**Abstract:**

This paper investigates the effects of neighborhood context on math and reading scores for youth who experience exogenous neighborhood change around them over time. Seldom-used restricted panel data from the National Longitudinal Survey of Youth (1986 – 2008) is used to estimate person fixed effects models that account for unobserved time-invariant characteristics of children and families. Black and Latino youth are found to reside amidst more disadvantaged neighborhoods throughout adolescence than Whites. Further, disparities in neighborhood quality are rigid as children mature. Fixed-effects models demonstrate that neighborhood poverty is a consistent detrimental force for achievement across racial and ethnic groups. Gentrification, however, is an inconsistent predictor of increased achievement across these groups. Theoretical and methodological implications are discussed.

**Keywords:**

neighborhood change, academic achievement, fixed effects, causality

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The neighborhoods that children and adolescents are exposed to while growing up play an important role in schooling, health, and life-course trajectories. Growing up in an affluent neighborhood can give youth access to the social and economic resources that lead to improvements in cognitive ability and that guard against teenage pregnancy. Conversely, growing up in an impoverished neighborhood can lead to the adoption of norms and behaviors that impede children’s early cognitive development and reduce the odds of graduating from high school by denying them access to important social and economic resources in their communities (Brooks-Gunn et al. 1993; Chase-Lansdale et al. 1997; Duncan et al. 1994).

The predominant approach in this literature has been to study movers and stayers together. While informative, this approach fails to consider the potentially differential effects of neighborhood change for youth who stay and experience it around them over time compared to those who move (Farrell and Lee 2011). One may wonder if there is any difference in the experiences of those who move and those who stay if the attributes of the neighborhood in which one lives are essentially unchanged. Moving may disrupt social and economic relationships that individuals have with their neighbors and their sense of belonging within a familiar physical environment (Briggs 1998). However, staying in the same neighborhood preserves these social and economic bonds between residents and their communities. Therefore, studying stayers may clarify the mechanisms that link neighborhood context and individuals’ outcomes.

Still, an analysis of what happens to stayers is conspicuously absent in the neighborhood effects literature. This is especially odd given that recent sociological interest in neighborhood
effects has been spurred by the question of what happens to individuals who are left behind once neighborhoods begin to change. For example, Wilson (1987; 1996) argued that neighborhoods that lost their manufacturing base due to broader shifts in the economy experienced decay in the social fabric between neighbors. This loss of social capital (Bourdieu 1986; Coleman 1988; Portes 1998b) then led to the eventual decline in socioeconomic prospects and life chances of children and youth who stayed and grew up in these environments (Wilson 1987). Importantly, social connections between neighbors are theorized to be the conduits through which neighborhood resources are transmitted between neighbors (Jencks and Mayer 1990). Such connections can only be achieved if people stay in the same neighborhood over time.

Studying stayers also allows us to depart from the traditional approach of studying neighborhoods as static entities and moves us toward a dynamic conceptualization and measurement of neighborhood change (H. et al. 2004; Leventhal and Brooks-Gunn 2001; Mortimer and Shanahan 2004; Robert et al. 2010). This conceptualization helps us understand neighborhoods as evolving entities that go through a cycle of growth, decay, and rebirth over time and is a central concern among neighborhood effects scholars (Tienda 1991).

Black and Latino children and White children, meanwhile, grow up in neighborhoods that are worlds apart (Massey and Denton 1993; Quillian and Campbell 2003; Timberlake 2007; Timberlake 2009). Economic inequalities between minorities and Whites are compounded by the intergenerational transmission of ecological inequality as parents pass down their neighborhood context to their children (Sharkey 2008). The potential dire consequences for the recent increased isolation of poor minorities from mainstream society are not lost upon sociologists (Massey 1996). Concurrently, however, many inner-cities have also experienced
gains in high-status residents (Massey 2002; Pattillo 2005; Sassen 2001; Vigdor 2002). Still, it remains unclear if social ties between neighbors in communities that are gentrifying are strong enough to allow minority residents who have lived their entire lives in these neighborhoods to benefit from the bounty of resources that result from infusions of high-status neighbors. This paper will investigate such heterogeneous neighborhood effects for White, Black, and Latino youth in neighborhoods undergoing gentrification.

This paper uses data from the National Longitudinal Survey of Youth (NLSY) to investigate how neighborhood disadvantage and advantage affects math and reading test scores for 5 – 14 year old youth living in urban areas across the United States between 1986 and 2008. While high school graduation and teen pregnancy have been frequently studied as outcomes (Harding 2003; Wodtke et al. 2011), academic achievement has only rarely been examined (Jackson and Mare 2007; Sampson et al. 2008; Sharkey and Elwert 2011). Achievement test scores are important because they serve as a precursor to stratification throughout the life-course on important outcomes such as high school completion, college and economic attainment, and health in adulthood (Auld and Sidhu 2005; Carbonaro 2007; Farkas et al. 1997; Herrnstein and Murray 1994; Kerckhoff et al. 2001; Kilbourne et al. 1994; Murnane and Levy 2006; Singh-Manoux et al. 2005; Winship and Korenman 1999). Investigating whether neighborhoods impact educational achievement beginning in early childhood can therefore provide a clearer picture of the ecological source of stratification that individuals experience throughout their lives (Sharkey 2008).

Natural variation in neighborhood context around youth over time reduces the self-selection problem that stifles much of the literature in this area. Further, within-person fixed effects models use individuals as their own controls to purge any biases from unobserved time-
invariant characteristics of individuals that impact staying as well as achievement scores (Allison 2009; Gangl 2010; Halaby 2004; Wooldridge 2002).

This findings augment the literature on segregation in showing that not only do youth from different racial and ethnic groups live in vastly different neighborhood types, but that they tend to stay in these same exact neighborhoods for prolonged periods of time early in life (Lee et al. 2008; Reardon et al. 2009). The economic composition of neighborhoods is more rigid over time than racial and ethnic composition. The fixed effects analyses demonstrate while neighborhood poverty reduces achievement scores for all groups, high-status neighbors increase achievement only for Whites. Moreover, unobserved fixed characteristics of youth and their families explain many spurious associations in estimates from OLS and random effects models.

NEIGHBORHOOD SOCIAL CONTEXT AND EDUCATIONAL OUTCOMES

Recently, the literature on neighborhood effects has experienced a resurgence as studies have proliferated across many disciplines (Diez-Roux and Mair 2010; Gephart 1997; Kawachi and Berkman 2003; Leventhal and Brooks-Gunn 2000; Sampson et al. 2002; Small and Newman 2001). To explain how and why neighborhoods generate their effects on individuals, scholars have identified five mechanisms that are each variants of social capital theory (Bourdieu 1986; Coleman 1988; Portes 1998a).

