Student Neighborhoods, Schools, and Test Score Growth: Evidence from Milwaukee, Wisconsin

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**Abstract:** Schools and neighborhoods are thought to be two of the most important contextual influences on student academic outcomes. Drawing on a unique dataset that permits estimation of both neighborhood and school contributions to student test score gains, we perform four analyses to examine the effects of these prominent contextual settings. First, we analyze the distributions of estimated neighborhood and school contributions to student test score gains to consider the relative importance of schools and neighborhoods in shaping student outcomes. Second, we assess whether estimates of school value-added are sensitive to the inclusion of an explicit measure of the neighborhood in which students reside. Third, we analyze how students are sorted across neighborhoods and schools to assess whether one context offsets or reinforces the effects of the other. Finally, we examine the observable characteristics of neighborhoods and schools that are associated with various levels of contribution to student test score gains. Taken together, the results of these analyses provide substantial insight into the influences of two of the most important contextual settings in students’ lives.

**Keywords:** Education; School value-added; Neighborhoods; Student achievement
1. Introduction

Schools and neighborhoods are thought to be two of the most important contextual influences on student academic outcomes. The importance of these contexts is evidenced by both the significant amount of policy attention they receive and the substantial scholarly literatures surrounding them. With respect to schools, studies of accountability systems (e.g. Dee and Jacob 2011; Jacob 2005; Hanushek and Raymond 2005; Carnoy and Loeb 2002), alternative schooling approaches—such as charter schools (e.g. Gleason et al. 2010; Witte et al. 2007; CREDO 2009) and private school vouchers (e.g. Wolf et al. 2013; Witte et al. 2012; Witte 2000; Rouse 1998; Howell et al. 2006)—and other topics inform policy debates over the best approach to improving school quality and, ultimately, student outcomes.

Policymakers have also initiated neighborhood-based interventions—most notably the Moving to Opportunity (MTO) experiment—in the hopes of improving student achievement and attainment, among other outcomes (see Sanbonmatsu et al. 2011). Such interventions rest on a body of studies demonstrating that the quality of the neighborhood in which a student resides is associated with his or her educational outcomes (e.g. Aaronson 1998; Brooks-Gunn et al. 1993; Crane 1991; Duncan, Brooks-Gunn, and Klebanov 1994; Rosenbaum 1995; Dornbusch, Ritter, and Steinberg 1991; Duncan 1994; Sharkey and Elwert 2011). Considered together, existing studies provide evidence that both schools and neighborhoods shape students’ academic outcomes, but the tendency to study these contexts in isolation—studies typically analyze either “school effects” or “neighborhood effects”—has limited our understanding of the relative influence of these two contexts, as well as the manners in which they interact to affect students’ educational outcomes.

Drawing on five years of student-level data from a large, urban school district that contain records of both the schools that students attend and the neighborhood in which they
reside, this paper examines the relationship between neighborhoods, schools, and student test score growth. With this intention, we perform four main analyses. First, we simultaneously estimate the contributions of neighborhoods and schools to student test score gains and analyze the distributions of these estimated neighborhood and school contributions. This analysis will provide insight into the relative importance of schools versus neighborhoods in shaping a major academic outcome. Second, we assess whether estimates of school value-added are sensitive to the inclusion of an explicit measure of the neighborhood in which students reside. Such an assessment is important given the increasing number of schools and teachers that are being sanctioned or rewarded at least partially on the basis of their estimated value-added. Third, we analyze student sorting across schools and neighborhoods to consider whether students who live in the worst neighborhoods also attend the worst schools, and whether students attending the most effective schools also reside in the best neighborhoods. These largely unanswered questions are particularly relevant in large urban settings with substantial parental choice. Finally, we examine the observable characteristics of neighborhoods and schools that are associated with low, average, and high levels of student test score growth. We place particular focus on assessing whether a specific dimension of neighborhood disadvantage—unemployment, poverty, housing stock, or others—is predictive of low or high test score growth for its residents.

Our results demonstrate that, relative to neighborhood contributions, there is substantially more variability in school contributions to student test scores, implying that the school a student attends is a more important determinant of their achievement scores than the neighborhood in which they live. Interestingly, our analyses indicate relatively little correlation between the estimated contribution of the school a student attends and the neighborhood in which he or she resides, but that observable characteristics of schools and neighborhoods correlate with their
estimated respective contributions to student test score gains in largely expected ways. Taken as a whole, the results of our analyses provide insight into the influences of two of the most important contextual settings in students’ lives on important academic outcomes.

We proceed with a brief review of existing studies relevant to our analysis of the relationship between neighborhoods, schools, and academic outcomes before moving on to provide an overview of the data that underlie our analyses. We then turn to a description of the empirical approach we use to isolate the relationships between schools, neighborhoods, and student test score growth. The description of our empirical approach sets the stage for the substantive portion of the paper, which addresses the four major topics described above. We close the paper with a discussion of the implications of our results for research and policy.

2. Background

Recognizing the potentially large influence of contextual settings on children’s lives, scholars have long investigated how neighborhoods and schools shape student academic outcomes. The large majority of prior work analyzes these two contexts in isolation—studies examine either neighborhood or school effects—but a small number of recent analyses address the two contexts simultaneously, either as quantities of substantive interest (e.g. Fryer and Katz 2013; Owens 2010) or as factors that must be accounted for in order to obtain valid estimates of some other substantive relationship (e.g. Betts, Zau, and Koedel 2010).

Most early studies analyzing the effect of neighborhoods on students’ achievement outcomes were observational in nature, typically relying on regression models that contain controls for socioeconomic and demographic characteristics (e.g., Brooks-Gunn et al. 1993; Duncan, Brooks-Gunn, and Klebanov 1994; Brooks-Gunn, Klebanov, and Duncan 1996; Chase-Lansdale and Gordon 1996; Duncan, Boisjoly, and Harris 2001; Ainsworth 2002; Kohen et al.
The general pattern emerging from these early analyses is one where the quality of a student’s neighborhood—as measured by socioeconomic characteristics—is positively associated with his or her cognitive test scores, although the studies demonstrate heterogeneity in the substantive magnitude of the detected relationships. Sharkey and Elwert (2011) note that these studies often control for factors that may be endogenous to neighborhood quality—they specify family income and health as examples—and thus potentially underestimate the influence of neighborhoods on relevant outcomes. Relying on observational data from the Panel Study of Income Dynamics and employing methods designed to mitigate the methodological issue noted above, the authors find statistically significant and substantively strong relationships between neighborhood and student achievement outcomes. Substantively similar results are found in Sampson, Sharkey, and Raudenbush (2008), which uses comparable methods and observational data from Chicago.

