Multigenerational Neighborhood Effects on Parental Educational Plans, and Child Health

Patrick Sharkey
pts1@nyu.edu
New York University

Felix Elwert
elwert@wisc.edu
University of Madison-Wisconsin

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Abstract

This study examines how the neighborhood environments experienced over multiple generations of a family influence parents' educational expectations and aspirations, children's cognitive skills, and children's health. Building on recent research showing strong continuity in neighborhood environments across generations of family members, we argue for a revised perspective on "neighborhood effects" that considers the ways in which the neighborhood environment in one generation may have a lingering impact on the next generation. Instead of traditional regression techniques that may obscure multigenerational effects of neighborhood disadvantage, we utilize newly developed methods designed to generate unbiased treatment effects when treatments and confounders vary over time. The results show strong multigenerational neighborhood effects on outcomes related to education and cognitive skills, but no statistically significant evidence for multigenerational neighborhood effects on child health outcomes.

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Previous research examining the effect of neighborhood characteristics on child developmental and health outcomes implicitly assumes that only the child's current neighborhood matters. For instance, observational research typically estimates the association between a child's own neighborhood environment, often measured at a single point in time, and a given outcome of interest. Experimental research estimates the effect of a point-in-time change in the neighborhood environment on child outcomes measured over the subsequent years. These strands of research typically ignore the possibility that the neighborhood environment may have lingering effects that persist over time, and possibly across generations.

This study estimates the effect on educational, cognitive, and health outcomes of exposure to poor neighborhoods over two consecutive generations of a family. In doing so we build on recent research showing that a large majority of families living in today's poorest residential areas have lived in similarly poor areas for at least two generations (Sharkey 2008), suggesting that neighborhood inequality might best be conceptualized and studied as a multigenerational process. If parents' neighborhood environments impact dimensions of their adult lives such as economic status, health, or parenting styles, then there is the potential for cross-generational pathways linking parents' childhood neighborhood environments with their children's development, a generation later. If parents and children spend their childhoods in similar neighborhood settings, there is the possibility that any impact of the neighborhood environment may be amplified due to continuity in public institutions such as schools, in cultural norms, or in exposure to toxic or violent environments. Sharkey and Elwert (2010) estimate multigenerational neighborhood effects on child cognitive skills and find that a family's exposure to two consecutive generations of neighborhood poverty substantially depresses children's test scores.

This study exploits various unique features of the Panel Study of Income Dynamics to examine the cumulative consequences of life in poor neighborhoods over multiple generations, with a particular focus on child outcomes related to education, cognitive skills, and health. Identifying the impact of effects in two generations is challenging. Commonly used regression techniques are not appropriate for investigating multigenerational effects if potentially endogenous dimensions of family background are controlled. Instead of traditional regression models, we utilize marginal structural models (MSMs) and, specifically, the method of inverse probability of treatment weighting to estimate the effect of multigenerational exposure to neighborhood poverty on child health. MSMs are a set of methods designed to generate unbiased treatment effects when treatments and confounders vary over time, or across generations as in our application (Hernán, Brumback, and Robins 2000a; Robins, Hernan, and Brumback 2000).

This paper begins by defining formally the concept of multigenerational effects (in contrast to intergenerational effects). Next, we briefly review some pathways linking parent and child neighborhood context across generations with child health outcomes. The methods section sketches the estimation challenge and justifies the use of marginal structural models. The results section contrasts our new findings with previous estimates of multigenerational effects. The conclusion offers a discussion of findings and limitations.

What Are Multigenerational Effects?

The primary object of this study is to estimate the joint effect of parent and child exposure to neighborhood poverty on child educational and health outcomes. The notion of multigenerational effects was defined by Sharkey and Elwert (2010). Multigenerational effects differ from intergenerational effects. Whereas intergenerational neighborhood effects describe the effect only of parental neighborhood conditions on the child's outcomes regardless of the child's own residential exposure, multigenerational effects capture the effect of placing both parents and children in particular neighborhood environments. Multigenerational effects therefore specifically capture the effect of enduring disadvantage.

