For suburban and rural schools, there was no such relationship. In suburban and rural schools, there were no significant differences between White parity and White over/underrepresentation. This is somewhat surprising considering the large differences between salary PPE across White representation categories. It appears, however, that the

4-5. Estimates from Ordinary Least Squares Regression of Logged Salary Expenditure Per Pupil on White Representation in Neighborhood School and Other School and Neighborhood Characteristics, by Urbanicity

	Urban	Suburban and Rural
	b (SE)	b (SE)
White representation in neighborhood school (vs. representative of neighborhood)		
Underrepresented	-0.026*	0.007
	(0.013)	(0.009)
Overrepresented	-0.012	-0.014
	(0.011)	(0.008)
% White K-4th graders (school)	0.003***	0.002***
	(0.002)	(0.000)
% Black K-4th graders (school)	0.002**	0.001*
	(0.001)	(0.001)
Median household income (ln) (neighborhood)	-0.039	-0.028
	(0.033)	(0.025)
Population (ln) (neighborhood)	0.015	-0.082***
	(0.019)	(0.011)
# Private schools within 2 miles (neighborhood centroid)	-0.003 (0.004)	0.015** (0.005)
# Magnet schools within 2 miles (neighborhood centroid)	0.007 (0.008)	0.000 (0.009)
# Charter schools within 2 miles (neighborhood centroid)	0.012 (0.013)	-0.045* (0.019)
Total # students (in 100s) (school)	-0.019***	-0.022***
	(0.005)	(0.004)
% Students with FRL (school)	0.000	-0.001
	(0.001)	(0.000)
% Students with disabilities (school)	0.003	0.001
	(0.002)	(0.001)
% Students with LEP (school)	0.002*	0.000
	(0.001)	(0.000)
Rural (school)		0.070***
		(0.018)
Constant	8.514	9.448
N	5,265	9,550
Adjusted R^2	0.153	0.296

*p<.05; **p<.01; ***p<.001

Note: Robust standard errors are clustered at the district level.

percentage of White students in a school, rather than White representation, explains these bivariate differences.

In contrast with my findings for mean teacher salary, for personnel PPE, the percentage of White students has a significant and positive effect, net of White representation at the school. For a ten-percentage point increase in White students, the neighborhood school spends on average 3.1% more per pupil on school staff in urban neighborhoods ($p<.001$) and 2.1% more per pupil in suburban and rural neighborhoods ($p<.001$). In contrast to mean teacher salary, the percentage of Black K-4th graders also predicts higher per pupil salary expenditure. Holding the percentage of White K-4th graders constant, a ten-percentage point increase in Black students predicts 2.1% more salary spending per pupil in urban areas ($p<.001$) and a more modest 1.0% increase in suburban and rural areas ($p<.001$).

If we take the findings for percentage White and White representation in urban schools together, holding the percentage of Black students constant, they suggest that schools with a smaller share of White students spend less on staff per pupil and that, on top of this, there is an additional financial penalty if the school is less proportionally White than the neighborhood. The double financial advantage of both White presence and White representation offers support to the opportunity hoarding hypothesis, though only in urban schools and not suburban and rural ones.

Student-Teacher Ratio

For the final school funding outcome, I observe the relationship between White representation and student-teacher ratio. Student-teacher ratio is the number of students per FTE teacher. In line with the theory of opportunity hoarding I hypothesize that student-teacher ratio will decrease with White representation, or in other words that White underrepresentation will predict more students per teacher. This hypothesis is unsupported both by the bivariate analyses and by the models presented here. Instead, student-teacher ratios are significantly higher for White overrepresented schools in urban settings and student-teacher ratios are significantly lower for schools with an underrepresented White student body in suburban and rural areas.

I regress the student-teacher ratio, led to 2015, on 2010 school and neighborhood independent variables, using the same specifications as the first two models. OLS regression estimates of student-teacher ratio on White representation are displayed in Table 4-6.

White overrepresentation predicts significantly higher student-teacher ratios in urban areas. Urban schools that are underrepresented White can expect a student-teacher ratio that is about half a student-per-teacher smaller than schools at White parity in urban areas and about three-quarters of a student-per-teacher larger than schools at White parity ($p<.05$). Conversely, White underrepresentation predicts significantly lower student-teacher ratios in suburban and rural settings, by a margin of nearly three-quarters of a student-per-teacher ($p<.01$).

The percentage of White K-4th graders in the school predicts significantly lower student-teacher ratio in both urban and suburban/rural areas. The higher the proportion of White students, the lower the student-teacher ratio can be expected to be ($p<001$). Similarly, the percentage of Black students also predicts a smaller student-teacher ratio, or more teachers per student, regardless of urbanicity ($p<.001$).

4-6. Estimates from Ordinary Least Squares Regression of Student-Teacher Ratio on White Representation in Neighborhood School and Other School and Neighborhood Characteristics, by Urbanicity

	Urban	Suburban and Rural
	b (SE)	b (SE)
White representation in neighborhood school (vs. representative of neighborhood)		
Underrepresented	-0.252 (0.220)	-0.721** (0.213)
Overrepresented	0.468* (0.224)	-0.017 (0.132)
% White K-4th graders (school)	-0.052*** (0.014)	-0.059*** (0.009)
% Black K-4th graders (school)	-0.074*** (0.014)	-0.078*** (0.013)
Median household income (ln) (neighborhood)	1.396* (0.571)	0.441 (0.428)
Population (ln) (neighborhood)	0.211 (0.274)	0.714*** (0.200)
# Private schools within 2 miles (neighborhood centroid)	0.175** (0.065)	-0.039 (0.087)
# Magnet schools within 2 miles (neighborhood centroid)	0.066 (0.132)	-0.312 (0.203)
# Charter schools within 2 miles (neighborhood centroid)	-0.122 (0.010)	0.174 (0.260)
Total # students (in 100s) (school)	0.173* (0.076)	0.139* (0.057)
% Students with FRL (school)	0.008 (0.011)	-0.002 (0.006)
% Students with disabilities (school)	-0.149*** (0.032)	-0.102*** (0.014)
% Students with LEP (school)	-0.047** (0.017)	-0.046*** (0.013)
Rural (school)		-0.906** (0.219)
Constant	4.317	10.547
N	5,265	9,550
Adjusted R^2	0.241	0.222

*p<.05; **p<.01; ***p<.001

Note: Robust standard errors are clustered at the district level.

Discussion

In this chapter I find partial support for the opportunity hoarding hypothesis. Schools with an underrepresentation of White students compared to their surrounding neighborhoods in 2010 experienced diminished school funding outcomes five years later, particularly in urban settings. There seems to be a monetary rift between schools that are underrepresented White and those that match or exceed the percent White in their neighborhood. This rift represents disparate funding outcomes. Interestingly, school funding outcomes do not betray a noticeable difference between White parity and White overrepresentation. This suggests that there may be a White underrepresentation "tax" for neighborhood schools. When families with White children disproportionately eschew the neighborhood school compared to other families in the neighborhood, there may be a financial cost to the school.

An alternate explanation is that families with White children tend to be more adept at avoiding underfunded schools. I find that White underrepresentation predicts lower spending five years later, but this does not necessarily demonstrate that White underrepresentation causes lower teacher salaries or personnel PPE. Instead, the findings here may demonstrate that White children and their families have the means (whether social or financial) to disproportionately avoid schools with less state and local funding.

Both monetary outcomes reflect personnel salary expenditures and therefore are likely responsive to teacher and administrator experience. Therefore, the funding gaps captured here may speak more to the presence of inexperienced teachers than to cases of underfunded schools. Most districts pay teachers based on years of teaching experience, so a school with lower teacher salaries is likely to be a school with less experienced teachers. If it is the case that the differences in teacher pay and per pupil salary expenditure reflect gaps in teacher experience, the negative effects of working with inexperienced, or less experienced, teachers may carry over to students (Ladd and Sorensen 2017).

The models predicting student-teacher ratio contradicted my hypotheses and did not demonstrate a lower student-teacher ratio for overrepresented White schools. Instead, schools with White underrepresentation can expect fewer students per teacher in suburban and rural areas and schools with White overrepresentation can expect more students per teacher in urban schools. A lower student-teacher ratio theoretically results in an improved schooling experience in which each student receives more individualized teacher attention. It is possible that the student-teacher ratio is responsive to families' demand for a school, which likely relates to White representation. A school in high demand will fill its available seats, thereby maximizing its teacher-student ratio, whereas an under-enrolled school may have not enough students to maximize classroom capacity. In an under-enrolled school, teachers are hired or let go based on the number of students, whereas at a school that is enrolled to maximum capacity, the number of teachers determines the maximum number of students. This conclusion aligns with the view that schools that are overrepresented White are more likely to be in high demand because Whites on average hold more wealth and social power.

CHAPTER 5

WHITE REPRESENTATION AND SCHOOL-SUPPORTING NONPROFITS

Introduction

Most public-school funding comes from public sources, so researchers should be careful not over-emphasize the relative importance of private donation to public schools (Brown, Sargrad, and Benner 2017; Murray et al. 2019). However, many public schools benefit in some way from private donations, whether through informal fundraising, such as bake sales, or through more formal fundraising via a dedicated foundation or nonprofit. Private donations to public schools are particularly of interest in this study because they represent community and family investment in public schools (Murray et al. 2019), which may be related to school composition. If most donations to a public school come from the families who send their child(ren) there, then having White families in attendance may directly and materially benefit the school, particularly because White families tend to be wealthier.

In this chapter, I investigate the relationship between White representation in neighborhood schools and school-supporting nonprofits. In a society in which the average White family is afforded both more material wealth and more social capital, I expect that White overrepresented schools are more likely to have a school-supporting nonprofit and, further, more likely to have a higher-revenue school supporting nonprofit. My hypotheses are in line with the theory of opportunity hoarding, which posits that in-group advantages can accumulate through the individual choices of a group of people who share an identity marker. I hypothesize the following:

Hypothesis 1	Neighborhood schools with White overrepresentation and White parity will be more likely to have a school-supporting nonprofit than schools with White underrepresentation.
Hypothesis 2	Neighborhood schools with White overrepresentation and White parity will be more likely to have a high-revenue school-supporting nonprofit than schools with White underrepresentation.

Racial Composition and School-Supporting Nonprofits

Previous research ties racial composition to school-supporting nonprofit revenue. A national study of school-supporting nonprofits found that the proportion of White residents in a district predicts higher nonprofit revenue, net of the economic composition of the district (Nelson and Gazley 2014). Similarly, in a panel study of school supporting nonprofits in North Carolina, Murray et al. (2019) finds that both the percentage of Black and the percentage of Hispanic students at a school are inversely related to the probability that a school has a high-revenue nonprofit (defined as a nonprofit with $50,000 or more in revenue).

In light of evidence that the racial makeup of a school relates to nonprofit revenue, paired with evidence that wealthier schools are also more likely to have a nonprofit (Brown, Sargrad, and Benner 2017), researchers have raised the concern that nonprofits tend to exacerbate school inequality (Frisch 2017; Good and Nelson 2020; Murray et al. 2019; Murray 2019; Nelson and Gazley 2014). Schools with nonprofits may offer enhanced academic opportunities their students. It is therefore concerning that students who need the least financial assistance tend to be in schools with wealthier nonprofits. Charitable support of a school does not correspond to a reduction in public funding (Nelson and Gazley 2014), so private funding represents a bonus on top of public funding. Private funding supports both schools' core academic needs and other non-essential academic enrichments that promote student performance. It follows that schools with nonprofits are linked to higher student performance, particularly for students who are not economically disadvantaged (Murray et al. 2019).

Data

To ascertain the relationship between neighborhood school racial composition and school-supporting nonprofits, I construct a novel dataset by matching the neighborhood schools in my analytical sample to two separate nonprofit datasets. I determine whether a school is associated with one or more nonprofit as well as whether a school is linked to a high-revenue nonprofit.

Although there are many nonprofits that support more than one school, the present study is limited to only single-school supporting nonprofits. A single-school supporting nonprofit is an organization that financially supports only one school. The most common example of a single-school supporting nonprofit is a Parent-Teacher Association (PTA), an organization typically administered by family and teacher volunteers.

I limit the analysis to single-school supporting nonprofits for three reasons. First, I aim to measure the smallest unit of community financial support for a school. I study nonprofits in an attempt to capture community investment in the local neighborhood school and a single-school supporting nonprofit is the finest-grain view of nonprofit support for a school.

Second, I aim to capture comparable organizations across varied contexts. Nonprofits that support more than one school come in many shapes and sizes; they can be national nonprofits, regional nonprofits, district foundations, private foundations, and more. By restricting the sample to single-school supporting nonprofits I limit the potential range of organizations to represent a consistent construct across district and state lines. Single-school supporting nonprofits are typically community- or parent-organized and represent roughly the same type of organization across school contexts, although of course there will be variation in roles and responsibilities between single-school supporting nonprofits as well.

Finally, and perhaps most importantly, studying only single-school supporting nonprofits ensures that any reported revenue benefits only the school of interest and not other schools in the sample nor other non-sampled schools. Nonprofits do not disaggregate their financial support by individual school, so it is not known how funds are distributed across schools in cases where one nonprofit supports more than one school. Furthermore, many district-wide nonprofits disproportionately fund high school students. The needs of high school students tend to be more specialized and advanced and therefore more expensive, particularly in artistic and athletic pursuits. Furthermore, as became clear to me during my review of dozens of district-wide nonprofit websites for this study, college preparation and college scholarships are often big-ticket items for district-wide foundations and are centrally featured on their websites. College preparatory and college access funds will tend to funnel to high school students or even alumni rather than elementary school students. Including district-wide nonprofits in a study interested only in elementary schools risks over-estimating the nonprofit funding attributed to elementary schools. Single-school nonprofits simplify this problem because any revenue raised by a single-school supporting nonprofit can be assumed to be in support of its only affiliated school.

Limiting the study to only single-school nonprofits means that many avenues of nonprofit support are not addressed in the present analysis. The summary of “nonprofit presence” presented in this chapter does not reflect a summary of all nonprofit support for a school. Many schools engage with multiple nonprofit partners, some local, some regional, and some national. If a nonprofit supports more than one school, it is not included in this study, but it may notwithstanding provide substantial assistance to one or more neighborhood schools in the sample. Furthermore, the revenue figures discussed here do not represent the total nonprofit money that a school might access, directly or indirectly. Instead, they represent the revenue of nonprofits associated with a singular school in the sample. The drawback of this approach is the lack of a clear picture of the full landscape of nonprofit support of schools, but the benefit is that there are no arbitrary assumptions about how nonprofit budgets are apportioned across schools.

The nonprofit data comes from two sources: The 2015 National Center of Charitable Statistics’ (NCCS) Core Financial Files (CFF) and the 2015 IRS Business Master File (IRS-BMF), accessed via the NCCS Data Archive (Internal Revenue Service 2019; National Center of Charitable Statistics 2017). The CFF is a limited set of nonprofits that includes only nonprofits that submit a tax Form 990, Form 990-EZ, or Form 990-PF (hereafter shortened to “a Form 990”) in a given year. Since 2010, filing a

Form 990 is a requirement for nonprofits with annual gross receipts over $50,000. The IRS-BMF casts a wider net and includes all nonprofits that are "active" in a given year. A nonprofit is considered "active" if it applied for or renewed its tax-exempt status within the past three years. The two nonprofit datasets overlap substantially. Inclusion in the BMF indicates that the organization is active, whereas inclusion in the CFF indicates both that the organization is active and that it has a revenue of over $50,000. However, some nonprofits choose to file a Form 990 despite a revenue lower than $50,000. Because the Form 990 collects financial data including annual revenue, such organization can be distinguished from the others in the CFF.