A separate strand of studies that analyze the relationship between neighborhood and academic outcomes relies on exogenous variation in an individual’s neighborhood to estimate the effect of neighborhood on student achievement. The most prominent study in this vein is the Moving to Opportunity (MTO) experiment, which recruited a sample of participants residing in public housing in five cities and randomly assigned them to one of three groups: 1) A control group assigned to remain in public housing; 2) A group that was offered a regular Section 8 housing voucher that could be used anywhere; and 3) A group that was offered a Section 8 housing voucher that could only be used in low-poverty neighborhoods. The final follow-up for MTO was recently completed and the results reveal no difference in average educational

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1 Aaronson (1998) takes a different approach to estimating neighborhood influence on children’s educational outcomes. To address household self-selection into neighborhoods, Aaronson relies on sibling data—he exploits over-time within-family variation in neighborhood environment—and generally finds a positive relationship between neighborhood quality and children’s academic outcomes.

2 See Carlson et al. 2012 for a description of the operation of the Section 8 voucher program.
achievement of students across the three groups 10 to 15 years after random assignment (Sanbonmatsu et al. 2011).

Jacob (2004) exploited plausibly exogenous variation in students’ neighborhood created by differences in the timing of high-rise public housing demolitions. Echoing the MTO results, Jacob (2004) also found no differences between the achievement of students whose public housing high-rises were demolished—resulting in relocation to a different, less impoverished neighborhood—and students who remained in public housing high rises. In contrast, Ludwig et al. (2009) took advantage of the fact that the Chicago Housing Authority opened the waiting list for the Section 8 voucher program for the first time in over a decade and randomly assigned applicants a place on that list. Focusing on applicants who lived in public housing, Ludwig et al. (2009) compared the achievement of students whose family came off the waiting list and received a voucher to the achievement of students whose families remained on the waiting list. The results demonstrate that the voucher offer increased students’ reading and math scores by 0.05 to 0.08 standard deviations.3 Taken together, the observational studies provide consistent evidence that neighborhoods are important determinants of student achievement outcomes whereas the experimental analyses are somewhat more varied in their conclusions regarding the relationship.4

The importance of schools in shaping student achievement outcomes seems self-evident. Indeed, implicit in any discussion of school accountability systems, alternative schooling

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3 Because less than 30 percent of recipients were able to use their voucher to secure housing, the corresponding treatment-on-the-treated estimates are in the range of 0.2 to 0.3 standard deviations.
4 Other potentially relevant evidence comes from the Gautreaux study. This study was the result of a 1976 Supreme Court decision requiring the Chicago Housing Authority to provide Black residents in public housing with vouchers. Some of these vouchers were used to move families to the suburbs while others remained in the city. Follow-up studies conducted about a decade after the court decision found that the educational attainment of youth whose families moved to the suburbs were significantly better than the attainment of children remaining in the city (Rubinowitz and Rosenbaum 2000). Although assigned moves to the suburbs and city were designed to be randomly assigned, evidence suggests that the assignments were not truly random, bringing into question the causal nature of the findings (Mendenhall, Deluca, and Duncan 2006).
options, governance arrangements, and other educational reform efforts is the assumption that schools strongly influence students’ educational outcomes. Empirical studies lend support to this assumption. Early studies of school effectiveness demonstrate that schools vary not only in their mean achievement levels, but also in their contributions to student test score growth (e.g. Kane and Staiger 2002). These findings are corroborated and extended in subsequent research. For example, Hanushek et al. (2007) demonstrate that the average combined math and reading achievement growth of students attending the highest value-added schools is over one standard deviation greater than the achievement growth of students attending schools with the lowest estimated value-added. Beteille, Kalogrides, and Loeb (2009) demonstrate similar variance in school contributions to student test scores and provide evidence that the variance in school effectiveness is larger in math than reading. Considered as a whole, and in contrast to analyses of neighborhood effects, studies of school effects on student achievement convincingly demonstrate that the contextual setting is an important determinant of students’ achievement levels.

Although large literatures separately analyze the effects of neighborhoods and schools on student achievement outcomes, only a few studies analyze these contexts—and their relationships to student outcomes—simultaneously. Cook et al. (2002) analyzed data from a sample over 12,000 students in Prince George’s County—a county bordering Washington D.C.—to examine how school, neighborhood, family, and friendship contexts affected the educational and developmental outcomes of adolescents. Drawing on multi-attribute indexes created separately for each of the four contexts, the authors found each context to be significantly related to changes in a “success index,” which included student achievement outcomes, over the course of 19 months. However, the strengths of the relationships, which are similar in magnitude
across contexts, are substantively modest. In pursuit of a similar objective, Owens’ (2010) uses data from the National Longitudinal Study of Adolescent Health to study the joint relationship between an individual’s educational attainment and his or her school and neighborhood contexts. The results indicate that an individual’s level of neighborhood advantage, relative to the average level of neighborhood advantage of peers in the same high school, predicts high school graduation. They also indicate, however, that an individual’s absolute level of neighborhood advantage predicts bachelor degree completion. Most recently, Fryer and Katz (2013) synthesized evidence from MTO and studies the Harlem Children Zone to conclude that schools and neighborhoods affect different dimensions of students’ lives; they find that schools exert a greater effect on academic and economic outcomes while neighborhoods are a more influential determinant of youth’s physical and mental health.