We use the potential outcomes framework of causal inference to give a precise definition of our estimand. Formally, let A_i be the health outcome of child i, and define the potential outcome A_i^N as the health outcome that would be observed if i's family had experienced the multigenerational neighborhood regime $N=\{N_P, N_O\}$ consisting of the ordered pair of consecutive neighborhood environments in the parent generation, N_P, and child generation, N_O. In each generation, we classify neighborhoods as either poor or non-poor. The contrast of potential outcomes $\partial_i = A_i^N - A_i^{N'}$ defines i's individual level causal effect of experiencing the multigenerational residential history N rather than some other residential history N'. Averaging across all i gives the average causal effect. The causal contrast of greatest interest to the present investigation is defined by $E[A_i^{N=\{poor, poor\}}] – E[A_i^{N=\{non\text{-}poor, non\text{-}poor\}}]$, which gives the average causal effect if all parents and all children had grown up in poor rather than non-poor neighborhoods.

Previous Research

Multigenerational neighborhood effects rely on a number of moving parts. In order to justify the expectation that multigenerational neighborhood effects on health are a promising pursuit, two broad pathways require consideration. First, do children's own neighborhoods of residence affect their health outcomes? Second, do parents' neighborhoods of origin influence parental characteristics that may in turn influence child health outcomes? Sharkey and Elwert (2010) review possible mechanisms linking parent and child neighborhoods to child educational and cognitive outcomes. Here, we therefore focus more specifically on neighborhood effects for health outcomes.

Neighborhood effects on child health outcomes

Research has hypothesized several potential mechanisms by which neighborhoods may affect (child) health outcomes, including density, quality, and proximity to medical infrastructure (e.g. doctors, emergency rooms); parents' economic and employment opportunities; place-based social stressors such as lack of social cohesion and trust, and the presence of crime and social disorder; the presence of social support networks, availability of food stores, walkability and spatial layout; and the presence of environmental toxins and the quality of housing stock. Since the mid 1990s, a fast-growing body of literature has substantiated many of these suppositions, although the evidence is at times contradictory, and established effects are often substantively small.

Almost all studies in the literature report strong associations between neighborhood level factors and child health outcomes—neighborhood disadvantage is non-trivially associated with worse health of the residents. Children exposed to disadvantaged neighborhoods experience worse general health, have lower birth weight, are more likely to be overweight or obese, and are more likely to suffer depression or depressive symptoms. Evidence is somewhat mixed, however, regarding the causal role of neighborhoods in the production of these health outcomes, as the association between neighborhood and health is sometimes reduced to non-significance by the inclusion of individual level control variables.

The strongest evidence in favor of neighborhood effects on child health outcomes comes from the randomized Moving to Opportunity (MTO) experiment. Evaluating 550 children form the New York site of MTO three years after randomization, Leventhal and Brooks-Gunn (2004) find that moving from a poor to a non-poor neighborhood reduces depression and dependence among boys, but not among girls. The study finds no effects of headstrong or antisocial behavior among boys or girls. Kling et al.'s (2007) more recent study of all MTO sites seven years after randomization, by contrast, finds that moving from a poor to a non-poor neighborhood greatly benefits girl's mental health, but fails to detect an effect on boy's mental health. For girls, moving to a non-poor neighborhood also markedly reduced risk behaviors and modestly improved physical health. For boys, however, moving to a non-poor neighborhood increased risk behaviors and worsened physical health.

Observational studies usually find negative effects of exposure to neighborhood disadvantage on child health outcomes after controlling for baseline differences between residents in different types of neighborhoods. A recent review of thirteen multilevel studies (Sellström and Bremberg 2006) reports that, on average, about 10% of variation in child health outcomes (birth weight, problem behavior, and injuries) is explained by neighborhood level factors. Another review on contextual effects on BMI and obesity reports on 21 studies involving children, in which about half of the findings support the conclusion that disadvantaged environments (relating to food environment, land use and transportation environment, and physical activity environment) lead to greater BMI and obesity, whereas the other half reports null findings. Xue et al. (2005) study 2805 children in Chicago and find that concentrated disadvantage was associated with more internalizing problems among children net of controls for family demographics, maternal depression, and child's prior mental health scores.