Jencks and Mayer (1990) summarized the theoretical mechanisms through which neighborhoods affect the social and cognitive development of youth. Each of the proposed mechanisms depends on the establishment of connections between social actors within the community. First, in the “epidemic” model, neighborhoods impart an influence on youth through peers and friends who interact with each other and adopt each other’s behaviors
(Crane 1991a). This is closely tied to the concept of social capital by which individuals access resources and information via the social connections they hold to significant others (Bourdieu 1986). The epidemic models predicts that youth who grow up in disadvantaged neighborhoods have worse test scores because they are exposed to peers who place little value on schooling and who spread negative attitudes about educational success throughout the community. Conversely, youth who grow up in affluent neighborhoods have better educational outcomes because of the positive reinforcement they receive from peers as a result of doing well in school. Several scholars have pointed to epidemic models as likely candidates for observed neighborhood effects (Ainsworth 2002; South and Baumer 2000; Turley 2003). Second, in the “collective socialization” or “social control” model, adults from within the community set normative boundaries and expectations that they enforce through the monitoring of youth’s behaviors. This is closely tied to social capital theory that predicts that involvement of parents in schooling decisions raises student achievement (Coleman 1988). Conversely, youth who grow up in neighborhoods where unemployment is rampant and where positive role models are lacking suffer. That is, success in school and work relies on youth’s exposure to neighborhood adults who can demonstrate the benefits of a disciplined and routinized lifestyle for success in life (Wilson 1987; Wilson 1996).

Third, in the “institutional” model, adults external to the neighborhood (e.g., teachers, police, or social workers) imbue youth with norms and values which affect their behaviors and outcomes. The Institutional model predicts that youth who grow up in disadvantaged neighborhoods have lower test scores because, for example, they attend dilapidated schools that are poorly administered and are constituted by ineffective teachers who fail at motivating students and providing them with the resources they need to succeed (Lee and Burkham 2002). Evidence about elements of school organization such as teacher training, student-teacher ratios,
and school financing have shown mixed results (Hanushek 1996; Hedges et al. 1994). However, studies of school peer context have shown more consistent results. For example, Krieg and Storer (2006) show that higher percentages of students from well-off families increase school performance.

While epidemic, collective socialization, and institutional models suggest that living near well-off neighbors can lead to positive outcomes because of greater access to social and economic resources, Jencks and Mayer (1990) also argue that contextual advantage can also lead to negative outcomes. In the fourth model, “relative deprivation,” youth evaluate themselves by comparing their family standing with the family standing of other youth in the neighborhood (Turley 2002). For example, a poor student that has been relocated to a middle-class suburb via a housing voucher may take a look around and notice that he and his family are much worse off than his peers are. This may lead to feelings of inferiority and may eventually lead such a student to lose motivation and, possibly, return to his original school or neighborhood (Clampet-Lundquist and Massey 2008). Similarly, the fifth, “competition,” model posits that youth in affluent communities compete with one another for scarce resources. This suggests that this displaced student may face much higher levels of academic competition in a school that is located in a well-off neighborhood – further discouraging the student since he may not have the educational foundation to keep up or to excel.

Each of these five mechanisms assumes that individuals are able to establish connections with peers, neighborhood adults, or adults in schools in order for neighborhood effects to take hold. Therefore, we would expect that moving would sever many of these ties and disrupt the social capital processes that Jencks and Mayer (1990) proposed. Yet, most neighborhood effects studies do not distinguish movers from stayers. By focusing on those who
stay in their neighborhoods we can therefore be most confident that it is indeed the social relationships between neighbors that is acting as the mechanism for neighborhood effects. Stayers also provide a way to ensure that we are isolating an exogenous neighborhood context effect since individuals’ observed and unobserved preferences are not driving the changes in neighborhood context – as they do among those who move.

Poor neighbors and high-status neighbors

The literature on the effects of neighborhood SES (i.e., neighborhood SES measured as poverty or affluence) on educational outcomes has yielded mixed findings – especially for achievement outcomes (Ainsworth 2002; Brooks-Gunn et al. 1993; Chase-Lansdale et al. 1997; Chase-Lansdale and Gordon 1996; Duncan et al. 1994; Sampson et al. 2008). Most often through regression-based approaches, sociologists have established weak associations between neighborhood disadvantage and educational outcomes such as early cognitive development (Jencks and Mayer 1990) and high school completion (Garner and Raudenbush 1991). However, most of the work in this area has focused on the latter. Some scholars have used quasi-experimental techniques to account for the systematic selection of neighborhoods that makes disentangling individual effects and neighborhood effects a daunting task. While economists have predominately used quasi-experimental techniques, sociologists such as Harding (2003), Sharkey and Elwert (2011), and Wodtke et al. (2011) have recently contributed robust estimates of neighborhood effects to the literature. Sharkey and Elwert (2011), in particular, found that neighborhood poverty has lasting negative consequences for cognitive ability. Using sibling fixed effects models, Aaronson (1998) found a negative effect for neighborhood poverty on high school completion. However, Plotnick and Hoffman (1999) (and Aaronson 1998) found no effect for neighborhood disadvantage on post-secondary schooling
using the same data and methods. Meanwhile, using PSID data and regression techniques that employed the Heckman (1979) sample selection correction, Datcher (1982) found that neighborhood income and racial makeup each independently predicted educational attainment and earnings.

In contrast to studying the impact of neighborhood poverty, scholars have also studied neighborhood advantage as a predictor of educational outcomes (Crane 1991a). Researchers have found that advantaged neighbors increase IQ scores among very young children (Brooks-Gunn et al. 1993; Duncan et al. 1994), scores on tests of verbal ability and reading among preschool and early-elementary age children (Chase-Lansdale et al. 1997), and high school completion (Brooks-Gunn et al. 1993; Clark 1992; Crane 1991b; Crowder and South 2011; Duncan 1994). Experimental findings from the Moving to Opportunity (MTO) and quasi-experimental findings from the Gatreaux study also yielded mixed results (Clampet-Lundquist and Massey 2008; Deluca and Rosenblatt 2010; Duncan and Ludwig 2008; Katz et al. 2001; Keels et al. 2005; Keels 2008; Kling et al. 2007; Orr et al. 2003; Rosenbaum 1995; Sampson 2008; Sanbonmatsu et al. 2006). The MTO project failed to yield any positive long-term effects for housing vouchers on educational achievement. In contrast, the Gatreaux study, while not an experiment, did yield positive short-term effects for suburban relocation on educational outcomes (Kaufman and Rosenbaum 1992; Rubinowitz and Rosenbaum 2000). However, issues of noncompliance with the treatment assignment and lack of randomization altogether have limited the scope of the findings from the MTO and Gatreaux studies, respectively.