Considered as a whole, prior studies clearly demonstrate the importance of schools in determining student achievement scores, but exhibit less unanimity in their conclusions regarding the relationship between neighborhoods and achievement outcomes; some studies find neighborhoods to be a significant determinant of student test scores (e.g. Sharkey and Elwert 2011; Sampson, Sharkey, and Raudenbush 2008; Cook et al. 2002) whereas others find little relationship (e.g., Sanbonmatsu et al. 2011; Jacob 2004). It is important to note, however, that these previous studies generally assess the relationship between neighborhood and student achievement outcomes on the basis of observable neighborhood characteristics. It is possible that the selection of specific characteristics contributes to these discrepant results, a possibility that we explore further in a later section of this paper. As we describe in greater detail below, we take a different approach to analyzing the relationship between neighborhoods and student achievement—one that is not reliant on observable neighborhood characteristics.
3. Data

All analyses to follow are based on a dataset containing records from the universe of students enrolled in Milwaukee Public Schools who took the Wisconsin Knowledge and Concepts Examination (WKCE)—the assessment that Wisconsin uses to comply with federal No Child Left Behind requirements—in the fall of the 2006-07, 2007-08, 2008-09, 2009-10, or 2010-11 academic years.⁵ Along with the WKCE results, which are standardized using the district-wide mean and standard deviation for the proper grade, subject, and year, the dataset contains additional valuable information, including a unique student identifier and standard student demographics such as sex, race, grade, free- or reduced-price lunch status, English language learner status, and special education status. The data also record the school attended by each student, which allows us to generate school-level characteristics—for all test takers in the school—such as average school achievement in reading and math, the percentage of female students, the racial composition of the school, the percentage of students eligible for free- or reduced-price lunch, and the percentages of students who are English language learners or receive special education services.⁶ Finally, the data include an annual record of students’ residential neighborhood, operationalized as the U.S. Census tract.⁷

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⁵ The data contain students attending charter schools operated by the Milwaukee Public School district.

⁶ To the extent that the population of test-takers in MPS differs from the population of students in MPS, the school-level characteristics computed from the file containing the universe of test-takers may differ from the true values for these characteristics. There are two primary scenarios that could result in the population of test-takers differing from the population of MPS students. First, the characteristics of students in tested grades could differ from the characteristics of students in untested grades. This is unlikely to be the case. Second, among students in tested grades, the characteristics of students who take the test could differ from students who do not take the test. However, due to No Child Left Behind’s strict requirement that nearly all students in tested grades sit for the assessment, the population of test-takers is very close to the population of all students in tested grades.

⁷ These data represent a portion of a larger set of data collected on public and private school students in Milwaukee for an evaluation of the city’s school voucher program that occurred during these years. The primary analytical strategy employed in that larger study was a matching procedure based on student neighborhoods as measured by Census tract. The present paper explicitly considers a key assumption behind that procedure: that academic heterogeneity between Milwaukee neighborhoods and schools represents meaningful substantive variation in outcomes.
Nested within county boundaries, Census tracts are small geographic units that generally contain between 1,500 and 8,000 individuals, with a targeted population of 4,000. Tracts are purposefully drawn to reflect the true character of a neighborhood—efforts are made to make them homogenous along dimensions such as socioeconomic status, demographic characteristics, and quality of the housing stock (Iceland and Steinmetz 2003). Furthermore, tracts are drawn to follow relevant physical boundaries, such as highways, waterways, and railroad tracks, among others. In short, Census tracts are the product of a comprehensive and systematic attempt to identify true neighborhood boundaries. Within our dataset, students reside in approximately 220 different Census tracts and attend about 160 unique elementary and middle schools across the City of Milwaukee.\(^8\)

With a record of each student’s annual Census tract of residence in hand, we then extracted—for each Census tract in Milwaukee—a number of observable tract characteristics from the American Community Survey (ACS) and appended them to our dataset.\(^9\) These tract-level characteristics are wide-ranging and diverse, including such measures as median rent, average income, income inequality, average poverty level, average educational attainment levels, household structure, average employment rates, and other demographic and socioeconomic characteristics.\(^10\) Addition of these tract measures represented the final stage in the construction of the dataset underlying the following analyses, a dataset that permits us to gain a better understanding several issues related to the educational effects of the neighborhoods in which students reside and the schools they attend.

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\(^8\) Throughout this paper we use the term “neighborhood” interchangeably with “Census tract.”

\(^9\) Tract-level characteristics are calculated from five years—2007 to 2011—of ACS administration, a time period that overlaps fully with the five years of student WKCE scores in our dataset. Consequently, our tract-level characteristics do not vary by year. See http://www.census.gov/acs/www/guidance_for_data_users/estimates/ for further description of the process used to produce estimates of observable tract-level characteristics.

\(^10\) A full list of observable tract characteristics is available from the authors upon request.
4. Estimating School and Neighborhood Contributions to Student Test Score Growth

Valid estimation of neighborhood and school contributions to student test score gains is only possible if students are sufficiently cross-classified in these two contextual settings. That is, estimation of the two sets of parameters requires neighborhoods to be linked through the schools that students attend and schools to be linked through the neighborhoods in which students reside. It is important to note that the linkages of neighborhoods through schools and schools through neighborhoods do not need to be direct—they can be linked indirectly (i.e. there does not have to be a student from each neighborhood attending each school and a student from each school living in each neighborhood).

In our data, there is substantial cross-classification between schools and neighborhoods—a pattern that may be explained in part by the fact that MPS provides families with substantial latitude in selecting the specific school that their child will attend.\textsuperscript{11} To illustrate the broad distribution of students across neighborhoods and schools, consider Figures 1 and 2, recalling that students in our dataset reside in approximately 220 unique Census tracts and attend about 160 different elementary and middle schools.\textsuperscript{12} Figure 1 presents the distribution of schools by the number of unique tracts in which students attending that school reside. It illustrates that most schools draw students from multiple neighborhoods, most often in excess of 50. Similarly, Figure 2 demonstrates that, in most tracts, students attended over 50 different elementary and middle schools across the five years we observe. These figures illustrate the cross-classification necessary to estimate the neighborhood and school parameters described above.