Neighborhood effects on parent risk factors of child health outcomes

The second facet of multigenerational neighborhood effects on child outcomes relates to the indirect effects of parents' neighborhood of origin on characteristics that in turn may affect child health outcomes. Research linking early neighborhood contexts to adult outcomes (which in turn may affect the health of these adults' children), however, is quite rare because the great majority of neighborhood studies probe the effects of *current* neighborhood context. Nevertheless, two lines of research substantiate the supposition. First, and most important for our expectation that parents' neighborhood of origin may affect their children's outcomes is research on the intergenerational transmission of neighborhood context. Specifically, it is known that the type of neighborhood that parents grow up in is strongly associated with the type of neighborhood their children grow up in. For example, Sharkey (2008) finds that more than 70 percent of African-Americans who grow up in the poorest quarter of American neighborhoods remain in the poorest quarter of neighborhoods as adults. If parent's youthful residential context influences where their children will live, and children's residential context influence child health outcomes, then we can expect that parent and child neighborhoods together exert a multigenerational effect on child well being. Second, early residential context is known to affect educational achievement. For example, Wodke, Harding, and Elwert (2010) estimate that sustained exposure to neighborhood disadvantage throughout the early life course causes substantial reductions in the probability of high school graduation. Educational achievement in parents, and parents' socio economic status more generally, in turn, is known to be associated with their children's mental health, the risk of adiposity, and general health measures. It is thus reasonable to expect that parent's neighborhood of origin may exert indirect effects on child outcomes via parental characteristics that partially embody parents' own youthful residential exposure.

Data

This research draws on data from the PSID main survey combined with data on child depression from the 2002 Child Development Supplement (Hofferth, Davis-Kean, Davis, and Finkelstein 1999; Mainieri 2006). Eligibility for the 2002 CDS was based on eligibility for the original (1997) CDS, which was restricted to PSID sample families active in the survey who had children age 0-12 in 1997. Neighborhood characteristics in families' census tracts of residence are identified using the PSID restricted-use geocode file, which contains tract identifiers for sample families from 1968 through 2003.[1] Data on the economic composition of census tracts is obtained from the Neighborhood Change Database (NCDB) (GeoLytics 2003) for Census years 1970, 1980, 1990 and 2000—tract characteristics in intercensal years are imputed using linear interpolation.

The 1997 CDS sample comprised 3,563 children, and the 2002 CDS successfully re-contacted and interviewed 2,907 children (Mainieri 2006) We use data from the 2002 CDS in order to increase the amount of time between the measurement of neighborhood poverty in the parent and child generations. Because we are utilizing data covering multiple generations of a family, the file structure and the temporal sequence of the various measures used in the analysis are complex. In order to be included in our sample families must meet several criteria. First, children must be assessed in the 2002 CDS and have non-missing data on measures of cognitive ability. Eligibility for the 2002 CDS was based on eligibility for the original (1997) CDS, which was restricted to PSID sample families active in the survey who had children age 0-12 in 1997. The 1997 CDS sample comprised 3,563 children, and the 2002 CDS successfully re-contacted

[1] The geocode file does not include tract identifiers for survey year 1969.

and interviewed 2,907 children (Mainieri 2006). Non-missing data from the cognitive assessments are available for 2,603 children.

Second, to measure treatment status for children, information on the census tract of residence must be available for children's families in at least one year among the three survey years prior to the 2002 CDS (survey years 1997, 1999, and 2001). Third, background characteristics from the child's family must be available in at least one year prior to the measurement of the treatment status—that is, prior to the 1997 survey. This information is used to predict selection into the treatment for children.[2] Fourth, to measure the treatment in the parent's generation at least one parent must be observed, and information on the parent's census tract of residence must be available, during "childhood"; that is, in at least one year from the age of 15 to 17. Fifth, background characteristics from the parent's family must be available in at least one year prior to the age of 15. This information is used to predict selection into the treatment for parents.

