Neighborhood Disadvantage and Children's Cognitive Skill Trajectories

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Abstract

This study examined how neighborhood disadvantage is associated with children's trajectories of growth in math and reading skills in early elementary school to better understand how where children attend school affects their academic success, and how these associations vary by student characteristics. We used multilevel growth models with nationally representative data from the 2011 Early Childhood Longitudinal Study-Kindergarten Cohort (ECLS-K:2011) to examine how the poverty level of children's schools relate to their initial levels and trajectories of growth in math and reading scores from Kindergarten through third grade, and how these trajectories vary by child gender, race, ethnicity, household poverty, whether parents were born outside of the U.S., and Kindergarten and early child care experiences.

More than one-quarter (27%) of children attended schools in communities of concentrated poverty (in which 20% or more residents were poor). Children attending elementary schools in higher-poverty communities – particularly moderate-high poverty communities (20-40% poverty) – had lower initial cognitive scores at the fall of Kindergarten and averaged lower scores through third grade. During Kindergarten, however, children attending schools in highly distressed communities showed 26 percent and 8 percent higher growth in math and reading, respectively, compared to their peers in schools in low poverty communities, but these higher growth rates were not large enough to close the initial gaps by neighborhood resources. Between the spring of Kindergarten and spring of first grade, this pattern reversed such that children in schools in high poverty neighborhoods grew at *slower* rates than their peers in low poverty neighborhoods in math and reading (27% slower in math and 13% slower in reading), widening achievement gaps. The growth rates of Black children appeared more vulnerable to the effects of attending school in higher-poverty neighborhoods than non-Black children, particularly between the second and third grades. By contrast, there was evidence that the neighborhood poverty-based gap narrows more for Hispanic children (in math), children with immigrant parents, and children in the highest poverty neighborhoods who had attended center-based early care and education (in reading).

Findings suggest that achievement gaps by neighborhood resources are large and present before Kindergarten, shrink during the Kindergarten year, but then widen the year following, and remain relatively consistent in the first years of elementary school. Results have implications for the academic preparation of the future workforce.

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Neighborhood Disadvantage and Children's Cognitive Skill Trajectories

Poverty in the United States has become increasingly concentrated (Bishaw, 2014), raising concerns about the implications of the growing proportions of today's children – tomorrow's workers – growing up in disadvantaged communities. In 2000, fewer than three percent of Americans lived in "extreme-poverty" communities, defined as census tracts in which 40 percent or more residents were poor; in 2010-2014, 4.4 percent – 14 million Americans – lived in these extremely poor communities, more than twice as many people as in 2000 (Kneebone, 2014; Kneebone & Holmes, 2016). Racial and ethnic minority individuals and children are more likely to both live in poor households and in poor neighborhoods than Whites or adults (Kneebone & Holmes, 2016). Concentrated poverty increased over the last decade in two-thirds of our nation's biggest cities, as well as in suburban locales, and the concentration of wealth and the concentration of disadvantage will likely continue in the future (Kneebone, 2014; Kneebone & Holmes, 2016). As shown in the maps in Figure 1, communities of concentrated poverty include those in urban centers such as Philadelphia, but also in suburban and rural communities like rural Maine and West Virginia. Although many residents of high-poverty communities are not poor themselves, they experience the same negative consequences of resource-poor neighborhoods; those that are poor face the double disadvantage of a lack of household resources and a lack of community resources.

Insert Figure 1 here.

The negative effects of family poverty for children's outcomes are well-documented (Duncan, Magnuson, Kalil, & Ziol-Guest, 2011; Duncan, Ziol-Guest, & Kalil, 2010; Shonkoff & Garner, 2012). A growing body of research demonstrates that in addition to family resources, the resources of the neighborhoods in which children learn and grow affect their short- and long-term health, academic, and economic success (Chetty, Stepner, et al., 2016; Chetty, Hendren, & Katz, 2016; Morrissey & Vinopal, 2018b; Wolf, Magnuson, & Kimbro, 2017). These neighborhood effects are particularly concerning given the increasing concentration of poverty.

One policy-relevant research question is whether the K-12 education system mitigates or exacerbates the effects of neighborhood poverty on longer-term educational and economic outcomes. While much of the neighborhood effects literature suggests that the neighborhood as experienced during early childhood appears to be more important to long-term economic outcomes than one's neighborhood in later periods (Chetty, Hendren, et al., 2016; Leventhal, 2018), the K-12 educational system represents our largest public investment in children (Isaacs et al., 2018) and a potential point of nationwide intervention. Previous research suggests that achievement gaps by children's family income shrink during the school year, and increase during the summer, suggesting that schools provide an equalizing force for income achievement gaps (Downey, Hippel, & Broh, 2004; von Hippel, Workman, & Downey, 2018). However, how achievement gaps by neighborhood poverty – specifically, the poverty levels of the neighborhoods in which children attend school – change as children move through elementary school has not yet been examined. This is important in shedding light on whether K-12 schools serve as an equalizing force across schools and neighborhoods, not only within schools.

This study uses recent, nationally representative data from the 2010-2011 Early Childhood Longitudinal Study-Kindergarten Cohort (ECLS-K:2011) to examine associations between neighborhood disadvantage and children's trajectories of cognitive growth in early elementary school to better understand how the communities in which children attend school relate to their academic success, and how these associations vary by child and family characteristics. Importantly, the children in the ECLS-K:2011 will be 45 years old in 2050.

Understanding the communities in which they live and attend school, and how these neighborhoods relate to their academic outcomes and growth, is important for understanding tomorrow's workforce. Although we cannot estimate the causal effects of school neighborhood poverty on children's growth in cognitive skills, as the school a child attends is associated with a range of family characteristics that are also associated with children's achievement, this descriptive analysis of how children learn across schools in communities with varying resources sheds light on the implications of concentrated poverty and a potential point for intervention.

Neighborhoods and Children's Development

Bio-social ecological theory asserts that children grow and develop via bidirectional interactions with the contexts within which they are embedded (Bronfenbrenner & Morris, 1998). As the most proximal context for most children, the family or household typically has a primary influence on development, but other contexts regularly and directly experienced, including the neighborhoods in which children live and learn, also have considerable influence. A large and growing body of research suggests that neighborhood characteristics, particularly the poverty rate of a neighborhood (defined as the proportion of residents living below the poverty line), are associated with children's achievement and academic outcomes (Alexander, Entwisle, & Olson, 2014; Roy, Mccoy, & Raver, 2014; Wodtke, 2013; Wodtke, Harding, & Elwert, 2011), including their earnings in adulthood (Altonji & Mansfield, 2018; Chetty & Hendren, 2017b; Chetty, Hendren, et al., 2016; Rothwell & Massey, 2015). Other research suggests that one's neighborhood during childhood can have intergenerational effects on their own children's cognitive abilities (Sharkey & Elwert, 2011). While the causal effects of neighborhoods are difficult to identify given that neighborhood sorting is associated with factors that affect children's outcomes (e.g., family income), evaluations of Moving to Opportunity (MTO), for which families were randomly assigned families housing vouchers, some of which could only be used in low-poverty areas, found relatively few short-term effects of low-poverty neighborhoods but strong longer-term effects on health, educational attainment, and earnings (Chetty, Hendren, et al., 2016; Ludwig et al., 2011, 2012). Further, research examining historical data suggests that observational estimates are quite predictive of neighborhood effects (Chetty, Friedman, Hendren, Jones, & Porter, 2018).

K-12 Education and Children's Development

One of the hypothesized mechanisms via which neighborhoods may affect children's development – for better or worse – is via the K-12 education system (Leventhal & Brooks-Gunn, 2000). Indeed, the quality of schools – typically measured by average test scores – is a driver of housing decisions and neighborhood housing prices (Kane, Staiger, & Reigg, 2006). Schools in lower-income areas average higher teacher turnover (Boyd, Lankford, Loeb, & Wykoff, 2005) and poorer curricula (Darling-Hammond, 1998). Historically, schools in lower-income communities have spent less per child on education than those in higher-income areas, although this varies considerably by state (Chingos & Blagg, 2017), particularly since the school finance reforms of the 1990s directed more funds toward low-income schools, which had large effects on student achievement (Lafortune, Rothstein, & Schanzenbach, 2018). The distribution of teacher quality tends to vary with school poverty, such that the worst teachers in higher-poverty schools are worse than those at lower-poverty schools, whereas the best teachers are relatively consistent across school poverty levels (Sass, Hannaway, Xu, Figlio, & Feng, 2010). In addition to what occurs within the schools' walls, environmental factors such as pollution from nearby factories, which are more commonly located near low-income schools, show substantial and sustained effects on children's academic achievement (Persico & Venator, 2018).

Although some mechanisms of neighborhood poverty may work via K-12 education, recent studies suggests that the effects of neighborhood disadvantage emerge early in life, well before school entry (Chetty & Hendren, 2017a; Leventhal, 2018). For example, a recent re-analysis of the MTO Study found that the neighborhood in which one lived as a young child was more predictive of college attendance and income in young adulthood than the neighborhood experienced as an adolescent (Chetty, Hendren, et al., 2016). Likewise, recent research suggests that, within a few months of entering Kindergarten, children from high-poverty neighborhoods have lower cognitive scores and higher rates of food insecurity (but not necessarily poorer behavior) compared to those from lower-poverty neighborhoods (Morrissey, Oellerich, Meade, Simms, & Stock, 2016; Morrissey & Vinopal, 2018b; Wolf et al., 2017). The associations between the level of neighborhood disadvantage as experienced during the Kindergarten year and children's cognitive outcomes appears to be sustained through second grade (Morrissey & Vinopal, 2018b). Likewise, although achievement gaps between children from high- and low-socioeconomic status (SES) families widen somewhat during the elementary school years, the majority of the gap appears well before children begin Kindergarten (Halle et al., 2009; Reardon, 2011), again highlighting the early childhood period as a particularly sensitive one for resources (or the lack thereof). Together, the research on neighborhood effects and achievement gaps suggest that variation in K-12 educational experiences may not be the main driver of social and economic inequalities.

Associations between Neighborhoods and Children's Skill Growth

Most research on the effects of neighborhoods or K-12 education on children's outcomes has focused on measures at a point in time (i.e., absolute differences between children from different backgrounds). Research on absolute score tests is important, given differences presumably reflect meaningful differences in skills or preparedness for higher education or the workforce, which educational policies should seek to narrow. However, the growth of, change in, or trajectories of cognitive outcomes have been less frequently studied, but have important implications for education and policy. For example, an analysis of trajectories over the early years of schooling may indicate a particular developmental period best suited for an intervention to narrow or close achievement gaps. Further, although absolute test scores are often used by policymakers and parents alike to compare, rank, and reward or penalize schools, test score differences may more accurately reflect children's experiences prior to Kindergarten entry, whereas growth in test scores may be a more meaningful proxy for the quality of teaching and education provided by the school (Reardon, 2018).

Research on growth in test scores has increased in recent years. For example, the value-added approach to assessing teacher quality finds relatively strong associations between students' SES and cognitive growth (Deming, 2014). Another example is Reardon (2018), who used national data from over 45 million students in 11,000 school districts to examine average test scores at third and eighth grades, and the changes in test scores between these two grades. Importantly, he found a very weak and negative correlation (-0.13) between average third grade test scores and the change or growth in test scores between third and eighth grades, and school district SES was more strongly associated with average test scores than growth (0.68 vs. 0.32). These results have several implications. First, there is considerable heterogeneity between school districts in children's learning within categories of initial performance (as assessed in third grade), and by school SES. That is, schools that may be labeled "low-performing" based on average test scores at third grade may be quite effective at promoting growth from third to eighth grade, whereas some schools labeled "high-performing" based on average test scores may show low levels of growth. Second, Reardon concluded that a neighborhood's early educational opportunities, in his study defined as prior to third grade (early elementary school, preschool, and child care), are largely uncorrelated with educational opportunities in middle childhood (later elementary and middle school, and out-of-school opportunities). He also identified some differential patterns of growth by race, ethnicity, and gender. For example, the Black-White gap in test score growth was substantial but much smaller than racial gaps in absolute scores, and Hispanic children had higher growth rates than White children, suggesting some narrowing of ethnic gaps in K-12. However, the use of district-level averages precluded an examination of how individual characteristics such as child gender, race/ethnicity, or family income may influence individual patterns of growth.

An emerging body of work uses individual-level data from the 1998 or 2010-2011 Early Childhood Longitudinal Study-Kindergarten Cohorts (ECLS-K) to examine growth in cognitive skills (McCoach, O'Connell, Reis, & Levitt, 2006) and growth by specific child characteristics, such as measures of English proficiency or approaches to learning at kindergarten (Li-Grining, Votruba-Drzal, Maldonado-Carreño, & Haas, 2010; Roberts & Bryant, 2011). von Hippel and colleagues found that achievement gaps by family SES shrink during the academic year (from fall to spring), and grow during the summer months (from spring to fall) (Downey et al., 2004; von Hippel et al., 2018). While this provides suggestive evidence that schools can narrow gaps between students, we lack an understanding of the patterns of inequality across K-12 schools in different SES and resource contexts.

To date, few studies have examined trajectories of children's outcomes by neighborhood or school characteristics using individual data. In one exception, Root and Humphrey (2014) examined measures of parent-reported health in the ECLS-K, finding that initial health assessments and growth in this measure were strongly associated with child race, household income, and parental marital status, but not with neighborhood racial composition. Arguably, however, health and cognitive development are affected by different neighborhood characteristics and via different pathways. Indeed, neighborhood characteristics appear to be less strongly associated with children's health, food security, or behavioral measures than cognitive outcomes (Morrissey et al., 2016; Morrissey & Vinopal, 2018b; Root & Humphrey, 2014; Wolf et al., 2017). In another paper, Pearman (2017) used nationally representative data from the Panel Study of Income Dynamics (PSID) to examine how neighborhood poverty related to growth in math achievement. Controlling for children's initial scores, he found that children in high-poverty neighborhoods experienced poorer growth, and estimated that they would need an additional 1.5 months of schooling to have math scores on par with children in low-poverty neighborhoods (Pearman, 2017). However, this study did not examine how the age or developmental period during which neighborhood poverty exposure occurred affects growth, how reading and math achievement measures differed from each other, or how growth in relation to neighborhood poverty varies with individual child characteristics. To our knowledge, research has not yet examined trajectories of growth in individual-level measures of cognitive development in relation to school neighborhood disadvantage.

The Current Study

Given the continuing growth in economic segregation (Bishaw, 2014; Kneebone, 2014; Kneebone & Holmes, 2016), better understanding how where one lives affects his or her life success is vital for creating policies to support future generations. To date, however, how neighborhood disadvantage relates to children's trajectories of growth in cognitive scores in elementary school, or how children's individual circumstances, including their demographic characteristics and experiences prior to Kindergarten, affect these trajectories, have not been investigated. These investigations are important for understanding how where people live affect their economic outcomes and inequality, when and where interventions to break the intergenerational cycle of poverty and neighborhood disadvantage can be most effective, and how and why returns to education vary by community, race, and ethnicity. Findings are increasingly relevant in responding to troubling current and future trends, as compared to the late 1990s, smaller proportions of early elementary-age children live in low-poverty areas, and the relationships between neighborhood disadvantage and children's outcomes appear stronger than in years past (Wolf et al., 2017).

This study uses nationally representative, longitudinal, child-level data merged with neighborhood-level contextual data to examine the associations between school neighborhood disadvantage and children's trajectories of cognitive growth, independent of children's household and family circumstances, to better understand how where children attend school affects their academic success, and how these associations vary by student characteristics. Specifically, we use data from the 2011 cohort of the ECLS-K:2011, with the census tract of children's schools merged with corresponding tract-level data from the 2010-2015 Five Year Estimates of the American Community Survey (ACS). Notably, the children of the ECLS-K:2011 will be 45 years old in 2050, representing an important segment of the future workforce, one necessary to better understand to predict future economic conditions. We examine two research questions:

1. How does neighborhood disadvantage (i.e., poverty rate) relate to children's trajectories of math and reading scores in early elementary school?
2. How do student characteristics (race/ethnicity, gender, immigrant status, household

poverty, urbanicity, early care and education experience, and full- or part-day Kindergarten attendance) influence the relationships between neighborhood disadvantage and children's trajectories of cognitive scores in elementary school?

Method

Data

The ECLS-K:2011 follows approximately 18,000 children from the fall of Kindergarten through elementary school. The data are collected by the National Center for Education Statistics (NCES), and were designed to be nationally representative of children attending Kindergarten the United States during the 2010-2011 academic year (including both first-time and repeating kindergarteners).[1] The data are ideal for our research questions given their large nationally representative sample sizes, longitudinal measures, and detailed information on children, their families, and their school environments.

Using children's school census tracts, we merged child-level data from the ECLS-K dataset with tract-level poverty rate from the 2010-2015 Five-year American Community Survey (ACS) estimates, to match the years in which child-level data were collected. The 2010-2015 period largely matches the period during which children attended elementary school. The multiyear data offer the advantage of increased statistical reliability for less populated areas and small population subgroups, and it is the only source for poverty rates at the census tract level. Although census tracts may not map on to neighborhoods as defined by residents, they represent small, relatively permanent subdivisions of a county or city containing a population size of 1,200 to 8,000 people (with an optimum size of 4,000) and are updated prior to each decennial census.[2]

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[1] The reported sample sizes are rounded to the nearest 10, per NCES regulations regarding disclosure of restricted-use data.

[2] For more information about census tracts, see: https://www.census.gov/geo/reference/gtc/gtc_ct.html

Census data are generally accepted as the only comprehensive source of detailed information at the tract level, and using the percent of households or residents below the federal poverty line is a common approach to assessing neighborhood disadvantage (Bishaw, 2011; Morrissey & Vinopal, 2018b; Wolf et al., 2017).