Racial and ethnic heterogeneity

Since race and class often combine to constrain housing decisions and create a highly stratified residential landscape (Charles 2000; Charles 2003; Lee et al. 1994; Lee et al. 2008;
Quillian 1999; Quillian 2002; Sampson and Sharkey 2008; Sharkey 2008), this study will investigate whether neighborhood effects differ by race and ethnicity. That is, since Whites and minorities live in communities with access to such disparate amounts of social and economic resources over many generations (Quillian and Campbell 2003; Sharkey 2008; Timberlake 2007; Timberlake 2009), I expect there to be differences in the manner that Whites and minorities respond to increases in high-status neighbors and the available level of resources in the community that result from it (Briggs 1998).

RESEARCH QUESTIONS

Previous literature has yet to investigate neighborhood effects among residents who stay and retain social and economic ties to their communities while those communities change over time. Indirectly, by using high-status neighbors as a proxy for gentrification, this study will also be able to assess the impact of mixed-income housing policies (e.g., HOPE VI) on educational achievement among minority youth in urban neighborhoods. The relevant research questions are:

1. Are there any differences by race and ethnicity in the level of exposure to neighborhood resources?
2. How much do neighborhoods change around youth over time?
3. Does neighborhood context impact academic achievement for stayers?
4. Do minority youth benefit from influxes of high-status neighbors?

Answering the first research question will provide a picture of how much neighborhoods change over time. This will also motivate further analyses. I hypothesize that while we should see neighborhoods changing over time, the amount of change will depend on the characteristic of the neighborhood we are examining. I expect that neighborhood racial and ethnic composition
as well as poverty and male unemployment should negatively impact achievement scores. Meanwhile, following previous findings for high-status neighbors, I expect gentrification to increase achievement scores. Finally, I expect there to be differences in the sensitivity to neighborhood social and economic change for White and minority youth since minorities’ exposures to social and economic resources in their communities have been stunted for so many years. Cultural adaptations to living in disadvantaged communities over generations may hamper the ability of minority children to interact with their new high-status neighbors and this may impede access to social capital resources embedded in those relationships.

DATA

The first set of panel data that I use are from the restricted tract-level NLSY – 79 (parent and neighborhood data). The second set of panel data continuously follows all of the children ever born to NLSY – 79 mothers from as early as when they are in the womb through as late as their early 30s (NLSY – Child and Young Adult) (Chase-Lansdale et al. 1991). The analytical sample is comprised of youth who have lived in the same urban neighborhood for at least four consecutive years between the ages of 5 and 14 and within the period of 1986 to 2008. Researchers have rarely used the NLSY sample to study neighborhood effects. These data contain developmental, demographic, educational, and labor force data on parents since 1979 and on youth since 1986 (CHRR, Center for Human Resource Research 2009).

I supplemented the individual-level NLSY data with tract-level contextual data from the National Historical Geographic Information Systems database (NHGIS 2004). I linked these data using mothers’ unique ID and mothers’ tract ID at each wave. I coded the Census code for tracts

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3 These data, which identify which tracts NLSY – 79 female respondents lived in at each survey wave, are protected by a federal clearance procedure and are only accessible on site at the Bureau of Labor Statistics (BLS) in Washington, D.C. Any and all analyses of these restricted data must be completed on-site at BLS and are vetted prior to release.
using the U.S. Census codes from the most recent U.S. Censuses. For example, Census codes for mothers in 1986 and 2008 correspond to Census codes in the 1980 and 2000 Census, respectively. Therefore, I am able to identify exactly where respondents lived in each year relative to the most recent Census. Sensitivity analyses revealed that tract boundary changes over time did not alter the findings. That is, most NLSY families did not live in tracts that experienced boundary changes over time. Finally, I multiply imputed all missing data that were assumed missing at random following standard procedures in the literature (Allison 2002; von Hippel 2007). The final analytical sample for multivariate analyses includes 1,463 Whites, 1,439 Blacks, and 1,753 Latinos.

Covariates

Time-varying controls include mother’s poverty status, mother’s unemployment status, number of children, income (logged 2010 dollars), marital status, mother’s education, and age of youth. I also include time-invariant controls in all models such as race, ethnicity, and foreign-born status of the mother and sex of the child in the model. I do so in order to reduce bias stemming from the possibility that these time-invariant variables may have different effects as children mature (Allison 2009; Wooldridge 2002).

Outcomes

The BLS measured achievement scores while children were between the ages of 5 and 14. The first measure of youth’s cognitive development is the Peabody Individual Achievement Test – Mathematics (PIAT-M). The PIAT-M is an encompassing measure of mathematics achievement for youth ages five and older that is common in educational and developmental research. The second cognitive development outcome is the PIAT-Reading Recognition (PIAT-RR)
score. The PIAT-RR measures word recognition and pronunciation ability which are essential components of reading achievement.

Neighborhood social context

Although neighborhoods are difficult to conceptualize and therefore measure and analyze (Lee and Campbell 1997), neighborhood effects researchers have commonly operationalized neighborhoods using government defined geographic units. In an effort to be compatible with previous studies, I used census tracts, which contain approximately 4,000 inhabitants, as the primary geographic unit of analysis. Following standard practice in the literature, I linearly-interpolated neighborhood characteristics between decennial Censuses, save for neighborhood unemployment (Jackson and Mare 2007; Sampson et al. 2008). Due to business cycle fluctuations in unemployment rates, I estimated annual neighborhood unemployment rates by comparing variation in annual state rates with variation in decennial tract rates from the Census.\(^4\)

The neighborhood variables of interest are: (1) percent Black; (2) percent Latino; (3) percent of children in poverty; (4) percent of men who are unemployed; and (5) percent of managers and professionals. Unfortunately, attempts to access data on employment to population ratios between 1980 and 2008 at BLS were unsuccessful due to data inconsistencies prior to 1994. Such data would have provided a more accurate depiction of the labor statuses of individuals. Nevertheless, the unemployment rates that are included in these analyses represent individuals who are in the labor force (i.e., those who have actively searched for work in the previous month). The variable for the percent of college-educated neighbors was highly correlated with managers and professionals and I excluded it due to difficulty interpreting

\(^4\) The formula for estimating annual neighborhood unemployment rates is available upon request from the author.
effects when both were retained in the model. I analyzed separate indicators of neighborhood context on two grounds: First, substantively, separate indicators have the power to direct policy makers to specific interventions that may have important impact on cognitive development. Second, empirically, the neighborhood indicators are not highly correlated with one another (neighborhood poverty and percent Black were the most highly correlated variables: $r = .36$).