The final sample comprises 1,556 parent-child pairs. Roughly 1,000 subjects with non-missing data from the cognitive assessments are not included in this sample because our sample selection criteria whittled down the number of cases with information in each generation. Virtually all of the lost cases are due to missing data in the parent's generation. Many cases are lost because parents have missing information on their childhood neighborhood characteristics, which is in part explained by the fact that not all U.S. areas had been assigned census tracts in the 1970s. Rural areas were less likely to be "tracted" in the 1970s, meaning our final sample is disproportionately urban, as is true for all studies of neighborhood effects using national data on

[2] If the measures of parents' or children's family characteristics are missing, but the family meets all other criteria for selection into the sample, we use a regression imputation method developed by Royston (2004) to impute data. Treatment status and the outcome measures are not imputed. Several variables have extensive missing data primarily because they are based on questions that were only asked in early years of the PSID survey, or in the case of the *occupational status* measure because some household heads were unemployed for several years.

census tracts from the 1980s or earlier. Our results are estimated among the children and grandchildren of the original PSID sample, which was a cross-section of the U.S. population in 1968. Therefore, by construction, our sample is not representative of the current U.S. population due to extensive immigration since the late 1960s.

Treatment variable

Treatment is defined as living in a high-poverty neighborhood during childhood, and is measured for children in the three survey years prior to the CDS, and for their parents when they were age 15-17. Specifically, we define high-poverty neighborhoods as those where the poverty rate is at least 20%. While various cutoffs have been used to define high-poverty neighborhoods in the literature (Harding 2003; Jargowsky 1997; Quillian 1999), we chose this threshold because it will allow for a pooled analysis of whites and African Americans in the sample. The Generation One treatment, or parental neighborhood poverty, is measured as the average poverty rate in parents' census tracts of residence over the three survey years from age 15 to 17. The Generation Two treatment, or child neighborhood poverty, is measured as the average poverty rate in children's neighborhoods in the three survey years prior to the 2002 CDS: survey years 1997, 1999, and 2001.[3] In each case we use a three-wave average in order to minimize measurement error in the treatment.

Outcome variables

We analyze two broad sets of outcomes, educational outcomes and health outcomes. First, we analyze parental aspirations and expectations for their children and compare these results to those previously reported for cognitive test scores (restated from Sharkey and Elwert

[3] From 1968 through 1997, the PSID interviewed families on an annual basis, but since 1997 families have been interviewed every other year.

2010). Second, we investigate three health outcomes, child-reported depression, BMI and obesity, and parent-reported general health.

Educational Outcomes:

Educational expectations/aspirations. Caregivers were asked about their expectations and aspirations for their children's educational futures using a set of questions widely used in surveys such as the National Longitudinal Survey of Youth and the National Education Longitudinal Survey of 1988. The measure of educational *aspirations* is based on responses to the following question: "In the best of all worlds, how much schooling would you like [your child] to complete?" Parents' responses were grouped into categories ranging from "11th grade or less" to "MD, law, PhD, or other doctoral degree." Our outcome measure is recoded as a dichotomous variable, with "low" aspirations defined as any category less than "Graduate from a 4 year college."

The measure of parental *expectations* is based on parents' responses to the follow-up question: "Sometimes children do not get as much education as we would like. How much schooling do you expect that [your child] will really complete?" The same categories were used, and we again define "low" expectations as any category less than "Graduate from a 4 year college."

Cognitive skills. Sharkey and Elwert (2010) analyzed two dimensions of child and adolescent cognitive skills measured using the Woodcock-Johnson Psycho-Educational Battery-Revised (WJ-R) (Woodcock and Johnson 1989): Broad Reading scores and Applied Problems scores. The Broad Reading score measures reading ability and combines results from two subscales, the Letter-Word assessment and the Passage Comprehension assessment. To measure ability in math, we used the Applied Problems score.[4] Raw results from each subtest were normalized to reflect the child's abilities relative to the national average for the child's age (Mainieri 2006). The Woodcock-Johnson assessments are well-established and are the same assessments used to measure cognitive ability in the Moving to Opportunity experiment (Leventhal and Brooks-Gunn 2004; Sonbonmatsu et al. 2006).