Matching Schools and Nonprofits

School-supporting nonprofits are not directly linked to the schools nor districts they support via administrative data. To identify nonprofits associated with neighborhood schools, I adapt the school-to-nonprofit matching methods of Murray et al. (2019). The process consists of four general steps: narrowing the pool of potential nonprofit matches, generating a list of likely school-nonprofit matches using *name* and *address*, reviewing the matches by hand, and then generating a final number of nonprofits per school by removing duplicates and combining records for schools that have more than one active nonprofit. I describe each step of the process in detail below. An overview of the process is presented in Table 5-1.

Following Murray et al. (2019), I first narrow down the available nonprofits to likely matches. The CFF categorizes nonprofits by National Taxonomy of Exempt Entities (NTEE) "major groups" and I restrict the CFF sample to only groups with the purpose of "Education" (major group B). This refines the original 429,338 nonprofits in the CFF dataset to 73,815. Although BMF data also provides NTEE codes, the codes are missing for 32% of the sample and so I do not refine the BMF by NTEE code.

Table 5-1. Summary of School-Nonprofit Matching Steps

		Dataset pair			
Step #	Description	CFF/CCD location address	CFF/CCD mailing address	BMF/CCD location address	BMF/CCD mailing address
1	Restrict to NTEE "Education" major group B	X	X		
2	Require relevant keywords (e.g. "Education")	X	X	X	X
3	Exclude irrelevant keywords (e.g. "Pharma")	X	X	X	X
4	Match 1: Both name and address, state and city required	X	X	X	X
5	Match 2: Address only, state and city required	X	X	X	X
6	Match 3: Address only, state required	X	X	X	X
7	Match 4: Name only, state required	X	X	X	X

An “X” indicates a completed step

Next, I use keywords to identify likely school-supporting nonprofits by their names. To be included in the final pool of potential nonprofit matches, the name of the organization must contain one or more of the following words: “**friends**,” “**school**,” “**education**,” “**foundation**,” “**booster**,” “**parent**,” “**PTO**,” “PTA,” “**trust**,” “**elementary**,” “junior high,” or “middle.” Words in bold are borrowed directly from the methods of Nelson and Gazley's (2014) similar search for school-supporting nonprofits. This step further winnowed the CFF data from 73,815 to 46,670 records and reduced the BMF data from over 1.1 million records to 276,443 records.

Next, I use Stata's record linking capability (*reclink*) to compare school names and addresses to the list of likely school-supporting nonprofits' names and addresses. This process generates likely school-nonprofit pairs. Murray et al. (2019) found that 90% of school-nonprofit pairs identified using this method were "unproblematic" when working with schools within a single state (North Carolina). Finally, I verified or rejected each match by hand to weed out false matches. I completed the matching procedure for my sample of schools twice, once for the CFF data and once for the BMF data.

Small-batch testing of the matching process revealed an additional step necessary to streamlining the matching process: *excluding* nonprofits from the pool of potential matches based on certain keywords in the nonprofits' names. For example, the "Kentucky Pharmacy Education and Research Foundation" appears in the CFF refined sample and contains two required keywords (education and foundation) but is clearly not a school-supporting nonprofit. The elimination of any nonprofits with the term "Pharma," to remove organizations with either "Pharmacy" or "Pharmacist" within their names, improves the efficiency of the matching process by dropping twenty-four pharmaceutical nonprofits that are not possible matches. I ultimately created a list of 160 words, prefixes, and phrases to exclude (the full list appears in Appendix A). Common words on the list include medical and religious terms. A nonprofit with any word from the list in its name is dropped from the pool of potential nonprofit matches. Removal of all nonprofits with one or more exclusion keywords in their names reduced the CFF data from 46,670 to

40,859 and reduced the BMF data from 276,443 to 203,975. However, in practice, the discovery of keywords to exclude from the sample was an iterative process that did not happen all at once. Instead, I built the list of keywords over several rounds of matching as I discovered new false-positive matches that contained a keyword I decided to exclude from the pool of potential matches.

I matched nonprofits to schools using three approaches: "fuzzy" matching using school/nonprofit address, "fuzzy" matching on school/nonprofit name, and "fuzzy" matching on school/nonprofit name *and* address, together. Fuzzy matching does not require an exact match and instead looks for near-matches. This is ideal for street addresses and organizational names, which may use similar words without following identical naming conventions. For example, in address data, it is common that one dataset says "Street" while another says "Road." For schools, it is common that one dataset says "Elem" when another completely spells out "Elementary." Small differences such as these should not be grounds for eliminating a potential match. Furthermore, a school-supporting nonprofit would not be expected to perfectly share a name with the school it supports, although they might be expected to have one or more words in common with the school, in a case such as "Friends of Canfield" supporting "Canfield Elementary School."

I conduct each of the three matching steps twice through, once for school *location* address and once for school *mailing* address (see Table 5-1). It is necessary to compare nonprofit addresses to both address types because school location and mailing addresses are identical for only 39% of schools in the sample. Each subsequent matching step searches for matches that might have been missed in previous steps.

The first step is to permit a fuzzy match on school/nonprofit name *and* school/nonprofit address, but require a perfect match for city and state. The address-fuzzy-match includes two distinct address fields, 1) the street or mailing address (e.g. 123 Main St) and 2) the zip code. The verified matches from this step are removed from the pool of potential matches before moving to step two.

The second step eliminates school/nonprofit name and again permits a fuzzy match on school/nonprofit address, while still requiring a perfect match for city and state. This step searches for school-nonprofit pairs that share an address but have disparate names (e.g. John Blacow Elementary and its nonprofit the Bobcat Booster Club).

The third step eliminates the exact match on the city and consists of a fuzzy match on school/nonprofit address, now including the street (or mailing) address, the zip code, *and the city*, while continuing to require a perfect match on the state. This step searches for school/nonprofit pairs with disparate city spellings (e.g. Virginia Beach and Virginia Bch) or even clear school-nonprofit matches that nevertheless list two different cities. Different city names typically occur for cities very close to one another, such as Richmond, VA and Henrico, VA. Eleven percent of the final list of school-nonprofit pairs had different city names or city spellings, which suggests this final step was worthwhile.

Each of the three steps listed here cast a slightly different net for school-nonprofit pairs using the address as the main link between school and nonprofit. In between each step, I found it necessary to verify each potential match by hand. The accuracy rate of the *reclink* matches was roughly 42% (out of 37,874 potential matches reviewed by hand, 42% were verified as real matches). However, this percentage should be interpreted cautiously as the accuracy rate differed depending on the matching criteria and the stage of the matching process. The list of nonprofit keywords to remove was developed alongside the record review process, so many nonprofits were reviewed in early stages of the process that would have been dropped in later stages of the process. Also, although the methods improved over time, record matching tended to increase in difficulty toward the end of the process. The first few matching attempts successfully linked the most obvious matches, so that subsequent rounds of matching were more likely to include edge cases that took more time to verify.

The record verification procedure is outlined in detail in Appendix B. At a high-level, the procedure begins by comparing the school and nonprofit names. If the names provided sufficient evidence for a match, I move to the next record. If not, I move to comparing addresses. If the match is still inconclusive, I search the nonprofit name on the internet. If a website provides sufficient support that the nonprofit links to the school listed, and no other school, I indicate the record is a verified match. Otherwise, the record in not a verified match and the nonprofit returns to the pool of potential matched for other schools. Throughout the entire matching process across both datasets, 571 matches were confirmed or rejected based on an internet search, making up about 1.5% of total number of records reviewed.

The *reclink* command helped with hand-verification by distinguishing between close- and distant-matches. *Reclink* generates a "matching score" between one and zero to capture how close a match each pair is across all compared fields (name, address, etc.). I limited potential school-nonprofit pairs to only those above a 0.6 matching score. I found in practice that pairs with a matching score below 0.89 were rarely worth reviewing and that sometimes even those pairs with a matching score of 1.0 were not true matches. The average match score in the final set of verified matches was 0.96. Ninety percent of matches were above a match score of 0.89.

After address matching, I conduct a final round of matching based on school/nonprofit name, excluding any reference to street or mailing address. Although initial pilot testing indicated that matching based on address was more accurate than matching on name, matching on name with neither street nor mailing address was an attempt to catch any nonprofits that did not share an address with their schools. When matching on name, I permitted a fuzzy match on school/nonprofit name, city, and zip code, requiring only a perfect match on state. Just like with address matching, each potential school-nonprofit pair was hand reviewed using the procedure described in Appendix B.

Finally, I merged the lists of CFF nonprofits and BMF nonprofits. I cleaned the data by removing duplicates (duplicates were expected due to the redundant nature of the CFF and BMF datasets). For duplicate cases, the CFF records are retained because they contain more detailed revenue information than the BMF records. I also ensure that no nonprofit matches to more than one school. Though rare, some schools did match to more than one nonprofit, typically to both a PTA and a foundation. All such cases were retained.

Once the list of school supporting nonprofits was finalized, I categorized nonprofits into two revenue categories: low-revenue, defined as $50,000 or less in revenue, and high-revenue, defined as more than $50,000 in revenue. As mentioned earlier, all nonprofits in the CFF filed a Form 990 and that organizations that raised more than $50,000 are required to file a Form 990. However, not all organization that complete a Form 990 report more than $50,000 in income. Many organizations file the form voluntarily. Organizations in the CFF that reported $50,000 or less in revenue are categorized as low-revenue. The rest of the organizations in the CFF reported more than $50,000 and are therefore categorized as high-revenue. The remaining organizations appear in the BMF, but not the CFF, and are consequently categorized as low-revenue. Out of a total of 9,565 nonprofits that matched into the sample of schools, only 21% are high-revenue nonprofits.

The 389 schools with more than one nonprofit were categorized into the highest revenue category available to them; if the school had any high-revenue nonprofits, they are assigned to the high-revenue category. A school with two or more *low*-revenue nonprofits remained in the low-revenue nonprofit category because of the absence of financial data for nonprofits without a Form 990. However, it is possible that a school with two or more low-revenue nonprofits could enjoy a combined financial benefit of over $50,000 across all nonprofits. If such a case exists, its designation here, in the low-revenue nonprofit category, would not reflect this.

Considerations of Selection Bias in School-Nonprofit Matching

Record matching is susceptible to biases and the matching process described here is no exception. Sample bias occurs when certain records have a higher likelihood of making an accurate match than other records. I offer a few thoughts here on potential biases that likely affected this specific matching process. I include a detailed account of each source of selection bias, as well as the steps I took to account for each source of bias, in Appendix C. I suspect that organizations affiliated with a national organization (such as the National PTA) had a higher likelihood of matching into the sample. In general, nonprofits with clearer and/or more common naming conventions were more likely to be matched due to my heavy reliance on nonprofit names. The two lists of keywords I developed (one for including relevant nonprofits and the other for excluding irrelevant nonprofits) may have been biased to include or exclude certain types of organizations. I also believe that schools with common names were more difficult to match to their associated nonprofit and therefore may have had lower odds of securing a match. The location of nonprofits, specifically whether the location overlapped with the school location or mailing address, undoubtedly affected the odds of matching into the sample. Finally, the exclusion of nonprofits that support more than one school likely biased which schools in the sample were matched with nonprofits. Again, for further thoughts on each source of bias mentioned here, see Appendix C.

The considerations about bias here are included for the consideration of future researchers who undertake similar matching work. They also speak to the limitations of my conclusions in this chapter. Of particular note is the two ways in which rural schools may be wrongfully underrepresented in the category of schools with supporting nonprofits: 1) rural schools are more likely to have a PO Box that may make them difficult to match to a nonprofit based on address, and 2) rural schools may be more likely to share a nonprofit with other schools to maximize efficiency in areas with small populations or co-located schools. Of all the sources of potential bias, I find the potential of underreporting nonprofits in rural schools to be of the most concern to the present study. Although I made every effort to counteract matching biases as I encountered them, it is probable that school-supporting nonprofits were missed during the matching procedure described here, and furthermore that the process disproportionately excluded rural school-supporting nonprofits. In future research, it may be fruitful to consider district-wide and single-school nonprofits *together* when evaluating school-supporting nonprofit presence and revenue.

Descriptive Analysis

Descriptive statistics for nonprofit presence and revenue category by urbanicity are presented in Table 5-2. Nearly half (48.8%) of elementary schools in the sample had at least one low- or high-revenue nonprofit. About eleven percent of schools had a high-revenue nonprofit, defined here as a nonprofit with a reported revenue of over $50,000 in 2015. This amounted to 1,874 total schools. School-supporting nonprofits are more common in urban schools (56.0%) than in suburban and rural ones (45.0%). Urban schools are not only more likely to have nonprofits, they are also more likely to have high-revenue nonprofits (13.3%) than suburban and rural schools (9.4%). Upon closer inspection, these differences in urbanicity are largely attributable to rural schools, where nonprofits are relatively rare. When considering rural and suburban schools separately, only 22.0% of rural schools have an associated nonprofit compared to 58.3% of suburban schools, which is a striking difference. Moreover, only 3.4% of rural schools have a high-revenue nonprofit, compared to 12.8% of suburban schools (note that the comparison between rural and suburban schools is not included in Table 5-2). In addition to the concerns about selection bias affecting rural schools described above, the low rate of nonprofits in rural schools may be related to a combination of low population and small school size.

5-2. Descriptive Statistics of Nonprofit Presence and Revenue by Urbanicity

	All	Urban	Suburban and Rural
	% (n)	% (n)	% (n)
No nonprofit	51.24 (8,970)	44.01 (2,657)	55.04 (6,313)
Low-revenue nonprofit	38.06 (6,663)	42.72 (2,579)	35.61 (4,084)
High-revenue nonprofit	10.70 (1,874)	13.27 (801)	9.35 (1,073)
N	17,507	6,037	11,470

5-3. Bivariate Relationships Between White Representation and School-Supporting Nonprofit Presence, By Urbanicity

	Urban			Suburban and Rural		
	Underrepresented White	Representative White	Overrepresented White	Underrepresented White	Representative White	Overrepresented White
	% (n)	% (n)	% (n)	% (n)	% (n)	% (n)
No nonprofit	46.90 (1,545)	44.66 (677)	35.45 (435)	52.68 (1,939)	54.28 (1,952)	57.76 (2,422)
Low-revenue nonprofit	41.71 (1,374)	42.22 (640)	46.05 (565)	39.93 (1,470)	35.12 (1,263)	32.22 (1,351)
High-revenue nonprofit	11.38 (375)	13.13 (199)	18.50 (227)	7.39 (272)	10.60 (381)	10.02 (420)
Chi-square	χ^2=65.03 p<.0005			χ^2=65.95 p<.0005		
N	6,037			11,470		

The bivariate relationship between White representation and school-supporting nonprofit presence appears to depend on the urbanicity of the school (Table 5-3). Interestingly, underrepresented White schools in urban areas are the *least* likely to have a nonprofit, whereas underrepresented White schools in suburban and rural areas are the *most* likely to have a nonprofit. This suggests, descriptively, that White opportunity hoarding may be at play in urban settings, but not suburban and rural ones.

In urban schools, overrepresented White schools are slightly more likely to have a high-revenue nonprofit (18.5%) compared to schools with White parity (13.1%) and underrepresented White schools (11.4%). In suburban and rural schools, there is a smaller difference between schools across different White representation rates. Ten percent of overrepresented White schools have a high-revenue nonprofit, a slightly higher percentage (10.6%) of representative White schools have a high-revenue nonprofit, and underrepresented White schools are the least likely to have a high revenue nonprofit at only 7.4%. Although in both settings underrepresented White schools are the least likely to have a high-revenue nonprofit, the difference is starker in urban schools.

Bivariate analyses (Table 5-4) also indicate that White presence and nonprofit presence are linked in urban schools, but not rural and suburban ones. This makes sense considering that rural schools have both the highest prevalence of White students and the fewest schools with nonprofits. In urban schools, there appears to be a strong, positive relationship between Whiteness and nonprofit presence. Urban schools without a nonprofit are 25.7% White, whereas schools with a low-revenue nonprofit are 38.1% White and schools with a high-revenue nonprofit are 56.2% White.