\textsuperscript{12} We restrict our analysis to elementary and middle schools because students are only tested once in high school (10\textsuperscript{th} grade), a reality that renders us unable—because of the inclusion of lagged achievement in Equation 1—to estimate a reliable school contribution to student test score gains at the high school level.
Given the requisite cross-classification of students in neighborhoods and schools, we isolate the relationships between neighborhoods, schools, and student test score growth using the following model:

\[ Y_{ijkt} = \beta Y_{ijkt-1} + \rho G_{it} + \tau H_{ijkt} + \theta N_k + \gamma S_j + \varepsilon_{ijkt} \]  

(1)

In this model, \( Y \) represents a measure of student achievement on the WKCE—the state test used for federal accountability purposes—standardized by the district mean and standard deviation for the proper year, grade, and subject for student \( i \) attending school \( j \) and living in neighborhood \( k \) at time \( t \). This achievement measure is modeled as a function of a vector of lagged achievement measures, a vector of grade dummies, \( G \), a vector of student characteristics, \( H \), a Census tract (i.e. neighborhood) fixed effect, \( N \), a school fixed effect, \( S \), and an error term, \( \varepsilon \). The vector of lagged reading scores contains a 1-year lag of the student’s standardized score as well as squared and cubed terms of that lag. The vector of lagged math scores contains an identical set of terms. The vector of student characteristics includes indicators for gender, race, English language learner status, free or reduced-price lunch status, and special-needs status. We estimate the model separately for reading and math. The coefficients associated with the neighborhood and school fixed effects—respectively denoted by \( \theta \) and \( \gamma \) in Equation (1)—represent the estimated neighborhood and school contributions to student test score gains that, along with their standard errors, we recover after estimation of Equation 1. The recovered neighborhood and school fixed effects were each parameterized using sum-to-zero constraints, implying that neighborhood and
school contributions to test score gains are estimated relative to the average neighborhood and school contribution, respectively.¹³

Because the estimated neighborhood and school contributions to student test score gains includes both the “true” contribution and measurement error, we use an empirical Bayes approach to shrink the estimated contributions of both neighborhoods and schools (e.g., Hanushek et al. 2007; Jacob and Lefgren 2005; Kane and Staiger 2002; Beteille, Kalogrides, and Loeb 2009). Except where explicitly noted, these shrunken estimates serve as the basis of all analyses that follow.

4.1 Robustness of School Value-Added Estimates

Although we have not explicitly referred to them as such, readers likely recognize the school fixed effects in Equation 1—represented by the $S$ term—as estimates of school value-added. Across states and districts, school value-added is increasingly being used to inform decisions related to educational policy and practice—Tennessee is an example of a state that makes extensive use of school value-added for these purposes. The increasing reliance on this metric for policy decisions renders its validity important.

In the context of teacher evaluation policies, recent work has shown estimates of teacher value-added to be biased by nonrandom sorting of students into classrooms (Rothstein 2009, 2010), suggesting that similar bias could also be present in school value-added estimates. Value-added approaches—including the one represented by Equation 1—assume that, conditional on the contents of the model, students are randomly distributed across schools. Such an assumption

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¹³ To recover neighborhood and school contributions that were each parameterized using sum-to-zero constraints we estimated Equation (1) twice using Stata’s user-written “felsdvregdm” command (Mihaly et al. 2010). In the first estimation, the neighborhood fixed effects were estimated and subsequently recovered using sum-to-zero parameterization while the school fixed effects were eliminated through the subtraction of group means. The reverse occurred in the second estimation—the neighborhood fixed effects were eliminated using the within transformation while the school fixed effects were estimated under a sum-to-zero parameterization and subsequently recovered.
allows the estimated school fixed effects to be interpreted causally as the school contribution to student test score growth—the school value-added. Most school value-added models, however, do not contain an explicit measure of the neighborhood in which students reside. Indeed, much more common is a model of the form:

$$Y_{ijkt} = \beta Y_{ijkt-1} + \rho G_{ik} + \tau H_{ijkt} + \gamma S_j + \epsilon_{ijkt}$$  \hspace{1cm} (2)

where the only difference between this model and that presented in Equation 1 is the lack of a neighborhood fixed effect. Although seemingly small, this difference has the potential to be significant from the standpoint of recovering unbiased estimates of $S$. Specifically, if neighborhood and school contributions to student test score growth are correlated, then exclusion of the student neighborhood measure from the model could result in biased estimates of the school fixed effects. To assess the extent of any potential bias in school value-added estimates from this source, we estimate Equation 2 over the same sample used in estimation of Equation 1, recover the school fixed effects, adjust them using the empirical Bayes procedure noted above, and compare the shrunken estimates to those obtained from estimation of Equation 1.

Figure 3 presents a scatterplot of school value-added estimates recovered after estimation of Equation 1—containing neighborhood fixed effects—and Equation 2, which did not contain neighborhood fixed effects. The scatterplot reveals a strong correlation between the two estimates. Indeed, for both math and reading, the correlation between the two estimates exceeds 0.99. This suggests that any bias resulting from the exclusion of neighborhood fixed effects is likely to be minimal. To facilitate a more precise understanding of this issue, Figure 4 presents a kernel density plot of the difference between the school value-added estimates recovered from estimation of Equations 1 and 2. The plot again indicates that school value-added estimates exhibit minimal change resulting from exclusion of neighborhood fixed effects from the model.
used to estimate them. The standard deviation of the distribution is 0.01 and, empirically, the difference between the two value-added estimates is less than one-hundredth of a standard deviation for approximately 80 percent of estimates. There are a small number of observations, however, that do exhibit somewhat larger differences between the two estimates—in the range to 0.02 to 0.03 standard deviations. Our analysis of the extent of student sorting across neighborhoods and schools presented below provides further into these schools. Taken as a whole, though, these results suggest that the exclusion of a measure of student neighborhood from the model does not introduce appreciable bias into the school value-added estimates, at least in the present context—one where we rely on five years of data to produce the value-added estimates.