Health Outcomes:

Body Mass Index and obesity. Children's *body mass index* (BMI) was calculated directly by PSID staff based on subjects' age, gender, height and weight. Height and weight were assessed directly by interview staff as part of the CDS assessment. As an additional measure of *obesity*, we used a dichotomous measure that classified subjects as obese if their BMI-for-age was at or above the 95th percentile, according to percentiles from growth charts developed by the Centers for Disease Control for U.S. children.

Child overall health. Parent-reported child health was measured using responses to the following question asked of caregivers: "In general, would you say [your child's] health is excellent, very good, good, fair, or poor?" Because of the very low number of parents reporting "poor" health, we grouped the categories for "poor" and "fair" to create a dichotomous measure that we refer to as *poor health.*

Child depression. The measure of c*hild depression* is based on children's responses to items from the Child Depression Inventory-Short Form (CDI:S), a standard diagnostic instrument with good psychometric properties (Kovacs 1992). In contrast to the majority of other standard instruments, the CDI is designed and validated for patients with a first-grade reading level and thus suited for children as young as seven years old. Few children reported

[4] A calculation assessment was administered in the 1997 CDS but was not administered in the 2002 CDS.

multiple symptoms, leading us to create a dichotomous measure of depression coded positively if the child reported any symptoms of depression in the two weeks prior to the interview.

Control variables

Selection into treatment is modeled as in Sharkey and Elwert (2010). These models draw on a wide range of measures to model selection into treatment status for parents and again for children (Sharkey 2008). Because the content of the PSID survey instrument changed slightly over the course of the survey, the measures available are slightly different in each generation.

In the parent generation, the measures refer to characteristics of parents' families during the parent's childhood but prior to the measurement of treatment status. That is, all measures represent family characteristics averaged, or aggregated, over the years when the parent is age 1 to 14. In the parent generation, we measure *household head disability*, *welfare receipt*, *family income*, *occupational status*, *educational attainment*, *annual hours worked*, *home ownership*, *marital status*, *gender* and *age* of the household head, the *number of children in the family*, and *parental efficacy*, *aspirations*, and *time horizons*, three "attitude" measures that have been found to be associated with neighborhood attainment in previous research (Sharkey 2008).

In Generation Two, control measures refer to average characteristics of the child's parents or family over the years when the parent is at least 18 years old and is a household head or the spouse of a household head, but prior to the measurement of the child's treatment status—that is, prior to survey year 1997. Due to changes in the survey, measures of *efficacy*, *aspirations/ambition*, and *time horizons* are not available in the second generation. However, a dichotomous indicator for whether the parent is the *first child* in his/her family is included, along with a measure of the household head's self-reported *health.* This measure represents the household head's response to the question: "Would you say your health is excellent, very good,

good, fair, or poor?" The corresponding scale ranges from 1 to 5, with lower values reflecting better self-reported health.

Methods

Estimating Multigenerational Neighborhood Effects using Marginal Structural Models

Traditional regression methods are ill suited to recover the multigenerational effect of neighborhood disadvantage because neighborhood disadvantage in the second generation is endogenous to neighborhood disadvantage in the first generation. Estimation faces two distinct endogeneity problems related to the dynamic selection of families into neighborhood contexts. If the goal is to estimate causal effects by comparing comparable individuals (and families), selection into neighborhood contexts in each generation must be accounted for. The first problem is that part of the effect of parents' neighborhood of origin on child outcomes may operate through parent characteristics (e.g. parent education or income) that are themselves responsible for selecting the family into Generation Two neighborhoods. Controlling for these intermediate factors, while necessary for controlling for selection into Generation Two neighborhoods, would control away part of the effect of interest and hence create bias. The second problem emerges because the factors responsible for selection into child neighborhood may be confounded in unobserved factors for their effect on child outcomes. If so, conditioning on Generation Two selection factors will induce an association between parental neighborhood exposure and child outcomes even if there is no causal effect. The direction of this bias is not predictable absent strong parametric assumptions.