5-4. Bivariate Relationship Between % White K-4th Graders in School and School-Supporting Nonprofit Presence		
	Urban % White K-4th Graders	Suburban and Rural % White K-4th Graders
No nonprofit	25.73	66.25
Low-revenue nonprofit	38.14	56.68
High-revenue nonprofit	56.16	65.33
ANOVA	R^2=.133 p<.00005	R^2=.023 p<.00005
N	6,037	11,470

Multivariate Analysis

I use multinomial logit models to predict whether neighborhood schools have no school-supporting nonprofit, a low-revenue nonprofit, or a high-revenue nonprofit, controlling for neighborhood and school characteristics. I reject ordinal logistic regression as an appropriate tool for this analysis because a Wald test by Brant indicates that ordinal logit models violate the parallel regression assumption. Although the three outcome categories appear to be ordered (none, low, and high), ordinal logistic regression is not an appropriate model in this case.

I estimate two multinomial logit models, one for urban and one for non-urban neighborhood schools. Both models control for the district means of each predictor. Including district means approximates district fixed effects. It provides insight into both differences between districts and differences within districts. Unlike the previous chapter in which there were insufficient within-district variation in the school funding outcome variables to justify district fixed effects, the outcome variable here (nonprofit presence) demonstrates substantial variation within districts. Clustered robust standard errors are also applied at the district level (Hosmer Jr, Lemeshow, and Sturdivant 2013).

A Wald test for combining alternative outcomes (not shown) did not offer any evidence that any of the outcomes should be combined ($p<.001$ for all outcome combinations in both urban and non-urban models). An additional Wald test, presented in Appendix D, tests whether all the coefficients associated with each predictor are zero for each model. I use Wald tests instead of likelihood-ratio (LR) tests because the logit model employs robust clustered standard errors, which preclude LR tests (Long and Freese 2014). Wald tests suggest that White representation is not an important predictor of nonprofit presence. All coefficients associated with White representation are not significantly different from zero across all outcome contrasts. This applies to both the school-level White representation measures and the district-level averages of White representation. The White representation measures and the percentage of White K-4th graders measure are the only variables for which this is the case. For both Whiteness measures, the coefficients are no different from zero in all cases. All other predictors have a coefficient in at least one model that is significantly different from zero (at the school-level, the district average, or both) and therefore a meaningful predictor of nonprofit presence. This suggests that future analyses should exclude White representation, although not racial measures entirely, as we shall see, from models that predict nonprofit presence in schools.

Table 5-5 displays the average marginal effects of White representation on nonprofit revenue category. The complete results, including AMEs for all control variables, are included in Appendix E. Results are separated by urban and non-urban schools. All models control for the following school and neighborhood characteristics: logged neighborhood population, logged median household income, the percentage of White K-4th graders in the school, the percentage of Black K-4th graders in the school, the total number of students in the school, the percentage of students with IEPs, the percentage of students with LEP, and the percentage of students eligible for FRL. The models also control for school choice landscape, specifically the numbers of charter, magnet, and private schools (each included separately) within a two-mile radius of the neighborhood centroid. I do not control for rural status in the rural and suburban model because by controlling for district-level aggregates, any school-level variables is effectively controlling for district urbanicity.

Average marginal effects such as those in Table 5-5 represent the mean marginal effect of each predictor variable calculated for all observed values for all observations in the sample. The table displays average marginal effects of White underrepresentation and White overrepresentation, both in comparison to White parity, on all three levels of nonprofit presence in schools (none, low-revenue, or high-revenue). Average marginal effects are presented here because they can be compared across models (Mood 2010).

Table 5-5. Average Marginal Effects (AME) on the Probability of School Supporting Nonprofit Presence Based on Multinomial Logistic Regression on White Neighborhood School Representation and Other School and Neighborhood Characteristics, by Urbanicity and Controlling for District-Level Means

	Urban schools			Suburban and rural schools		
	No Nonprofit	Low-Revenue Nonprofit	High-Revenue Nonprofit	No Nonprofit	Low-Revenue Nonprofit	High-Revenue Nonprofit
	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)
White underrepresentation (compared to parity)	-0.015 (0.014)	0.013 (0.017)	0.003 (0.010)	-0.020 (0.012)	0.024 (0.013)	0.004 (0.008)
White overrepresentation (compared to parity)	-0.011 (0.017)	0.010 (0.018)	0.001 (0.009)	0.021 (0.012)	0.028* (0.013)	-0.008 (0.006)
% White K-4th graders	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)	0.001 (0.001)	-0.001 (0.001)	0.000 (0.000)
N	6,037			11,470		

*p< .05 **p<.01 ***p<.001, two-tailed tests

Note: Model controls for other neighborhood and school characteristics and all predictors at district means; full model in Appendix E.

The results contradict my hypothesis that we might find evidence of opportunity hoarding in diminished nonprofit outcomes in White underrepresented schools. There are no significant contrasts for White underrepresentation nor overrepresentation, which suggests that White representation does not factor into a school's chances of affiliating with a nonprofit. I also find no evidence of a connection between the share of White students in schools and nonprofit presence.

In urban districts, the percentage of White K-4th graders does not appear to affect the chances of having a school-supporting nonprofit. The percentage of Black K-4th graders was the only significant racial composition variable (full model in Appendix E). In urban schools, an increase in the percentage of Black students increases the likelihood that a school does not have nonprofit ($p<.05$) and decreases the likelihood that a school has a high-revenue nonprofit ($p<.001$). In suburban and rural schools, a larger share of Black students decreases the likelihood that a school has a high-revenue nonprofit ($p<.001$).

The insignificant Whiteness measures might seem puzzling considering the bivariate analyses above, which established a connection between both White representation and the share of White students with nonprofit presence in urban schools. Bivariate analyses found, for example, that schools with no nonprofit are about 30 percentage points less White than schools with a high-revenue nonprofit. However, this difference is explained by other variables in the model, including neighborhood median income, student poverty, and the percentage of Black students in the school. This strongly supports the second theoretical pathway outlined in Chapter 2, which posits that any differences in White underrepresented schools are explained by the covariates of White representation.

Continuing in urban schools, as one might expect, wealthier neighborhoods are significantly less likely to have a neighborhood school without a nonprofit ($p<.001$) and were significantly more likely to have a high-revenue nonprofit ($p<.01$) (Appendix E). Conversely, schools with a higher percentage of students that qualify for FRL are significantly more likely to go without a nonprofit ($p<.001$) and are significantly less likely to have a high-revenue nonprofit ($p<.001$) (the percent of students with FRL does not affect the chances in either direction of affiliating with a low-revenue nonprofit).

In suburban and rural districts, the only significant contrast for White representation is for overrepresented schools, which can be expected on average to have 2.8 percentage point higher chance of support from a low-revenue nonprofit, compared to schools with White parity ($p<.05$). I hesitate to give much credence to this result, despite its significance, in light of the Wald test that finds the combined coefficients of White overrepresentation on all nonprofit outcome categories are no different from zero in this model. However, if taken at face value, the result indicates an advantage for White overrepresented schools compared to representative White schools in terms of low-revenue nonprofits, but not high-revenue ones.

In suburban and rural districts, White presence in the neighborhood and school is also largely unrelated to school nonprofit presence. Like in urban districts, the percentage of White K-4th graders is not a significant predictor of whether a school has a supporting nonprofit, but the percentage of Black K-4th graders is. Unlike urban schools, the percentage of Black students does not affect a school's chances of having no nonprofit.

Again, however, a larger share of Black students in the school predicts significantly lower chances of associating with a high-revenue nonprofit (p<.01) and has no measured effect on the chances of having a low-revenue nonprofit.

In suburban and rural schools, we find again that wealth appears to be a more salient driver of nonprofit presence than race. In this case, neighborhood median income does not alter the chances of having no nonprofit, but significantly *lowers* the chances of having a low-revenue nonprofit (p<.01) and significantly *raises* the chances of having a high-revenue nonprofit (p<.001). Like in urban schools, a poorer student body is less likely to have exposure to a nonprofit (p<.001). A larger share of students with FRL lowers the likelihood of affiliation with either a low-revenue nonprofit (p<.01) or a high-revenue nonprofit (p<.001).

Discussion

In this chapter, I construct a novel dataset of neighborhood schools and their affiliated nonprofits to assess whether White presence in the schools, relative to the neighborhood, is associated with access to a nonprofit. One concern about White underrepresentation in neighborhood schools is its effects on opportunities for students in the school. Of particular concern is whether the "human, social, and cultural capital" of White families presents a missed opportunity for the students in White underrepresented schools, where there are a larger share of White families living around the school than are sending their children to the school (Bischoff and Tach 2018). I have termed this concern the "opportunity hoarding" hypothesis. School-supporting nonprofits and their revenue are one manifestation of the family social and financial capital associated with a school. If there were a connection between White underrepresentation and family social capital, we might expect to find it in a relationship between White representation and nonprofit presence.

The evidence presented here finds very little connection between White representation in neighborhood schools and nonprofit presence, or at least very little connection that cannot be explained by other school and neighborhood covariates. The cross-sectional nature of the data makes it impossible to support the selection of one causal direction. It appears that either White underrepresented schools do not affect a school's chances of affiliating with a nonprofit or, conversely, that a school's nonprofit offering does not drive White underrepresentation.

This analysis offers support for the second theoretical pathway outlined in Chapter 2, namely that covariates explain the differences between in nonprofit presence and revenue at schools with differing levels of White representation. The connection between student poverty and nonprofit presence indicates that economic representation, rather than White representation, may be a more direct and informative avenue to learn about neighborhood investment (or disinvestment) in a school. However, higher quality student poverty data would be necessary to investigate this question; the FRL measure is notoriously imprecise (Harwell and LeBeau 2010).

It may be that nonprofit presence is too vague a measure to assess the nuance inherent in family social capital. The measure of revenue in this chapter (either below $50,000 or above it) is a blunt measure that captures very little detail about the differences between nonprofits. The evidence presented here is certainly not sufficient to say that White underrepresentation might not be associated with a loss of aggregate family social capital for a school in some other way. Moreover, these data do not speak to whether nonprofit resources are distributed uniformly across students within schools. Previous research warns that the school-supporting nonprofits is sometimes wielded to benefit a subset of students in a school (Cucchiara 2013).

Overall, taking the findings of both this and the preceding chapter together offer a puzzling result. One might expect a more direct connection between enrollment in a school and its nonprofit revenue than enrollment in a school and its tax base. If racially disproportionate enrollment in a neighborhood school were to make any difference, it seems more likely to directly affect charitable donations to the school than it would affect the larger landscape of public-school funding. However, I find a significant connection between White representation and public funding, but not nonprofit funding.

CHAPTER 6

WHITE REPRESENTATION, ACADEMIC OUTCOMES, AND GIFTED AND TALENTED PROGRAMMING

Introduction

Schools serve many purposes, but perhaps none is more central than fostering learning. The primary charge of U.S. elementary schools is to keep students at or above grade level in literacy and math. Measuring student achievement in these two subjects is a central way that elementary schools evaluate themselves and are evaluated by their local education agencies and states.

In this chapter, I examine the relationship between White representation in neighborhood schools and academic outcomes. I examine two very different academic measures: mean 4th grade standardized test scores and Gifted and Talented (GAT) programs. I hypothesize the following:

Hypothesis 1	Neighborhood schools with White overrepresentation and White parity will have higher mean standardized test scores than schools with White underrepresentation.
Hypothesis 2	Neighborhood schools with White overrepresentation and White parity are more likely to have a GAT program than schools with White underrepresentation.

Hypothesis 3	Neighborhood schools with White overrepresentation and White parity will be less likely to have an overrepresented White GAT program than schools with White underrepresentation.

Standardized tests are imperfect tools that do not make the measure of a school. However, standardized tests are unique in their widespread reach. They are administered consistently to nearly every student in each tested grade level each year, making them perhaps the most broadly applicable litmus test of academic performance. Furthermore, the Stanford Education Data Archive (SEDA) repackaging of the publicly available EDFacts standardized test data allows for comparisons across states, rather than only within states (Reardon, S. F. et al. 2019).

However, average standardized test results should be interpreted cautiously for many reasons. First, they are a unidimensional measure of a school. There are arguably better measures of academic achievement collected at each individual school which are not aggregated at a national level. Secondly, standardized tests are susceptible to racial and cultural biases (De Lamo White and Jin 2011; Walton and Spencer 2009). Differences in test scores may reflect race-varying psychological responses to test-taking, such as stereotype threat, rather than true academic differences (Mendoza-Denton 2014; Steele and Aronson 1995). Finally, each state sets its own standard for academic achievement on standardized tests, which means that the definition of proficiency is regional. The mean test scores presented here are normalized using the National Assessment of Educational Progress (NAEP), which means the scores are translated to a national standard, but that does not fully sidestep the concern that the raw test scores were collected using different measurement instruments depending on the state of origin.

Compared to standardized tests, it is less common to examine GAT programming as an academic outcome variable. GAT programming is not a measure of academic achievement and is instead an academic resource that some schools provide and other do not. I measure GAT programming here because it seems particularly prone to producing and/or reflecting inequality. There is no federal mandate to provide GAT services and no universal definition of a GAT student (Reis and Renzulli 2010; Rinn, Mun, and Hodges 2020). While 24 states mandate that LEAs provide gifted and talented options, the options themselves are largely left to the LEA and are not widely understood (Rinn, Mun, and Hodges 2020). In states where GAT options are required, it is not clear that such options are available in every school (Rinn, Mun, and Hodges 2020). In the present study, for example, not a single state reported 100% GAT programming coverage in its sampled elementary schools. Furthermore, both the availability of GAT programs and the identification of GAT students is known to differ based on race. Black students are less likely to attend schools with a GAT offering (Grissom and Redding 2015). In schools that do have GAT programs, White students are on average overrepresented in them (Ford, Grantham, and Whiting 2008; Grissom and Redding 2015; McBee 2006).

There is not a universally applied definition of "gifted and talented," so assessing and conferring GAT status varies across schools (Reis and Renzulli 2010; Sternberg and Davidson 2005). GAT programs are also implemented in a variety of ways. In elementary schools, GAT programs most commonly manifest as either differentiated instruction within a general education classroom (such as small group instruction, self-paced learning, and accelerated classwork) or pull-out GAT resource rooms in which GAT students spend part of the school day (Rinn, Mun, and Hodges 2020). In some cases, both approaches can be found within the same school (Rinn, Mun, and Hodges 2020). The variation in implementation makes GAT programming a slippery construct about which it is difficult to generalize. In schools where it is available, “GAT” is a label that comes with a set of services. The label partially separates a subset of students within a school and designates the students as more advanced than others in at least one academic area (Sternberg and Davidson 2005). However, the services themselves are varied and may not represent a similar level of benefit to GAT students across different schools, or even to GAT students within the same school.

Fortunately, the label itself is interesting, regardless of the quality and quantity of benefit that comes with it. The label is particularly interesting in its inconsistent application to students across schools, districts, and racial groups (Grissom and Redding 2015). It represents a favorable designation by adults in the school that is, by definition, applied to some students over others.

Data

School-level academic achievement is captured in a summary measure of literacy and math standardized test scores pooled across grades over eight school years from 2008-9 to 2015-16. SEDA provides school-level scores for literacy and math combined, rather than separate, so scores reflect achievement averaged across the two subjects. Mean school achievement scores refer to the state-administered standardized test scores, which were subsequently standardized by SEDA for use across states. Scores are reported on a "Cohort Standardized” (CS) scale, which can be interpreted standard deviations from the mean, where the mean is set to zero and represents the mean of a national reference cohort (Fahle et al. 2019). For example, a school with 0.25 on the CS scale indicates that the average student at the school scored a quarter of a standard deviation higher than the national reference cohort.