[Insert Figures 3 and 4 about here]

5. Distribution of Neighborhood and School Effects

As the first step in analyzing the relationship between neighborhoods and student test score growth we present in Figure 5 the kernel density distribution of estimated neighborhood contributions to student test score gains. We present separate density plots for reading (left-hand panel of Figure 5) and math (right-hand panel of Figure 5). In both subjects, the distributions range from approximately -0.1 to 0.1 with means of approximately 0 and standard deviations of 0.030 to 0.035. As a point of comparison, Figure 6 presents the kernel density plot of estimated school contributions to student test score gains. Like the neighborhood contributions, the school contributions were estimated under sum-to-zero constraints, which results in the means of approximately zero. In both reading and math, the range and standard deviation of the

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14 Prior to Bayesian shrinkage, the means of the distributions were exactly zero. In addition, the distributions of the unshrunkened estimates were similarly shaped, but with a larger range and standard deviation. Distributional plots of the unshrunkened estimates are available from the authors upon request.
distribution of estimated school contributions are substantially larger than the corresponding statistics for the distribution of estimated neighborhood contributions, a finding we discuss in further detail below.

[Insert Figures 5 and 6 about here]

The results presented in Figures 5 and 6 begin to address a number of questions concerning the contributions of neighborhoods and—to a lesser extent—schools to student test score growth.\(^\text{15}\) At the most basic level, they are relevant to the questions of whether and how much neighborhoods matter with respect to student test score outcomes. As reviewed above, existing research draws competing conclusions on the extent to which neighborhoods are important determinants of student academic outcomes. By demonstrating that—conditional on the school they attend and their demographic characteristics—students residing in different neighborhoods exhibit different average levels of test score growth, the results presented in Figure 5 align more closely with the line of research concluding that neighborhoods are an important determinant of student academic outcomes, particularly test scores (e.g. Sharkey and Elwert 2011; Aaronson 1998).\(^\text{16}\)

Given this evidence that neighborhoods do indeed matter, the question that naturally follows is one of magnitude: Just how much do neighborhoods matter? This question can be addressed from both an absolute and a relative perspective. From an absolute perspective, the data underlying the distributions presented in Figure 5 indicate that a student residing in a neighborhood in the 95\(^{th}\) percentile of the distribution would, on average, exhibit one-year test score gains about 0.05 standard deviations greater than those of a student residing in the median neighborhood.

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\(^\text{15}\) The contributions of schools to student test score outcomes have been analyzed at length in other research (e.g. Kane and Staiger 2002; Hanushek et al. 2007). Consequently, we focus primarily on neighborhood contributions here, although we recognize that schools are a natural point of comparison and use them as such.

\(^\text{16}\) In the concluding section we provide a more in-depth discussion of the relationship between our results and those presented in existing research.
neighborhood. The results suggest a similarly sized difference in the expected test score gains for a student in a 5th percentile neighborhood versus a student in the median neighborhood. Together, these results suggest about a 0.1 standard deviation difference in test score gains for students residing in a 5th vs. 95th percentile neighborhood. In the context of educational interventions, such a difference would likely be considered substantively modest. That said, these estimates are one-year differences in growth. If these annual differences accrue over time—and there are reasons to suspect that they can and do—then neighborhood contributions alone could account for nearly a standard deviation difference in the test scores of students residing in the best and worst neighborhoods.

[Insert Figure 7 about here]

In addition to analyzing neighborhood contributions to student test score from an absolute perspective, it can also be informative to consider them from a relative perspective. Indeed, an obvious question to ask when considering the size of neighborhood contributions is: Relative to what? There are several potentially meaningful comparisons that could be made in response to this question, but schools represent perhaps the most natural point of comparison. As a result, Figure 7 presents overlaid kernel density plots of the estimated neighborhood and school contributions to student test score gains. When interpreting these density plots, it is important to recall that there are about 60 more neighborhoods than schools in our data; there are approximately 220 Census tracts and about 160 schools. With this in mind, it is clear that—in both math and reading—the distribution of estimated school contributions is much more variable than the distribution of estimated neighborhood contributions. In reading, the standard deviation of the distribution of estimated school contributions is nearly four times larger than the standard deviation of the estimated neighborhood contributions. In math, the school standard deviation is
six times larger. One clear implication of this fact is that—at least for one-year test score gains—the school that a student attends is more important than the neighborhood in which the student resides. Indeed, any gains a student achieves from living in a high quality neighborhood would be more than offset if she attended one of the lowest quality schools in the city. Of course, the reverse of that statement holds as well—neighborhood disadvantage can be more than offset by attendance at a high-quality school.

6. Student Sorting Across Neighborhoods and Schools

To assess whether neighborhoods reinforce or offset the contributions of schools to student test score gains—and vice versa—we analyze how students are sorted across these two contextual settings. We first briefly explore each of these contexts in isolation before moving on to assess how students are jointly distributed across neighborhoods and schools.

If students were evenly distributed across neighborhoods, then the distribution of estimated neighborhood contributions to test scores weighted by the number of students residing in each neighborhood would be identical to the unweighted distribution presented in Figure 5. Through its simultaneous presentation of the weighted and unweighted distributions, Figure 8 demonstrates that students are not evenly distributed across neighborhoods. Although more pronounced for reading than math, the weighted distribution lies to the left of the unweighted distribution in both subjects. Substantively, this implies that students disproportionately reside in neighborhoods with below-average contributions to student test score gains. Indeed, the mean of the unweighted distribution is -0.012 while the corresponding figure for the weighted distribution is -0.023. Inspection of the distributions in Figure 8 indicate that—relative to the unweighted distribution—high-contribution neighborhoods are underrepresented in terms of student
residence while neighborhoods with slightly below-average contributions are most heavily overrepresented.