METHODS

Analytical strategy

Selection bias remains a critical issue for all studies of neighborhood effects that rely on observational data (Durlauf 2004; Hauser 1970; Jencks and Mayer 1990; Mayer and Jencks 1989; Sampson et al. 2002; Small and Newman 2001). This paper relies on a two-part strategy to address the key issue of selection bias: (1) natural variation in neighborhood context and (2) person fixed-effects models (FE). Since individuals are staying in their neighborhoods, unobserved factors associated with individual preferences are not at play in determining neighborhood conditions. To further minimize selection bias, the FE model controls for anything that may be unobserved and time-invariant for both children and their families that could possibly affect which neighborhoods they live in as well as impact achievement scores. (Allison 2009; Gangl 2010; Greene 2008; Halaby 2004; Oakes 2004; Wooldridge 2002). Results from these models are accompanied by estimates from OLS and random effects (RE) models to gain a sense of the conditions under which unobserved confounders may undermine findings from these “traditional” models.

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5 While scholars have questioned the ability of previous neighborhood effects studies to inform federal housing policy (Lehman, Jeffrey S. 1997), it is the goal of this study to provide clear avenues for policy makers to improve educational achievement through effective neighborhood interventions.
While unobserved time-varying variables could bias FE estimates of neighborhood effects, examples of the types of variables that could pose possible threats to causal inference that scholars have posited are weak – since motivation, initiative, or impactful needs are usually fixed characteristics of youth that would be accounted for in the FE model (see Ludwig et al. 2008). Furthermore, results from FE analysis that rely on nationally representative observational panel data have more external validity compared to tightly controlled experiments (Heckman and Smith 1995).

RESULTS

Descriptive results

Table 1 reports means and standard deviations for all NLSY youth ages 5 - 14. Since all youth experienced both being a mover and stayer at some point, I cannot exclude movers from Table 1. The standard deviations have been decomposed into between and within components.\(^6\) The between component refers to differences between separate youth. The within component refers to differences within the same child between separate years. The analyses are based on over fifty-four thousand person-year observations. The mean number of measurements taken for each child was 4.5 which cover the 9 years between ages 5 – 14.

[Table 1 about here]

Variables that do not change over time (e.g., race, foreign-born status, and child sex variables) have a within standard deviation of zero. The mother and household characteristics standard deviations show somewhat surprising results: levels of variation within youth over time are as high as that for youth from different households for many variables. For example, the

\(^6\) Disparities between the summation of within and between components and the total standard deviation are due to rounding.
within SD for poverty is .32 and the between SD is .338. That is, if one were to draw two youth randomly from the dataset, the difference in poverty between these two youth would be expected to be similar to the difference for the same child in two random years. By contrast, the neighborhood variables show much less similarity between youth compared to within youth. That is, there is much more variation between youth in neighborhood poverty, for instance, compared to within a child over time, as one would expect since individuals tend to stay in neighborhoods that experience gradual changes over time.

In general, mothers have been unemployed for about 3 weeks in the past year, 40 percent are single, 17 percent have obtained at least a bachelor’s degree, and 7 percent are foreign born. The means also show that 31 percent of youth live in households that are in poverty, 26 percent are White, 27 percent are Black, 35 percent are Latino, and 17 percent are obese. On average, the neighborhoods were 28 percent Black, 18 percent Latino, 20 percent poor and were composed of 10 percent unemployed males. By and large, this is a sample of urban youth – 91 percent of whom live in tracts with at least 60 percent of residents defined as “urban” by the United States Census Bureau. The average child lived in a neighborhood with 26 percent managers and professionals. Finally, the means for PIAT math and reading scores show that average students scored 100 and 104, respectively. Differences in each of these test scores between two randomly drawn students are shown to also be about equivalent as differences one would find when randomly sampling two separate years for the same child.

Figure 1 shows the distribution of neighborhood context for Whites, Blacks, and Latinos. This answers the question: “Are there any differences by race and ethnicity in the level of exposure to neighborhood resources?” The answer is yes. The findings show that Blacks have more than twice as many Black neighbors as Whites or Latinos do. Conversely, Latinos have
more than twice as many Latino neighbors as Whites or Blacks do. Blacks are the most likely to live among poor neighbors followed by Latinos. Blacks and Latinos are about equal in their likelihood to live among unemployed neighbors. Finally, Whites are the most likely group to live among managers and professionals followed by Latinos. This evidence shows that Blacks and Latinos live in socioeconomically segregated communities and may have access to fewer resources than Whites (Lee et al. 2008; Reardon et al. 2009). Indeed, descriptive analyses not shown here demonstrate that Black and Latino NLSY youth have lower mean scores for both math and reading achievement compared to White youth. These disparities suggest that neighborhood context may indeed provide access to social and economic resources in the neighborhood that affect achievement scores.

Dynamic neighborhood change over time is the central focus of this paper. Figure 2 shows how much elasticity there is in neighborhood conditions for Whites, Blacks, and Latinos over time. These are within-person standard deviations for each group of stayers. Figure 2 answers the question: “How much do neighborhoods change around youth over time?” The overall answer is that there was not much variation in neighborhood conditions over time. However, the degree of change varied from one neighborhood variable to another as well as from one group to another.

Neighborhood racial and ethnic context shows the most variation across all three groups compared to measures of neighborhood economic composition. This indicates that neighborhood economic conditions are much more stable than race and ethnic composition for all three groups. While Blacks have more Black neighbors than Whites, they experience less change in Black neighbors over time compared to Whites. This may suggest a “stickiness”
feature of neighborhood racial and ethnic composition for minorities. In contrast, while Latinos have more Latino neighbors compared to Whites, they experience more change in Latino neighbors compared to Whites. These findings suggest that there exists greater neighborhood elasticity than what has been suggested by previous studies that have only compared Whites and Blacks (Sharkey 2008).