I had also hoped to observe racial test score gaps (alternately called "achievement gaps" or "opportunity gaps"), but these were only available at the district and not the school level (Fahle et al. 2019).

GAT programming is captured in three ways: 1) a dichotomous measure of whether a school has a GAT program, 2) a continuous measure of White over/underrepresentation in GAT programs, and 3) a categorical measure of White over-underrepresentation in GAT programs, divided into overrepresentation, parity, and underrepresentation. GAT data is self-reported by schools to the CRDC in the 2015-16 school year. Schools that reported a GAT program but did not report any students enrolled in the program were reassigned to the group of schools without a GAT program.

Results

Descriptive Analysis of Standardized Test Scores

I now observe the relationships between the two racial variables of interest, White representation and the percentage of White students, and standardized test scores. I find a bivariate link between test scores to both Whiteness measures, as expected. However, after controlling for school and neighborhood characteristics, I find no link between White representation and mean school test scores.

Note that all analyses separate urban from non-urban schools. I occasionally refer to both school types together when a result is shared across urbanicity. When discussing the two school types separately, I always note which sample I describe.

Table 6-1 presents descriptive statistics for standardized test scores by urbanicity. The mean CS score for all schools in the sample is 0.004 standard deviations, or near zero, which indicates that there is little difference between the sample mean and the reference cohort used to develop the CS scale. Urban schools are lower performing than suburban and rural ones (-0.115 and 0.067 on the CS scale, respectively).

Table 6-1. Descriptive Statistics of Standardized Test Scores by Urbanicity

	Total				Urban	Suburban and rural
	Mean	SD	Minimum	Maximum	Mean	Mean
Cohort-standardized mean test scores	0.004	0.402	-1.277	1.582	-0.115	0.067
N	17,490				6,032	11,458

When we look at bivariate associations between the White composition of schools and the outcomes of this chapter, we see that White students and test scores are highly, positively correlated in the sample (Table 6-2). The positive bivariate relationship between the percentage of White students in a school and its standardized test scores mirrors previous research linking Whiteness and higher average standardized test scores (Mendoza-Denton 2014). In urban schools, there is a very strong correlation (r=.688) between the percentage of K-4th graders who are White and a school's mean 4th grade test scores. In suburban and rural schools, the relationship is a less overwhelming but still very strong (r=.447).

Table 6-2. Bivariate Relationship Between % White K-4th Graders in School and Mean Standardized Test Scores				
	Urban % White K-4th grade		Suburban and Rural % White K-4th grade	
	Pearson's r/ %	p-value/ R^2	Pearson's r/ %	p-value/ R^2
Mean standardized test scores (cohort standardized)	r=0.688	p<.0005	r=0.447	p<.0005
N	6,032		11,458	

Table 6-3 presents bivariate relationships between White representation and academic variables. In both urban and non-urban settings, overrepresented White schools perform higher on standardized tests than racially balanced and White underrepresented schools. This result tentatively supports the opportunity hoarding hypothesis. This result is also likely related to the higher average percentage of White students in White overrepresented schools. We saw in Chapter 3 that White overrepresented schools enroll a larger share of White K-4th graders (58% in White overrepresented urban schools and 79% in White overrepresented suburban and rural schools).

In suburban and rural schools, the differences between average test scores by White representation level are less stark but suggest a positive relationship between White representation and test scores, namely that a higher representation of White students corresponds with higher test scores (Table 6-3). As we shall see in the multivariate analysis, this relationship is not significant once other school and neighborhood variables are controlled for.

Table 6-3. Bivariate Relationships Between White Representation and Mean Standardized Test Scores by Urbanicity

	Urban				Suburban and Rural			
	Under-represented White	Representative White	Over-represented White	ANOVA/ Chi-square	Under-represented White	Representative White	Over-represented White	ANOVA/ Chi-square
	Mean (SD)	Mean (SD)	Mean (SD)	R^2/ χ^2 p-value	Mean (SD)	Mean (SD)	Mean (SD)	R^2 / χ^2 (p-value)
Cohort-standardized mean test scores	-0.21 (0.41)	-0.29 (0.47)	0.08 (0.45)	R^2=.081 p<.00005	-0.06 (0.35)	0.06 (0.38)	0.14 (0.33)	R^2=0.047 p<.00005
N	7,336				12,104			

Multivariate Analysis of Standardized Test Scores

I regress standardized test scores on White representation and other school and neighborhood characteristics. Regression estimates are presented in Table 6-4. I analyze urban schools separately from suburban and rural ones. Both models apply district fixed effects and robust standard errors clustered at the district level. The models control for neighborhood size and wealth, namely the logged median household income and the neighborhood population. The models also control for the following school characteristics: the percentage of White K-4th graders, the percentage of Black K-4th graders, the total number of students attending the school, the percentage of students eligible for FRL, the percentage of students with disabilities (IEPs), and the percentage of students with LEP. The model further controls for the school choice context by controlling for the number of private, magnet, and charter schools within a 2-mile radius of the neighborhood.

In urban schools, White representation is a not significant predictor of mean school test scores, which indicates that what appeared to be a positive relationship between the two measures is completely explained by covariates in the model. Similarly, the percentage of White K-4th graders does not predict a change in average 4th grade test scores in either model ($p<.001$). The only racial composition variable that is significant is the percentage of Black K-4th graders, which predicts significantly lower mean test scores in both models ($p<.001$). The lack of a relationship between White representation and test scores runs contrary to my hypothesis that White underrepresentation would predict lower mean test scores than other schools.

6-4. Estimates from Ordinary Least Squares Regression of Standardized Test Scores on White Representation in Neighborhood School and Other School and Neighborhood Characteristics, by Urbanicity

	Urban b (SE)	Suburban and rural b (SE)
White representation in school (vs. representative)		
Underrepresented White	-0.002	0.001
	(0.007)	(0.005)
Overrepresented White	-0.009	0.001
	(0.008)	(0.005)
% White K-4th grade (school)	0.000	-0.001
	(0.001)	(0.000)
% Black K-4th grade (school)	-0.004***	-0.004***
	(0.000)	(0.000)
Median household income (ln)	0.079***	0.098***
(neighborhood)	(0.019)	(0.014)
Population (ln) (neighborhood)	-0.042***	-0.045***
	(0.009)	(0.008)
# Private schools within 2 miles	0.009***	0.009***
(neighborhood)	(0.001)	(0.002)
# Magnet schools within 2 miles	0.003**	0.000
(neighborhood)	(0.001)	(0.004)
# Charter schools within 2 miles	-0.005*	-0.005
(neighborhood)	(0.003)	(0.006)
Total # students (in 100s) (school)	-0.001	-0.001
	(0.002)	(0.002)
% Students with FRL (school)	-0.010***	-0.010***
	(0.001)	(0.000)
% Students with disabilities (school)	-0.010***	-0.008***
	(0.001)	(0.001)
% Students with LEP (school)	0.003***	0.002***
	(0.001)	(0.000)
Constant	0.279	0.108
District fixed effects	X	X
N	6,032	11,458
Adjusted R^2	0.762	0.766

Descriptive Analysis of Gifted and Talented Programs

Next, I observe GAT programs as a dependent variable. GAT programming is an academic outcome that is very different from standardized tests. Unlike standardized tests, GAT programs are optional for schools. GAT programs are also, by definition, not available to all students at a school. In this way, GAT programs can be inequitable in one of two ways. They can be unavailable at the school level, which, if a GAT program is considered an asset, equally deprives all students at a school the opportunity to enroll. Alternately, they can be available in a school but fail to reflect the school population in some way, for example by race, gender, or language learner status, and disproportionately bar one or more groups of students from benefitting from the program. In the U.S., GAT programs are most commonly criticized for being disproportionately White (Ford, Grantham, and Whiting 2008; Grissom and Redding 2015; McBee 2010; McBee 2006) and that is the angle through which I measure GAT enrollment here.

I consider the relationship between GAT programs and the Whiteness of a school, in terms of both the percentage of White students and the school's White representation in comparison to its neighborhood. I look at both the presence of GAT programs as well as the White representation within GAT programs where they exist. I find strong evidence that in suburban and rural schools, the presence of GAT programs is responsive to the percentage of White students in the school; namely, a lower percentage of White students increases the chances that a suburban or rural school has a GAT program. I also find that in all schools regardless of urbanicity, there is a strong and inverse link between White representation in a school and White representation in its GAT program. Namely, White *under*representation at the school level increases the chances that the GAT program is *over*represented White, whereas White *over*representation in the school increases the chances that a GAT program is *under*represented White. Both these results, as well as my definition of White representation in GAT programs, are discussed in detail below.

GAT programs are the norm in elementary schools; 76% of all sampled schools offer a GAT program and report that students are enrolled in the GAT program in the 2015-16 school year. A descriptive summary of GAT programming by urbanicity is presented in Table 6-5. GAT programs are slightly more prevalent in urban schools (82%) than suburban and rural schools (73%).

When we look at the bivariate relationships between GAT programs, on the one hand, and White composition and White representation on the other hand, we see that in urban schools, schools that have a larger White composition or that over-represent Whites vis-à-vis their neighborhoods, are more likely to have GAT programs (Tables 6-6 and 6-7). In suburban and rural schools, we see the opposite pattern; schools with a smaller White composition or that underrepresent White students vis-à-vis their neighborhoods are the ones more likely to have a GAT program. It may follow that if GAT programs are created as an effort of White parents or administrators to create a Whiter school-within-a-school, this is more likely to be the case in suburban and rural schools.

Table 6-5. Descriptive Statistics of GAT Program Measures by Urbanicity						
	Total				Urban	Suburban and rural
	Mean	SD	Minimum	Maximum	Mean	Mean
GAT program offered (share)	0.762				0.820	0.732
GAT program White representation (continuous, percentage points)[1]	2.027	16.954	-100.000	98.645	3.544	2.140
GAT program White representation (categorical, share)[1]						
Underrepresented White	0.368				0.361	0.372
Representative White	0.134				0.142	0.130
Overrepresented White	0.498				0.500	0.498
N	17,490				6,032	11,458

Table 6-6. Bivariate Relationship Between % White K-4th Graders in School and GAT Program Measures

	Urban % White K-4th grade		Suburban and Rural % White K-4th grade	
	Pearson's r/ %	p-value/ R^2	Pearson's r/ %	p-value/ R^2
GAT program		R^2=.022		R^2=.069
No	26.27%	p<.00005	75.69%	p<.00005
Yes	36.98%		58.02%	
GAT program White representation[1]		R^2=.024 p<.00005		R^2=.014 p<.00005
Underrepresented White	41.66%		62.50%	
Representative White	28.46%		56.58%	
Overrepresented White	36.01%		55.05%	
N	6,032		11,458	

[1] GAT White representation is only calculated for schools with a GAT program.

Next, I examine White representation within GAT programs. I construct a continuous measure of White representation in GAT programs. The measure is intended to determine whether a GAT program closely reflects its school setting in terms of the percentage of White students enrolled. I construct the GAT program White representation measure by subtracting the percentage of White program-4th graders in a school from the percentage of White K-4th graders in a GAT program. A positive difference indicates that the GAT program is Whiter than the school, or overrepresented White. A negative difference indicates that the GAT program is less White than the school, or underrepresented White. Note that GAT program White representation always uses the *school* as a reference, which is different from the school-level White representation variable. White underrepresentation in a GAT program is a *comparison to the school,* whereas White underrepresentation in neighborhood schools, is a *comparison to the neighborhood*.

Table 6-7. Bivariate Relationships Between White Representation and GAT Program Measures by Urbanicity

	Urban				Suburban and Rural			
	Under-represented White	Representative White	Over-represented White	ANOVA/ Chi-square	Under-represented White	Representative White	Over-represented White	ANOVA/ Chi-square
	Mean (SD)	Mean (SD)	Mean (SD)	R^2/ χ^2 p-value	Mean (SD)	Mean (SD)	Mean (SD)	R^2 / χ^2 (p-value)
GAT program offered (share)	0.79	0.74	0.88	χ^2=99.54 p<.0005	0.78	0.75	0.67	χ^2=127.23 p<.0005
GAT program White representation (continuous)[1]	6.96 (16.59)	1.12 (12.66)	-1.98 (17.14)	R^2=.052 p<.00005	7.48 (17.39)	1.28 (14.61)	-2.69 (16.34)	R^2=0.0617 p<.00005
GAT program White representation (categorical, %)[1]				χ^2=551.86 p<.0005				χ^2=551.86 p<.0005
Underrepresented White	26.05	29.60	51.20		25.67	35.06	48.21	
Representative White	17.87	35.96	10.13		13.28	18.40	13.77	
Overrepresented White	56.08	34.44	38.67		61.05	46.54	38.02	
N	7,336				12,104			

In schools that have a GAT program, White students are on average slightly overrepresented in the program, in comparison to the larger student body of the school (Table 6-5). Average White overrepresentation in GAT programs is similar between urban and non-urban schools. Urban GAT programs are an average of 3.5 percentage points Whiter than the schools to which they belong. Suburban and rural GAT programs (combined) are 2.1 percentage points Whiter than the schools to which they belong.

I construct a categorical measure of GAT White representation that resembles the categorical measure of school-level White representation. I divide GAT White representation into three categories: 1) underrepresented White GAT, 2) representative White GAT, and 3) overrepresented White GAT. Underrepresented White GAT programs are defined as at least two percentage points less White than the school at large. Representative White GAT programs are defined as within -2 percentage points and +2 percentage points of the percentage of White students at the school. Overrepresented White GAT programs are defined as Whiter than the school overall by at least two percentage points.

Regardless of urbanicity, about half of schools with a GAT program have an overrepresented White GAT program (50.0% for urban schools and 49.8% for suburban and rural schools) (Table 6-5). This coincides with previous research that finds disproportionately high White presence in GAT programs (McBee 2010). However, a sizeable share of GAT programs, over a third (36.8%), are underrepresented White.

Whiter schools seem to go hand in hand with underrepresented White GAT programs (Table 6-6). Urban schools with an underrepresented White GAT program have a higher-than-average share of White students (42% White) compared to all other urban schools. In suburban and rural schools, we see the same pattern. Whiter schools have White underrepresented GAT programs. Schools with White underrepresented GAT programs are 63% White compared to 57% for schools with representative White GAT programs and 55% White for schools with overrepresented White programs.

I now turn to White representation in the school in relation to White representation in the GAT program (Table 6-7). Schools that are less White than their neighborhoods tend to have GAT programs that are Whiter than the schools. In urban settings, White underrepresented schools have GAT programs that are an average of 7.0 percentage points Whiter than would be expected based on the racial makeup of the schools. Similarly, in suburban and rural schools, White underrepresented schools have GAT programs that are 7.5 percentage points Whiter than expected. This suggests that in schools that do not reflect the neighborhood in terms of Whiteness, the subset of GAT students may still reflect the Whiteness of the neighborhood or in many cases exceed it. This tentatively supports White opportunity hoarding, in this case of GAT program resources, particularly in schools where White students are less prevalent than expected based on their presence in the neighborhood.

Examining GAT representation in categorical terms does not change the result but may add a helpful frame (Table 6-7). In urban areas, 56% of underrepresented White schools with a GAT program have an overrepresented White GAT program (compared to 34% of representative White schools and 39% of overrepresented White schools). In suburban and rural areas, 61% of underrepresented White schools with a GAT program have an overrepresented White GAT program (compared to 47% of representative White schools and 38% overrepresented White schools). In sum, GAT programs are more likely to draw disproportionately from the White student population in schools where Whites are underrepresented.

Multivariate Analysis of Gifted and Talented Programs

I use logistic regression to predict the presence of a GAT program in a school. Average marginal effects for select variables are presented in Table 6-8. I do not use district fixed effects because many districts have no within-district variation (either all schools either have a GAT program or none of them do) and because some schools in the sample represent the only elementary school in their district. Instead, to approximate district fixed effects, I control for every predictor at its district mean. These values are also z-standardized and therefore represent their deviation from the districtwide mean. This achieves a similar purpose as applying district fixed effects, which is to differentiate between between-district and within-district effects.