[Insert Figure 8 about here]

As is the case with neighborhoods, Figure 9 demonstrates that students are not evenly distributed across schools. However, in contrast to the neighborhood results, the distribution of students across schools is such that—relative to the unweighted distribution—it produces an increase in the mean of the distribution. In reading, the unweighted and weighted means are 0.026 and 0.051, respectively. The corresponding figures for math are 0.001 and 0.033. The density plots in Figure 9 indicate that these increased means are primarily driven by disproportionately low enrollment levels in the least effective schools, coupled with disproportionately high enrollment levels in schools with near-average test score contributions. The distributions also indicate that the most effective schools are slightly underrepresented in terms of student enrollment, but the extent of this underrepresentation is smaller than that of the least effective schools.

[Insert Figure 9 about here]

In addition to separately analyzing the distribution of students across neighborhoods and schools, we also analyze their joint distribution across these two contextual settings. Such an analysis provides a better understanding of whether each of these contexts reinforces or offsets the contributions of the other. Separately for reading and math, Figure 10 presents a scatterplot of the students by the contribution of the school they attend and the neighborhood in which they reside. Included in the scatterplot is a line representing the locally smoothed mean, an approach
that allows the data to convey the relationship between students’ schools and neighborhoods in the absence of any parametric assumptions.17

[Insert Figure 10 about here]

Figure 10 indicates that, in reading, there is generally a positive relationship between the test score contributions of the school that a student attends and the neighborhood in which they reside. The strength of this relationship, however, appears to vary by the level of estimated school contribution. In general, Figure 10 suggests that the positive relationship between school and neighborhood contributions is stronger for students attending relatively high-contribution schools than for students attending low- or medium-contribution schools, an observation we subject to further testing below. Substantively, such a relationship would imply that—for the majority of students—there is little systematic relationship between the test score contributions of the neighborhood where they live and the school they attend. However, there is a subset of students—generally those attending relatively high-contribution schools—for whom the relationship between neighborhood and school contributions is stronger.

In math, Figure 8 suggests a more variable—and perhaps somewhat weaker—relationship between the test score contributions of schools that students attend and the neighborhoods in which they reside. Indeed, the relationship between neighborhood and school contributions appears slightly negative in the far lower reaches of the distribution of estimated school contributions. The relationship seems to trend slightly positive throughout the heart of the distribution before becoming more volatile in the very upper tail.

Although the nonparametric approach used above is useful for understanding the general contours of the relationship between the test score contributions of students’ schools and neighborhoods, additional information—such as the estimated magnitude of the relationship—

17 A bandwidth of 0.05 was used in estimation of the locally smoothed means.
can be gained by imposing parametric assumptions. The first column of Table 1 presents the results of a simple OLS regression of the estimated test score contributions of students’ neighborhoods on the estimated test score contributions of their schools. In both math and reading, the results indicate a positive and statistically significant relationship. Substantively, however, the relationship can best be characterized as weak. In reading, a one standard deviation increase in estimated school test score contributions is associated with a 0.04 standard deviation increase in neighborhood test score contributions. The relationship is even weaker in math—the same one standard deviation increase in school contribution corresponds to only a 0.02 standard deviation increase in neighborhood contribution.

OLS only produces the mean response function and Figure 10 provides evidence of heterogeneity in the relationship between students’ school and neighborhood contributions. To further explore this potential heterogeneity, we estimate a series of quantile regressions of neighborhood contributions on school contributions. We estimate this simple model at five quantiles—10th, 25th, 50th, 75th, and 90th—separately for reading and math. The results of these models are presented in the second through sixth columns of Table 1. The reading results indicate that the relationship between students’ school and neighborhood contributions tightens as the estimated school contribution increases. Indeed, there is no statistically significant relationship between these two contextual settings at the 10th or 25th quantiles, but significant positive relationships at the 50th, 75th, and 90th. Moreover, the magnitude of the positive relationship increases at each point across the distribution.

A slightly different picture emerges in math. Likely reflecting the relatively sparse data—and corresponding volatility—there is no significant relationship between students’ school and neighborhood contributions at either the 10th or 90th percentile. In contrast, there is a
statistically significant, but substantively small, relationship between school and neighborhood contributions at the 25th, 50th, and 75th percentiles. Taken as a whole, the picture that emerges is one where the relationship between students’ neighborhood and school contributions is positive, and somewhat variable, but generally weak. We discuss some normative implications of these patterns in the concluding section of the paper.

[Insert Table 1 about here]

7. Observable Characteristics Related to Estimated Neighborhood and School Contributions

To this point, our empirical approach demonstrates that both schools and neighborhoods are significant contributors to one-year student test score gains and that there is substantially more variation in the contributions of schools than neighborhoods. We have not, however, shed light on the observable characteristics of neighborhoods or schools associated with large and small estimated contributions to student test score gains. In this section, we attempt to gain insight into this issue by correlating observable characteristics of neighborhoods and schools with their estimated contributions to student test score gains.

7.1 Neighborhoods

As described earlier, our dataset contains a wide variety of observable socioeconomic and demographic characteristics for each Census tract in Milwaukee. Here we assess how 12 of these characteristics—selected to measure multiple dimensions of a neighborhood environment—relate to estimated neighborhood contributions to student test score gains. For each of the 12 observable socioeconomic and demographic characteristics, Figure 11 presents a

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18 The 12 characteristics we analyze are the percentage of households headed by a single parent, the unemployment rate, the percent of adults with a BA or higher, the Gini coefficient, the percentage of households with income less than half the poverty level, the percentage of households with income at least twice the poverty level, the percentage of children living with at least one parent, the percentage of households headed by a married adult, the percentage of households headed by a never-married adult, median family income, the percentage of dwellings that are owner-occupied, and the percentage of dwellings that are vacant.
scatterplot of each neighborhood’s estimated contribution to student test score gains and its value on the relevant observable characteristic. Each plot contains a line of best fit—the solid line—and the 95 percent confidence interval for that line—the dashed lines. The plots in Figure 11 contain estimated contributions to student gains in math, but the results for reading are substantively similar and available from the authors upon request.