[Figure 2 about here]

Turning to neighborhood economic conditions, Whites experience the lowest levels of neighborhood poverty and, as Figure 2 shows, and they also experience the least amount of change in neighborhood poverty over time. Black and Latino youth stay in neighborhoods that are both poorer and experience greater volatility in neighborhood poverty compared to Whites. Black and Latino stayers experience higher levels of neighborhood unemployment than Whites and are also in neighborhoods that experience slightly more volatility in employment compared to Whites. The neighborhood poverty and unemployment findings suggest that economic conditions are worse and more volatile for minorities than they are for Whites. Economic instability may lead to the deterioration of mainstream social norms and behaviors in Black and Latino neighborhoods, leading to lower test scores (Wilson 1987).

Meanwhile, Whites experience slightly more variation in high-status neighbors over time compared to Blacks and Latinos. In contrast, Black stayers experience the least amount of exposure to high-status neighbors and also experience the least amount of change in high-status neighbors over time. This means that Black youth are unlikely to ever be exposed to many high-status neighbors who may bring greater social and economic resources to the neighborhood that could increase achievement. Latinos experience only slightly less change in exposure to
high-status neighbors compared to Whites. Overall, however, Figure 2 shows that exposure to high-status neighbors is less elastic for minorities compared to Whites.

For a slightly different perspective on the amount of change in neighborhood conditions that White, Black, and Latino youth experienced, we turn to Figure 3. This answers the question of: “Were there any differences by race and ethnicity in the level of exposure to neighborhood resources between 1986 and 2008?” While Figure 2 summarized changes within a given person over time, Figure 3 summarizes mean exposures for all youth combined in a given year between 1986 and 2008. Importantly, one must keep in mind that a given individual could not be followed throughout the entire period when the BLS collected data (1986 – 2008). This means that a stayer in 1990 may not necessarily be a stayer in 2008. That is, an individual could only be deemed a stayer for a maximum of ten years since the sample is composed of youth between the ages of 5 – 14. For example, a 5 year old in 1986 could only have been included in the sample until 1994 since he would have aged out of the sample by 1996 (when he would have been 15 years old). Therefore, the changes in neighborhood context in Figure 3 may differ somewhat from the within person standard deviations for neighborhood context summarized in Figure 2.

Nevertheless, Figure 3 demonstrates that inequalities in exposure to neighborhood advantage persisted throughout the study period. For example, Black and Latino youth, no matter when they entered or exited the study, were exposed to higher levels of co-ethnics, poverty, and unemployment compared to Whites. Conversely, Whites were consistently exposed to higher levels of high-status neighbors. The trends in Figure 3 tell a story of inequitable access to neighborhood social and economic resources. Furthermore, Figure 3
demonstrates that this inequality was maintained throughout the twenty-two year study period. These inequalities suggest that the lack of resources in the communities where Blacks and Latinos live may play a role in the observed disparities for academic achievement.

Multivariate results

The findings from the fixed effects models support the findings from the descriptive analysis and provide an affirmative answer to the question of whether neighborhoods impact academic achievement for stayers. Table 2 summarizes the effect of neighborhood context on math scores for Whites, Blacks, and Latinos. The results show no statistically significant effects for neighborhood racial and ethnic composition on math scores for any group. This finding does not support previous research insomuch as we believe Black and Latino neighbors to signal reductions in social and economic resources associated with racial segregation (Massey and Denton 1993).

When examining neighborhood poverty, we notice a consistent negative association with math scores in the OLS and random effects models. These findings align with previous research and suggest that a lack of social resources in poor neighborhoods reduces academic achievement (Jencks and Mayer 1990; Sharkey and Elwert 2011; Wilson 1987). We may have further confidence in these negative associations since neighborhood self-selection has been ruled out by focusing the analysis on stayers. However, for White and Black youth, the FE models demonstrate that these results are explained by unobserved time-invariant characteristics of youth and families. The only FE coefficient for neighborhood poverty that is statistically significant is that for Latinos. Furthermore, the FE coefficient for Latinos is more than four times stronger than the coefficients for neighborhood poverty among Whites. This
suggests that neighborhood poverty has a stronger impact on math scores of Latinos compared to Whites and provides an answer to the research question regarding heterogeneous effects. Epidemic models may explain the neighborhood poverty effect on Latinos if anti-school norms and behaviors manifest among youth in the community. Finally, the FE model among Latinos also demonstrates that unobserved time-invariant variables explained the negative association between neighborhood unemployment and math scores.

Turning to high-status neighbors and gentrification, Table 2 shows that traditional models support the argument that exposing youth to high-status neighbors provides them with the social capital resources necessary to score higher on math tests. However, Black youth receive no such premium for living in gentrifying communities. Furthermore, the FE models show that only White youth benefit from increases in high-status neighbors. Unobserved time-invariant variables explain the association between gentrification and math scores found in the OLS and RE models among Latinos shows. I consider the FE coefficient for Whites to be a “real” effect since the difference between its standard error and the RE standard error (which has a coefficient of similar magnitude) has to do with sample size (Allison 2009; Wooldridge 2002). Within person comparisons in the FE model causes a significant loss in information and larger standard errors compared to OLS and RE models. I define similarity in the RE and FE coefficients as an FE coefficient that is within +/- 50 percent magnitude of the RE coefficient. These findings support the argument that due to generations of isolation in disadvantaged neighborhoods (Sharkey 2008), minority youth face difficulties tapping into the resources that come with gentrification. This also supports the argument that establishing relationships between minority youth who have lived most of their lives in isolation from the mainstream and high-status immigrants may prove difficult (Briggs 1998). Without these relationships, gentrification alone
may be insufficient link minority children to the social capital resources that comes with influxes of high-status neighbors.

Turning to Table 3, we see results for the effect of neighborhood context on reading scores. As with math scores, neighborhood racial and ethnic composition does not impact reading scores. This suggests that racial and ethnic composition alone does not presuppose access to resources at the neighborhood level that can translate into meaningful impacts on achievement scores.

Meanwhile, neighborhood poverty does have a consistent negative impact on reading scores for all groups. This also aligns with the predictions of the epidemic model in which poor neighborhood youth influence one another to devalue schooling. Each of the FE coefficients for neighborhood poverty for White, Black, and Latino youth are within +/- 50 percent of the magnitude of the RE coefficients while their standard errors show the expected increase in size since the FE model uses less information than the RE model.

The size of the coefficient for neighborhood poverty is largest for Latinos. That is, compared to Whites, the magnitude of the negative effect of neighborhood poverty is 60 percent larger for Latinos. Black youth experience only half as much of a decline in reading scores compared to Whites. However, the coefficients for neighborhood poverty for each group are not statistically significantly different from one another.