Models are presented for urban and non-urban schools separately. Both models control for school and neighborhood characteristics, including neighborhood population, neighborhood median income, school size, the percentage of White K-4th graders, the percentage of Black K-4th graders, the percentage of students who receive FRL, the percentage of students with disabilities (IEPs), the percentage of students with LEP, and the number of private, magnet, and charter schools within two miles of the school.

I find no evidence that White representation in the school is a significant predictor of whether a school offers at GAT program. In suburban and rural schools, however, a larger percentage of White students significantly decreases the chances that a school has

Table 6-8. Average Marginal Effects (AME) on the Probability of GAT Program Offering Based on Logistic Regression on School and Neighborhood Characteristics, By Urbanicity and Controlling for the District Means of Predictors

	Urban	Suburban and rural
	AME (SE)	AME (SE)
White underrepresentation (compared to parity)	0.006	-0.002
	(0.007)	(0.008)
White overrepresentation (compared to parity)	0.003	0.004
	(0.007)	(0.008)
% White K-4th graders (school)	0.000	-0.001***
	(0.000)	(0.000)
Model controls for all predictors at district means	X	X
N	6,032	11,458

a GAT program ($p<.001$). The magnitude of the average marginal effect is not large; one standard deviation increase in schoolwide Whiteness (a 29.8 percentage point increase) decreases the likelihood that a suburban or rural school will have a GAT program by only 5.0 percentage points. In urban schools, I find no connection between the percentage of White students in a school and the presence of a GAT program. Suburban and rural GAT program offerings are responsive to race in a way that they are not in urban schools, but the magnitude of the effect is relatively small.

Next, I use multinomial logistic regression to predict White representation *in GAT programs* on school and neighborhood characteristics. AMEs for the separate urban and non-urban models are presented in Table 6-9. Like before, both models presented control for all predictors at their z-standardized district means, in an approximation of district fixed effects. The full model, with all control variables and district means, is available in Appendix F. Schools without a GAT program are excluded from this analysis because they cannot have GAT White representation one way or another.

As in prior analyses, neighborhood and school controls include neighborhood population, median household wealth, school size, the percentage of students who receive FRL, the percentage of students with disabilities (IEPs), the percentage of students with LEP, and the number of private, magnet, and charter schools within two miles of the school.

In general, the models reinforce a pattern that emerged in the bivariate analysis; underrepresented White schools have overrepresented White GAT programs, and vice versa.

Table 6-9. Average Marginal Effects (AME) on the Probability of White Representation in GAT Programs Based on Multinomial Logistic Regression on School and Neighborhood Characteristics

	Urban schools			Suburban and rural schools		
	GAT Underrepresented White	GAT Representative White	GAT Overrepresented White	GAT Underrepresented White	GAT Representative White	GAT Overrepresented White
	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)
White underrepresentation (compared to parity)	-0.138*** (0.019)	-0.058*** (0.013)	0.079*** (0.019)	-0.066*** (0.016)	-0.008 (0.011)	0.074*** (0.018)
White overrepresentation (compared to parity)	0.048* (0.023)	0.011 (0.015)	-0.060* (0.024)	0.064*** (0.018)	0.001 (0.013)	-0.065*** (0.019)
% White K-4th graders	0.002* (0.001)	0.001 (0.001)	-0.003** (0.001)	0.002* (0.001)	0.001 (0.001)	-0.003** (0.001)
District mean White underrepresentation (z-standardized)	-0.036 (0.022)	-0.007 (0.013)	0.043 (0.025)	-0.024 (0.015)	0.006 (0.012)	0.018 (0.017)
District mean White overrepresentation (z-standardized)	-0.011 (0.021)	-0.004 (0.016)	0.007 (0.027)	0.024 (0.014)	0.020 (0.011)	-0.044** (0.014)
District mean % White K-4th graders (z-standardized)	-0.047 (0.037)	-0.040 (0.023)	0.087* (0.038)	-0.102** (0.031)	-0.006 (0.016)	0.108*** (0.023)
N	4947			8389		

*p< .05 **p<.01 ***p<.001, two-tailed tests

Note: Includes only observations with a GAT program. Both models control for other neighborhood and school characteristics as well as all predictors at district means; full models and models without district-level controls in Appendix F.

Beginning with urban schools, White *under*representation in the school significantly increases the chances that a GAT program will be *over*represented White by 7.9 percentage points ($p<.001$). White underrepresentation in the school also decreases the chances that a GAT program is representative White by 5.8 ($p<.001$) and decreases the chances that a GAT program is underrepresented White by 13.8 percentage points ($p<.01$). White *over*representation in the school, on the other hand, significantly increases, by 4.8 percentage points, the chances that a GAT program is *under*represented White ($p<.05$). White overrepresentation in the school also significantly decreases the chances that a GAT program is overrepresented White by 6.0 percentage points ($p<.01$), but does not alter the chances that a GAT program is representative White.

Continuing with urban schools, the percentage of White K-4th graders in the school is also a significant predictor of White representation in GAT programs. An increase in the percentage of White K-4th graders increases the probability that a GAT program will be underrepresented White and significantly increases the chances of a program that is Whiter than the school. A standard deviation increase (27.6 percentage points) in the percentage of White K-4th graders increases the probability of an underrepresented White GAT program by 6.9 percentage points ($p<.05$). The same one standard deviation increase in the portion of White students in the school decreases the chances by 8.8 percentage points that a GAT program will be overrepresented White.

Suburban and rural schools follow a similar pattern. White underrepresentation in the school increases by 7.4 percentage points the chances that a GAT program is overrepresented White ($p<.001$). White underrepresentation in schools also decreases by 6.6 percentage points the probability that a GAT program is underrepresented White

($p<.001$). Conversely, White overrepresentation predicts a higher chance of White underrepresentation in the GAT program, by 6.4 percentage points ($p<.001$). White overrepresentation also predicts a 6.5 percentage point lower chance that a GAT program is overrepresented White ($p<.001$).

In suburban and rural schools, the percentage of White K-4th graders significantly decreases the chances that a GAT program is underrepresented and increases the chances it is overrepresented White. This closely mirrors urban catchment areas. A one standard deviation increase in the percentage of White K-4th graders (which again, for suburban and rural schools amounts to 29.8 percentage points) predicts a 6.9 percentage point increase in the likelihood that a GAT program is underrepresented White and a 8.8 decrease in the likelihood that a GAT program is overrepresented White.

Discussion

This chapter finds no connection between White representation in neighborhood schools and school standardized test scores. A test of the relationship between White representation in schools and mean standardized test scores did not provide support for the hypothesis that underrepresented White schools fare any differently than schools that racially match the White presence in their neighborhood.

I also test the relationship between White representation and GAT programming. GAT programming measures an altogether different academic aspect of a school. Unlike standardized test scores, GAT programming is not a direct measure of student academic performance. It also differs from standardized testing in that it does not "touch" every student nor even every school. The decision to offer a GAT program rests at the school-or district-level. I find that GAT program offerings in suburban and rural schools appear to respond to the racial makeup of the school. Whiter schools are less likely to offer a GAT program and schools that are less White are more likely to offer one.

In this chapter, I measure White racial disproportionality (or representation) in GAT programming and its relationship with White representation at the school level. Once a GAT program is formed, it is the role of school staff to identify and enroll GAT students. In this chapter so far, I have largely written about GAT program White representation as if it is free of human actors, when really GAT program enrollment is a bureaucratic progress of student identification, administrative approval, and sometimes parental approval. Like any bureaucratic process, racism can interfere both structurally and interpersonally to prevent an equitable chance for all students to access GAT programs. For schools with GAT programs, I find that in underrepresented White schools, White students disproportionately cluster in GAT programs in a way that they do not in schools with higher White representation.

CHAPTER 7

CONCLUSION

Findings

In the introduction, I outlined three theoretical pathways for how White representation might, or might not, affect neighborhood schools: 1) opportunity hoarding, 2) covariates explain differences, and 3) crowding out. I hypothesized that White underrepresented schools might receive fewer resources due to unmeasured opportunity hoarding by White families with school age children. In his book *Dream Hoarders*, Richard Reeves (2018) provides a helpful framing of Tilly's (1998) theory of opportunity hoarding. Reeves explains that "opportunity hoarding does not result from the workings of a large machine but from the cumulative effect of individual choices and preferences." Seemingly independent individual choices may accumulate in a way that produces group-level inequality. I predicted that the disproportionate exit from neighborhood schools by individuals of a powerful racial group might manifest in financial or academic losses for neighborhood schools. I cast a wide net of school outcomes, from teacher salaries to GAT programs, to test this hypothesis.

Overall, the findings here offer mixed support for the "covariates explain differences" and the opportunity hoarding views of White representation. In general, school outcomes are less favorable for White underrepresented schools compared to representative and overrepresented schools. Controlling for school and neighborhood covariates explains many, but not all, of these differences.

White underrepresented schools have significantly lower mean teacher salaries, net of the percentage of White students within the school and other covariates, as well as lower per-pupil personnel expenditures in urban schools. Because White representation is not exogenous to school funding variables, I cannot eliminate the possibility that unobserved covariates are responsible for the association. Should the association between White representation and school funding not be spurious, I suspect that the lower salary expenditure, for both metrics, may be reflective of a lack of teacher experience. This is supported by the finding that White underrepresented schools have significantly lower student-teacher ratios. In combination with lower funding, lower student-teacher ratios suggest that schools are not experiencing staffing shortages, but rather have a greater number of staff in the building who are poorly compensated compared to staff at other schools. I propose two possible explanations, both of which warrant further study: either White underrepresented schools struggle to attract and retain more experienced teachers or, alternately, White families are more adept than non-White families at avoiding schools with inexperienced and/or underpaid staff. Both potentialities are in line with the theory of opportunity hoarding. In the former, the mechanism is the hiring and retention of experienced teachers that results in a larger share of such teachers in representative White and overrepresented White schools. In the latter, the mechanism is the family knowledge and resources that permits White families a better chance of exiting a neighborhood school with inexperienced teachers. In either case, the finding is interesting and suggests the need for further research. We need to know more about the connection between White underrepresentation and teacher experience to confirm my hypothesis that a higher prevalence of inexperienced teachers is the cause of lower teacher salaries and (in urban schools) per pupil personnel expenditures in White underrepresented schools.

I find no connection between White representation and whether a school has a school-supporting nonprofit. Descriptive analyses indicate that White underrepresented schools are less likely to have a high-revenue nonprofit, but this association disappears after controlling for school and neighborhood characteristics. I similarly find no connection between the percentage of White students in a school and nonprofit presence. Instead, the economic composition of the school and neighborhood are the most salient drivers of school nonprofit presence and nonprofit revenue. This points to opportunity hoarding by those who are economically advantaged, but not White opportunity hoarding net of economic measures. This result contradicts my hypothesis. I hypothesized that White opportunity hoarding might materialize in the form of diminished nonprofit outcomes for White underrepresented schools, in line with previous research that connects Whiteness in schools to nonprofit outcomes (Murray et al. 2019; Nelson and Gazley 2014) and to White opportunity hoarding via school supporting nonprofits (Murray et al. 2020; Murray 2019). For example, Murray and coauthors (2019), find that high-revenue nonprofits are overwhelmingly in White, homogenous schools in North Carolina in 1999-2015. I do not replicate this finding, perhaps because of differences in the geography studied, years included, or neighborhood economic measures (rather than median household income, Murray et al. (2019) use the unemployment rate and single parent household rate as neighborhood controls). My finding instead supports the second theoretical pathway, that covariates explain the differences between schools that differ in terms of White representation. White underrepresented schools tend to sit in poorer neighborhoods and to serve poorer students, and both conditions predict a lower probability of having a school supporting nonprofit and a lower probability of having a high-revenue nonprofit. While it may seem an obvious conclusion, that money leads to well-funded nonprofits, it echoes the findings of other researchers who have found that philanthropic funds tend to be funneled to the students who need them the least (Brown, Sargrad, and Benner 2017; Colby and Ortman 2015; Murray et al. 2019). I echo the call of previous researchers (Brown, Sargrad, and Benner 2017) for the better accounting of private dollars to public schools and for district policies that redistribute donations to the schools that need them most. There is also a need for more research on policies that redistribute donations across public schools while minimizing the risks associated with doing so. Such risks include sparking animosity between schools and decreasing total donation funds. The research has established that private donations to public schools exacerbate school funding inequity but has done a less thorough job of evaluating which state and district policies most effectively foster a progressive, rather than regressive, distribution of private funding (Brown, Sargrad, and Benner 2017).

I also find no statistically significant relationship between White representation and mean school test scores. The test score advantage for White overrepresented school that appeared in the descriptive bivariate analysis is attributed to other covariates in the model, again supporting the second theoretical pathway that the covariates of White representation are more important for school outcomes. For future research, I suggest an investigation into the relationship between White representation and racial test score gaps. It may be that White representation is connected to within-school test score disparities rather than average differences between schools. There is evidence that schoolwide achievement and racial achievement gaps are uncorrelated (Matheny et al. 2021).

White representation appears to influence the racial composition of GAT programs in a manner that supports the theory of opportunity hoarding. Schools that are less White than their neighborhoods tend to have GAT programs that are significantly Whiter than the schools. This is a concerning finding that suggests that White underrepresentation leads to inequity in access to GAT programming for non-White students. This finding is consistent with a story of GAT programming becoming a Whiter school-within-a-school for White students (McBee 2010). White parents may advocate more forcefully for a GAT placement for their child in an environment in which they feel underrepresented. In addition, administrators may encourage such disparate placements in an attempt to appease White parents and retain their children in the school. More research on the connection between school composition, neighborhood composition, and GAT placement is needed to understand why White representation in the school is so tightly connected to racially imbalanced GAT programs.

Study Limitations

All three substantive chapters of this dissertation have limitations. The foremost limitation is that the cross-sectional analyses presented here do not support causal inference. The relationship between White representation and school characteristics is not unidirectional, but rather goes both ways; White representation likely affects school characteristics and school characteristics likely impact White representation. A longitudinal conception of the analyses here would provide more insight into the relationship between White representation and school characteristics. Indeed, a longitudinal study is a logical extension of this research.

The tradeoff to working with national school-level data is a loss of texture and detail. A few of the measures employed in this study may be too blunt to capture the nuanced reality of what I intend to address in the research questions. For example, the dichotomous measure of nonprofit revenue data (below $50,000 vs. $50,000 and above) may miss important differences in nonprofit spending that fall outside that binary. I also do not capture how nonprofit practices differ across schools. In another example, mean school test scores may wash out student-level and group-level differences in student achievement. The mean school test scores represent aggregates of aggregates (aggregates of student proficiency levels that subsequently aggregated across grades and years), all of which ultimately represent a variety of different assessments depending on the state of origin. A study of individual student data or achievement gap measures might paint a different picture than what I am able to capture here. The decision to observe a wide breadth of data may have sacrificed the depth of some of the conclusions included in this study.

Due to a lack of data availability and data validity concerns, I was unable to include many variables that would have been relevant to this study. Variables of interest that were not available include mean teacher experience, parental involvement in schools, the sources of nonprofit donations, and racial achievement gap measures. I also excluded non-personnel school expenditures due to concerns about data validity (Shores and Ejdemyr 2017).

The lack of reliable student income data is a limitation to this and many other studies. Overall, this study employs a large amount of administrative data of relatively high quality at the level of the school, for which I am grateful. The one metric that is of high importance and unfortunately low validity is the percentage of students who receive free or reduced lunch, a measure which has been critiqued as a flawed representation of student poverty (Harwell and LeBeau 2010). I use this metric in the absence of an alternative but hesitate to give too much credence to the conclusions related to this variable.