Because census tracts are relatively small geographic areas, most children attend schools in census tracts different from their residential census tracts (approximately 33% of children attended Kindergarten in a school located within their own residential census tracts), and these different tracts may have higher or lower rates of disadvantage. However, given growing rates of economic segregation, most children attend schools in neighborhoods very similar to those in which they live.[3] Further, the (dis)advantage of the neighborhood in which a school is embedded reflects its catchment area and is typically correlated with rankings on school quality (often based on average test scores) or of the resources available to children outside of school. We also replicated this analysis with children's residential tract poverty rate, described in the sensitivity analysis section below.

We limited our sample to children with nonmissing data on measures of math and reading scores at the fall and spring of Kindergarten, the spring of first grade, the spring of second grade, and the spring of third grade, and on school-level census tracts, as well as all covariates described below ($N \approx$ 49,000 child-year observations; or about 10,020 children out of a possible 18,170 in fall of Kindergarten). Dropping observations due to missing data means that, compared to observations left out of our sample, as of fall of Kindergarten, our analysis relies on a group of students with higher test scores and lower levels of neighborhood and household poverty, and who are more likely to be White, speak English, have married and more educated parents, live in

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[3] As shown in Appendix Table 3, the poverty rate of the tract in which a child's school was located was highly correlated with the poverty rate of the child's residential tract (0.72).

a rural area, attend part day (as opposed to full day) Kindergarten, and attend center-based care before kindergarten. There were no differences in gender, age, or household size. The largest amount of missing data was generated by variables reporting on household size, parents' marital status, and whether the student is a child of immigrants, with about 4,780 observations missing information for those variables.

Measures

Dependent variables. Dependent variable construction relied on the ECLS-K-administered direct child assessments that track respondents' academic growth in math and reading over time. These assessments were adapted from national and state standards and accommodate children who speak a language other than English at home. A theta score is provided in the ECLS-K:2011 data file for each child who participated in the direct cognitive assessment for each cognitive domain assessed and for each administration. We used the reading and math theta scores in this analysis. The theta score is an estimate of a child's ability in a particular domain (e.g., reading) based on his or her performance on the items he or she was actually administered. Theta scores for reading and mathematics are provided in for the fall and spring kindergarten, and spring of first, second, and third grade data collection rounds. Theta is iteratively estimated and re-estimated; therefore, the theta score is derived from the means of the posterior distribution of the theta estimate. The theta scores are reported on a metric ranging from -6 to 6, with lower scores indicating lower ability and higher scores indicating higher ability. Theta scores tend to be normally distributed because they represent a child's latent ability and are not dependent on the difficulty of the items included within a specific test,[4] and have

[4] For more information, see the ECLS-K:2011 user's guide.

been used in previous research to examine children's cognitive growth by household income (von Hippel et al., 2018). Thus, theta scores are useful in assessing growth in skills over time.

Independent variables. Neighborhood disadvantage was measured using the poverty level of the census tract in which children attended elementary school. The census tracts of children's schools at the fall of kindergarten were merged with information from the ACS on the average value of the percent of residents living below the federal poverty line (FPL) from 2010-2015. Following previous work (Bishaw, 2011), we classified tracts into one of four categories: *low poverty neighborhoods*, census tracts with less than 14 percent of residents living below the FPL (i.e., representing a neighborhood with a poverty rate below the national average); *moderate-low poverty neighborhoods,* tracts in which 14-19 percent of residents live below the FPL; *moderate-high poverty neighborhoods*, in which 20-39 percent of residents live below the FPL; and *high poverty neighborhoods*, in which 40 percent or more residents live below the FPL. Previous research suggests that the 20 and 40 percent poverty thresholds are particularly meaningful, finding that poor individual outcomes like crime, school drop-out, and longer spells of poverty duration increase with neighborhood poverty between 20 to 40 percent levels (Galster, 2010). In our analysis sample, in the fall of kindergarten 61 percent of children lived in low-poverty neighborhoods, 12 percent in moderate-low poverty neighborhoods, 23 percent in moderate-high poverty neighborhoods, and 4 percent in high-poverty neighborhoods.[5] These proportions are similar to those found from other work that examines children's residential census tracts in the ECLS-K:2011 (Morrissey & Vinopal, 2018a, 2018b; Wolf et al., 2017). For children who moved

[5] Four percent of our sample attended schools in neighborhoods in which the poverty rate is between 40 and 50 percent; 1.3 percent in neighborhoods in which the poverty rate is between 50 and 60 percent, and 0.12% in neighborhoods in which the poverty rate is 60 percent or greater. Due to power considerations, in our analyses, we analyze this as one group attending schools in neighborhoods where 40 percent or more residents are poor.

schools between waves[6], we use the poverty level of the tract that their new school is in, and add a dummy variable indicating the move.

Covariates. Covariates included child gender, grade in school, age (in continuous months at assessment), race/ethnicity (*non-Hispanic Black*, *Hispanic, non-Hispanic White*, *American Indian, Asian, Other*), whether the child was a twin, whether the child speaks a language other than English in the household, household size (centered to the mean), household poverty level (calculated using respondents' reports of household size and income; *under 100% FPL, 100-200% FPL, or over 200% FPL*), highest level of parental education (*neither parent graduated high school, at least one parent has a high school degree, at least one parent had some college, and at least one parent graduated from college*), the urbanicity (*urban, rural*, or *suburban*) of the child's residential census tract, whether the child has at least one parent born outside the United States (*immigrant)*, whether the child attended full or part day Kindergarten, and whether the child attended center-based care before entering Kindergarten.

Empirical Strategy

To address Research Question (RQ) 1, individual growth models were used to predict children's test score levels and trajectories from measures of neighborhood disadvantage. Growth models simultaneously examine within- and between-person change over time to assess how both levels and growth in levels vary across children (Rabe-Hesketh & Skrondal, 2008; Singer & Willett, 2003). Exploratory inspection of the raw data indicated a curvilinear shape of change over time. Likelihood-ratio tests comparing the linear, quadratic, and cubic growth models indicated that the cubic model best fits the data. However, especially given our interest in interactive effects, a cubic model quickly becomes difficult to estimate and is not straightforward

[6] 14.9% of children in our analytical sample move at some point during the analyzed waves.

in interpretation. Further, treating time as a dummy variable uses the same number of parameters for our five waves of data and offers greater flexibility and easier interpretation (McCoach et al., 2006). This model also enables understanding of whether neighborhood poverty rates predict cognitive growth rates unique to particular periods of students' lives. Therefore, we estimated a three-level (grade-child-school) mixed model of student cognitive growth—treating time as a categorical variable—to estimate four separate growth slopes (from fall to spring of kindergarten, from spring of kindergarten to spring of first grade, from spring of first grade to spring of second grade, and from spring of second grade to spring of third grade) interacted with each category of neighborhood poverty, described above. The low-poverty census tract (less than 14% poverty) served as the reference group for neighborhood poverty. We allowed for random intercepts at both the child and school levels. Our main model is displayed in Equation 1:

$$Y_{ijk} = \beta_1 + \beta_2\,\text{GRADE} + \beta_3\text{SCH\_POV} + \beta_4(\text{GRADE})(\text{SCH\_POV}) + \beta_5 X_{ij} + V_{00k} + U_{0j0} + S + R_{ijk} \tag{1}$$

In Equation 1, Y_{ijk} represents the math or reading theta score for child *j* in neighborhood *k* at time *i*. GRADE is a series of dummy variables representing the child's grade in school (fall of K [reference], spring of K, spring of first, spring of second, and spring of third grades). SCH_POV represents the key independent predictor of interest, the poverty level of the census tract in which the elementary school is located (i.e., our measure of neighborhood disadvantage), also a series of dummy variables (low poverty [reference], moderate-low poverty, moderate-high poverty, and high poverty). X_{ij} represents background characteristics for child *j* at time *i*. V_{00k} represents the random intercept for the school, and U_{0j0} represents the random intercept for the child within schools. These represent the level-2 residuals that permit the level-1 individual growth parameters to vary stochastically across children; both are assumed to have bivariate normal distributions with means of zero and unstructured covariance matrices. The interaction terms between GRADE and SCH_POV (producing a total of 12 interaction terms, as each is represented by a series of dummy variables) serve as our main parameters of interest, representing how the linear rate of growth in math or reading scores varies with neighborhood poverty between each data wave. The residual R_{ijk} represents the portion of unexplained child *j*'s cognitive scores (Singer & Willett, 2003). Models also include state fixed effects (S).

For RQ2, we added triple interaction terms to Equation 1, interacting our grade dummy variables, our school neighborhood poverty dummy variables, and, separately, key student characteristics. These student characteristics are: race (Black or non-Black); ethnicity (Hispanic or non-Hispanic); gender; whether the child's parents were immigrants; whether the school is located in a rural area (rural or urban/suburban); and household poverty status (poor versus non-poor households). We also tested two characteristics regarding children's educational experiences: early care and education experience (the child attended any center-based care prior to Kindergarten vs. no experience in center care); and part- or full-day Kindergarten attendance.

Results

Descriptive Results

Weighted average math and reading scores by school neighborhood poverty category are provided in Figure 2. Children's average test scores increased with grade, showing skill growth over time. Consistent with previous research on neighborhood poverty using children's residential census tracts (Morrissey & Vinopal, 2018b), children attending school in higher-poverty tracts averaged lower math and reading scores than those attending school in more advantaged tracts at every grade. In general, there was a stepwise association between poverty level and average math or reading score. Notably, the gap in math scores between the average scores of children in schools in low poverty neighborhoods and those in higher-poverty neighborhoods was more than a full theta point (which represents approximately one year of learning) at the fall of Kindergarten (school entry). This math score gap was reduced from fall to spring of Kindergarten because the scores of children in higher-poverty schools grew, whereas children in low-poverty schools averaged nearly identical math scores in fall and spring of Kindergarten (average scores were 0.005 points *lower* in the spring of K compared to the fall of K). This pattern was not true for reading scores, for which children at all neighborhood poverty levels showed growth at each wave. However, following Kindergarten the raw gaps in both math and reading scores by neighborhood SES appeared relatively consistent through the spring of third grade.

Insert Figure 2 here

Sample children's weighted background characteristics by their school's neighborhood poverty are provided in Table 1. Children attending schools in low-poverty communities were more likely to be White or Asian, to live in households above 200 percent of the FPL, and to have parents who had graduated college compared to those attending schools in high-poverty areas, who were more likely to be Black or Hispanic, to live under the poverty level, to have parents who were immigrants, and to have parents with a high school degree or less. Children in schools in higher-poverty neighborhoods were more likely to be attending full versus part day Kindergarten. Neither speaking a language other than English nor experience in center-based early care and education (ECE) prior to Kindergarten followed a stepwise pattern with school neighborhood poverty, although those in low poverty schools were more likely than their counterparts in higher-poverty schools to have attended center-based ECE.

Insert Table 1 here.

Regression Results

Results from the main models without control variables (unconditional models) are shown in columns 1 and 3 of Table 2 for math and reading scores, respectively, and our full models are shown in columns 2 and 4. The unconditional models demonstrate the expected stepwise relationship between neighborhood poverty and test scores as shown in the descriptives.

Once all control variables, described above, are included, the pattern regarding neighborhood poverty remains but the coefficients are much smaller. Coefficients from the categorical grade variables indicate that, as expected, children's scores grow as they progress through elementary school. By the spring of third grade, children attending schools in low poverty communities (the reference group) have gained an average of 1.95 and 1.89 points in their theta scores for math and reading, respectively. As expected, a school's neighborhood poverty category has a main effect of lowering average scores at fall of Kindergarten, before students are exposed to formal schooling. Children attending schools in high poverty neighborhoods average 0.10 lower average scores in both math and reading compared to those in low-poverty schools. Surprisingly, however, children attending schools in moderate-high poverty neighborhoods average lower scores than those attending schools in high poverty neighborhoods (math: -0.19 vs. -0.10; reading: -0.12 vs. -0.10 lower than low-poverty schools).

Insert Table 2 here.

The main parameters of interest for the first research question in this study are the interactions between the neighborhood poverty of the child's school and grade, which reflect the rates of growth in children's scores between each data wave. Figure 3 depicts these relationships graphically. For ease of interpretation, the Slope Estimates table in Figure 3 provides the growth rates for math and reading scores between each grade. Statistical significance is calculated based on the difference between the slope for the reference group, low poverty, and each of moderate-low, moderate-high, and high poverty.

As shown in Figure 3, children in schools in high poverty neighborhoods displayed higher rates of growth in their test scores during Kindergarten, suggesting some “catch-up” to their peers in low income communities who entered school with higher scores. Children in low poverty schools grew an average of 0.61 and 0.75 points in math and reading from fall to spring of Kindergarten, whereas children in high poverty schools grew an average of 0.77 and 0.81 points (translating to 26% and 8% higher growth rates). Between the spring of Kindergarten and first grade, however, this pattern reversed such that children in schools in high poverty neighborhoods grew at *slower* rates than their peers in schools in low poverty neighborhoods in math and reading (27% slower in math and 13% slower in reading). There is limited evidence for more “catch-up” later in elementary school, as children in schools in the highest poverty communities grew at higher rates in reading (a 30% higher growth rate) between first and second grade, and in math between second and third grades (a 45% higher growth rate). For reading skills, children across all the school neighborhood poverty groups grew in parallel between the second and third grades, maintaining but not widening or narrowing gaps.

Insert Figure 3 here.

While the background characteristics we controlled were not our main variables of interest, it is notable that in Table 2, the main associations between the poverty of schools’ census tracts and math or reading test scores were similar to or larger than those between test scores and children’s own household poverty. Relative to children in households above 200 percent of poverty, poor children scored 0.085 and 0.086 points lower in math and reading, respectively; these differences were smaller than those of attending school in a moderate-high poverty neighborhood in fall of Kindergarten (-0.189 and -0.122 for math and reading) and slightly smaller than those of attending school in a high poverty neighborhood (-0.097 and -0.101 for math and reading), after controlling for other factors. Importantly, however, this may be an artifact of a child's household poverty correlating highly with school neighborhood poverty.[7] In low poverty schools, 67 percent of children had incomes above 200 percent FPL, compared to only 17 percent of those in high poverty neighborhoods (see Table 1). Further, it is likely that, within these broad household income categories, those attending schools in poorer communities were on average more disadvantaged, and thus the coefficients for household poverty status underestimate the true associations between family income and test scores. In addition to family poverty, moving between waves, low parental education, household size, and being a twin, Black, Hispanic, or the child of immigrants were associated with lower average math and reading scores in early elementary school. Age in months, having married parents, and experience in center-based ECE prior to Kindergarten were associated with higher scores.

Variation in Growth by Student Characteristics

Our second research question relates to whether student characteristics moderate relationships between neighborhood poverty and growth in cognitive scores. In our regressions for RQ2, our main parameters of interest are the triple interactions between grade, neighborhood poverty, and the student characteristic. Results from these models predicting math and reading scores are shown in Tables 3 and 4, respectively. Figures 4 through 11 show these relationships graphically and provide Slope Estimates tables for each neighborhood poverty level by student characteristic. Importantly, in the Slope Estimates tables, the significance indicators do not compare the slopes across school neighborhood poverty groups, but between the subgroups'

[7] See Appendix Table 3 for correlations among various measure of neighborhood, school, and family disadvantage.

slope estimates (e.g., boys vs. girls) relative to that subgroup's low-poverty slope estimate. For example, we calculate whether the difference in growth rates for boys in high poverty neighborhoods versus boys in low poverty neighborhoods is statistically significantly different from the difference in growth rates for girls in high poverty neighborhoods versus girls in low poverty neighborhoods. This reveals whether patterns of growth across poverty category and time differed across subgroups.

Insert Tables 3 and 4 here.

Gender. In general, as shown in the first columns of Tables 3 and 4, the triple interaction terms for female, school neighborhood poverty, and grade were small and not statistically significant, indicating that males and females exhibit similar associations between school neighborhood poverty and rates of growth in math and reading scores during early elementary school. These patterns are shown graphically in Figure 4. Indeed, few significant differences in their slopes by school neighborhood poverty category are found (see Slope Estimates). One notable exception: the gap between moderate-high poverty and low-poverty growth rates from first to second grade were larger for boys than for girls.

Insert Figure 4 here.

Race. As displayed in the second columns of Tables 3 and 4 and in Figure 5, Black children in high poverty schools did not show as strong of a "catch-up" pattern in terms of higher growth rates in math and reading scores as non-Black students, though Black students in high-poverty neighborhoods did gain on their low-poverty peers during Kindergarten. In general, however, non-Black children appeared to drive the higher growth rates shown by children in schools in higher poverty communities during the first and last years of our data for math, and the first year for reading. By contrast, Black children attending schools in moderate- and high poverty communities grew at slower than or similar rates to Black children attending schools in low poverty communities, particularly in the later grades. These findings suggest that Black children's growth in math may be particularly vulnerable to the effects of school poverty, or that Black children in high-poverty neighborhoods are clustered in particularly low-quality schools.

Insert Figure 5 here.

Ethnicity. Results for testing whether rates of growth by neighborhood poverty vary between Hispanic and non-Hispanic students are shown in the third columns of Tables 3 and 4 and Figure 6. Whereas both Hispanic and non-Hispanic children in schools in higher poverty communities displayed higher math growth than their peers in schools in low poverty neighborhoods during Kindergarten, the magnitude was greater among Hispanic children during Kindergarten for moderate-low and moderate-high poverty neighborhoods. Further, this higher math growth rate was more consistent for Hispanic students such that, by the spring of third grade, Hispanic children attending schools in high poverty neighborhoods scored on average *higher* than their Hispanic counterparts attending schools in lower poverty neighborhoods (adjusting for background characteristics). In reading, Hispanic students in moderate-low poverty neighborhoods catch up to Hispanic students in low poverty neighborhoods during Kindergarten, but Hispanic students in higher poverty neighborhoods had slower rates of growth than lower poverty Hispanic students. This pattern reversed slightly during first grade, however: non-Hispanic students in higher poverty schools lost more ground to their peers at low poverty schools than Hispanic students.

Insert Figure 6 here.