[Insert Figure 11 about here]

Substantively, the bivariate relationships depicted in Figure 11 are largely consistent with expectations. For example, the percentage of single parent households, the percentage of households headed by never-married individuals, and the percentage of dwellings that are vacant are all negatively—and statistically significantly—related to estimated neighborhood contributions to student test score gains. In addition, the point estimates for the unemployment rate and the percentage of households with income less than half the poverty level are also negative, but the estimates are not statistically significant. On the other hand, the percentage of households with income at least twice the poverty level and the percentage of households headed by married individuals exhibit positive and statistically significant relationships with estimated neighborhood test score contributions; point estimates for the percentage of kids living with at least one parent, median family income, and the percentage of homes that are owner-occupied are positive, but not statistically significant. Relationships between estimated neighborhood contribution and income inequality—as measured by the Gini coefficient—and the percentage of adults with at least a bachelor’s degree are entirely nonexistent.

In addition to lending face validity to the estimates of neighborhood contributions to student test score gains, Figure 11 provides some substantive insight into the observable

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19 The p-values for these relationships are 0.21 and 0.42, respectively.
20 The p-values for these relationships are 0.35, 0.16, and 0.37, respectively.
neighborhood characteristics associated with estimated contributions. Specifically, the results indicate that the observable dimension most consistently related to estimated test score contribution is that of household composition and family structure. The prevalence of single parent households and the measures of marital status all exhibit relatively strong relationships with estimated neighborhood contributions to student test score gains. Many of the income-based characteristics are also related to estimated neighborhood test score contributions, but these relationships are neither as strong nor as consistent. Of course, in making these observations we are not making any claims about the causal nature of the relationships between any of the observable characteristics and neighborhood effects on student test score gains—they are simply intended to help paint a descriptive portrait of the association between these two features of the broader neighborhood context.

7.2 Schools

Although we are primarily focused on student neighborhoods, in this section we briefly analyze the relationship between estimated school contributions and observable school characteristics; the results of this analysis are presented in Figure 12. The figure demonstrates that estimated school contributions to student test scores are related to observable features of the school in ways that would be predicted by prior research. Specifically, Figure 12 reveals that estimated school contributions are negatively related to the percentage of students with learning disabilities, the percentage of students eligible for free or reduced-price lunch, and the percentage of students who are Black. In contrast, the results demonstrate positive relationships between estimated school contributions and the percentage of students who are Black.

21 In bivariate regressions, the relationships between estimated school contribution and both the percentage of students with a learning disability and the percentage of students who are Black are statistically significant at \( p < 0.01 \). The \( p \)-value of the relationship between estimated school contribution and the percentage of students eligible for free or reduced-price lunch is 0.149.
white, the percentage of students who are Asian, and school enrollment.\textsuperscript{22} This enrollment result is consistent with the results presented in Figure 9 showing that students are sorted into disproportionately effective schools. Finally, and perhaps somewhat surprisingly, the bivariate relationship between estimated school contribution and the percentage of students classified as English Language Learners (ELLs) is positive and fairly strong from both a substantive and statistical standpoint.

[Insert Figure 12 about here]

\section*{8. Discussion and Conclusion}
This paper presented the results of a wide-ranging exploration of the contributions of schools and neighborhoods—two of the most important contextual settings in students’ lives—to student test score gains. In Milwaukee there is sufficient cross-classification of students in neighborhoods and schools to permit simultaneous estimation of neighborhood and school contributions to test score gains, a fact that may be explained by a particularly broad open-enrollment environment in the public school system. We estimated these neighborhood and school contributions using a single model over a single sample of students in metrics that are directly comparable. Throughout the course of this analysis four main findings emerged. First, the analyses presented above make clear that the contributions of schools to student test score gains are substantially more variable than the contributions of neighborhoods. As a substantive illustration of this finding, our results indicate that, on average, a student attending a school at the 90\textsuperscript{th} percentile of effectiveness will exhibit test score gains that are 0.15 standard deviations greater than a student attending the median school. This contrasts with the neighborhood context, where the test score gains of a student residing in a neighborhood at the 90\textsuperscript{th} percentile

\textsuperscript{22} In bivariate regressions, the $p$-values for the percentage of students who are white, Asian, and school enrollment are 0.002, 0.071, and 0.030, respectively.
of effectiveness are only estimated to be about 0.04 standard deviations greater than a student residing in the median neighborhood. As evidenced by this example, our analysis could reasonably be interpreted as providing evidence that schools are more important than neighborhoods with respect to determining one-year test score gains.

Second, our analysis provides valuable insight into the manners in which students are sorted across the two contextual settings we analyze. The results reveal that students are disproportionately concentrated in neighborhoods with below-average estimated contributions, but in schools with above-average effectiveness. Perhaps most interesting, however, is the joint distribution of students across these two contextual settings. Specifically, our results demonstrate only a weak positive relationship between the estimated contribution of the neighborhood in which students reside and the schools they attend. The normative complication of such a finding is complex. In one sense, it may be a relief that the relationship is only weakly positive and not strongly positive, which many people likely hold as their a priori expectation. In another sense, though, it may be disappointing that the relationship is positive at all. We may hope that children residing in the most disadvantaged neighborhoods receive high-quality schooling—this could help offset the negative effects of the neighborhood contexts and potentially mitigate the test score gaps that we routinely observe between students of different socioeconomic and demographic backgrounds.

Third, the analysis reveals that observable characteristics of neighborhoods and schools are related to their estimated contributions in ways that are largely predictable given prior research; such a pattern lends face validity our estimates of neighborhood and school contributions to student test score gains. From a substantive standpoint, the results indicating that household composition and family structure represent the observable dimension of
neighborhoods most consistently related to estimated test score contribution is a pattern than would seem to warrant future empirical exploration.

Finally, this paper demonstrated that estimates of school value-added are quite robust to the exclusion of explicit measures of students’ neighborhood contexts. Given the movement toward holding educational institutions and employees accountable on the basis of their estimated value-added, it was somewhat reassuring to find that our estimates of school effectiveness were insensitive to the inclusion or exclusion of neighborhood measures. We stress that this study says little, however, about the sensitivity of teacher value-added estimates—the primary focus of current policy debates—to the inclusion or exclusion of measures of student neighborhood.