Another limitation is the measure of White representation itself. In general, using a racial composition variable, in this case White representation, as an independent variable is like measuring a symptom rather than the disease, or, put another way, measuring a correlate of the desired object of study when the object itself is difficult to measure. What one hopes to measure is inequitable practices based on race, not the effects of the racial categories themselves. In the absence of a method to observe the complex ways that families act within school systems and school systems respond to families, White representation serves as a stand-in measure for the different ways that White families might use their political, social, and financial power in a school setting.

Future Research

Moving beyond a White/non-White binary is a critical next step in the research of racial representation in schools and, unlike other suggestions here, is immediately actionable from a data availability standpoint. White underrepresentation comes, by definition, with an overrepresentation of other racial groups and White overrepresentation comes with a corresponding underrepresentation of other racial groups. In this study I did not closely examine the patterns associated with any racial group besides White, but I think that observing the enrollment patterns of other racial groups, and particularly Latino children, as I explain more below, would be a fruitful object of future study.

Another avenue for future research based on this study is a further investigation of White *over*represented neighborhood schools. This dissertation from the outset was intended to interrogate the differences between White underrepresented schools and those that represent their neighborhoods, with White overrepresentation as a secondary focus. An unanticipated finding in this study was an abundance of White overrepresented schools. White overrepresentation occurs when White children cluster in a neighborhood school at a higher rate than the children of other racial groups. This could be due to families with non-White children availing themselves of school choice options at a higher rate or it could be due to intra-district choice options that permit out-of-catchment White students to enroll in a neighborhood school at a higher rate. Thirty-one percent of neighborhood schools in the sample are overrepresented White. I was surprised to find that even the elementary school across the street from my house, which I gazed upon frequently while working on this project, was in fact nine percentage points Whiter than you would expect based on the racial makeup of the children living in my own neighborhood (I further learned that I know at least one culprit; I have an acquaintance who sends her White child to that school from another catchment area). In the story of White representation in public schools, overrepresentation may be as interesting a phenomenon as underrepresentation. More research is needed to understand the causes and effects of White overrepresentation in neighborhood schools.

The changes over time in White representation are also worthy of further study. It is even possible that the average neighborhood school in the U.S. is no longer underrepresented White. The White representation data used for this study captures the state of schools in 2010, but trends in school choice seem to have shifted in the intervening decade. This is not mere speculation; there is evidence of a recent exit from neighborhood schools of Latino students that may have shifted the balance for White representation. In 2007, 75% of Latino students attended their neighborhood school compared to only 70% of White students. By 2016, the roles reversed and only 67% of Latino students attended their neighborhood school compared to 72% of White students (Wang, Rathburn, and Musu 2019). This shift coincides with a decline in private school enrollment, and particularly religious Catholic schools, which is White Americans' preferred method for exiting neighborhood schools (Murnane and Reardon 2018). The recent shift of Latino students away from neighborhood schools deserves a closer look, particularly considering the Latino school-age children are the fasted growing racial group in the country.

Finally, as stated previously, there is a need for better data on the economic composition of children in traditional public schools. Many of the analyses in this dissertation offer support for the notion that the economic composition of a school may be more important than its racial composition. However, administrative datasets published by government agencies such as the CRDC and the NCES consistently collect more accurate data about the race of students than the economic position of students. High-quality data for both measures are essential in order to monitor and eradicate school inequality.

REFERENCES

References

Alesina, Alberto, Reza Baqir and William Easterly. 1999. "Public Goods and Ethnic Divisions." *The Quarterly Journal of Economics* 114(4):1243-1284.

Altenhofen, S., Berends, M., & White, T. G. 2016. School choice decision making among suburban, high-income parents. AERA Open, 2(1), 2332858415624098.

Atchison, Drew, Bruce Baker, Jesse Levin and Karen Manship. 2017. "Exploring the Quality of School-Level Expenditure Data: Practices and Lessons Learned in Nine Sites." *Office of Planning, Evaluation and Policy Development, US Department of Education*.

Belfield, Clive R., and Henry M. Levin. 2002. "The Effects of Competition between Schools on Educational Outcomes: A Review for the United States." *Review of Educational Research* 72(2):279-341.

Bischoff, Kendra, and Laura Tach. 2018. "The Racial Composition of Neighborhoods and Local Schools: The Role of Diversity, Inequality, and School Choice." *City & Community* 17(3):675-701.

Bonilla-Silva, Eduardo. 2010. Racism without racists: Color-blind racism and racial inequality in contemporary America. Rowman & Littlefied.

Brown, Catherine, Scott Sargrad and Meg Benner. 2017. "Hidden Money: The Outsized Role of Parent Contributions in School Finance." *Washington, DC: Center for American Progress. Accessed March* 5:2018.

Burdick-Will, Julia. 2017. "Neighbors but Not Classmates: Neighborhood Disadvantage, Local Violent Crime, and the Heterogeneity of Educational Experiences in Chicago." *American Journal of Education* 124(1):37-65.

Candipan, Jennifer. 2019. "Neighbourhood Change and the Neighbourhood-School Gap." *Urban Studies* 56(15):3308-3333.

Chetty, Raj, Nathaniel Hendren and Lawrence F. Katz. 2016. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment." *American Economic Review* 106(4):855-902.

Chmielewski, Anna, and Sean Reardon. 2016. "Pathways State of the Union: The Poverty and Inequality Report 2016.".

Colby, Sandra, and Jennifer M. Ortman. 2015. ""Projections of the Size and Composition of the US Population: 2014 to 2060"." *Projections of the Size and Composition of the US Population: 2014 to 2060*.

College of William and Mary and the Minnesota Population Center. 2011. "School Attendance Boundary Information System (SABINS): Version 1.0." (http://www.sabinsdata.org).

Cordes, Sarah A. 2018. "In Pursuit of the Common Good: The Spillover Effects of Charter Schools on Public School Students in New York City." *Education Finance and Policy* 13(4):484-512.

Cucchiara, Maia. 2013. *Marketing Schools, Marketing Cities: Who Wins and Who Loses when Schools Become Urban Amenities.* University of Chicago Press.

De Lamo White, Caroline, and Lixian Jin. 2011. "Evaluation of Speech and Language Assessment Approaches with Bilingual Children." *International Journal of Language & Communication Disorders* 46(6):613-627.

Denice, Patrick and Bethany Gross. 2016. "Choice, preferences, and constraints: Evidence from public school applications in Denver." Sociology of Education. 89(4):300-320. SAGE Publications: Los Angeles, CA.

Denison, Dwight V., William T. Hartman, Leanna Stiefel and Michele M. Deegan. 2011. "A Model for School-Level Resource Reporting: Benefits and Challenges." *Public Performance & Management Review* 35(1):29-53.

Dhar, Paramita, and Stephen L. Ross. 2012. "School District Quality and Property Values: Examining Differences Along School District Boundaries." *Journal of Urban Economics* 71(1):18-25.

Dika, Sandra L., and Kusum Singh. 2002. "Applications of Social Capital in Educational Literature: A Critical Synthesis." *Review of Educational Research* 72(1):31-60.

Downey, Douglas B., and Dennis J. Condron. 2016. "Fifty Years since the Coleman Report Rethinking the Relationship between Schools and Inequality." *Sociology of Education*:0038040716651676.

Epple, Dennis, Richard Romano and Ron Zimmer. 2016. "Charter schools: A survey of research on their characteristics and effectiveness." Pp. 139-208 in *Handbook of the Economics of Education.* Vol. 5"Charter schools: A survey of research on their characteristics and effectiveness." Elsevier.

Fahle, Erin M., Benjamin R. Shear, Demetra Kalogrides, Sean F. Reardon, Belen Chavez and Andrew D. Ho. 2019. "Stanford Education Data Archive Technical Documentation Version 3.0 July 2019.".

Ford, Donna Y., Tarek C. Grantham and Gilman W. Whiting. 2008. "Culturally and Linguistically Diverse Students in Gifted Education: Recruitment and Retention Issues." *Exceptional Children* 74(3):289-306.

Frankenberg, Erica, Stephen Kotok, Kai Schafft and Bryan Mann. 2017. "Exploring School Choice and the Consequences for Student Racial Segregation within Pennsylvania's Charter School Transfers." *Education Policy Analysis Archives/Archivos Analíticos De Políticas Educativas* (25):1-34.

Frey, William. 2019. *Less than half of US children under 15 are White, Census shows.*

Frisch, Abigail M. 2017. "The Class is Greener on the Other Side: How Private Donations to Public Schools Play into Fair Funding." *Duke LJ* 67:427.

Galton, Francis. 1869. *Hereditary Genius: An Inquiry into its Laws and Consequences.* Macmillan.

Glomm, Gerhard, Douglas Harris and Te-Fen Lo. 2005. "Charter School Location." *Economics of Education Review* 24(4):451-457.

Goldhaber, Dan D., and Eric R. Eide. 2003. "Methodological Thoughts on Measuring the Impact of Private Sector Competition on the Educational Marketplace." *Educational Evaluation and Policy Analysis* 25(2):217-232.

Good, Ryan M., and Katharine L. Nelson. 2020. "With a Little Help from our Friends: Private Fundraising and Public Schools in Philadelphia." *Journal of Education Policy*:1-24.

Goyette, Kimberly. 2008. "Race, Social Background, and School Choice Options." *Equity & Excellence in Education* 41(1):114-129.

Goyette, Kimberly, John Iceland and Elliot Weininger. 2014. "Moving for the Kids: Examining the Influence of Children on White Residential Segregation." *City & Community* 13(2):158-178.

Grady, Sarah, Stacey Bielick and Susan Aud. 2010. "Trends in the use of School Choice: 1993 to 2007. Statistical Analysis Report. NCES 2010-004." *National Center for Education Statistics*.

Grissom, Jason A., and Christopher Redding. 2015. "Discretion and Disproportionality: Explaining the Underrepresentation of High-Achieving Students of Color in Gifted Programs." *Aera Open* 2(1):2332858415622175.

Hall, Matthew, and Jacob Hibel. 2017. "Latino Students and White Migration from School Districts, 1980-2010." *Social Problems* 64(4):457-475.

Harwell, Michael, and Brandon LeBeau. 2010. "Student Eligibility for a Free Lunch as an SES Measure in Education Research." *Educational Researcher* 39(2):120-131.

Hosmer Jr, David W., Stanley Lemeshow and Rodney X. Sturdivant. 2013. *Applied Logistic Regression.* John Wiley & Sons.

Houston, David M., and Jeffrey R. Henig. 2019. "The Effects of Student Growth Data on School District Choice: Evidence from a Survey Experiment.".

Iceland, John, Daniel H. Weinberg and Erika Steinmetz. 2002. *Racial and Ethnic Residential Segregation in the United States 1980-2000.*Bureau of Census.

Internal Revenue Service. 2019. "Exempt Organizations Business Master File Extract 2015." (https://www.irs.gov/charities-non-profits/exempt-organizations-business-master-file-extract-eo-bmf).

Jackson, C. K., Rucker C. Johnson and Claudia Persico. 2016. "The Effects of School Spending on Educational and Economic Outcomes: Evidence from School Finance Reforms." *The Quarterly Journal of Economics* 131(1):157-218.

Kids Count Data Center. 2019. "Child population by race and age group in the United States.", Retrieved 1/20/, 2020. (https://datacenter.kidscount.org/data/tables/8446-child-population-by-race-and-age-group?loc=1&loct=1#detailed/1/any/false/37/68,69,67,12,70,66,71,13|63,30/17077,17078).

Lacireno-Paquet, N., & Brantley, C. 2008. Who chooses schools and why: The characteristics and motivations of families who actively choose schools. Brief for Great Lakes Center for Education Research and Practice, East Lansing, MI.

Ladd, Helen F., and Lucy C. Sorensen. 2017. "Returns to Teacher Experience: Student Achievement and Motivation in Middle School." *Education Finance and Policy* 12(2):241-279.

Lareau, Annette, and Kimberly Goyette. 2014. *Choosing Homes, Choosing Schools.* Russell Sage Foundation.

Lichter, Daniel T. 2013. "Integration Or Fragmentation? Racial Diversity and the American Future." *Demography* 50(2):359-391.

Long, J. S., and Jeremy Freese. 2014. *Regression Models for Categorical Dependent Variables using Stata.* College Station, Texas: Stata Press Publication, StataCorp LP.

Massey, Douglas S., and Nancy A. Denton. 1988. "The Dimensions of Residential Segregation." *Social Forces* 67(2):281-315.

Matheny, Kaylee, Marissa Thompson, Carrie Flores and Sean Reardon. 2021. *Uneven Progress: Recent Trends in Academic Performance Among U.S. School Districts (DRAFT).*The Educational Opportunity Project at Stanford University.

McBee, Matthew. 2010. "Examining the Probability of Identification for Gifted Programs for Students in Georgia Elementary Schools: A Multilevel Path Analysis Study." *Gifted Child Quarterly* 54(4):283-297.

McBee, Matthew T. 2006. "A Descriptive Analysis of Referral Sources for Gifted Identification Screening by Race and Socioeconomic Status." *Journal of Secondary Gifted Education* 17(2):103-111.

McWilliams, Julia A. 2019. *Compete Or Close: Traditional Neighborhood Schools Under Pressure.* ERIC.

Mendoza-Denton, Rodolfo. 2014. "A Social Psychological Perspective on the Achievement Gap in Standardized Test Performance between White and Minority Students: Implications for Assessment." *The Journal of Negro Education* 83(4):465-484.

Monarrez, Tomas, Brian Kisida and Matthew Chingos. 2019. "When is a School Segregated? Making Sense of Segregation 65 Years After" Brown V. Board of Education." Research Report." *Urban Institute*.

Mood, Carina. 2010. "Logistic Regression: Why we Cannot do what we Think we can do, and what we can do about It." *European Sociological Review* 26(1):67-82.

Murnane, Richard J., and Sean F. Reardon. 2018. "Long-Term Trends in Private School Enrollments by Family Income." *AERA Open* 4(1):2332858417751355.

Murray, Brittany C. 2019. "PTAs, Parent Involvement, and the Challenges of Relying on Private Money to Subsidize Public Education." *Phi Delta Kappan* 100(8):42-46.

Murray, Brittany, Thurston Domina, Linda Renzulli and Rebecca Boylan. 2019. "Civil Society Goes to School: Parent-Teacher Associations and the Equality of Educational Opportunity." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 5(3):41-63.

Murray, Brittany, Domina Thurston, Amy Petts, Linda Renzulli and Rebecca Boylan. 2020. "“We’re in this Together”: Bridging and Bonding Social Capital in Elementary School PTOs." *American Educational Research Journal* 57(5):2210-2244.

National Center for Education Statistics. 2011a. "Common Core of Data Public Elementary/Secondary School Universe Survey: School Year 2009–10.".

------. 2011b. "Local Education Agency (School District) Universe Survey 2009-10." *Institute of Education Sciences. U.S. Department of Education.*

National Center of Charitable Statistics. 2017. "NCCS Data Core Financial Files 2015.".

National Center of Education Statistics. 2012. "Private School Universe Survey 2010-11." *Institute of Education Sciences. U.S. Department of Education.*

------. 2016. "Comparable Wage Index for Teachers 2015 (LEA, County, and National)." *Education Demographic and Geographic Estimates. Institute of Education Sciences. U.S. Department of Education.*

------. 2019. "Common Core of Data School District Finance Survey (F-33) 2015-16 School Year.".

Nelson, Ashlyn A., and Beth Gazley. 2014. "The Rise of School-Supporting Nonprofits." *Education Finance and Policy* 9(4):541-566.

Nguyen-Hoang, Phuong, and John Yinger. 2011. "The Capitalization of School Quality into House Values: A Review." *Journal of Housing Economics* 20(1):30-48.

O'Brien, Rourke L. 2017. "Redistribution and the New Fiscal Sociology: Race and the Progressivity of State and Local Taxes." *American Journal of Sociology* 122(4):1015-1049.