Household poverty. Results for the tests of whether rates of cognitive growth by neighborhood poverty varied between children growing up in poor and non-poor households are shown in the fourth columns of Tables 3 and 4 and Figure 7. There was very little evidence that poor children's growth rates are differentially affected by their schools' neighborhood disadvantage, compared to non-poor children (see the non-significant triple interactions and Slope Estimates). However, the double interactions between household poverty and grade are positive and significant for both math and reading (and particularly large for reading), indicating that, in low poverty schools, poor students have higher growth rates than non-poor children in Kindergarten, suggesting some narrowing of the income achievement gap – at least in high-resourced schools – and consistent with other research (von Hippel et al., 2018).

Insert Figure 7 here.

Urbanicity. Results for testing whether cognitive growth by school neighborhood poverty differ in rural vs. urban or suburban areas are shown in the fifth column of Tables 3 and 4, and graphically in Figure 8. Children attending schools in rural communities showed starker initial gaps in math by school neighborhood poverty at the fall of Kindergarten, and these gaps remained relatively steady through third grade. However, in reading, these initial gaps by neighborhood poverty in Kindergarten were smaller and shrank over time for children in rural areas, such that by third grade, children in schools in high poverty neighborhoods scored similar to those in low and moderate-low poverty neighborhoods, although children in schools in moderate-high poverty neighborhoods continued to score worse than their counterparts. These patterns in reading mirrored the experiences of non-rural students, though students in moderate-high poverty rural neighborhoods fared worse than non-rural students in such neighborhoods between first and second grade.

Insert Figure 8 here.

Children of immigrants. The sixth column of Tables 3 and 4 show results from models testing the moderating effect of having immigrant parents, and Figure 9 displays predicted scores results graphically. In general, the test scores of children of immigrants in schools in moderate-low and moderate-high poverty grew at faster rates during Kindergarten than their counterparts in similar schools. This indicates that the children of immigrants in higher-poverty neighborhoods (but not the highest-poverty neighborhood) caught up to their counterparts in lower-poverty neighborhoods faster during Kindergarten, compared to non-immigrant children. However, the initial gaps by neighborhood poverty status at fall of Kindergarten were wider for children of immigrants. These patterns were not significantly different in later grades, however.

Insert Figure 9 here.

Full- vs. part-day Kindergarten. The second-to-last column in Tables 3 and 4, and Figure 10, display the results from differences in the relationship between school poverty and cognitive growth by whether the child attended full-day Kindergarten compared to part-day. Gaps by neighborhood poverty in scores in both math and reading at Kindergarten entry for part-day students were much wider than for full-day students. Interestingly, children in schools in higher poverty neighborhoods showed *lower* math growth during Kindergarten and between Kindergarten and first grade after attending full-day Kindergarten relative to those who attended part-day Kindergarten. This may reflect a selection issue regarding the types of schools that implement full-day Kindergarten, and the general lack of variation in full-day Kindergarten attendance (93% of children in moderate-high poverty schools and 97% in high poverty schools attended full-day Kindergarten; see Table 1). It may also reflect the high initial levels of disadvantage facing the higher-poverty part-day students, relative to children in part-day Kindergarten in more advantaged communities.

Insert Figure 10 here.

Early care and education (ECE) experience. The final column in Tables 3 and 4 and Figure 11 display the results for testing whether cognitive growth by school neighborhood poverty differs by children's experiences in center-based ECE prior to Kindergarten entry. Children in schools in moderate-low and moderate-high poverty neighborhoods who had center care experience showed *lower* growth rates in math than those who lacked center ECE before school entry (and in reading for those in moderate-low poverty neighborhoods). Again, this may reflect the relatively larger gaps in initial test scores by neighborhood poverty that are apparent among children who did not attend center-based care. By contrast, those in schools in high-poverty neighborhoods who had center ECE experience exhibited *higher* growth rates in reading during Kindergarten relative to their low-poverty counterparts, compared the gap in growth by neighborhood poverty for children with no center-based care. In other words, focusing on children in the highest-poverty group during Kindergarten, the neighborhood poverty-based gap in reading closed more for students who attended center-based ECE than for those that did not.

Insert Figure 11 here.

Sensitivity Analyses

Our main models were chosen to more fully illustrate trajectories of cognitive growth over the first years of elementary school and importantly, to include growth during the Kindergarten year. While generating causal estimates between a child's school's neighborhood poverty level and growth in test scores was not the main goal of this study, we ran a sensitivity analysis that controlled for children's baseline test scores (at the fall of Kindergarten) to predict levels of and growth in test scores between the spring of Kindergarten, first, second, and third grades. Essentially, this model can be thought of as providing more conservative, lower-bound estimates, given they control for children's initial levels. Results (available upon request) were substantively similar to our main models discussed above, with weaker main associations between school neighborhood poverty and average test scores, as one would expect, but consistent findings for growth in test scores.

Second, our main models merged census tract-level poverty data onto the tracts in which children's elementary schools were located to approximate neighborhood disadvantage. However, the ECLS-K also provides information on the percentage of students eligible for free or reduced-price lunch at respondent children's schools, another proxy for school-level disadvantage. Using this information and cutoff by quartiles of the distribution, we categorized schools into low- (less than 19% of children eligible), moderate-low- (between 19% and 44% of children eligible), moderate-high- (44% to 74% of children eligible), and high-poverty (greater than 74% of children eligible), and re-ran our primary models. Results can be found in Appendix Table 1. Results were similar to our primary models in direction; however, the magnitude of effects were larger, with children in schools with higher rates of free or reduced-price lunch showing even higher rates of growth relative to children in schools with lower rates.

Finally, we re-ran our models using census tract-level poverty rates merged onto children's residential (instead of school) tracts (33% of whose residential tracts matched their school's census tract; relevant correlations can be found in Appendix Table 3). Findings for our primary models were substantively similar, with some differences in the magnitude of effects, but not in general trends. Results are presented in Appendix Table 2. As with the free and reduced-price lunch results, finding showed a stepwise pattern in which children living in high poverty tracts scored lower than those in moderate-high poverty tracts.

Discussion

This study sought to examine how neighborhood disadvantage, as measured by the poverty level of the census tract in which their school is located, relates to both children's cognitive skill levels but also their growth in cognitive skills during the first four years of elementary school. Previous research indicates that children in low-resource communities and schools score lower, on average, than those in more advantaged communities and schools (Chetty, Hendren, et al., 2016; Reardon, 2018), but their growth in skills during early elementary school – arguably a better measure of learning and potentially of school quality – is less-often attended to in research or in public or policy discussions (Reardon, 2018). Examining patterns of learning by neighborhood resources can shed light on how the K-12 education system can be better positioned to narrow SES inequalities. Results have implications for the timing and targeting of policy interventions, as well as for school accountability and the narrative surrounding the effectiveness of elementary schools.

Consistent with this previous research (e.g., Reardon, 2018), this study finds that children exhibit large average gaps in test scores by the poverty level of the neighborhood in which their elementary school is located, with children attending schools in high-poverty neighborhoods (40% or greater poverty) scoring one-tenth of a point lower in math and reading in early elementary school compared to their peers attending schools in low-poverty neighborhoods (less than 14% poverty), after controlling for a range of background characteristics. This association is approximately 28 percent and 26 percent of the average differences in math and reading scores between fall and spring of Kindergarten, or what can be thought of as what children learn in those years. This is approximately one-sixth of the main effect of having neither parent graduate high school (compared to a college degree or more), and more than twice that of having unmarried parents. Further, our sensitivity models show that these effects are similar but generally larger in magnitude (19-24% larger for math, and 8-14% for reading) when using the poverty levels of children's residential tracts or the school's rates of participation in free or reduced-price lunch.

Somewhat surprisingly, children in moderate-high poverty neighborhoods (20-40% poverty) averaged lower math and reading test scores in the fall of Kindergarten in than those in high poverty neighborhoods – nearly twice the effect of high poverty neighborhoods for math, and about 20 percent higher for reading – which may be due to greater public or philanthropic attention or intervention for schools in the most distressed neighborhoods. However, this pattern was not apparent in our sensitivity models that used other measures of disadvantage (school free/reduced-price lunch participation rates or children's residential tracts), where both children in moderate-high and high poverty communities consistently scored worse than their counterparts.

Notably, across models using various measures of disadvantage, the main association between attending school in a highly distressed neighborhood and test scores was about 15 percent larger than the main association between growing up in a poor household relative to growing up in a household with income 200 percent of the federal poverty line. It is important to note that this represents the association between being poor and test scores after controlling for a host of background characteristics, particularly parent education, which is highly correlated with poverty but appears to drive math and reading scores more so than income alone. Our findings are consistent with recent research showing that children growing up in very similar household conditions in different neighborhoods can have vastly different outcomes later in life, with school measures accounting for less than half of the variation in social mobility across neighborhoods (Chetty et al., 2018). Thus, a school's surrounding neighborhood poverty level may be an important indicator for policy interventions, arguing for place-based interventions in addition to means-tested programs.

Importantly, the patterns of association between schools' neighborhood poverty and growth in math and reading were different than those of average test scores. Children attending schools in higher-poverty communities showed higher rates of cognitive growth – presumably a measure of learning or skill development – during Kindergarten compared to their counterparts attending schools in lower-poverty communities. These higher growth rates were particularly strong for math scores. Growth rates in math for children in more disadvantaged communities slowed relative to their low-poverty peers between Kindergarten and second grade, but grew faster again between second and third grade. In reading, the slow-down in growth for children in higher-poverty neighborhoods is briefer, occurring only during first grade. Rates picked up again between first and second grade and are statistically identical to the growth rates of children in low-poverty neighborhoods between second and third grade. These findings provide some evidence for "catch-up", or a narrowing of gaps by school neighborhood poverty, particularly during the first year of formal schooling, but also point to first grade as an important intervention year to keep children in high poverty schools an upward trajectory. Results are consistent with previous research finding that elementary schools may serve as an equalizing force, narrowing SES inequalities in achievement (Downey et al., 2004; Raudenbush & Eschmann, 2015; von Hippel et al., 2018).

That this catch-up phenomenon was most apparent between the fall and spring of Kindergarten may derive from children's experiences prior to Kindergarten entry relative to the content of what is taught in Kindergarten. Children in low-resourced communities have different early experiences than those in higher-income communities, including differential access and attendance of high-quality early care and education, which can promote school readiness (Chaudry, Morrissey, Weiland, & Yoshikawa, 2017; Gordon & Chase-Lansdale, 2001; McCoy, Connors, Morris, Yoshikawa, & Friedman-Krauss, 2015; Morris et al., 2018). Recent research shows both that Kindergarten teaches much of the same content as preschool (Engel, Claessens, & Finch, 2013) and that Kindergarten has become more academically-orientated over time, with teachers spending more time on literacy and math and less on other areas such as art, social sciences, or physical education (Bassok & Rorem, 2014). It may be that Kindergarten and other early grade teachers are spending more time on academics than in past years, but doing so to target the children who enter with the lowest-developed skills such that all children are on a more even playing field when they leave Kindergarten. These findings suggest that enhancing the rigor of Kindergarten curricula or tailoring content to individual skill levels may better support the cognitive growth of all children.

Indeed, our findings that children with center-based care experience prior to Kindergarten grew in math at slower rates than those without provide additional evidence for this theory, whereas those in schools in high poverty neighborhoods who had center care experience exhibited higher growth rates in reading during Kindergarten compared to their counterparts who did not. Our results also highlight the importance of distinguishing math and reading scores in research, and suggest that the application of the “skill begets skill” theory – that children who enter Kindergarten better prepared to learn can best build upon these skills (Cunha & Heckman, 2007) – may vary by cognitive domain. Further, results underscore the need for interventions prior to Kindergarten, particularly in moderate-high and high poverty communities where only about half of children attend center-based early care and education.

Results also have implications for the debate surrounding the long-term “fade-out” of the effects of early education on children’s cognitive measures (Yoshikawa et al., 2013). Research has documented that preschool and other types of early education produce short-term increases in cognitive skills, but the test score gaps between children who attended ECE and those that did not narrows over time. Some researchers (Ansari, 2018; Yoshikawa et al., 2013) argue that this pattern should be called “convergence” rather than fade-out to represent the phenomenon of two groups of children’s scores coming together over time. Indeed, our study indicates that children who begin Kindergarten with lower test scores – particularly those attending schools in higher poverty communities – display higher growth rates from fall to spring of Kindergarten, especially in math, than their peers in lower poverty communities, indicating some “catch-up”. Further, these differential findings by cognitive domain underscore the importance of separating math and reading scores in research.

The patterns identified between neighborhood poverty and growth in cognitive skills did not meaningfully vary by child gender or household poverty. To varying degrees, however, patterns of growth did differ by children’s experience in center-based ECE (discussed above), part versus full day Kindergarten, child race, ethnicity, parents’ immigrant status, and across rural and non-rural communities. Specifically, Black children appeared particularly vulnerable to the negative effects of schools located in higher poverty areas in terms of absolute and growth in test scores, particularly between the second and third grades in math, which is consistent with earlier work on neighborhood poverty (Wodtke et al., 2011). On the other hand, the neighborhood poverty-based gap in math closes more so during the Kindergarten year for the children of immigrants than for children with non-immigrant parents. These patterns did not hold in later grades, however. Similar to recent research (Reardon, 2018), Hispanic children appeared particularly resilient to the negative effects of high-poverty schools. It may be that the schools in higher-poverty neighborhoods that Black children and those with immigrant parents attend are of lower-quality than those attended by other children in high-poverty schools, whereas Hispanic children attend higher-quality schools in higher-poverty neighborhoods. Children in rural communities showed larger initial gaps in math scores by neighborhood poverty level at the fall of Kindergarten, and despite some catch up during Kindergarten, these gaps remain relatively steady through third grade. This pattern of growth is similar to non-rural students. In reading, however, urban and suburban students in higher-poverty communities show more evidence of catching up to their low-poverty peers, compared to students in higher-poverty rural communities.

Together, these findings regarding differences in average absolute test scores and growth in test scores suggest that gaps by neighborhood poverty emerge before school entry, and dependent on select student characteristics, these gaps narrow during Kindergarten, then vary as they progress through third grade. Other research, utilizing a random assignment experiment, has demonstrated that Kindergarten test scores are strongly related to outcomes in adulthood, including earnings, college attendance, home ownership, and retirement savings (Chetty et al., 2011). This is true even though test score gains attributed to beneficial classroom interventions in Kindergarten may fade out in later grades, implying that contemporaneous (i.e., end of school year) test scores are a good measure of the quality of a classroom, and that classroom quality matters for children's long-term outcomes (Chetty et al., 2011).

This works suggests that the gains of children in higher poverty neighborhoods during Kindergarten we document here are important in their own right. The widening of the gap that occurs during first grade, however, represents a lost opportunity for promoting the skills and earning potential of tomorrow's workforce. Chetty and colleagues (2011) estimate that a one percentile increase in end-of-Kindergarten test scores is associated with an increase in annual earnings at age 27 of about $94, after controlling for parental characteristics. Other important positive educational and economic outcomes, including college attendance, college quality, home ownership, and retirement savings, are also correlated with these scores. Twenty-seven percent of Kindergarteners attended school in high or moderate-high poverty neighborhoods in the 2010-2011 academic year – representing about one-quarter of those who will be age 45 in 2050. If trajectories of gains for children in higher poverty schools could be continued past Kindergarten, instead of stalling or reversing during first grade, reflecting continued quality of classrooms in high-poverty neighborhoods, perhaps such lifetimes gains would be amplified. This could dramatically reduce the difference in lifetime earnings between those raised in low and high poverty neighborhoods, and produce an overall more productive 2050 workforce by capitalizing on the potential of all students, regardless of the circumstances of their birth.

This lost opportunity for promoting the cognitive skills of tomorrow's workforce argues for policy changes and intervention. While both school and many factors outside of school contribute to children's learning trajectories, our findings add to the literature suggesting that the use of average test scores as a measure of school quality is likely not accurately assessing how well a school promotes learning among its students, and may simply measure the initial gaps in children's performance at school entry. Second, more research is needed on policies that can promote both overall growth across children's SES, neighborhood, and other characteristics, while narrowing gaps – that is, "lifting all boats" but promoting greater growth among the most disadvantaged. High-quality early care and education has been found to do this (e.g., Yoshikawa et al., 2013), and can prevent or mitigate inequalities by family and neighborhood SES before children enter Kindergarten (Chaudry et al., 2017). Other policies such as K-12 resource redistribution, which we know can narrow gaps (Lafortune et al., 2018), or the more targeted use of Title I funds directed at schools in highly distressed communities to support instruction in the first through third grades, may also help accomplish these goals. Resource allocation in the upper grades based on school- or neighborhood-level poverty may help ameliorate the gaps by neighborhood SES that are already apparent for the cohort we examined – children who are 15 years old in 2019.

Results must be interpreted within the context of the study's limitations. First, the associations between neighborhood poverty, cognitive scores, and growth in scores identified in this study cannot be interpreted as causal, given selection of families into specific neighborhoods and schools. Second, although we use a large, nationally representative, longitudinal dataset, the data experienced contain missing values which may bias our results. Third, census tracts are typically used, but imperfect, measures of neighborhoods. Further, our data lack measures of cognitive growth before kindergarten or after third grade, preventing us from examining how these gaps emerge before entering the K-12 education system, or how growth progresses after early elementary school.

Finally, our analyses focused on associations between measures of neighborhood poverty and children's test scores and growth. Other measures of neighborhood disadvantage may generate different relationships with children's cognitive growth. For example, racial and ethnic segregation, while highly correlated with other measures of neighborhood disadvantage, is a separate phenomenon from poverty (Leventhal & Brooks-Gunn, 2000; Wilson, 2012). A relatively large body of work indicates that minority racial isolation is linked with achievement inequality (Billings, Deming, & Rockoff, 2014; Mickelson, 2015; Mickelson, Bottia, & Lambert, 2013). Income and racial segregation are so intertwined that recent work finds that only White, affluent families live in high-income school districts (Owens, 2018). However, whereas SES gaps seem to narrow during the academic year (von Hippel et al., 2018), research on the effects of racial segregation on children's achievement suggests that the gaps (in math scores) widen as children age (Mickelson et al., 2013), and that White and Asian children have slightly higher access to schools showing high growth in student achievement (Hanselman & Fiel, 2017). More research is needed to better understand how racial segregation across neighborhoods and schools relates to children's learning.