Perhaps as important as the discussion of the four main findings of our analysis is a discussion of what we did not find. Specifically, we highlight two main “nonfindings.” First, we did not find that neighborhoods do not matter for student educational outcomes. To the contrary, our analysis revealed significant variation across neighborhoods with respect to their estimated contributions to student test score gains. Moreover, because children often reside in a single—or at least comparable—neighborhood context for much longer periods of time than they attend any given school, the cumulative contribution of neighborhood on a student’s achievement level may be at least as large, if not larger, than the contribution of a school, even if the year-to-year contributions of the best neighborhoods are smaller than that of the best schools. As a final word on this point, we also highlight that student test score gains—the outcome of interest in our study—is precisely the educational outcome over which schools would be expected to have the most influence. The substantive conclusions drawn from this study are clearly not generalizable to student attainment or other educational outcomes of interest.
Second, the findings presented above do not imply that policies designed to move students from a neighborhood or school with a low estimated contribution to one with a higher one will necessarily result in improved student achievement. Indeed, prior research that has directly assessed such behaviors—or policies designed to induce such behavior—provides reason for skepticism. In the neighborhood context, both Jacob’s (2004) study and the MTO evaluation (Sanbonmatsu et al. 2011) found that children residing in households that relocated to neighborhoods with lower levels of poverty did not exhibit any discernible improvements in educational outcomes, relative to control groups that remained in high-poverty neighborhoods. Such findings are consistent with our results in Figure 11 demonstrating only a weak relationship between estimated neighborhood contribution and the poverty rate of the Census tract. Furthermore, the character and culture of a neighborhood is something that develops over a long period of time, and it is unlikely that simply relocating households to a better neighborhood will immediately imbue them with all the virtues of that neighborhood; new arrivals may change the character and culture of a neighborhood at least as much as it has any effect on them. Such realities underlie our decision to use the terminology of “neighborhood contribution,” rather than “neighborhood value-added.” Our choice of terminology was designed to stress that it was all aspects of the neighborhood—the composition and activities of the families residing there—and not just living in a specific geographic area that affects students’ educational outcomes.

In the context of schools, a significant body of research has demonstrated that changing schools has a negative effect on student educational outcomes (e.g., Hanushek, Kain, and Rivkin 2004; Xu, Hannaway, and D’Souza 2009; Zimmer et al. 2009; Engberg et al. 2012). Consequently, movement to a different school—even one of higher quality—must overcome the disruptive effects of such a move. Although multiple educational reform strategies, such as
school closures, are predicated on the assumption that moving kids to better schools will more than offset the disruptive effects of changing schools, whether this assumption holds in practice is ultimately empirical question.

Few studies have simultaneously analyzed the role of both neighborhoods and schools in shaping student academic outcomes, and to our knowledge, none have done so in the manner presented in this paper. At the same time, relatively few cities have the extent of public school choice that is present in Milwaukee and it is unclear whether the results produced by our analyses would emerge in contexts where students have fewer options. That said, the results may provide some insight into what might happen if public school choice became more widespread in other large urban areas as it is in Milwaukee. For example, our results demonstrate that school and neighborhood effectiveness are related, but perhaps not as closely as might be the case in cities and school districts where residence-based assignment is the dominant system for determining the school that a student will attend. More generally, this study demonstrates that the relationship between schools, neighborhoods, and student outcomes is a complex one, and the analyses in this paper represent an initial effort to gain a better, but still incomplete, understanding.

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References


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Retrieved July 24, 2013, from


Figures and Tables

Figure 1. Distribution of schools
By number of unique tracts in which students reside

Figure 2. Distribution of tracts
By number of unique schools that students attend
Figure 3. School value-added estimates with and without neighborhood fixed effects

Reading

Math

Figure 4. Difference between estimated school value-added with and without neighborhood fixed effects
Figure 5. Distribution of estimated neighborhood contributions to student test score gains

Emp. Bayes Estimates
Mean: -0.01
Std. dev.: 0.035
Min: -0.11
Max: 0.13

Emp. Bayes Estimates
Mean: 0.00
Std. dev.: 0.030
Min: -0.10
Max: 0.09

Figure 6. Distribution of estimated school contributions to student test score gains

Emp. Bayes Estimates
Mean: 0.03
Std. dev.: 0.132
Min: -0.64
Max: 0.32

Emp. Bayes Estimates
Mean: 0.00
Std. dev.: 0.180
Min: -1.04
Max: 0.62
**Figure 7. Distribution of estimated neighborhood & school contributions to student test score gains**

**Reading**
- **School Estimates**
  - Mean: 0.03
  - Std. dev.: 0.132
  - Min: -0.64
  - Max: 0.32
- **Neighborhood Estimates**
  - Mean: -0.01
  - Std. dev.: 0.035
  - Min: -0.11
  - Max: 0.13

**Math**
- **School Estimates**
  - Mean: 0.00
  - Std. dev.: 0.180
  - Min: -1.04
  - Max: 0.62
- **Neighborhood Estimates**
  - Mean: 0.00
  - Std. dev.: 0.030
  - Min: -0.10
  - Max: 0.09

**Figure 8. Distribution of estimated neighborhood contributions to student test score gains**

**Reading**
- **Weighted Estimates**
  - Mean: -0.023
  - Std. dev.: 0.029
  - Min: -0.11
  - Max: 0.13
- **Unweighted Estimates**
  - Mean: -0.012
  - Std. dev.: 0.035
  - Min: -0.11
  - Max: 0.13

**Math**
- **Weighted Estimates**
  - Mean: -0.005
  - Std. dev.: 0.028
  - Min: -0.10
  - Max: 0.09
- **Unweighted Estimates**
  - Mean: -0.001
  - Std. dev.: 0.030
  - Min: -0.10
  - Max: 0.09
Figure 9. Distribution of estimated school contributions to student test score gains

Figure 10. Student sorting across neighborhoods and schools
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Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by school in parentheses below coefficient.
Figure 11: Relationships Between Estimated Neighborhood Contribution and Observable Neighborhood Characteristics (Math Scores)
Figure 12: Relationships Between Estimated School Contribution and Observable Neighborhood Characteristics (Math Scores)