Office of Civil Rights. 2011. "2009-10 Civil Rights Data Collection." *U.S. Department of Education*.

------. 2017. "2015-16 Civil Rights Data Collection.".

Omi, Michael, and Howard Winant. 2014. *Racial Formation in the United States.* Routledge.

Orfield, Gary, and Chungmei Lee. 2006. "Racial Transformation and the Changing Nature of Segregation.".

Owens, Ann. 2017. "Racial Residential Segregation of School-Age Children and Adults: The Role of Schooling as a Segregating Force." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 3(2):63-80.

------. 2020. "Unequal Opportunity: School and Neighborhood Segregation in the USA." *Race and Social Problems*(Online January 2020):1-13.

Reardon, S. F., A. D. Ho, B. R. Shear, E. M. Fahle, D. Kalogrides, H. Jang, B. Chavez, J. Buontempo and R. DiSalvo. 2019. "Stanford Education Data Archive (Version 3.0).".

Reardon, Sean F., and Ann Owens. 2014. "60 Years After Brown: Trends and Consequences of School Segregation." *Annual Review of Sociology* 40:199. doi: 10.1146/annurev-soc-071913-043152.

Reeves, Richard V. 2018. *Dream Hoarders: How the American Upper Middle Class is Leaving Everyone Else in the Dust, Why that is a Problem, and what to do about It.* Brookings Institution Press.

Reis, Sally M., and Joseph S. Renzulli. 2010. "Is there Still a Need for Gifted Education? an Examination of Current Research." *Learning and Individual Differences* 20(4):308-317.

Rinn, Anne, Rachel Mun and Jaret Hodges. 2020. *State of the States in Gifted Education 2018-19.*The Council of State Directors of Programs for the Gifted.

Saporito, Salvatore, Jana M. Chavers, Laura C. Nixon and Megan R. McQuiddy. 2007. "From here to there: Methods of Allocating Data between Census Geography and Socially Meaningful Areas." *Social Science Research* 36(3):897-920.

Saultz, Andrew, Dan Fitzpatrick and Rebecca Jacobsen. 2015. "Exploring the Supply Side: Factors Related to Charter School Openings in NYC." *Journal of School Choice* 9(3):446-466.

Schneider, Mark, and Jack Buckley. 2002. "What do Parents Want from Schools? Evidence from the Internet." *Educational Evaluation and Policy Analysis* 24(2):133-144.

Shapiro, Thomas. 2017. ""Wealth" in "State of the Union: The Poverty and Inequality Report."." *Stanford Center on Poverty and Inequality, Pathways Magazine*(Special Issue).

Shores, Kenneth, and Simon Ejdemyr. 2017. "Pulling Back the Curtain: Intra-District School Spending Inequality and its Correlates." *Available at SSRN 3009775*.

Sohoni, Deenesh, and Salvatore Saporito. 2009. "Mapping School Segregation: Using GIS to Explore Racial Segregation between Schools and their Corresponding Attendance Areas." *American Journal of Education* 115(4):569-600.

Sosina, Victoria E., and Ericka S. Weathers. 2019. "Pathways to Inequality: Between-District Segregation and Racial Disparities in School District Expenditures." *AERA Open* 5(3):2332858419872445.

Steele, Claude M., and Joshua Aronson. 1995. "Stereotype Threat and the Intellectual Test Performance of African Americans." *Journal of Personality and Social Psychology* 69(5):797-811.

Stein, M. L., Goldring, E. B., & Cravens, X. 2010. Do parents do as they say? Choosing Indianapolis charter schools. In M. Berends, M. Cannata, & E. B. Goldring (Eds.), School choice and school improvement.

Sternberg, Robert J., and Janet E. Davidson. 2005. *Conceptions of Giftedness.* Cambridge University Press.

Tilly, Charles. 1998. *Durable Inequality.* University of California Press.

U.S. Census. 2018. *Comparative Demographics Estimate Table CP05.*

U.S. Census Bureau. 2014. "2008-2012 American Community Survey 5-Years Public use Microdata Samples.".

Usher, Alexandra, and Nancy Kober. 2011. "Keeping Informed about School Vouchers: A Review of Major Developments and Research." *Center on Education Policy*.

Walton, Gregory M., and Steven J. Spencer. 2009. "Latent Ability: Grades and Test Scores Systematically Underestimate the Intellectual Ability of Negatively Stereotyped Students." *Psychological Science* 20(9):1132-1139.

Wang, Ke, Amy Rathburn and Lauren Musu. 2019. "School Choice in the United States: 2019. NCES 2019-106." *National Center for Education Statistics*.

Whitehurst, Grover J., N. Joo, R. V. Reeves and E. Rodrique. 2017. "Balancing Act: Schools, Neighborhoods, and Racial Imbalance." *Brookings Institution*.

Zuberi, Tukufu. 2001. *Thicker than Blood: How Racial Statistics Lie.* University of Minnesota Press.

APPENDIX A

LIST OF NONPROFIT EXCLUSION KEYWORDS

The following is a list of keywords that, when they appeared in a nonprofit name, resulted in the exclusion of that nonprofit organization from the pool of potential school-supporting nonprofit matches (with a few exceptions, detailed in Appendix C). The words were identified after extensive testing of the nonprofit matching procedure (described in Chapter 5 and Appendix B).

Words marked with a * are partial/root words intended to exclude either 1) a common abbreviation (such as “Assoc” for “Association” or 2) all iterations of the word, such as “Preserv” for “Preserve” and “Preservation.” Some words have more than one variation (e.g. 4H and 4-H). The elimination of the words below improved the precision of the school-to-nonprofit matching process.

4H	Band	Choir
4-H	Baptist	Choral
Abuse	Bar Assoc*	Christian
Acupuncture	Baseball	Church
Addiction	Bible	College
Adopt	Blood	Community College
Adventist	Botanical	Cultural
Animal	Cancer	Day School
Arboretum	Cardiovasc*	Dental
Assisted Living	Care	Diabetes
Athletic	Catholic	Diocese
Autism	Cemetery	Disabilit*
Basketball	Chamber	Disabl*
Ballet	Charitable	Disease

Dog Park
Drug
Economic
Epilep*
Episcopal
Evangel*
Fam* Foundation
Family Foundation
Fire Dep*
Fire Fight*
Food
Football
Furry
Golf
Gymnastic
Health
Healthcare
High School
Higher Education
Highschool
Hillel
Historic
Historical Preserv*
Holy Family
Homeless
Hospice
Hospital
Housing
Illness
Industrial
Inns of Court
Insurance
Islam
Jesuit
Jesus
Jewish
K9
K-9
Kidney
Kiwanis
Land Trust
Law Enforcement
Law School
Legal Aid
Legal Assistance
Lesbian
Libraries
Library
Lions Club
Lutheran
Make a Wish
Martial
Medicaid
Medical
Medical School
Medicine
Methodist
Minist*
Montessori
Mosque
Murdered
Museum
Muslim
Neuro*
Nursery
Nursing
Oncology
Orchestra
Orphan
Osteopathic
Our Lady
Parochial
Pediatric
Pharma*
Physician
Police
Pre School
Presbyterian
Preschool
Pre-School
Private
Pro Choice
Pro Life
Psychology
Radiology
Real Estate
Realtors
Rehab*
Research
Retired
Rotary
Sailing
Scholarship
School for the Blind
School for the Deaf
Schools (when "Elem" *not* included)
Scottish Rite
Senior Center
Senior Citizens
Sheriff
Sickle Cell
Softball
Special Education
Sports
Surgery
Tennis
Theater
Theatre
Theolo*
Troops
Unitarian
University
Veteran
Wildlife
Women
Wrestling
Yacht
Zoo

APPENDIX B

PROCEDURE FOR VERIFYING SCHOOL-NONPROFIT MATCHES

For cases that were matched by address, city, zip code, and state

1. Do the names match and does the nonprofit specify the school type (eg “elementary”)?

Nonprofit	School
PTA CALIFORNIA CONGRESS OF PARENTS TEACHERS AND STUDENTS INC WILLIAM F PRISK ELEMENTARY PTA	PRISK ELEMENTARY

It’s a match! Type “Yes” into the SSNP column.

2. If the names don’t match or if the school type (eg. “elementary”) is not specified in the nonprofit name, check the addresses. Do the addresses match? Don’t worry about little differences in the address (like “st” vs. “street”).

Nonprofit	School	St	NP city	Sch city	NP address	Sch address
FRIENDS OF CANFIELD	CANFIELD AVENUE ELEMENTARY	CA	LOS ANGELES	LOS ANGELES	9233 AIRDROME STREET	9233 AIRDROME ST
BOBCAT BOOSTERS CLUB	JOHN BLACOW ELEMENTARY	CA	FREMONT	FREMONT	40404 SUNDALE DR	40404 SUNDALE DRIVE

It’s a match! Type “Yes” into the SSNP column.

3. If neither the names nor address are perfect matches, then type “No” into the SSNP column.

BUT if you suspect that it still might be a match, Google the NONPROFIT NAME and/or NONPROFIT ADDRESS. If you can find evidence that the nonprofit ONLY supports the matched school, then…

It’s a match! Type “Yes” into the SSNP column.

4. If you can find no evidence that the school and nonprofit match, type “No” into the SSNP column.

If you had to look up the nonprofit whether or not it was a match, a “1” into the “Verified” column to indicate that you checked this record on the internet.

APPENDIX C

SELECTION BIAS IN THE SCHOOL-NONPROFIT MATCHING PROCESS

In this appendix I offer detailed thoughts about selection biases I believe are inherent in the school-to-nonprofit matching process I conducted for this research. These thoughts are included in the appendix because they are lengthy and largely tangential to the central question Chapter 5, which addresses the relationship between White representation and nonprofit presence. However, I believe they are still important to include because they may affect the conclusions presented in Chapter 5 and because they may help other researchers embarking on similar or parallel matching processes.

The first source of bias is *affiliation with a national organization*, such as the National Parent Teacher Association (PTA), the National Parent Teacher Organizations (PTO), or the National Congress of Parents and Teachers (CPT). Affiliation with a national organization likely increases the chance that a nonprofit matches into the sample for two reasons. First, nationally affiliated nonprofits tend to use consistent naming conventions across nonprofits, which makes them easy to identify. To illustrate, 59.6% of matched nonprofits (5,702 out of the total 9,565) follow the naming convention of the National PTA by including the words "PTA" and "Congress" in their name (for example, "**PTA** Florida **Congress** Pride Elem"). Once I identified the pattern of school-supporting nonprofits that all share the name "PTA [State Name] Congress [School Name]," it became clear they are a potential match, whereas the lone nonprofit more creatively named the "Bobcat Booster Club" was less definitively a school-supporting nonprofit. I address this bias in part by relying on nonprofit address more heavily than nonprofit name to identify matches. Regardless of nonprofit name, a school-nonprofit address match secures its inclusion as a school-supporting nonprofit.

The second reason that an affiliation with a national organization might increase the chances of a nonprofit appearing in the sample is that affiliation with a national organization may increase the likelihood that a nonprofit is registered with the IRS and up to date on its tax paperwork. This in turn determines whether an organization appears in the list of potential matches in the first place. The National PTA, for example, provides reminders and support to its affiliated PTAs in the completion of tax-exemption forms to the IRS (Murray et al. 2019). Unaffiliated schools without centralized support may be more likely to drop out of the IRS database due to unfiled tax forms; the IRS removes an organization from the Business Master File after three years without tax forms, regardless of whether the organization actually dissolved. Of course, without tax-exempt status, an organization is no longer a "nonprofit," so would not formally fit the constraints of this sample. However, it is possible that an organization could, informally and without tax-exempt status, perform the functions of a school-supporting nonprofit that would be of interest to this study, such as fundraising and event planning. If such organizations exist, they will be entirely missed by the present research.

A related source of sample bias is the *variation in nonprofit names* in general. The pool of potential nonprofits is winnowed based on keyword searches. The nonprofit names are restricted to *include* at least one of a list of relevant words, such as: "friend," or "elementary." Any nonprofit name that does not include one or more of these words is not included in the sample. I made an unsuccessful attempt to track down any school-supporting nonprofits *without* any of these terms as a final stage of the matching process.

For both the CFF and the BMF, I compared the list of unmatched schools to the list of unmatched nonprofits, without requiring any word(s) in the name, by mailing address (fuzzy), city (fuzzy), and state (required). Although 75 additional matches were identified during this step, all of them contain at least one of the words listed above, likely because those words are not only a way to refine the list of nonprofits, but also an important clue to me, the researcher reviewing the records, that the record is a school-supporting nonprofit.

A final important word in the hand-reviewing process was the word "Elementary" (and its variants "Elem," "El," and "ES"). Nonprofits with the term "Elementary" in the name are more easily matched to a school because one can instantly verify that the nonprofit was not affiliated with a similarly-named high school nor an entire district. In the hypothetical example of Pine Grove Elementary School, "Pine Grove Elem PTA" is a clearer match than "Pine Grove PTA," because Pine Grove PTA could instead be the Pine Grove *High School's* PTA or an umbrella PTA for the whole Pine Grove *District*. Nonprofits without the term "Elementary" required more scrutiny on the address fields and were more likely to be verified using the organization's website to ensure that they were indeed affiliated with an elementary school. Of course, many nonprofits without "Elementary" in their names were true matches; 63% of nonprofits matched to schools did not have the word "Elementary" nor its variants in their names.

As described above, I also developed a list of 160 irrelevant words and phrases to *exclude* based on a review of thousands of nonprofit records (Appendix A). As I reviewed potential matches, many false-positive matches had words in common that I chose to drop from the list of potential matches. For example, religious nonprofits are common false-positive matches. Dropping nonprofits with terms such as “Islam,” “Church,” and “Hillel” in their names makes the matching process more efficient, as there are fewer false positives to comb through. However, the listwise deletion of potential matches risks eliminating real matches. I mitigate this risk by searching for each excluded word within the list of *school* names. For example, nonprofits with the keyword “University” are typically university-supporting nonprofits and not elementary-school-supporting nonprofits, so “University” made the list of excluded keywords. However, I discovered that there are ten schools in my sample with the word “University” in their name (including three “University Park Elementary Schools” in three different states). There were 72 schools with an excluded keyword in their names and nine nonprofits associated with one of these schools. These schools and nonprofits were retained in the sample, despite containing words that were otherwise excluded.

Another potential source of matching bias comes from the increased chance of a mismatch for schools with *common school names*. Because either the matching step or the verification step (and sometimes both) involve the comparison of school name to nonprofit name, schools with common names are at a higher risk of *mis*matching with a nonprofit of a similarly-named school, simply because schools with common names are more numerous by definition. School names across the country often have many words in common, beyond merely “Elementary” and/or “School.” School names commonly include descriptor terms, such as “Park” (N=379), “Creek” (N=270), and “Valley” (N=213) and common person names such as “John” (N=152), “Lincoln” (N=97), and “William” (N=92). A list of the most common school-name terms is not included here but is available upon request. I mitigate the bias introduced by common school names by primarily matching schools based on address. Address should be an effective check on the increased likelihood of mismatches between schools with common names because two schools with the same name are not likely to have the same address. However, this does not entirely preclude the possibility that a nonprofit is mis-assigned to a school in cases where two similarly-named schools are near each other, particularly if one school appears in the sample and the other does not.

Nonprofit location may also be a source of bias. The most important clue by far that a nonprofit is a match to a school is its mailing address. In the final sample of matched nonprofits, 56% share an exact match with the school address, whereas less than half of a percent share an exact match with the school name. However, without the clue of an address match, school-supporting nonprofits are much more difficult to identify, which means that nonprofits that do not share an address with their school are more likely to be missed as a part of an address-heavy matching process. This is of particular concern in rural areas, where schools and nonprofits are more likely to use PO boxes as mailing addresses. It seems more practical for a school and its nonprofit to share a physical mailing address, where there might be a school office to take in and organize mail, than a PO box, which would require the sharing of a key to access the box. In the final analytical sample, 1,937 schools used a PO Box as a mailing address, six of which also used the same PO Box as their physical location address. Of the schools that used a PO Box, 84% were in rural districts (whereas rural districts make up only 28% of the full sample). To mitigate this bias, I added an additional matching step (described in more detail above) in which I match nonprofits to schools based on name, city, and state, ignoring the street address. However, nonprofits that match their school in neither name nor address are virtually impossible to identify using the procedure described here.