Conclusion

This study found that children's neighborhood disadvantage – of their school or their residential neighborhood – is associated with both average math and reading test scores, and growth in test scores. There was largely a stepwise pattern between a school's neighborhood disadvantage and average test scores, but students attending schools in higher-poverty communities displayed some higher growth rates – or "catch-up" – compared to their peers in schools in more advantaged communities during their Kindergarten year in particular, but then fall behind again in first grade. Given the importance of early math scores for longer-term academic success (Claessens, Duncan, & Engel, 2009; Duncan et al., 2007) and the growing phenomenon of concentrated poverty (Bishaw, 2014), findings have important implications for neighborhood, educational, and family interventions to narrow achievement gaps, as well as for education accountability measures. Importantly, we find that more than one-quarter – 27 percent – of children who represent an important segment of the 2050 workforce attended elementary school in disadvantaged communities. The short- and long-term implications of this early disadvantage have bearing on the preparation of the workforce of tomorrow. Looking to the future, results both suggest that the unraveling of neighborhood economic segregation is key for narrowing SES achievement gaps.

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T1. Analytic Sample Descriptive Statistics by Neighborhood Poverty, Weighted

	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
Reading				
Fall K	-0.332	-0.536	-0.670	-0.749
Spring K	0.622	0.467	0.293	0.218
Spring 1st	1.781	1.606	1.450	1.276
Spring 2nd	2.367	2.182	2.043	1.931
Spring 3rd	2.789	2.615	2.453	2.269
Math				
Fall K	0.616	-0.486	-0.719	-0.883
Spring K	0.611	0.426	0.288	0.162
Spring 1st	1.885	1.667	1.462	1.271
Spring 2nd	2.670	2.460	2.259	2.037
Spring 3rd	3.265	3.057	2.858	2.683
In Fall K:				
Female	48.32%	52.31%	46.85%	50.88%
Is a twin	0.25%	0.09%	0.31%	0.37%
Household size (centered at mean)	-0.148	0.028	0.005	0.069
Speaks language other than English in household	1.61%	2.47%	1.02%	0.00%
Parents married	80.72%	71.40%	65.36%	45.56%
Lives in urban area	21.26%	34.30%	44.57%	56.62%
Lives in suburban area	54.57%	39.06%	31.82%	25.26%
Lives in a rural area	24.18%	26.65%	23.62%	18.12%
Family income under poverty line	12.32%	29.90%	39.85%	55.17%
Family income between 100 and 200 percent of poverty line	20.84%	24.79%	27.77%	27.60%
Family income over 200 percent of poverty line	66.85%	45.32%	32.38%	17.23%
White	67.86%	52.83%	37.66%	8.69%
Black	7.63%	15.11%	18.14%	46.93%
Hispanic	14.38%	23.41%	35.04%	41.50%

American Indian	0.34%	0.23%	3.33%	0.00%
Asian	4.69%	2.83%	2.26%	0.62%
Other race	4.71%	5.22%	3.30%	2.26%
Child of an immigrant	18.60%	23.14%	29.82%	29.87%
Full day K (versus part day)	75.35%	87.09%	92.70%	97.90%
Attended center-based early care	58.92%	49.96%	51.66%	48.26%
Parents education less than high school	2.70%	9.72%	13.48%	19.46%
Parent education high school only	13.37%	23.07%	25.61%	33.91%
Parent education some college	31.28%	41.39%	34.97%	36.76%
Parent education college or more	52.64%	25.82%	25.95%	9.87%
Observations (Fall K)	6,040	1,230	2,270	400

T2. Math and Reading Score Growth by Neighborhood Poverty

	Math Score		Reading Score	
	1	2	3	4
Spring K	0.874***	0.612***	0.966***	0.755***
	(0.006)	(0.012)	(0.006)	(0.012)
Spring 1st	2.091***	1.399***	2.104***	1.544***
	(0.006)	(0.026)	(0.006)	(0.024)
Spring 2nd	2.894***	1.750***	2.697***	1.772***
	(0.006)	(0.041)	(0.006)	(0.037)
Spring 3rd	3.477***	1.947***	3.117***	1.890***
	(0.007)	(0.055)	(0.007)	(0.050)
Moderate-Low Poverty Neighborhood	-0.242***	-0.060**	-0.197***	-0.040
	(0.028)	(0.026)	(0.026)	(0.025)
Moderate-High Poverty Neighborhood	-0.455***	-0.189***	-0.346***	-0.122***
	(0.022)	(0.022)	(0.019)	(0.021)
High Poverty Neighborhood	-0.479***	-0.097**	-0.400***	-0.101**
	(0.044)	(0.044)	(0.040)	(0.042)
Moderate-Low Poverty Neighborhood X				
Spring K	0.081***	0.079***	0.052***	0.056***
	(0.014)	(0.016)	(0.013)	(0.017)
Spring 1st	0.089***	0.073***	0.051***	0.040**
	(0.015)	(0.018)	(0.015)	(0.018)
Spring 2nd	0.062***	0.068***	0.036**	0.023
	(0.015)	(0.019)	(0.015)	(0.019)
Spring 3rd	0.061***	0.063***	0.019	0.020
	(0.016)	(0.020)	(0.016)	(0.020)
Moderate-High Poverty Neighborhood X				
Spring K	0.156***	0.157***	0.035***	0.024*
	(0.010)	(0.013)	(0.010)	(0.013)
Spring 1st	0.090***	0.064***	0.034***	0.013
	(0.011)	(0.014)	(0.011)	(0.015)

Spring 2nd	0.089***	0.077***	0.045***	0.020
	(0.012)	(0.015)	(0.012)	(0.015)
Spring 3rd	0.094***	0.084***	0.023*	-0.002
	(0.012)	(0.016)	(0.012)	(0.016)
High Poverty Neighborhood X				
Spring K	0.137***	0.161***	0.008	0.051*
	(0.021)	(0.028)	(0.021)	(0.028)
Spring 1st	-0.066***	-0.049	-0.059**	-0.044
	(0.024)	(0.031)	(0.024)	(0.032)
Spring 2nd	-0.082***	-0.060*	-0.021	0.032
	(0.025)	(0.033)	(0.025)	(0.033)
Spring 3rd	-0.027	0.037	-0.052**	0.011
	(0.027)	(0.035)	(0.027)	(0.036)
Female		-0.030**		0.155***
		(0.012)		(0.011)
Age in months		0.036***		0.029***
		(0.001)		(0.001)
Moved between waves		-0.038***		-0.035***
		(0.008)		(0.008)
Is a twin		-0.208**		-0.243***
		(0.090)		(0.080)
Household size (centered at mean)		-0.008**		-0.024***
		(0.003)		(0.003)
Speaks language other than English in household		-0.022		-0.072**
		(0.040)		(0.036)
Parents married		0.041***		0.059***
		(0.009)		(0.009)
Lives in rural area		-0.012		0.014
		(0.016)		(0.015)
Family income under poverty line		-0.085***		-0.086***
		(0.011)		(0.011)

Family income between 100 and 200 percent of poverty line		-0.037***		-0.036***
		(0.009)		(0.009)
Black		-0.351***		-0.130***
		(0.023)		(0.021)
Hispanic		-0.168***		-0.098***
		(0.019)		(0.017)
American Indian		-0.064		-0.118*
		(0.075)		(0.067)
Asian		0.216***		0.199***
		(0.028)		(0.025)
Other race		-0.030		0.031
		(0.028)		(0.025)
Child of an immigrant		-0.068***		-0.030***
		(0.009)		(0.009)
Full day K (versus part day)		0.011		0.018
		(0.021)		(0.019)
Attended center-based early care		0.046***		0.045***
		(0.012)		(0.011)
Parents education less than high school		-0.618***		-0.590***
		(0.026)		(0.024)
Parent education high school only		-0.449***		-0.429***
		(0.019)		(0.017)
Parent education some college		-0.271***		-0.260***
		(0.016)		(0.014)
Constant	-0.380***	0.765***	-0.450***	0.499***
	(0.013)	(0.069)	(0.012)	(0.065)
Observations	68,790	43,460	68,920	43,490
Number of groups	2,880	2,010	2,880	2,010

Models 2 and 4 include state fixed effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

T3. Math Score Growth by Neighborhood Poverty and Student Characteristics

	Female	Black	Hispanic	Poor	Rural	Immigrant	Full day K (vs. part day)	Center-based ECE
Spring K	0.610***	0.616***	0.593***	0.590***	0.604***	0.608***	0.540***	0.652***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.017)	(0.015)
Spring 1st	1.450***	1.411***	1.394***	1.386***	1.386***	1.402***	1.410***	1.429***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.028)	(0.027)
Spring 2nd	1.800***	1.765***	1.736***	1.733***	1.749***	1.753***	1.799***	1.791***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.043)	(0.042)
Spring 3rd	2.017***	1.955***	1.933***	1.929***	1.935***	1.948***	1.987***	1.991***
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.057)	(0.056)
Moderate-Low Poverty Neighborhood	-0.087***	-0.071***	-0.029	-0.053*	-0.065**	-0.030	-0.147**	-0.041
	(0.034)	(0.027)	(0.029)	(0.028)	(0.030)	(0.027)	(0.070)	(0.035)
Moderate-High Poverty Neighborhood	-0.225***	-0.208***	-0.139***	-0.181***	-0.179***	-0.131***	-0.444***	-0.245***
	(0.027)	(0.023)	(0.026)	(0.024)	(0.024)	(0.023)	(0.061)	(0.029)
High Poverty Neighborhood	-0.132**	-0.132**	-0.072	-0.090*	-0.051	-0.077	-0.417	-0.071
	(0.056)	(0.054)	(0.057)	(0.054)	(0.046)	(0.047)	(0.282)	(0.056)
Moderate-Low Poverty Neighborhood X STUDENT CHARACTERISTIC X								
Spring K	0.023	-0.124**	0.113***	-0.003	-0.065*	0.114***	-0.039	-0.069**
	(0.033)	(0.052)	(0.040)	(0.039)	(0.036)	(0.038)	(0.051)	(0.033)
Spring 1st	0.004	-0.133**	0.144***	-0.027	-0.041	0.018	-0.110*	-0.087**
	(0.036)	(0.061)	(0.045)	(0.045)	(0.040)	(0.121)	(0.058)	(0.036)
Spring 2nd	-0.010	-0.020	0.108**	0.041	-0.008	0.001	-0.051	-0.045
	(0.038)	(0.063)	(0.046)	(0.048)	(0.042)	(0.148)	(0.061)	(0.038)
Spring 3rd	-0.023	-0.148**	0.113**	0.014	-0.027	0.028	-0.057	-0.023
	(0.039)	(0.068)	(0.048)	(0.051)	(0.044)	(0.259)	(0.064)	(0.039)
Moderate-High Poverty Neighborhood X STUDENT CHARACTERISTIC X								
Spring K	-0.013	-0.103***	0.067**	0.004	-0.004	0.162***	-0.105**	-0.101***
	(0.026)	(0.040)	(0.030)	(0.030)	(0.032)	(0.028)	(0.044)	(0.026)
Spring 1st	0.092***	-0.023	0.009	-0.009	0.004	0.137	-0.115**	-0.134***

	(0.029)	(0.046)	(0.033)	(0.034)	(0.035)	(0.084)	(0.049)	(0.029)
Spring 2nd	0.037	-0.058	0.070**	-0.013	0.024	0.034	-0.100**	-0.146***
	(0.030)	(0.048)	(0.034)	(0.036)	(0.036)	(0.113)	(0.051)	(0.030)
Spring 3rd	0.042	-0.179***	0.115***	0.003	-0.037	-0.003	-0.082	-0.129***
	(0.032)	(0.052)	(0.036)	(0.039)	(0.038)	(0.169)	(0.053)	(0.032)
High Poverty Neighborhood X STUDENT CHARACTERISTIC X								
Spring K	0.038	0.023	-0.097*	-0.034	0.009	-0.035	0.051	0.079
	(0.055)	(0.061)	(0.057)	(0.058)	(0.068)	(0.060)	(0.197)	(0.055)
Spring 1st	0.087	0.041	-0.041	0.068	0.171**	-0.180	-0.399*	0.056
	(0.062)	(0.068)	(0.065)	(0.068)	(0.075)	(0.142)	(0.205)	(0.062)
Spring 2nd	0.096	-0.010	0.025	-0.068	0.175**	-0.020	-0.605***	0.090
	(0.065)	(0.072)	(0.067)	(0.073)	(0.079)	(0.182)	(0.216)	(0.065)
Spring 3rd	0.073	-0.342***	0.363***	-0.023	0.166**	-0.387	-0.455**	0.091
	(0.070)	(0.079)	(0.072)	(0.077)	(0.083)	(0.435)	(0.231)	(0.070)
Moderate-Low Poverty Neighborhood X								
Spring K	0.068***	0.095***	0.043**	0.058***	0.096***	0.052***	0.099**	0.110***
	(0.023)	(0.017)	(0.018)	(0.019)	(0.019)	(0.019)	(0.047)	(0.024)
Spring 1st	0.073***	0.095***	0.038*	0.069***	0.083***	0.045**	0.175***	0.114***
	(0.026)	(0.019)	(0.020)	(0.021)	(0.021)	(0.020)	(0.054)	(0.026)
Spring 2nd	0.074***	0.081***	0.036*	0.044**	0.070***	0.039*	0.125**	0.086***
	(0.027)	(0.020)	(0.021)	(0.022)	(0.022)	(0.021)	(0.057)	(0.027)
Spring 3rd	0.077***	0.086***	0.029	0.043*	0.070***	0.033	0.123**	0.069**
	(0.028)	(0.021)	(0.022)	(0.022)	(0.023)	(0.021)	(0.060)	(0.028)
Moderate-High Poverty Neighborhood X								
Spring K	0.164***	0.175***	0.101***	0.112***	0.160***	0.101***	0.237***	0.205***
	(0.018)	(0.014)	(0.016)	(0.016)	(0.015)	(0.016)	(0.042)	(0.019)
Spring 1st	0.019	0.082***	0.053***	0.044**	0.065***	0.006	0.173***	0.131***
	(0.020)	(0.015)	(0.018)	(0.018)	(0.016)	(0.016)	(0.047)	(0.021)
Spring 2nd	0.058***	0.105***	0.025	0.051***	0.072***	0.019	0.180***	0.149***
	(0.021)	(0.016)	(0.019)	(0.019)	(0.017)	(0.017)	(0.048)	(0.022)
Spring 3rd	0.062***	0.125***	0.017	0.048**	0.094***	0.025	0.169***	0.147***

	(0.022)	(0.017)	(0.019)	(0.020)	(0.018)	(0.018)	(0.051)	(0.023)
High Poverty Neighborhood X								
Spring K	0.143***	0.149***	0.166***	0.114***	0.160***	0.170***	0.088	0.115***
	(0.039)	(0.036)	(0.035)	(0.042)	(0.031)	(0.033)	(0.195)	(0.039)
Spring 1st	-0.092**	-0.022	-0.040	-0.128***	-0.085**	-0.061*	0.345*	-0.081*
	(0.044)	(0.041)	(0.040)	(0.049)	(0.035)	(0.036)	(0.202)	(0.044)
Spring 2nd	-0.108**	0.002	-0.103**	-0.066	-0.097**	-0.081**	0.545**	-0.110**
	(0.045)	(0.042)	(0.044)	(0.054)	(0.038)	(0.037)	(0.214)	(0.045)
Spring 3rd	-0.001	0.204***	-0.184***	-0.008	-0.000	0.018	0.492**	-0.015
	(0.048)	(0.044)	(0.048)	(0.055)	(0.041)	(0.039)	(0.228)	(0.049)
STUDENT CHARACTERISTIC X								
Spring K	0.003	0.002	0.135***	0.146***	0.037**	0.024	0.096***	-0.066***
	(0.013)	(0.028)	(0.019)	(0.020)	(0.015)	(0.016)	(0.015)	(0.014)
Spring 1st	-0.106***	-0.109***	0.049**	0.081***	0.058***	0.073	-0.014	-0.049***
	(0.015)	(0.031)	(0.021)	(0.023)	(0.017)	(0.052)	(0.017)	(0.015)
Spring 2nd	-0.107***	-0.166***	0.108***	0.105***	0.011	0.135*	-0.064***	-0.067***
	(0.015)	(0.032)	(0.022)	(0.024)	(0.017)	(0.079)	(0.017)	(0.015)
Spring 3rd	-0.151***	-0.128***	0.105***	0.128***	0.045**	0.316**	-0.051***	-0.073***
	(0.016)	(0.035)	(0.023)	(0.027)	(0.018)	(0.139)	(0.018)	(0.016)
STUDENT CHARACTERISTIC X								
Moderate-Low Poverty Neighborhood	0.055	0.059	-0.115**	0.029	0.019	-0.128***	0.102	-0.028
	(0.042)	(0.070)	(0.055)	(0.038)	(0.053)	(0.034)	(0.074)	(0.043)
Moderate-High Poverty Neighborhood	0.076**	0.054	-0.098**	0.057*	-0.073	-0.180***	0.284***	0.112***
	(0.033)	(0.054)	(0.041)	(0.029)	(0.047)	(0.026)	(0.064)	(0.034)
High Poverty Neighborhood	0.069	0.003	-0.027	0.074	-0.247***	-0.061	0.339	-0.044
	(0.070)	(0.086)	(0.084)	(0.056)	(0.079)	(0.054)	(0.285)	(0.070)
Female	-0.007	-0.030**	-0.031**	-0.030**	-0.031***	-0.030**	-0.031***	-0.030**
	(0.018)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)