Turning to neighborhood unemployment, we see that while coefficients for minorities were mostly in the expected negative direction, the coefficients among Whites were consistently positive for reading scores. Moreover, the FE model shows a positive effect of
neighborhood unemployment on reading scores for Whites, consistent with theories of relative deprivation and competition and cohering with findings from previous research on high school completion among Whites (Crowder and South 2011).

Gentrification, however, does not seem to impact the reading scores of youth. Among Whites and Latinos, unobserved time-invariant variables explain positive associations between gentrification and reading scores. As with math scores, Black youth do not benefit from influxes of high-status neighbors in any of the models. These findings for reading scores support those for math scores and suggest that minorities face difficulty in accessing the social and economic resources that are embedded in relationships with high-status neighbors (Briggs 1998).

Table 4 translates the statistically significant fixed effects in terms of increases or decreases of a percent of a month of schooling. On average, 5 – 14 year old youth gain about 7 and 6 percent of a standard deviation in math and reading per month, respectively (Bloom et al. 2008). The top panel shows what we would expect for a 1 standard deviation change in neighborhood conditions (see Crowder and South 2011 for a similar interpretation strategy) while the bottom panel shows what we would expect if one’s neighborhood were to experience a 95 percent increase in a given neighborhood condition (see Jackson and Mare 2007; Sampson et al. 2008; Sharkey and Elwert 2011 for other examples of extreme changes in neighborhood conditions). We see that a one standard deviation increase in neighborhood conditions does not impact math or reading scores more than +/- 1 month of schooling. Meanwhile, when we consider situations that greatly increase the percent of poor neighbors, for instance, we see that youth may lose the equivalent of up to 27 months of schooling (i.e., math scores for Latinos).

---

7 These grades approximate the beginning and end points of the 5 -14 year old analytical sample.
Such changes highlight the importance of reversing current trends in the isolation of minorities in impoverished neighborhoods (Massey 1996).

CONCLUSIONS

This paper investigated neighborhood effects for 5 – 14 year old NLSY youth. In line with theories of Wilson (1987) and Jencks and Mayer (1990), this paper sought to study outcomes for those who maintain relationships with their communities as change occurs around them over time. While much of the neighborhood effects literature has focused on movers only, the current analysis, in contrast, has shed light on those who stay in place and maintain their relationships within the community while change takes place around them over time. Studying those who stay in their neighborhoods as their social context changes around them over time and using fixed effects minimized biases associated with self-selection and unobserved fixed confounders.

Overall, the descriptive results presented here support previous findings regarding the segregation of Black and Latino youth in disadvantaged neighborhoods. These disadvantaged neighborhoods that minorities tend to live in contain fewer social and economic resources and are characterized by disintegrating social structures that in turn produce negative social capital that reduces academic achievement (Jencks and Mayer 1990; Wilson 1987; Wilson 1996). Further, the findings demonstrate that minority youth are much more likely than Whites to remain stuck in these poor neighborhoods over time. This rigidity in neighborhood stratification has important implications for the maintenance of social and economic inequality over generations (Sharkey 2008; Sharkey and Elwert 2011). These descriptive findings describe a
world in which there exist large disparities in the availability of social and economic resources in neighborhoods where minorities live compared to those where Whites do over time.

The multivariate results demonstrate support for the argument that neighborhood quality reduces achievement scores through the abundance (or absence) of social and economic resources in the neighborhood (Brooks-Gunn et al. 1993; Chase-Lansdale et al. 1997; Duncan 1994; Jackson and Mare 2007; Sampson et al. 2008; Sharkey and Elwert 2011). Importantly, the study’s focus on those who stay in their neighborhoods as change occurs around them over time provides support for the theoretical mechanisms provided by Jencks and Mayer (1990).

For example, the results show consistent negative impacts for neighborhood poverty on achievement scores. This supports the epidemic model that predicts that youth living in poor neighborhoods will experience reductions in test scores due to negative influences from local peers. Among Latinos, collective socialization may partly explain the negative impact of poor neighbors on reading scores since ethnic enclaves may produce environments where Spanish language and culture dominate – thereby reducing English language skills among children in these immigrant communities (Massey et al. 1998; Massey and Taylor 2004; Portes and Rumbaut 1996). Whites, however, experience gains in reading scores due to increases in neighborhood unemployment. This finding adheres to the relative deprivation or competition models and support findings from recent research (Crowder and South 2011). The findings show that gentrification does not have an impact on minority youth’s achievement scores but does increase Whites’ math scores. This finding is also in line with the epidemic model and suggests that minority youth may lack the cultural capital resources needed to access the social and economic resources that are embedded within relationships with high-status neighbors (Briggs 1998). Moreover, the focus on stayers allows for a clear theoretical link between the
results and Jencks and Meyer’s (1990) explanation for neighborhood effects since these youth are actually staying in their neighborhoods and maintaining social bonds with their neighbors over many years. The social capital (positive and negative) that explains neighborhood effects can manifest most clearly when the social relationships between neighbors remain intact and are not disrupted by moving to a new neighborhood.

Considering that students only gain 60 percent of a standard deviation on math scores per academic year and 54 percent of a standard deviation on reading scores per year (Bloom et al. 2008), the results for stayers were not the same as those found in previous studies that did not distinguish between movers and stayers. For example, Sampson et al. (2008) found that Black children living in the most disadvantaged neighborhoods in Chicago experienced declines in verbal ability scores upwards of a full year of schooling – or about half of a standard deviation. In contrast, the current study found that living in an extremely impoverished neighborhood reduced Black stayer’s reading scores equivalent to missing only 55 percent of a year of schooling (-5.172 months; Table 4). Jackson and Mare (2007) found that children living in completely poor neighborhoods experienced declines in math achievement between 14 and 20 points – amounting to a full standard deviation or greater. However, only Latino stayers experienced declines that approximated these large declines in math scores (-27.292 months; Table 4). Incidentally, the current findings suggest that experiencing extreme increases in neighborhood poverty would reduce Latinos’ match scores equivalent to missing 3 full years of schooling. Finally, Sharkey and Elwert (2011) found that poverty in the child’s neighborhood (≥20%) reduced children’s reading scores by more than one-fourth of a standard deviation (see Table 4 in Sharkey and Elwert 2011). This equates to missing about 2.25 months of schooling. We would expect similar findings for the effect of neighborhood poverty on reading scores for Whites ([-0.102*20/15]/0.06 = -2.267) but not for Blacks ([-0.049*20/15]/0.06 = -1.089). These
disparities in effect magnitudes are likely due to the fact that stayers are able to establish and maintain social capital with neighbors that both amplify and attenuate the negative effects of neighborhood poverty.