The final source of bias inherent in the nonprofit-school matching process is *the exclusion of schools that share nonprofits with other schools*. The nonprofits of interest to this study are *single*-school-supporting nonprofits, not nonprofits that support multiple schools or multiple districts. This is a necessary constraint because there is no way to determine how multi-school nonprofits share resources across schools. However, I have reason to believe that the exclusion of district-wide nonprofits from the study affects rural schools more than it affects urban and suburban schools. First of all, rural districts tend to have lower populations than suburban and urban areas and therefore have fewer adults to administer school-supporting nonprofits. It may be inefficient to administer multiple nonprofits in smaller districts and, instead, one larger nonprofit may fill the role that many single-school nonprofits fill in larger districts. Secondly, many rural elementary schools in the sample share a building with both the local middle- and high schools. I discovered this when dozens of false-positive matches were clearly high-school-supporting nonprofits with the exact same address as elementary schools in the sample. In communities with a single school building for K-12 students, it may be nonsensical to found three separate nonprofits to support each “school” (elementary, middle, and high) within the building, even if each technically operates as a separate school. The shared physical space may blur the lines between the distinct school entities. Furthermore, maintaining consistency across grade levels may be perceived as a benefit. However, to remain consistent across the sample and to refrain from falsely attributing high-school-supporting funds to an elementary school, I chose to exclude all district and multi-school-supporting nonprofits, even in rural districts.

APPENDIX D

WALD TEST FOR INDEPENDENT VARIABLES, NONPROFIT PRESENCE OUTCOMES

Wald Test for Independent Variables of Nonprofit Presence Outcomes

	Urban χ^2	Suburban and rural χ^2
White representation in school (vs. representative)		
Underrepresented White	1.33	3.22
Overrepresented White	0.45	5.11
% White K-4th grade (school)	0.29	1.02
% Black K-4th grade (school)	13.83**	10.82**
Median household income (ln) (neighborhood)	40.88***	17.27***
Population (ln) (neighborhood)	7.15*	16.62***
# Private schools within 2 miles (neighborhood)	15.98***	6.78*
# Magnet schools within 2 miles (neighborhood)	54.89***	3.81
# Charter schools within 2 miles (neighborhood)	9.69**	3.88
Total # students (in 100s) (school)	1.08	11.44**
% Students with FRL (school)	95.16***	109.01***
% Students with disabilities (school)	26.14***	14.50**
% Students with LEP (school)	31.72***	3.83
Underrepresented White (District mean)	3.68	1.00
Overrepresented White (District mean)	3.03	0.84
% White K-4th grade (school) (District mean)	1.98	0.34
% Black K-4th grade (school) (District mean)	6.35	6.14*

Median household income (ln) (neighborhood) (District mean)	33.76***	28.29***
Population (ln) (neighborhood) (District mean)	6.68*	0.32
# Private schools within 2 miles (neighborhood) (District mean)	1.56	3.78
# Magnet schools within 2 miles (neighborhood) (District mean)	12.37**	1.26
# Charter schools within 2 miles (neighborhood) (District mean)	14.69**	2.58
Total # students (in 100s) (school) (District mean)	0.91	14.44**
% Students with FRL (school) (District mean)	4.19	8.34*
% Students with disabilities (school) (District mean)	6.21*	5.77
% Students with LEP (school) (District mean)	19.51***	6.02*

*p<.05 **p<.01 ***p<.001

APPENDIX E

AVERAGE MARGINAL EFFECTS OF WHITE REPRESENTATION ON NONPROFIT PRESENCE, FULL MODEL

[Full Model] Average Marginal Effects (AME) on the Probability of School Supporting Nonprofit Presence Based on Multinomial Logistic Regression on White Neighborhood School Representation and Other School and Neighborhood Characteristics, by Urbanicity and Controlling for District-Level Means

	Urban schools			Suburban and rural schools		
	No Nonprofit AME (SE)	Low-Revenue Nonprofit AME (SE)	High-Revenue Nonprofit AME (SE)	No Nonprofit AME (SE)	Low-Revenue Nonprofit AME (SE)	High-Revenue Nonprofit AME (SE)
White underrepresentation (compared to parity)	-0.015 (0.014)	0.013 (0.017)	0.003 (0.010)	-0.020 (0.012)	0.024 (0.013)	0.004 (0.008)
White overrepresentation (compared to parity)	-0.011 (0.017)	0.010 (0.018)	0.001 (0.009)	0.021 (0.012)	0.028* (0.013)	-0.008 (0.006)
% White K-4th graders	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)	0.001 (0.001)	-0.001 (0.001)	0.000 (0.000)
% Black K-4th grade (school)	0.001* (0.001)	0.000 (0.001	-0.002*** (0.000)	0.001 (0.001)	0.001 (0.001)	-0.002** (0.001)
Median household income (ln) (neighborhood)	-0.154*** (0.025)	0.000 (0.000)	0.050** (0.018)	0.014 (0.024)	-0.084** (0.030)	0.070*** (0.017)

Appendix E. Average Marginal Effects (AME) on the Probability of School Supporting Nonprofit Presence (continued)

Population (ln) (neighborhood)	-0.020 (0.016)	-0.009 (0.017)	0.029 (0.011)	-0.053*** (0.015)	0.028 (0.015)	0.025** (0.009)
# Private schools within 2 miles (neighborhood)	-0.010** (0.003)	0.004 (0.003)	0.006** (0.002)	0.000 (0.003)	-0.004 (0.003)	0.004* (0.002)
# Magnet schools within 2 miles (neighborhood)	-0.005 (0.004)	-0.004 (0.004)	0.010*** (0.001)	0.001 (0.007)	-0.007 (0.006)	0.007 (0.004)
# Charter schools within 2 miles (neighborhood)	-0.008 (0.006)	0.001 (0.008)	0.007* (0.003)	0.017 (0.009)	-0.014 (0.008)	-0.003 (0.006)
Total # students (in 100s) (school)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
% Students with FRL (school)	0.004*** (0.001)	-0.001 (0.000)	-0.003*** (0.000)	0.005*** (0.001)	-0.002** (0.001)	-0.003*** (0.000)
% Students with disabilities (school)	0.001 (0.001)	0.004* (0.002)	-0.005*** (0.0010	-0.001 (0.001)	0.004* (0.002)	-0.003*** (0.001)
% Students with LEP (school)	0.002*** (0.001)	0.001 (0.001)	-0.003*** (0.001)	0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Underrepresented White (District mean)	0.003 (0.035)	-0.029 (0.033)	0.027 (0.015)	0.004 (0.017)	-0.009 (0.013)	0.005 (0.010)
Overrepresented White (District mean)	0.061 (0.034)	-0.054 (0.033)	-0.007 (0.012)	0.004 (0.012)	-0.010 (0.013)	0.006 (0.008)
% White K-4th grade (school) (District mean)	-0.010 (0.037)	-0.011 (0.037)	0.056 (0.011)	-0.012 (0.028)	0.015 (0.025)	-0.002 (0.016)

Appendix E. Average Marginal Effects (AME) on the Probability of School Supporting Nonprofit Presence (continued)						
% Black K-4th grade (school) (District mean)	0.000 (0.025)	-0.027 (0.023)	0.028*-0.10 (0.012)	-0.042* (0.017)	0.034* (0.016)	0.008 (0.010)
Median household income (ln) (neighborhood) (District mean)	-0.107** (0.032)	0.050 (0.033)	0.056*** (0.011)	-0.088*** (0.016)	0.080*** (0.015)	0.008 (0.010)
Population (ln) (neighborhood) (District mean)	-0.015 (0.025)	-0.032 (0.020)	0.017 (0.011)	0.015 (0.027)	-0.010 (0.023)	-0.004 (0.012)
# Private schools within 2 miles (neighborhood) (District mean)	0.024 (0.019)	-0.024 (0.019)	0.000 (0.007)	-0.017 (0.009)	0.015 (0.008)	0.002 (0.003)
# Magnet schools within 2 miles (neighborhood) (District mean)	0.015 (0.009)	-0.004 (0.009)	-0.011 (0.004)	0.004 (0.005)	-0.002 0.004	-0.002 (0.002)
# Charter schools within 2 miles (neighborhood) (District mean)	0.073*** (0.021	-0.067** (0.023)	-0.006 (0.006)	0.008 (0.006)	-0.005 (0.006)	-0.003 (0.002)
Total # students (in 100s) (school) (District mean)	0.022 (0.023)	-0.020 (0.022)	-0.002 (0.010)	-0.069* (0.021)	0.016 (0.020)	0.034* (0.013)
% Students with FRL (school) (District mean)	-0.052 (0.034)	0.030 (0.033)	0.022 (0.013)	-0.050* (0.021)	0.016 (0.020)	0.034* (0.013)

Appendix E. Average Marginal Effects (AME) on the Probability of School Supporting Nonprofit Presence (continued)						
% Students with disabilities (school) (District mean)	0.015 (0.019)	-0.029 (0.019)	0.014 (0.006)	0.024 (0.015)	-0.037* (0.016)	0.013 (0.010)
% Students with LEP (school) (District mean)	0.001 (0.027)	-0.052* (0.026)	0.051*** (0.012)	-0.035* (0.014)	0.022 (0.013)	0.013 (0.009)
N	6,037			11,470		
*p< .05 **p<.01 ***p<.001, two-tailed tests						

APPENDIX F

AVERAGE MARGINAL EFFECTS OF WHITE REPRESENTATION ON GAT WHITE REPRESENTATION, FULL MODEL

[Full Model] Average Marginal Effects (AME) on the Probability of White Representation in GAT Programs Based on Multinomial Logistic Regression on School and Neighborhood Characteristics

	Urban schools			Suburban and rural schools		
	GAT Underrepresented White AME (SE)	GAT Representative White AME (SE)	GAT Overrepresented White AME (SE)	GAT Underrepresented White AME (SE)	GAT Representative White AME (SE)	GAT Overrepresented White AME (SE)
White underrepresentation (compared to parity)	-0.138*** (0.019)	-0.058*** (0.013)	0.079*** (0.019)	-0.066*** (0.016)	-0.008 (0.011)	0.074*** (0.018)
White overrepresentation (compared to parity)	0.048* (0.023)	0.011 (0.015)	-0.060* (0.024)	0.064*** (0.018)	0.001 (0.013)	-0.065*** (0.019)
% White K-4th graders	0.002* (0.001)	0.001 (0.001)	-0.003** (0.001)	0.002* (0.001)	0.001 (0.001)	-0.003** (0.001)
% Black K-4th grade (school)	0.003*** (0.001)	0.001 (0.001)	-0.004*** (0.001)	0.000 (0.001)	0.001* (0.001)	-0.002 (0.001)
Median household income (ln) (neighborhood)	0.037 (0.030)	-0.096*** (0.026)	0.059 (0.035)	0.072* (0.030)	-0.023 (0.029)	-0.049 (0.033)

Appendix F. Average Marginal Effects (AME) on the Probability of White Representation in GAT (continued)						
Population (ln) (neighborhood)	-0.040* (0.017)	-0.022 (0.015)	0.063*** (0.018)	-0.070** (0.024)	0.029* (0.013)	0.014*** (0.004)
# Private schools within 2 miles (neighborhood)	-0.012** (0.004)	0.001 (0.002)	0.010* (0.005)	-0.011* (0.005)	-0.003 (0.003)	0.014*** (0.004)
# Magnet schools within 2 miles (neighborhood)	-0.002 (0.008)	-0.008 (0.004)	0.010 (0.008)	-0.016 (0.018)	0.000 (0.005)	0.017 (0.016)
# Charter schools within 2 miles (neighborhood)	0.003 (0.007)	0.004 (0.004)	-0.006 (0.007)	-0.002 (0.012)	0.014** (0.005)	-0.012 (0.012)
Total # students (in 100s) (school)	0.004 (0.005)	0.008* (0.004)	-0.013* (0.005)	0.004 (0.004)	0.001 (0.002)	-0.006 (0.005)
% Students with FRL (school)	-0.001 (0.001)	-0.001 (0.001)	0.002* (0.001)	-0.001 (0.001)	0.000 (0.001)	0.000 (0.001)
% Students with disabilities (school)	-0.003 (0.002)	-0.002 (0.002)	0.004 0.002)	0.000 (0.002)	0.000 (0.001)	0.000 (0.002)
% Students with LEP (school)	0.003 (0.001)	0.002*** (0.001)	-0.005*** (0.001)	0.001 (0.001)	0.002* (0.001)	-0.003* (0.001)
% Black K-4th grade (school) (District mean)	-0.050* (0.024)	-0.030* (0.014)	0.080** (0.026)	-0.048* (0.020)	-0.003 (0.010)	0.051** (0.016)

Appendix F. Average Marginal Effects (AME) on the Probability of White Representation in GAT (continued)						
Median household income (ln) (neighborhood) (District mean)	-0.024 (0.026)	-0.003 (0.013)	0.028 (0.028)	0.028* (0.013)	-0.015 (0.014)	-0.041 (0.027)
Population (ln) (neighborhood) (District mean)	0.001 (0.023)	0.027* (0.013)	-0.028 (0.020)	0.056* (0.024)	-0.015 (0.014)	-0.041 (0.027)
# Private schools within 2 miles (neighborhood) (District mean)	0.054*** (0.014)	0.015* (0.008)	-0.069*** (0.017)	0.035*** (0.007)	0.008 (0.005)	-0.043*** (0.009)
# Magnet schools within 2 miles (neighborhood) (District mean)	-0.002 (0.020)	0.007 (0.009)	-0.005 (0.021)	-0.003 (0.004)	0.006** (0.002)	-0.003 (0.004)
# Charter schools within 2 miles (neighborhood) (District mean)	-0.022 (0.020)	-0.008 (0.011)	0.030 (0.023)	-0.010 (0.005)	0.002 (0.002)	0.007 (0.005)
Total # students (in 100s) (school) (District mean)	-0.027 (0.020)	0.005 (0.011)	0.021 (0.023)	0.002 (0.014)	-0.004 (0.014)	-0.001 (0.023)

Appendix F. Average Marginal Effects (AME) on the Probability of White Representation in GAT (continued)						
% Students with FRL (school) (District mean)	-0.035 (0.028)	0.005 (0.015)	0.030 0(.032)	0.004 (0.022)	-0.004 (0.014)	-0.001 (0.023)
% Students with disabilities (school) (District mean)	0.006 (0.013)	-0.022* (0.013)	0.027 (0.026)	0.015 (0.015)	0.001 (0.009)	-0.17 (0.016)
% Students with LEP (school) (District mean)	-0.004 (0.023)	-0.023) (0.013)	0.027 (0.026)	-0.046** (0.018)	-0.003 (0.009)	0.049** (0.016)
White underrepresentation (District mean)	-0.036 (0.022)	-0.007 (0.013)	0.043 (0.025)	-0.024 (0.015)	0.006 (0.012)	0.018 (0.017)
White overrepresentation (District mean)	-0.011 (0.021)	-0.004 (0.016)	0.007 (0.027)	0.024 (0.014)	0.020 (0.011)	-0.044** (0.014)
% White K-4th graders (District mean)	-0.047 (0.037)	-0.040 (0.023)	0.087* (0.038)	-0.102** (0.031)	-0.006 (0.016)	0.108*** (0.023)
N	4947			8389		

*p< .05 **p<.01 ***p<.001, two-tailed tests
Note: Includes only observations with a GAT program.