Age in months	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Moved between waves	-0.037***	-0.033***	-0.037***	-0.041***	-0.036***	-0.036***	-0.037***	-0.037***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Is a twin	-0.206**	-0.211**	-0.204**	-0.206**	-0.209**	-0.206**	-0.206**	-0.209**
	(0.089)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)
Household size (centered at mean)	-0.008**	-0.008**	-0.008**	-0.008***	-0.008**	-0.008**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Speaks language other than English in household	-0.023	-0.022	-0.025	-0.021	-0.019	-0.021	-0.019	-0.022
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Parents married	0.041***	0.043***	0.042***	0.041***	0.041***	0.042***	0.042***	0.041***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Lives in rural area	-0.014	-0.014	-0.018	-0.013	-0.021	-0.013	-0.009	-0.013
	(0.016)	(0.016)	(0.016)	(0.016)	(0.021)	(0.016)	(0.016)	(0.016)
Family income under poverty line	-0.084***	-0.085***	-0.084***	-0.203***	-0.085***	-0.084***	-0.084***	-0.085***
	(0.011)	(0.011)	(0.011)	(0.021)	(0.011)	(0.011)	(0.011)	(0.011)
Family income between 100 and 200 percent of poverty line	-0.038***	-0.037***	-0.037***	-0.036***	-0.037***	-0.037***	-0.037***	-0.037***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Black	-0.349***	-0.278***	-0.354***	-0.350***	-0.354***	-0.354***	-0.352***	-0.351***
	(0.023)	(0.038)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Hispanic	-0.168***	-0.172***	-0.234***	-0.169***	-0.167***	-0.167***	-0.168***	-0.169***
	(0.019)	(0.019)	(0.027)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
American Indian	-0.062	-0.064	-0.066	-0.059	-0.060	-0.065	-0.066	-0.065
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)
Asian	0.216***	0.212***	0.211***	0.216***	0.218***	0.213***	0.212***	0.216***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Other race	-0.031	-0.030	-0.032	-0.030	-0.030	-0.032	-0.031	-0.029

	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Child of an immigrant	-0.069***	-0.056***	-0.054***	-0.066***	-0.073***	-0.051***	-0.066***	-0.067***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.014)	(0.009)	(0.009)
Full day K (versus part day)	0.009	0.010	0.009	0.012	0.010	0.010	-0.023	0.011
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.026)	(0.021)
Attended center-based early care	0.047***	0.046***	0.046***	0.046***	0.047***	0.047***	0.045***	0.098***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.018)
Parents education less than high school	-0.618***	-0.620***	-0.619***	-0.618***	-0.619***	-0.617***	-0.619***	-0.618***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Parent education high school only	-0.450***	-0.449***	-0.450***	-0.448***	-0.450***	-0.449***	-0.449***	-0.450***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Parent education some college	-0.271***	-0.271***	-0.271***	-0.269***	-0.271***	-0.271***	-0.269***	-0.271***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Constant	0.759***	0.763***	0.771***	0.782***	0.777***	0.757***	0.782***	0.734***
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.070)	(0.069)
Observations	43,460	43,460	43,460	43,460	43,460	43,460	43,460	43,460
Number of groups	2,010	2,010	2,010	2,010	2,010	2,010	2,010	2,010

Models include state fixed effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Note: "STUDENT CHARACTERISTIC" refers to the student characteristic at the top of each column

T4. Reading Score Growth by Neighborhood Poverty and Student Characteristics

	Female	Black	Hispanic	Poor	Rural	Immigrant	Full day K (vs. part day)	Center-based ECE
Spring K	0.748***	0.757***	0.744***	0.742***	0.741***	0.762***	0.677***	0.811***
	(0.014)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.017)	(0.015)
Spring 1st	1.516***	1.549***	1.532***	1.532***	1.536***	1.557***	1.561***	1.612***
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.027)	(0.025)
Spring 2nd	1.752***	1.779***	1.756***	1.755***	1.768***	1.787***	1.807***	1.847***
	(0.038)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.039)	(0.038)
Spring 3rd	1.872***	1.901***	1.876***	1.879***	1.884***	1.903***	1.923***	1.951***
	(0.051)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.052)	(0.051)
Moderate-Low Poverty Neighborhood	-0.056*	-0.039	-0.022	-0.044	-0.054*	-0.006	-0.067	-0.019
	(0.032)	(0.026)	(0.027)	(0.027)	(0.028)	(0.026)	(0.066)	(0.033)
Moderate-High Poverty Neighborhood	-0.132***	-0.122***	-0.123***	-0.114***	-0.129***	-0.076***	-0.164***	-0.135***
	(0.026)	(0.022)	(0.024)	(0.023)	(0.023)	(0.022)	(0.059)	(0.027)
High Poverty Neighborhood	-0.152***	-0.131**	-0.103*	-0.032	-0.104**	-0.044	0.124	0.006
	(0.053)	(0.052)	(0.054)	(0.052)	(0.044)	(0.045)	(0.267)	(0.053)
Moderate-Low Poverty Neighborhood X STUDENT CHARACTERISTIC X								
Spring K	0.031	-0.138***	0.071*	0.001	-0.051	0.122***	-0.097*	-0.080**
	(0.033)	(0.053)	(0.041)	(0.039)	(0.037)	(0.039)	(0.051)	(0.033)
Spring 1st	-0.051	-0.078	-0.052	-0.074	-0.011	-0.141	-0.112*	-0.021
	(0.037)	(0.062)	(0.046)	(0.045)	(0.041)	(0.122)	(0.059)	(0.037)
Spring 2nd	-0.059	-0.029	-0.003	-0.012	-0.030	0.047	-0.035	0.006
	(0.038)	(0.064)	(0.047)	(0.048)	(0.043)	(0.148)	(0.062)	(0.038)
Spring 3rd	-0.058	-0.026	-0.018	-0.010	-0.028	-0.155	-0.053	-0.009
	(0.040)	(0.068)	(0.049)	(0.052)	(0.044)	(0.259)	(0.064)	(0.040)
Moderate-High Poverty Neighborhood X STUDENT CHARACTERISTIC X								
Spring K	0.026	-0.103**	-0.040	-0.029	0.037	0.092***	0.015	-0.022
	(0.026)	(0.040)	(0.030)	(0.030)	(0.032)	(0.029)	(0.045)	(0.026)
Spring 1st	0.024	-0.050	-0.101***	-0.058*	-0.015	0.170**	0.084*	-0.032

	(0.029)	(0.046)	(0.034)	(0.035)	(0.035)	(0.085)	(0.050)	(0.029)
Spring 2nd	0.005	-0.068	-0.072**	-0.027	-0.093**	0.230**	0.063	-0.058*
	(0.030)	(0.049)	(0.035)	(0.037)	(0.037)	(0.115)	(0.052)	(0.030)
Spring 3rd	0.033	-0.064	-0.029	0.015	-0.087**	0.037	0.052	-0.087***
	(0.032)	(0.052)	(0.037)	(0.040)	(0.039)	(0.169)	(0.054)	(0.032)
High Poverty Neighborhood X STUDENT CHARACTERISTIC X								
Spring K	0.031	0.055	-0.206***	0.012	-0.144**	-0.054	0.190	0.209***
	(0.056)	(0.062)	(0.059)	(0.059)	(0.070)	(0.061)	(0.200)	(0.056)
Spring 1st	-0.050	-0.147**	-0.009	0.047	-0.037	0.174	-0.044	0.227***
	(0.063)	(0.070)	(0.066)	(0.069)	(0.077)	(0.143)	(0.208)	(0.063)
Spring 2nd	-0.044	-0.191***	0.045	0.113	0.080	0.275	-0.158	0.242***
	(0.066)	(0.073)	(0.069)	(0.073)	(0.080)	(0.184)	(0.220)	(0.066)
Spring 3rd	-0.133*	-0.178**	0.128*	0.143*	0.176**	-0.230	-0.009	0.195***
	(0.071)	(0.080)	(0.074)	(0.078)	(0.085)	(0.441)	(0.234)	(0.071)
Moderate-Low Poverty Neighborhood X								
Spring K	0.040*	0.074***	0.033*	0.043**	0.069***	0.028	0.128***	0.091***
	(0.024)	(0.018)	(0.019)	(0.019)	(0.020)	(0.019)	(0.048)	(0.024)
Spring 1st	0.064**	0.051***	0.042**	0.047**	0.042*	0.010	0.144***	0.041
	(0.026)	(0.019)	(0.021)	(0.021)	(0.022)	(0.020)	(0.055)	(0.027)
Spring 2nd	0.052*	0.029	0.010	0.010	0.031	-0.010	0.062	0.011
	(0.027)	(0.020)	(0.022)	(0.022)	(0.023)	(0.021)	(0.058)	(0.027)
Spring 3rd	0.048*	0.032	0.012	0.012	0.028	-0.013	0.074	0.017
	(0.028)	(0.021)	(0.022)	(0.023)	(0.024)	(0.021)	(0.061)	(0.029)
Moderate-High Poverty Neighborhood X								
Spring K	0.012	0.044***	0.019	0.012	0.021	-0.002	-0.007	0.029
	(0.018)	(0.014)	(0.016)	(0.016)	(0.015)	(0.016)	(0.043)	(0.019)
Spring 1st	0.002	0.026	0.024	0.014	0.021	-0.033**	-0.061	0.023
	(0.020)	(0.016)	(0.018)	(0.018)	(0.017)	(0.017)	(0.047)	(0.022)
Spring 2nd	0.018	0.036**	0.009	-0.004	0.043**	-0.027	-0.030	0.043*
	(0.021)	(0.016)	(0.019)	(0.019)	(0.017)	(0.017)	(0.049)	(0.022)
Spring 3rd	-0.017	0.024	-0.024	-0.029	0.020	-0.049***	-0.043	0.037

	(0.022)	(0.017)	(0.020)	(0.020)	(0.018)	(0.018)	(0.051)	(0.024)
High Poverty Neighborhood X								
Spring K	0.037	0.029	0.113***	0.007	0.083***	0.072**	-0.160	-0.060
	(0.039)	(0.037)	(0.036)	(0.043)	(0.031)	(0.034)	(0.198)	(0.039)
Spring 1st	-0.020	0.029	-0.072*	-0.110**	-0.036	-0.102***	0.004	-0.166***
	(0.044)	(0.041)	(0.041)	(0.050)	(0.036)	(0.036)	(0.206)	(0.045)
Spring 2nd	0.053	0.121***	-0.041	-0.099*	0.009	-0.031	0.196	-0.098**
	(0.046)	(0.043)	(0.045)	(0.055)	(0.038)	(0.038)	(0.217)	(0.046)
Spring 3rd	0.074	0.127***	-0.103**	-0.112**	-0.039	-0.047	0.028	-0.094*
	(0.049)	(0.045)	(0.049)	(0.056)	(0.042)	(0.040)	(0.231)	(0.049)
STUDENT CHARACTERISTIC X								
Spring K	0.016	-0.006	0.085***	0.083***	0.058***	-0.029*	0.104***	-0.094***
	(0.014)	(0.028)	(0.019)	(0.020)	(0.016)	(0.016)	(0.016)	(0.014)
Spring 1st	0.058***	-0.019	0.127***	0.086***	0.038**	-0.002	-0.022	-0.116***
	(0.015)	(0.032)	(0.022)	(0.023)	(0.017)	(0.053)	(0.017)	(0.015)
Spring 2nd	0.045***	-0.030	0.166***	0.126***	0.028	-0.059	-0.043**	-0.126***
	(0.015)	(0.033)	(0.022)	(0.025)	(0.017)	(0.080)	(0.018)	(0.016)
Spring 3rd	0.039**	-0.144***	0.148***	0.084***	0.030*	0.206	-0.039**	-0.107***
	(0.016)	(0.035)	(0.024)	(0.027)	(0.018)	(0.139)	(0.019)	(0.016)
STUDENT CHARACTERISTIC X								
Moderate-Low Poverty Neighborhood	0.033	-0.043	-0.046	0.050	0.054	-0.147***	0.031	-0.028
	(0.039)	(0.065)	(0.051)	(0.038)	(0.051)	(0.034)	(0.070)	(0.040)
Moderate-High Poverty Neighborhood	0.022	-0.054	0.054	0.035	0.012	-0.156***	0.049	0.036
	(0.031)	(0.050)	(0.038)	(0.029)	(0.046)	(0.026)	(0.061)	(0.031)
High Poverty Neighborhood	0.106	-0.023	0.057	-0.053	0.034	-0.190***	-0.224	-0.203***
	(0.065)	(0.081)	(0.080)	(0.056)	(0.079)	(0.055)	(0.270)	(0.065)
Female	0.113***	0.154***	0.155***	0.155***	0.154***	0.155***	0.154***	0.155***
	(0.016)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age in months	0.029***	0.029***	0.029***	0.029***	0.029***	0.029***	0.029***	0.029***

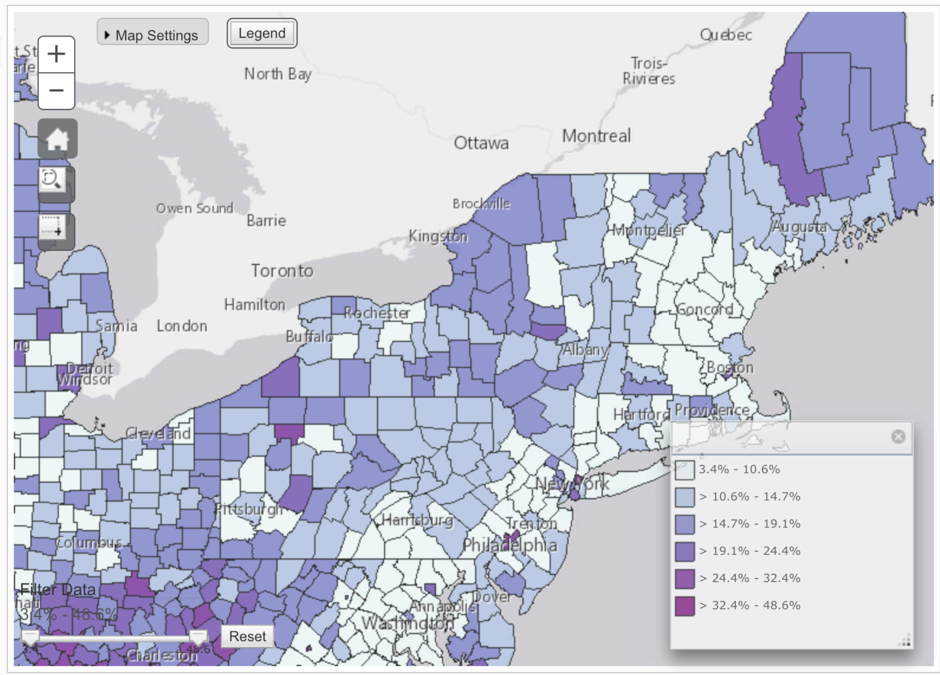
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Moved between waves	-0.035***	-0.032***	-0.034***	-0.037***	-0.034***	-0.033***	-0.035***	-0.034***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Is a twin	-0.242***	-0.243***	-0.240***	-0.243***	-0.243***	-0.242***	-0.242***	-0.248***
	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)
Household size (centered at mean)	-0.023***	-0.024***	-0.024***	-0.024***	-0.024***	-0.023***	-0.023***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Speaks language other than English in household	-0.072**	-0.071**	-0.078**	-0.073**	-0.073**	-0.070*	-0.070*	-0.072**
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Parents married	0.060***	0.060***	0.058***	0.059***	0.059***	0.060***	0.060***	0.059***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Lives in rural area	0.015	0.013	0.009	0.012	-0.021	0.013	0.019	0.013
	(0.015)	(0.015)	(0.015)	(0.015)	(0.021)	(0.015)	(0.015)	(0.015)
Family income under poverty line	-0.086***	-0.086***	-0.087***	-0.170***	-0.085***	-0.085***	-0.085***	-0.086***
	(0.011)	(0.011)	(0.011)	(0.021)	(0.011)	(0.011)	(0.011)	(0.011)
Family income between 100 and 200 percent of poverty line	-0.035***	-0.036***	-0.036***	-0.034***	-0.036***	-0.035***	-0.036***	-0.036***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Black	-0.130***	-0.039	-0.130***	-0.130***	-0.131***	-0.135***	-0.130***	-0.131***
	(0.021)	(0.035)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Hispanic	-0.097***	-0.102***	-0.198***	-0.100***	-0.099***	-0.097***	-0.098***	-0.099***
	(0.017)	(0.017)	(0.025)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
American Indian	-0.119*	-0.119*	-0.117*	-0.115*	-0.117*	-0.120*	-0.120*	-0.119*
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Asian	0.198***	0.195***	0.190***	0.196***	0.197***	0.191***	0.198***	0.198***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Other race	0.031	0.031	0.028	0.031	0.031	0.028	0.032	0.032
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Child of an immigrant	-0.030***	-0.023***	-0.004	-0.025***	-0.026***	0.029**	-0.030***	-0.029***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.015)	(0.009)	(0.009)

Full day K (versus part day)	0.018	0.018	0.018	0.019	0.018	0.017	0.005	0.019
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.024)	(0.019)
Attended center-based early care	0.045***	0.045***	0.045***	0.045***	0.045***	0.045***	0.044***	0.135***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.017)
Parents education less than high school	-0.590***	-0.593***	-0.594***	-0.589***	-0.591***	-0.588***	-0.591***	-0.590***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Parent education high school only	-0.430***	-0.430***	-0.431***	-0.428***	-0.430***	-0.429***	-0.429***	-0.429***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Parent education some college	-0.261***	-0.260***	-0.260***	-0.259***	-0.260***	-0.260***	-0.259***	-0.260***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Constant	0.521***	0.506***	0.515***	0.512***	0.510***	0.483***	0.503***	0.447***
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.066)	(0.065)
Observations	43,490	43,490	43,490	43,490	43,490	43,490	43,490	43,490
Number of groups	2,010	2,010	2,010	2,010	2,010	2,010	2,010	2,010

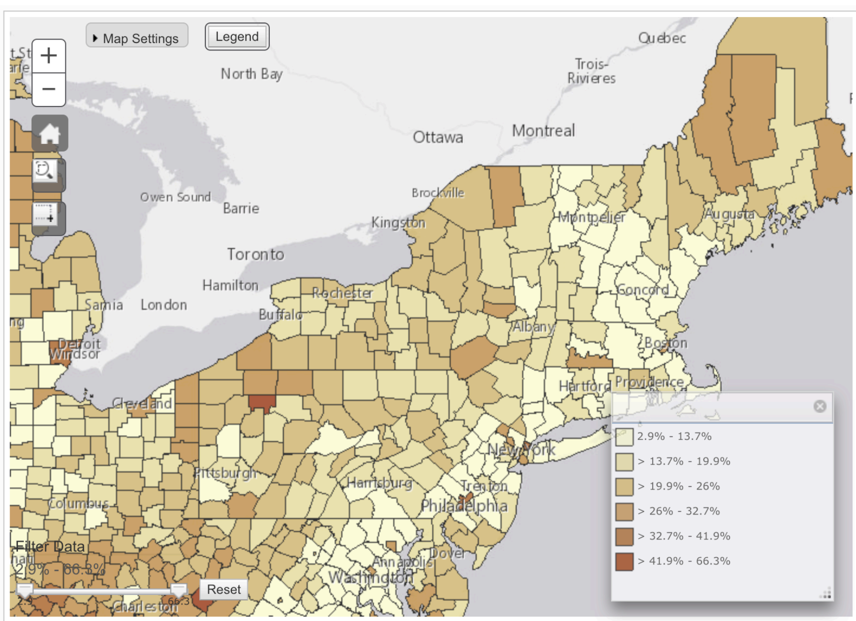
Models include state fixed effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Note: "STUDENT CHARACTERISTIC" refers to the student characteristic at the top of each column

Figure 1. Map of Poverty Rates in the Northeast by County for all Ages and for Children under 18.