Natural variation in neighborhood context around youth minimizes biases stemming from neighborhood self-selection. However, while the fixed effects models in this study controlled for time-invariant unobserved selection bias stemming from children and their families, there remains the possibility that unobserved time-varying factors that affect neighborhood selection and cognitive development may bias these results. However, the current analysis includes a vector of variables that address many of the time-varying sources of influence such as age, education of parents, and income. This study has also not studied age-specific effects. However, previous studies have shown that timing of exposure does not alter findings for academic achievement to any serious degree (Sharkey and Elwert 2011). Future scholars may also do well to investigate the role of schools. Given that neighborhoods and schools are closely aligned, it is an unfortunate limitation that the NLSY does not provide school-level data. Finally, many of the statistically significant findings from OLS and RE models were explained by unobserved time-invariant confounders.

This study has established a causal link between neighborhood conditions and achievement scores among youth who maintain social capital links with neighbors. The focus on stayers may provide policy makers with more nuanced guidance about the effectiveness of increasing the resources around them over time. The findings for gentrification indicated that minority youth may not be able to access the social and economic resources that come with the immigration of high-status neighbors that is necessary to increase academic achievement.
Contemporary scholars have demonstrated that neighborhood social context matters for success in school (Crane 1991a; Garner and Raudenbush 1991; Harding 2003). Educational success in turn has an impact on labor market attainment, marriage, and health in adulthood (Auld and Sidhu 2005; Mare 1991; Schwartz and Mare 2005; Sewell et al. 1969). Given the findings from these related lines of research, stratification researchers are increasingly providing evidence for the idea that the neighborhoods in which youth grow up may contribute to observed inequalities in occupation, income, wealth, and health across the life-course and across generations. The current analysis has contributed to this line of research and demonstrates that academic achievement is indeed nested within a social context that reaches beyond the confines of the family and may have lasting impacts on life-course trajectories.
Figure 1. Neighborhood characteristics by race and ethnicity.

Figure 2. Variation in neighborhood characteristics by race and ethnicity.
Figure 3. Mean levels of exposure to neighborhood conditions over time (1986 – 2008)
### Table 1. Descriptive statistics for 5 - 14 year old children of NLSY

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>overall</td>
<td>between</td>
</tr>
<tr>
<td><strong>Mother &amp; household characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In poverty</td>
<td>0.313</td>
<td>0.464</td>
</tr>
<tr>
<td>Weeks unemployed</td>
<td>3.418</td>
<td>12.801</td>
</tr>
<tr>
<td>Number of children</td>
<td>2.488</td>
<td>1.197</td>
</tr>
<tr>
<td>Income (logged 2010 dollars)</td>
<td>10.548</td>
<td>1.038</td>
</tr>
<tr>
<td>Single</td>
<td>0.401</td>
<td>0.490</td>
</tr>
<tr>
<td>Less than high school</td>
<td>0.057</td>
<td>0.232</td>
</tr>
<tr>
<td>High school</td>
<td>0.498</td>
<td>0.500</td>
</tr>
<tr>
<td>Some college</td>
<td>0.187</td>
<td>0.390</td>
</tr>
<tr>
<td>Associate's degree</td>
<td>0.089</td>
<td>0.284</td>
</tr>
<tr>
<td>Bachelor's degree or higher</td>
<td>0.169</td>
<td>0.375</td>
</tr>
<tr>
<td>White</td>
<td>0.258</td>
<td>0.437</td>
</tr>
<tr>
<td>Black</td>
<td>0.270</td>
<td>0.444</td>
</tr>
<tr>
<td>Latino</td>
<td>0.348</td>
<td>0.476</td>
</tr>
<tr>
<td>Foreign born</td>
<td>0.077</td>
<td>0.266</td>
</tr>
</tbody>
</table>

Between standard deviations pertain to differences between separate children while within standard deviations pertain to differences between the same child in separate years.
## Table 1. Descriptive statistics for 5 - 14 year old children of NLSY

<table>
<thead>
<tr>
<th>Child characteristics</th>
<th>Mean</th>
<th>Standard Deviation overall</th>
<th>between</th>
<th>within</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>9.474</td>
<td>2.841</td>
<td>0.870</td>
<td>2.749</td>
</tr>
<tr>
<td>Obese</td>
<td>0.170</td>
<td>0.376</td>
<td>0.285</td>
<td>0.287</td>
</tr>
<tr>
<td>Female</td>
<td>0.490</td>
<td>0.500</td>
<td>0.500</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neighborhood characteristics</th>
<th>Mean</th>
<th>Standard Deviation overall</th>
<th>between</th>
<th>within</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Black</td>
<td>27.775</td>
<td>30.621</td>
<td>29.719</td>
<td>9.582</td>
</tr>
<tr>
<td>Percent Latino</td>
<td>18.038</td>
<td>24.265</td>
<td>23.427</td>
<td>7.647</td>
</tr>
<tr>
<td>Percent of children in poverty</td>
<td>20.166</td>
<td>16.798</td>
<td>16.177</td>
<td>5.424</td>
</tr>
<tr>
<td>Percent of male unemployment</td>
<td>9.801</td>
<td>6.573</td>
<td>5.951</td>
<td>3.233</td>
</tr>
<tr>
<td>Percent living in urban neighborhoods</td>
<td>0.907</td>
<td>0.291</td>
<td>0.256</td>
<td>0.142</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test scores</th>
<th>Mean</th>
<th>Standard Deviation overall</th>
<th>between</th>
<th>within</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIAT Math</td>
<td>100.263</td>
<td>14.125</td>
<td>9.977</td>
<td>10.289</td>
</tr>
<tr>
<td>PIAT Reading</td>
<td>103.692</td>
<td>14.908</td>
<td>10.696</td>
<td>10.659</td>
</tr>
</tbody>
</table>