2016 All Ages in Poverty

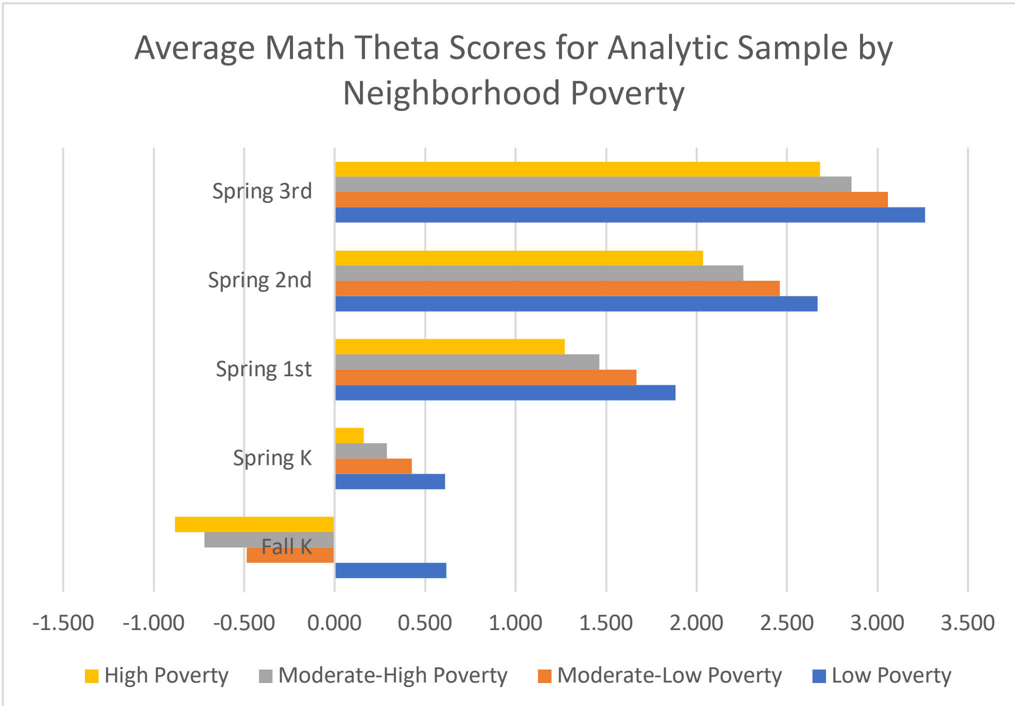


2016 Under Age 18 in Poverty



Source: Authors' calculation using the census website mapping tool: https://www.census.gov/data-tools/demo/saipe/saipe.html?s_appName=saipe&map_yearSelector=2016&map_geoSelector=aa_c&s_state=36&s_measures=aa_snc

Figure 2. Weighted Average Standardized Math and Reading Scores by Neighborhood Poverty



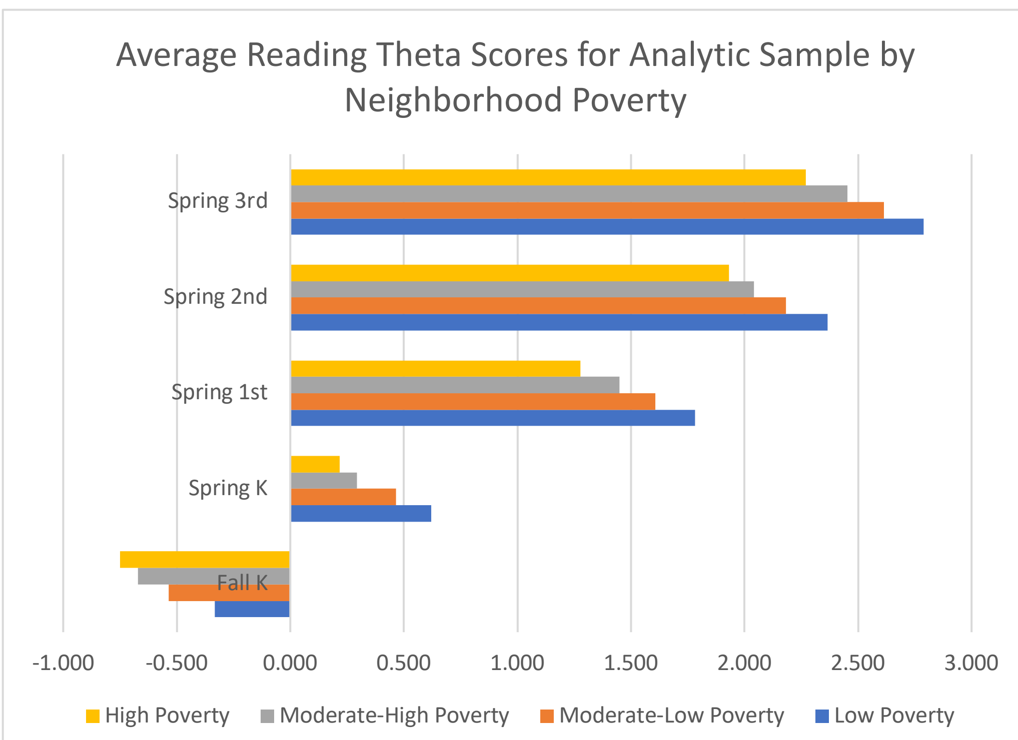
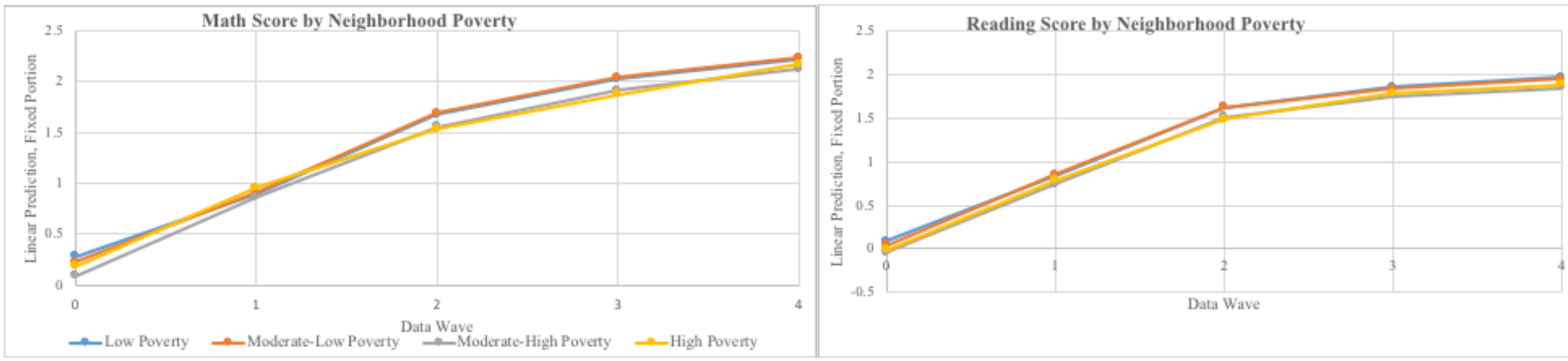


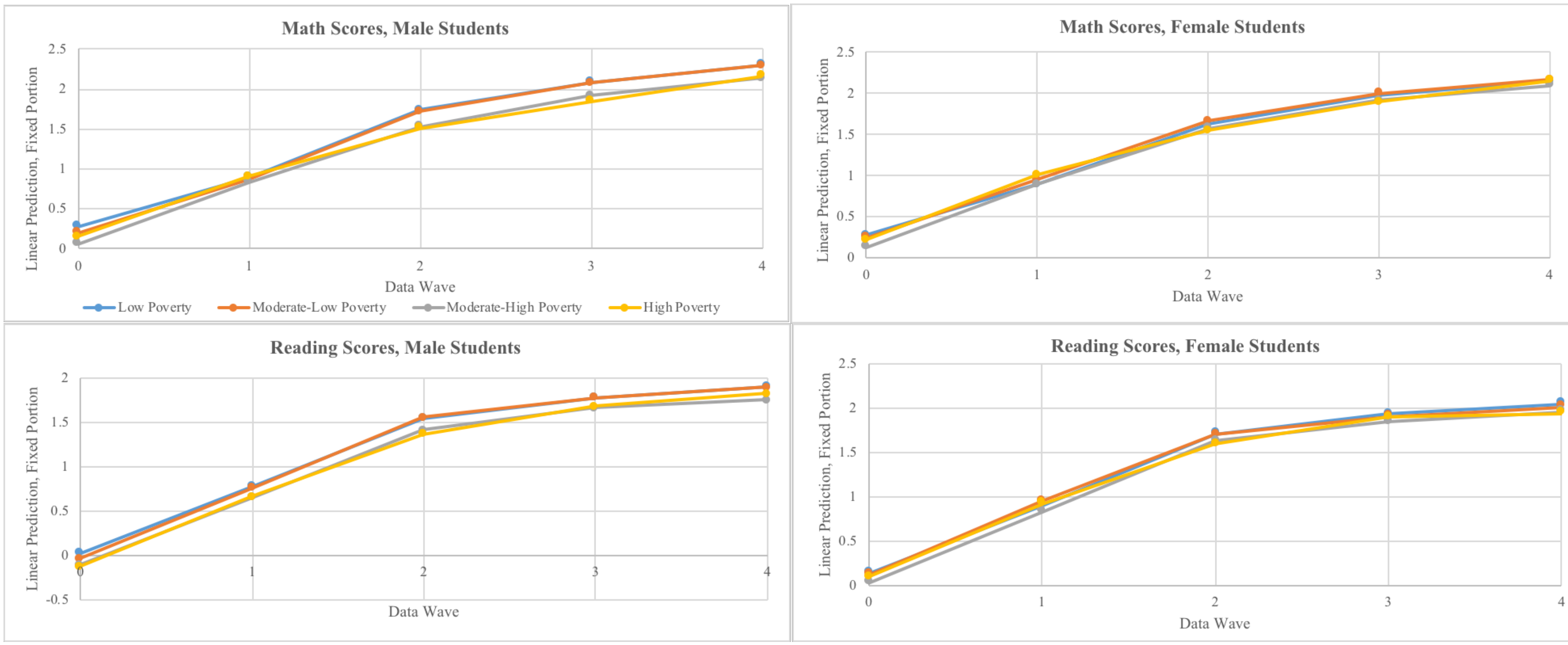
Figure 3. Predictive Margins, Test Scores by Neighborhood Poverty



Slope Estimates									
Math					**Reading**				
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty		Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.61	0.69***	0.77***	0.77***	0 to 1	0.75	0.81***	0.78*	0.81*
1 to 2	0.79	0.78	0.69***	0.58***	1 to 2	0.79	0.77	0.78	0.69***
2 to 3	0.35	0.35	0.36	0.34	2 to 3	0.23	0.21	0.24	0.30**
3 to 4	0.20	0.19	0.20	0.29***	3 to 4	0.12	0.11	0.10	0.10

Here, statistical significance indicates that the difference between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different. *** p<.001, ** p<.05, * p<.01

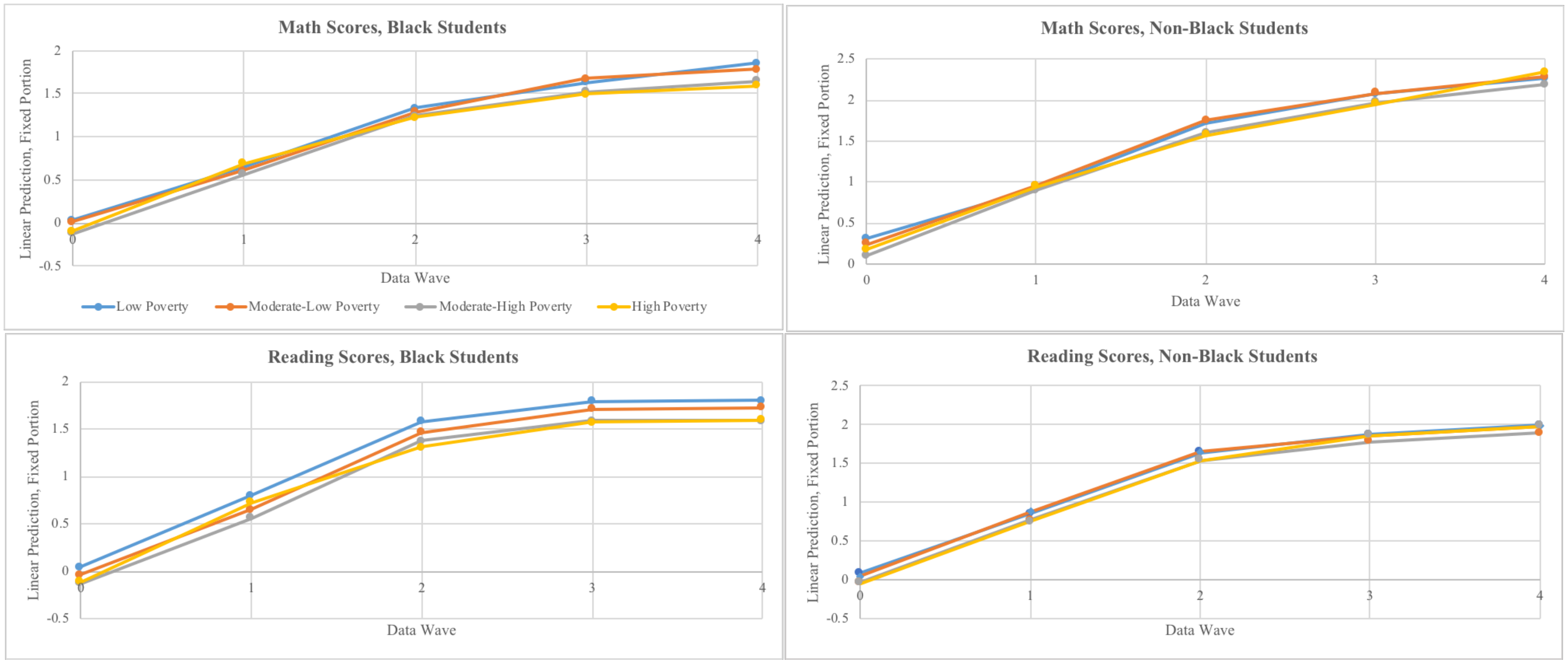
Figure 4. Predictive Margins, Test Scores by Neighborhood Poverty by Gender



Slope Estimates									
	Math, Male					**Math, Female**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty		Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.61	0.68	0.77	0.75		0.61	0.70	0.76	0.79
1 to 2	0.84	0.84	0.69	0.60		0.73	0.72	0.69***	0.54
2 to 3	0.35	0.35	0.39	0.33		0.35	0.34	0.33*	0.34
3 to 4	0.22	0.22	0.22	0.32		0.17	0.16	0.18	0.26
	Reading, Male					**Reading, Female**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty		Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.75	0.79	0.76	0.78		0.76	0.83	0.80	0.83
1 to 2	0.77	0.79	0.76	0.71		0.81	0.75**	0.80	0.67
2 to 3	0.24	0.22	0.25	0.31		0.22	0.20	0.22	0.30
3 to 4	0.12	0.12	0.09	0.14		0.12	0.11	0.11	0.05

Here, statistical significance indicates that the <u>difference</u> between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different for male versus female students. Note that statistical significance is not presented for differences in slopes within sex. *** p<.001, ** p<.05, * p<.01

Figure 5. Predictive Margins, Test Scores by Neighborhood Poverty by Black vs Non-Black Students

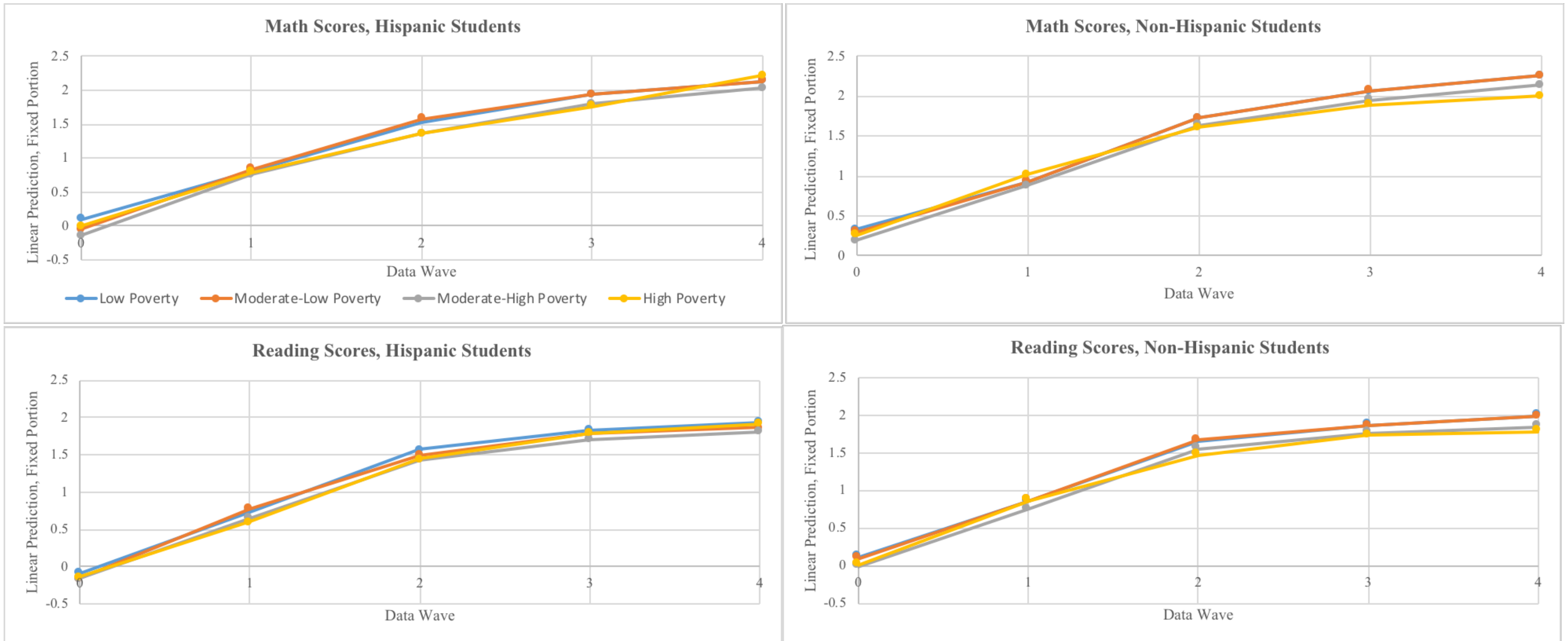


Slope Estimates

	Math, Black				Math, Non-Black			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.62	0.59	0.69	0.79	0.62	0.71**	0.79***	0.76
1 to 2	0.68	0.68	0.67	0.53	0.80	0.80	0.70*	0.62
2 to 3	0.30	0.40	0.28	0.27	0.35	0.34*	0.38	0.38
3 to 4	0.23	0.11	0.13	0.10	0.19	0.20*	0.21***	0.39***
	Reading, Black				**Reading, Non-Black**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.75	0.69	0.69	0.84	0.76	0.83***	0.80**	0.79
1 to 2	0.78	0.82	0.81	0.58	0.79	0.77	0.77	0.79***
2 to 3	0.22	0.25	0.21	0.27	0.23	0.21	0.24	0.32
3 to 4	0.01	0.01	0.00	0.03	0.12	0.12	0.11	0.13

Here, statistical significance indicates that the difference between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different for black versus non-black students. Note that statistical significance is not presented for differences in slopes within race. *** p<.001, ** p<.05, * p<.01

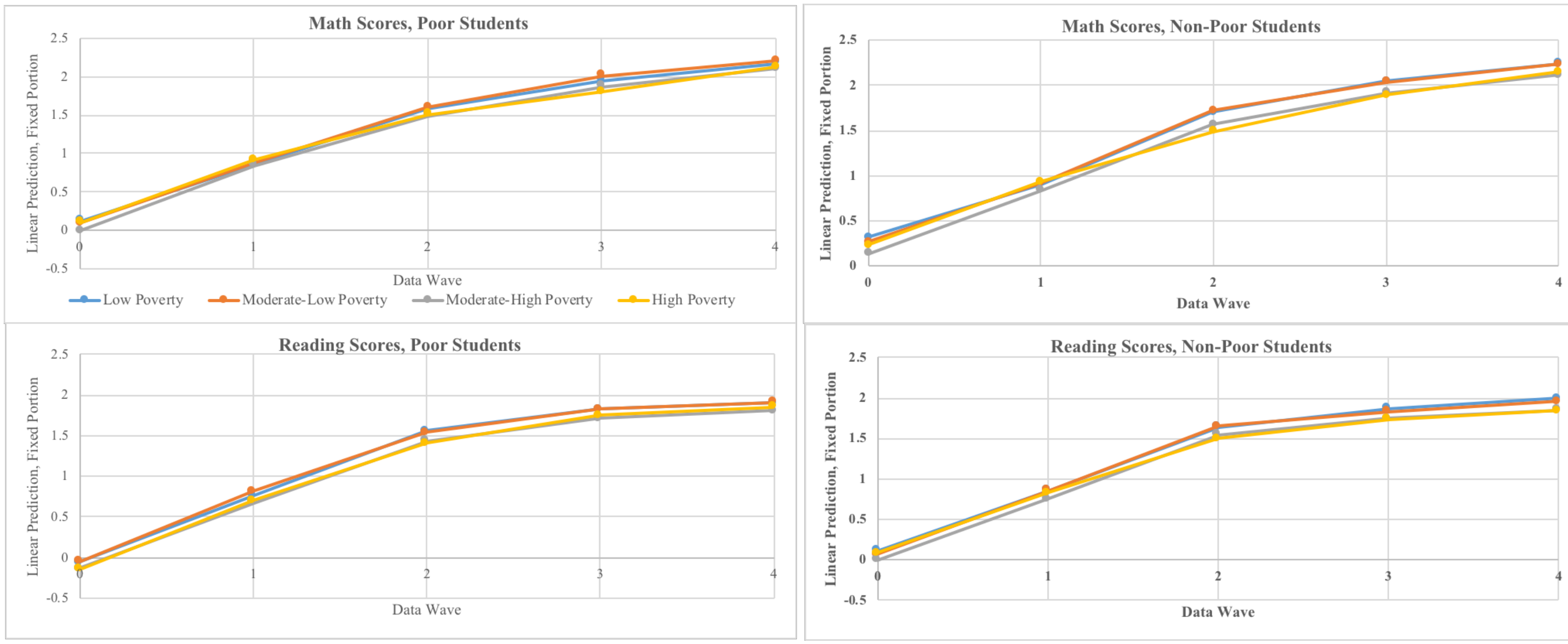
Figure 6. Predictive Margins, Test Scores by Neighborhood Poverty by Hispanic vs Non-Hispanic Students



Slope Estimates								
	Math, Hispanic				**Math, Non-Hispanic**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.73	0.88	0.90	0.80	0.59	0.64***	0.69**	0.76*
1 to 2	0.72	0.74	0.61	0.57	0.80	0.80*	0.75	0.60
2 to 3	0.40	0.36	0.43	0.40	0.34	0.34	0.31*	0.28
3 to 4	0.19	0.19	0.23	0.45	0.20	0.19	0.19	0.12***
	Reading, Hispanic				**Reading, Non-Hispanic**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.83	0.93	0.81	0.74	0.74	0.78*	0.76	0.86***
1 to 2	0.83	0.72	0.78	0.84	0.79	0.80***	0.79*	0.60***
2 to 3	0.26	0.28	0.28	0.35	0.22	0.19	0.21	0.25
3 to 4	0.10	0.09	0.11	0.12	0.12	0.12	0.09	0.06

Here, statistical significance indicates that the difference between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different for Hispanic versus non-Hispanic students. Note that statistical significance is not presented for differences in slopes within ethnicity. *** p<.001, ** p<.05, * p<.01

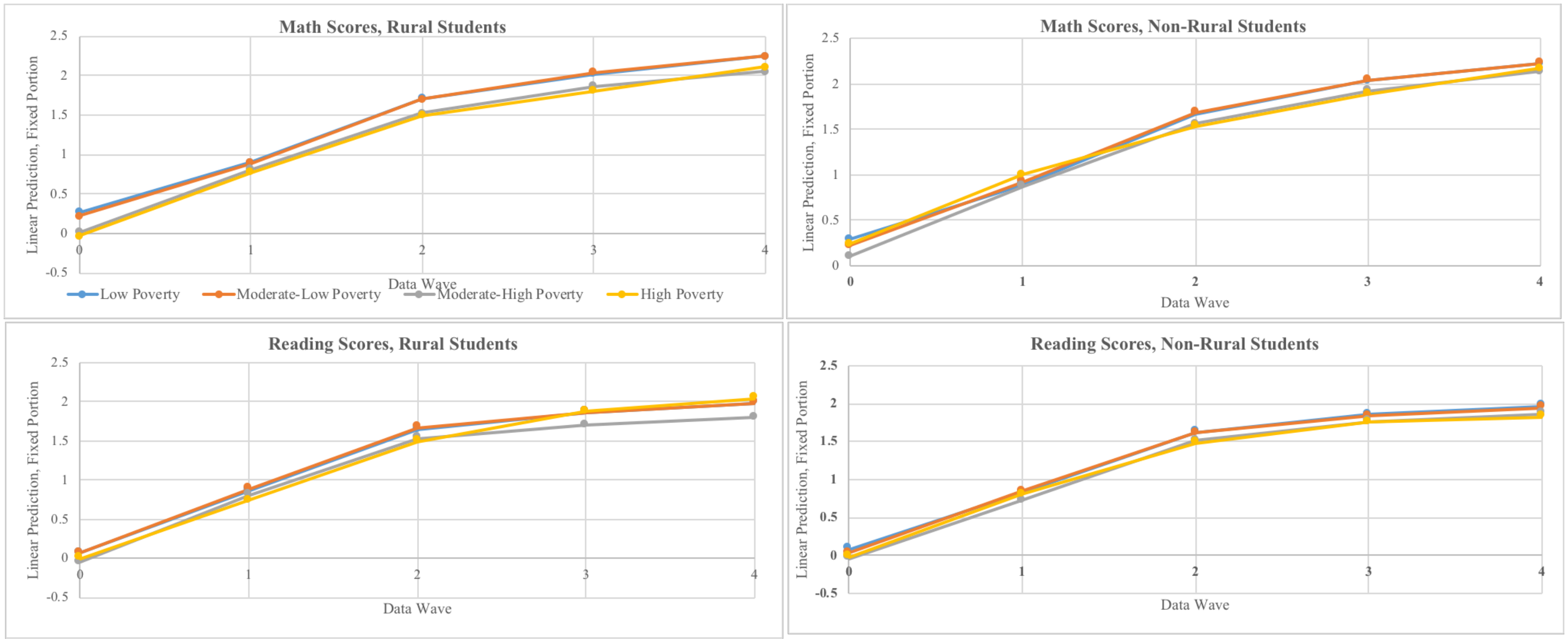
Figure 7. Predictive Margins, Test Scores by Neighborhood Poverty by Poor vs. Non-Poor Student



Slope Estimates								
	Math, Poor				**Math, Non-Poor**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.74	0.79	0.85	0.82	0.59	0.65	0.70	0.70
1 to 2	0.73	0.72	0.65	0.59	0.80	0.81	0.73	0.55
2 to 3	0.37	0.41	0.37	0.30	0.35	0.32	0.35	0.41*
3 to 4	0.22	0.19	0.23	0.32	0.20	0.20	0.19	0.25
	Reading, Poor				**Reading, Non-Poor**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.83	0.87	0.81	0.84	0.74	0.79	0.75	0.75
1 to 2	0.79	0.72	0.76	0.71	0.79	0.79*	0.79	0.67
2 to 3	0.26	0.29	0.28	0.34	0.22	0.19	0.20	0.23
3 to 4	0.08	0.09	0.10	0.10	0.12	0.13	0.10	0.11

Here, statistical significance indicates that the difference between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different for poor versus non-poor students. Note that statistical significance is not presented for differences in slopes within poverty status. *** p<.001, ** p<.05, * p<.01

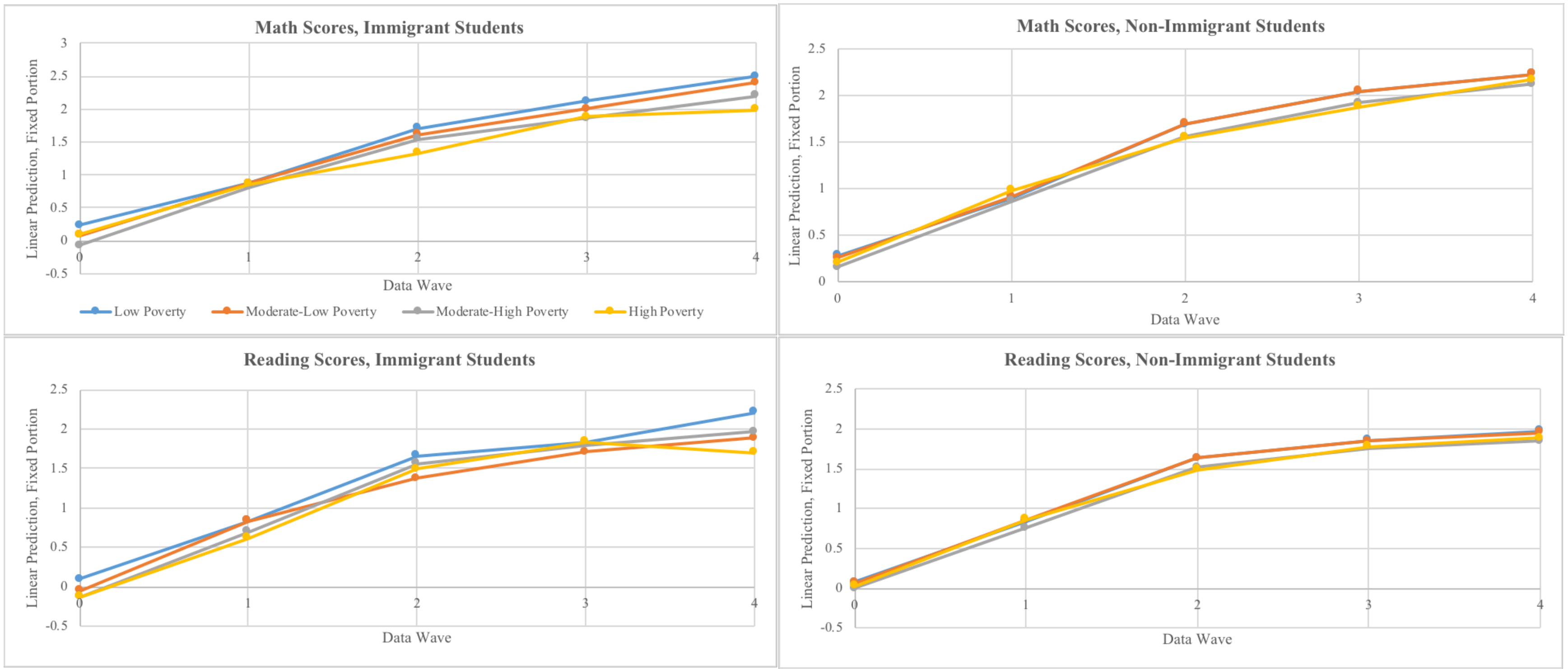
Figure 8. Predictive Margins, Test Scores by Neighborhood Poverty by Rural vs. Non-Rural Student



Slope Estimates								
	Math, Rural				**Math, Non-Rural**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.64	0.67	0.80	0.81	0.60	0.70*	0.76	0.76
1 to 2	0.80	0.81	0.71	0.72	0.78	0.77	0.69	0.54**
2 to 3	0.32	0.34	0.34	0.31	0.36	0.35	0.37	0.35
3 to 4	0.22	0.20	0.18	0.31	0.19	0.19	0.21	0.28
	Reading, Rural				**Reading, Non-Rural**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.80	0.82	0.86	0.74	0.74	0.81	0.76	0.82**
1 to 2	0.78	0.79	0.72	0.76	0.80	0.77	0.79	0.68
2 to 3	0.22	0.19	0.17	0.38	0.23	0.22	0.25**	0.28
3 to 4	0.12	0.12	0.10	0.17	0.12	0.11	0.09	0.07

Here, statistical significance indicates that the difference between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different for rural versus non-rural students. Note that statistical significance is not presented for differences in slopes within rural status. *** p<.001, ** p<.05, * p<.01