Between standard deviations pertain to differences between separate children while within standard deviations pertain to differences between the same child in separate years.
<table>
<thead>
<tr>
<th></th>
<th>White youth</th>
<th>Black youth</th>
<th>Latino youth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS RE FE</td>
<td>OLS RE FE</td>
<td>OLS RE FE</td>
</tr>
<tr>
<td>Percent Black</td>
<td>-0.004 (0.013)</td>
<td>-0.007 (0.013)</td>
<td>-0.036 (0.044)</td>
</tr>
<tr>
<td>Percent Latino</td>
<td>0.028 (0.020)</td>
<td>0.021 (0.020)</td>
<td>0.006 (0.055)</td>
</tr>
<tr>
<td>Percent in poverty</td>
<td>-0.068* (0.032)</td>
<td>-0.060 (0.036)</td>
<td>-0.058 (0.147)</td>
</tr>
<tr>
<td>Percent of male joblessness</td>
<td>-0.128 (0.075)</td>
<td>-0.089 (0.071)</td>
<td>0.095 (0.129)</td>
</tr>
<tr>
<td>Percent of managers/professionals</td>
<td>0.183** (0.030)</td>
<td>0.187** (0.031)</td>
<td>0.101 (0.188)</td>
</tr>
<tr>
<td>Constant</td>
<td>101.103*** (5.148)</td>
<td>100.381*** (4.357)</td>
<td>100.405** (7.964)</td>
</tr>
</tbody>
</table>

Results are for observations that were not missing data on the outcome variable

** p<0.01, * p<0.05

Standard errors reported in parentheses are corrected for clustering

Controls: single mother; weeks unemployed; in poverty; number of children in the household; net household income; mother foreign born; mother education; race/ethnicity; child age; child age squared; child obesity; child female
Table 3. OLS, random effects, and fixed effects coefficients for the effect of neighborhood context on reading achievement: Chronic stayers

<table>
<thead>
<tr>
<th>demographic measure</th>
<th>White youth</th>
<th>Black youth</th>
<th>Latino youth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS RE FE</td>
<td>OLS RE FE</td>
<td>OLS RE FE</td>
</tr>
<tr>
<td>Percent Black</td>
<td>0.004 -0.000 -0.046</td>
<td>0.002 0.016 0.156</td>
<td>-0.033* -0.027 0.052</td>
</tr>
<tr>
<td></td>
<td>(0.014) (0.016) (0.043)</td>
<td>(0.014) (0.017) (0.086)</td>
<td>(0.014) (0.018) (0.052)</td>
</tr>
<tr>
<td>Percent Latino</td>
<td>0.024 0.007 -0.018</td>
<td>-0.018 -0.029 -0.006</td>
<td>-0.004 -0.001 0.082</td>
</tr>
<tr>
<td></td>
<td>(0.022) (0.020) (0.048)</td>
<td>(0.020) (0.022) (0.066)</td>
<td>(0.014) (0.017) (0.079)</td>
</tr>
<tr>
<td>Percent in poverty</td>
<td>-0.161*** -0.141** -0.102</td>
<td>-0.070* -0.082*** -0.049</td>
<td>-0.076** -0.079* -0.161</td>
</tr>
<tr>
<td></td>
<td>(0.035) (0.038) (0.112)</td>
<td>(0.028) (0.031) (0.103)</td>
<td>(0.028) (0.032) (0.132)</td>
</tr>
<tr>
<td>Percent of male joblessness</td>
<td>0.098 0.108 0.247*</td>
<td>-0.006 -0.039 -0.043</td>
<td>-0.220** -0.142* 0.047</td>
</tr>
<tr>
<td></td>
<td>(0.082) (0.076) (0.124)</td>
<td>(0.058) (0.054) (0.075)</td>
<td>(0.060) (0.058) (0.091)</td>
</tr>
<tr>
<td>Percent of managers/professionals</td>
<td>0.152** 0.138** -0.132</td>
<td>-0.077 -0.046 -0.001</td>
<td>0.106** 0.129** 0.240</td>
</tr>
<tr>
<td></td>
<td>(0.033) (0.033) (0.173)</td>
<td>(0.047) (0.054) (0.169)</td>
<td>(0.034) (0.039) (0.195)</td>
</tr>
<tr>
<td>Constant</td>
<td>103.068** 104.965** 110.368**</td>
<td>101.850** 107.439** 101.043**</td>
<td>92.740** 93.496** 85.576**</td>
</tr>
<tr>
<td>Observations</td>
<td>1463 1463 1463</td>
<td>1439 1439 1439</td>
<td>1753 1753 1753</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.115 . 0.038</td>
<td>0.125 . 0.108</td>
<td>0.148 . 0.030</td>
</tr>
<tr>
<td>Number of cid</td>
<td>912 912 954</td>
<td>954 954 954</td>
<td>1193 1193 1193</td>
</tr>
</tbody>
</table>

Results are for observations that were not missing data on the outcome variable
** p<0.01, * p<0.05
Standard errors reported in parentheses are corrected for clustering
Controls: single mother; weeks unemployed; in poverty; number of children in the household; net household income; mother foreign born; mother education; race/ethnicity; child age; child age squared; child obesity; child female
Table 4. Effects of neighborhood context on children's math and reading test scores as a percent of a month of schooling

<table>
<thead>
<tr>
<th></th>
<th>Math</th>
<th></th>
<th>Reading</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>White</td>
<td>Black</td>
<td>Latino</td>
<td>White</td>
</tr>
<tr>
<td>1 standard deviation change in neighborhood context:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Black</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Percent Latino</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Percent in poverty</td>
<td>−</td>
<td>−</td>
<td>−0.900</td>
<td>−0.343</td>
</tr>
<tr>
<td>Percent of male unemployment</td>
<td>0.277</td>
<td>−</td>
<td>−</td>
<td>0.388</td>
</tr>
<tr>
<td>Percent of manager/professionals</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| 95 percentage point change in neighborhood context: |            |                          |             |                          |                          |             |
| Percent Black        | −          | −                        | −           | −                        | −                        | −           |
| Percent Latino       | −          | −                        | −           | −                        | −                        | −           |
| Percent in poverty   | −          | −                        | −27.292     | -10.767                  | -5.172                   | −           |
| Percent of male unemployment | 9.605 | −                        | −           | 26.072                   | −                        | −           |
| Percent of manager/professionals |         |                          |             |                          |                          |             |

Note a: Formula: (((Fixed effects coefficient*magnitude)/PIAT standard deviation))/average effect of a single month of schooling on learning for grades kindergarten through ninth

Note b: The PIAT SD for both math and reading is 15

Note c: The average (K-9) effect of a single year of schooling on learning is .6 of a SD for math and .54 of a SD for reading (Bloom et al. 2008).
REFERENCES


Massey, D.S. 2002. "Commentary on: Does Gentrification Harm the Poor by Jacob L. Vigdor.".


NHGIS. 2004. "National Historical Geographic Information System: Pre-release Version 0.1.".


Alvarado; Neighborhoods and Achievement Scores


Vigdor, J.L. 2002. "Does Gentrification Harm the Poor?"