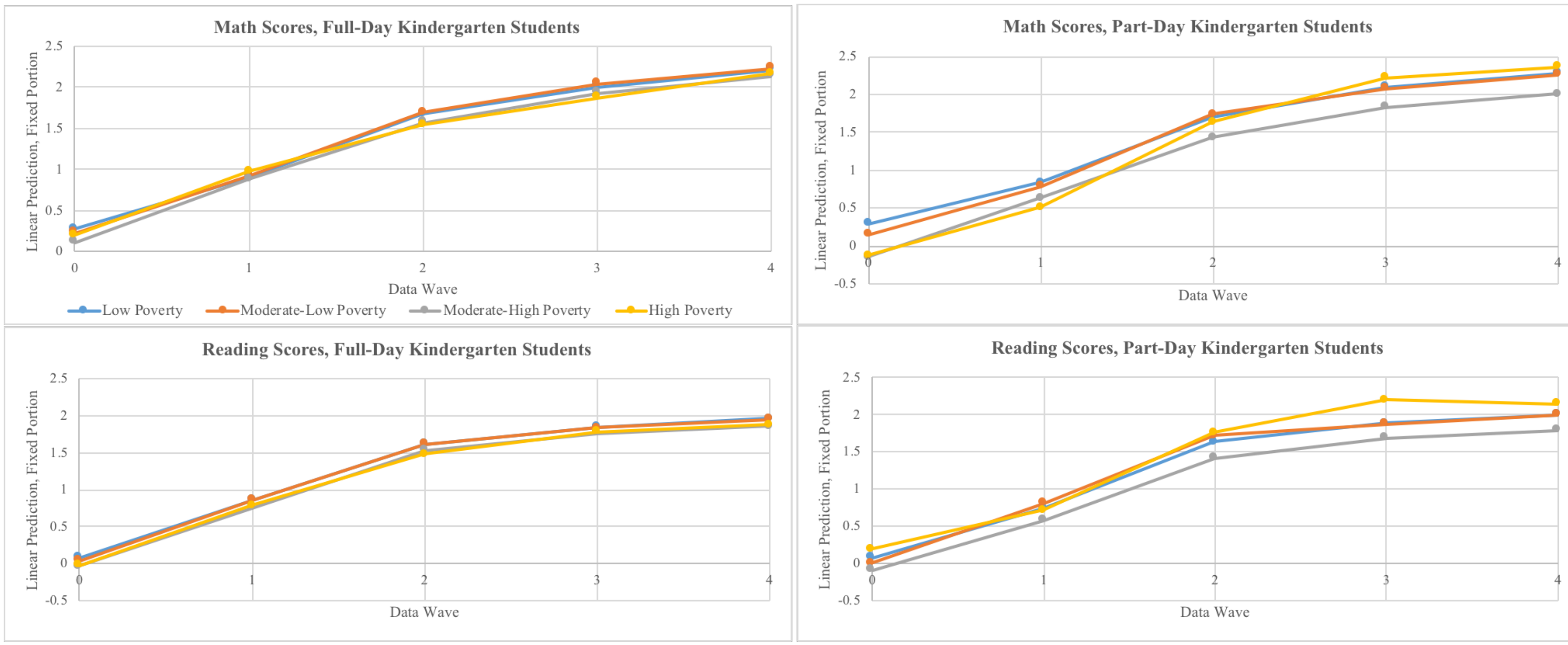
Figure 9. Predictive Margins, Test Scores by Neighborhood Poverty by Immigrant vs. Non-Immigrant Student



Slope Estimates								
	Math, Immigrant				**Math, Non-Immigrant**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.63	0.80	0.89	0.77	0.61	0.66***	0.71***	0.78
1 to 2	0.84	0.74	0.72	0.47	0.79	0.79	0.70	0.56
2 to 3	0.41	0.39	0.32	0.55	0.35	0.34	0.36	0.33
3 to 4	0.38	0.40	0.34	0.11	0.19	0.19	0.20	0.29
	Reading, Immigrant				**Reading, Non-Immigrant**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.73	0.88	0.82	0.75	0.76	0.79***	0.76***	0.83
1 to 2	0.82	0.54	0.87	0.88	0.80	0.78**	0.76	0.62
2 to 3	0.17	0.34	0.24	0.34	0.23	0.21	0.24	0.30
3 to 4	0.38	0.18	0.17	-0.14	0.12	0.11	0.09	0.10

Here, statistical significance indicates that the difference between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different for immigrant versus non-immigrant students. Note that statistical significance is not presented for differences in slopes within immigrant status. *** p<.001, ** p<.05, * p<.01

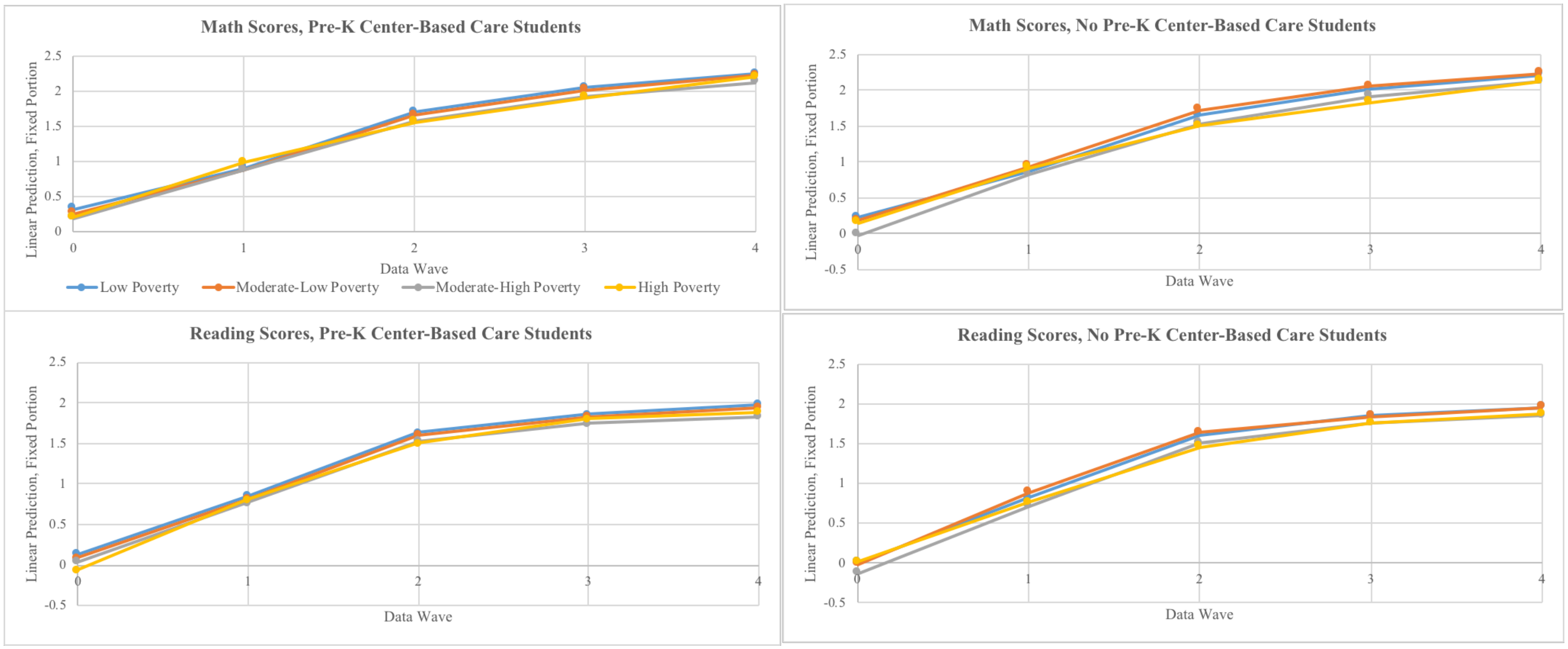
Figure 10. Predictive Margins, Test Scores by Neighborhood Poverty by Full vs. Half-Day Kindergarten Student



Slope Estimates								
Math, Full Day Kindergarten Students					**Math, Part Day Kindergarten Students**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.64	0.70	0.77	0.78	0.54	0.64	0.78**	0.63
1 to 2	0.76	0.77	0.69	0.57	0.87	0.95	0.81	1.13**
2 to 3	0.34	0.35	0.36	0.33	0.39	0.34	0.40	0.59
3 to 4	0.20	0.19	0.21	0.30	0.19	0.19	0.18	0.13
Reading, Full Day Kindergarten Students					**Reading, Part Day Kindergarten Students**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.78	0.81	0.79	0.81	0.68	0.80*	0.67	0.52
1 to 2	0.76	0.76	0.77	0.69	0.88	0.90	0.83	1.05
2 to 3	0.22	0.22	0.23	0.30	0.25	0.16	0.28	0.44
3 to 4	0.12	0.11	0.10	0.10	0.12	0.13	0.10	-0.05

Here, statistical significance indicates that the difference between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different for full day kindergarten versus part day kindergarten students. Note that statistical significance is not presented for differences in slopes within kindergarten attendance status. *** p<.001, ** p<.05, * p<.01

Figure 11. Predictive Margins, Test Scores by Neighborhood Poverty by Pre-K Center-Based Care vs. Non-Center-Based Care Student



Slope Estimates								
Math, Pre-K Center Based Care Students					**Math, No Pre-K Center Based Care Students**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.59	0.63	0.69	0.78	0.65	0.76**	0.86***	0.77
1 to 2	0.79	0.78	0.69	0.57	0.78	0.78	0.70	0.58
2 to 3	0.34	0.36	0.35	0.35	0.36	0.33	0.38	0.33
3 to 4	0.19	0.20	0.21	0.29	0.20	0.18	0.20	0.29
Reading, Pre-K Center Based Care Students					**Reading, No Pre-K Center Based Care Students**			
	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty	Low Poverty	Moderate-Low Poverty	Moderate-High Poverty	High Poverty
0 to 1	0.72	0.73	0.72	0.87	0.81	0.90**	0.84	0.75***
1 to 2	0.78	0.79	0.76	0.69	0.80	0.75	0.80	0.69
2 to 3	0.22	0.22	0.22	0.31	0.23	0.20	0.25	0.30
3 to 4	0.12	0.12	0.09	0.08	0.10	0.11	0.10	0.11

Here, statistical significance indicates that the difference between the indicated poverty category and low poverty (the reference group) for the indicated slope is statistically signicantly different for pre-K center-based versus non-center-based students. Note that statistical significance is not presented for differences in slopes within pre-K arrangements. *** p<.001, ** p<.05, * p<.01

Appendix

Appendix T1. Math and Reading Score Growth by School Free and Reduced Price Lunch Eligibility

	Math Score	Reading Score
Spring K	0.563***	0.699***
	(0.014)	(0.014)
Spring 1st	1.346***	1.516***
	(0.027)	(0.025)
Spring 2nd	1.670***	1.726***
	(0.042)	(0.038)
Spring 3rd	1.838***	1.840***
	(0.056)	(0.051)
Moderate-Low Poverty School	-0.085***	-0.062***
	(0.014)	(0.015)
Moderate-High Poverty School	-0.131***	-0.057***
	(0.017)	(0.017)
High Poverty School	-0.177***	-0.078***
	(0.018)	(0.018)
Moderate-Low Poverty School X		
Spring K	0.061***	0.088***
	(0.014)	(0.014)
Spring 1st	0.086***	0.057***
	(0.015)	(0.015)
Spring 2nd	0.110***	0.066***
	(0.017)	(0.017)
Spring 3rd	0.137***	0.097***
	(0.018)	(0.018)
Moderate-High Poverty School X		
Spring K	0.163***	0.118***
	(0.015)	(0.015)
Spring 1st	0.125***	0.064***
	(0.016)	(0.017)
Spring 2nd	0.144***	0.074***

	(0.018)	(0.018)
Spring 3rd	0.174***	0.052***
	(0.019)	(0.019)
High Poverty School X		
Spring K	0.259***	0.120***
	(0.015)	(0.015)
Spring 1st	0.111***	0.029*
	(0.017)	(0.018)
Spring 2nd	0.182***	0.105***
	(0.018)	(0.018)
Spring 3rd	0.228***	0.080***
	(0.019)	(0.019)
Female	-0.030**	0.156***
	(0.012)	(0.011)
Age in months	0.037***	0.029***
	(0.001)	(0.001)
Moved between waves	-0.035***	-0.033***
	(0.008)	(0.008)
Is a twin	-0.228**	-0.264***
	(0.091)	(0.081)
Household size (centered at mean)	-0.008**	-0.024***
	(0.003)	(0.003)
Speaks language other than English in household	-0.022	-0.072**
	(0.040)	(0.036)
Parents married	0.039***	0.058***
	(0.009)	(0.009)
Lives in rural area	-0.011	0.021
	(0.016)	(0.015)
Family income under poverty line	-0.088***	-0.091***
	(0.011)	(0.011)
Family income between 100 and 200 percent of poverty line	-0.039***	-0.039***

	(0.009)	(0.009)
Black	-0.368***	-0.147***
	(0.023)	(0.021)
Hispanic	-0.183***	-0.113***
	(0.019)	(0.017)
American Indian	-0.071	-0.126*
	(0.075)	(0.067)
Asian	0.215***	0.197***
	(0.028)	(0.025)
Other race	-0.023	0.034
	(0.028)	(0.025)
Child of an immigrant	-0.069***	-0.032***
	(0.009)	(0.009)
Full day K (versus part day)	0.003	0.008
	(0.021)	(0.020)
Attended center-based early care	0.046***	0.045***
	(0.012)	(0.011)
Parents education less than high school	-0.628***	-0.601***
	(0.026)	(0.024)
Parent education high school only	-0.454***	-0.435***
	(0.019)	(0.017)
Parent education some college	-0.273***	-0.264***
	(0.016)	(0.014)
Constant	0.782***	0.489***
	(0.069)	(0.065)
Observations	43,500	43,530
Number of groups	2,030	2,020

Models include state fixed effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix T2. Math and Reading Score Growth by Home Tract Neighborhood Poverty

	Math Score		Reading Score	
	1	2	3	4
Spring K	0.872***	0.636***	0.961***	0.779***
	(0.006)	(0.012)	(0.006)	(0.012)
Spring 1st	2.090***	1.426***	2.097***	1.570***
	(0.006)	(0.026)	(0.006)	(0.024)
Spring 2nd	2.890***	1.769***	2.684***	1.791***
	(0.006)	(0.041)	(0.006)	(0.037)
Spring 3rd	3.471***	1.924***	3.102***	1.867***
	(0.007)	(0.055)	(0.007)	(0.050)
Moderate-Low Poverty Neighborhood	-0.297***	-0.163***	-0.252***	-0.135***
	(0.019)	(0.023)	(0.018)	(0.021)
Moderate-High Poverty Neighborhood	-0.401***	-0.182***	-0.326***	-0.114***
	(0.017)	(0.020)	(0.015)	(0.019)
High Poverty Neighborhood	-0.520***	-0.227***	-0.407***	-0.139***
	(0.032)	(0.038)	(0.029)	(0.036)
Moderate-Low Poverty Neighborhood X				
Spring K	0.094***	0.094***	0.049***	0.059***
	(0.013)	(0.016)	(0.013)	(0.016)
Spring 1st	0.075***	0.072***	0.043***	0.037**
	(0.014)	(0.018)	(0.014)	(0.018)
Spring 2nd	0.047***	0.059***	0.051***	0.040**
	(0.015)	(0.019)	(0.014)	(0.019)
Spring 3rd	0.062***	0.083***	0.030**	0.035*
	(0.015)	(0.020)	(0.015)	(0.020)
Moderate-High Poverty Neighborhood X				
Spring K	0.157***	0.152***	0.069***	0.066***
	(0.010)	(0.013)	(0.010)	(0.013)
Spring 1st	0.072***	0.049***	0.059***	0.033**
	(0.011)	(0.014)	(0.011)	(0.015)

Spring 2nd	0.089***	0.073***	0.080***	0.048***
	(0.011)	(0.015)	(0.011)	(0.015)
Spring 3rd	0.089***	0.088***	0.059***	0.033**
	(0.012)	(0.016)	(0.012)	(0.016)
High Poverty Neighborhood X				
Spring K	0.206***	0.218***	0.009	-0.001
	(0.021)	(0.026)	(0.020)	(0.027)
Spring 1st	0.030	-0.009	-0.043*	-0.088***
	(0.023)	(0.030)	(0.022)	(0.030)
Spring 2nd	0.003	-0.023	0.019	-0.010
	(0.023)	(0.031)	(0.023)	(0.031)
Spring 3rd	0.073***	0.091***	0.001	-0.011
	(0.025)	(0.033)	(0.024)	(0.034)
Female		-0.025**		0.161***
		(0.012)		(0.011)
Age in months		0.037***		0.030***
		(0.001)		(0.001)
Moved between waves		-0.003		0.005
		(0.008)		(0.008)
Is a twin		-0.210**		-0.244***
		(0.089)		(0.080)
Household size (centered at mean)		-0.008**		-0.023***
		(0.003)		(0.003)
Speaks language other than English in household		0.003		-0.055
		(0.041)		(0.036)
Parents married		0.040***		0.060***
		(0.009)		(0.009)
Lives in rural area		-0.009		0.023
		(0.016)		(0.016)
Family income under poverty line		-0.083***		-0.083***
		(0.011)		(0.011)

Family income between 100 and 200 percent of poverty line		-0.035***		-0.033***
		(0.009)		(0.009)
Black		-0.335***		-0.120***
		(0.023)		(0.021)
Hispanic		-0.158***		-0.095***
		(0.019)		(0.017)
American Indian		-0.065		-0.110
		(0.075)		(0.067)
Asian		0.215***		0.201***
		(0.028)		(0.026)
Other race		-0.020		0.035
		(0.028)		(0.025)
Child of an immigrant		-0.070***		-0.031***
		(0.009)		(0.009)
Full day K (versus part day)		0.022		0.023
		(0.021)		(0.020)
Attended center-based early care		0.042***		0.042***
		(0.013)		(0.011)
Parents education less than high school		-0.619***		-0.590***
		(0.027)		(0.024)
Parent education high school only		-0.439***		-0.421***
		(0.019)		(0.017)
Parent education some college		-0.268***		-0.260***
		(0.016)		(0.014)
Constant	-0.378***	0.722***	-0.444***	0.438***
	(0.011)	(0.069)	(0.010)	(0.064)
Observations	72,110	43,070	72,240	43,100
Number of groups	3,090	2,020	3,090	2,020

Models 2 and 4 include state fixed effects. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix T3. Correlations Among Various Measures of Poverty

	School Census Tract Poverty	Home Census Tract Poverty	Percent Eligible for Free and Reduced Price Lunch	Household Under FPL (binary)
School Census Tract	1			
Home Census Tract	0.7167	1		
Percent Eligible for Free and Reduced Price Lunch	0.5954	0.6042	1	
Household Under FPL (binary)	0.3559	0.3875	0.4309	1