In response to this estimation challenge, we use marginal structural models (MSM) with inverse probability of treatment (IPT) weighting (Hernán, Brumback, and Robins 2000b; Robins 1999; Robins, Hernan, and Brumback 2000) to estimate the multigenerational effects of neighborhood disadvantage on child health. MSM were specifically developed for causal inference for time-varying treatments in biostatistics and are more powerful than traditional regression models because they can resolve the endogeneity problems of multigenerational exposure while making *fewer* rather than more assumptions than conventional models (Robins 1999; Robins, Hernan, and Brumback 2000).

The assumptions enabling the unbiased estimation of multigenerational neighborhood effects via MSM are straight-forward. The causal effect of multigenerational neighborhood poverty on child's cognitive ability, A, can be identified from observational data if neighborhood of residence in each generation, N_P and N_O, is statistically independent of the potential outcomes, A^N, given observed covariates and previous treatments:

$$A^N \perp N_P \mid C_P \quad \text{and}$$

$$A^N \perp N_O \mid C_P, C_O, N_P \ ,$$

where C_P and C_O refer to the observed covariates that influence the selection of parents' and children's neighborhood of residence, respectively, and the symbol $\perp$ denotes statistical independence. These conditions encode the assumption of no unobserved confounders, collectively known as sequential ignorability or unconfoundedness of treatment assignment (Robins 1986; 1999). Substantively, these assumptions state that individuals with the same combination of observed covariate values do not preferentially select into poor or non-poor neighborhoods. These assumptions are weaker compared to conventional regression in that they do not require that the selection variables C_0 and C_P are themselves conditionally independent of the potential outcomes A^N.

The estimation of marginal structural models proceeds in two steps. First, we estimate a logistic model of childhood residence in a poor neighborhood separately for each generation, G, as a function of baseline and time-varying confounders, C_G, influencing each generation's neighborhood poverty,

$$P(N_G)/(1- P(N_G)) = \exp[\alpha_G + C_G\beta_G], \text{ for } G \in \{P, O\}, \qquad (2)$$

where C_O includes C_P to permit the possibility that factors influencing parent's childhood neighborhood of residence may extend their reach to also influence the child's neighborhood of residence. From (2), we predict each family's probability of residing in the type of neighborhood that it did indeed reside in (actual treatment status) separately for each generation. The product of these two probabilities gives the probability, W, of the multigenerational residential history experienced by each family,

$$W = P(N_P|C_P)*P(N_O|N_P,C_P,C_O). \qquad (3)$$

Next, we weight each case by the inverse of the probability of its family's residential history, W^{-1}.[5] Weighting creates a pseudo-population in which the values of all variables that contributed to the estimation of the weights are balanced, such that treatment status in each generation is no longer confounded in the observables (Robins 1999). Figure 1 shows the stylized causal relationships between multigenerational neighborhood poverty and child health, highlighting the endogeneity of neighborhood poverty. Figure 2 represents the weighting process graphically by removing from Figure 1 all arrows from observables into N_P and N_O and illustrates that the structure of the reweighted data corresponds to the data structure of an experiment in which both N_P and N_O are randomized. The causal pathways between N and A in the original population (Figure 1) are maintained in the weighted pseudo-population (Figure 2). Under sequential ignorability, simply conditioning on each generation's neighborhood poverty in the weighted pseudo-population thus recovers the potential outcomes distribution, such that $E[A^N]= E[A|\ N_P,$

[5] To increase efficiency, our final models actually employ so-called stabilized weights (Robins et al. 2000), $SW = [P(N_P)*P(N_O|N_P)]* [P(N_P\ |C_P)*P(N_O\ |N_P,C_P,C_O)]^{-1}$. We compute sandwich standard errors to account for the weighting (Robins et al. 2000) and clustering of siblings within families.

N_O]. Controlling for C_O (or C_P) is no longer necessary, and conventional statistical models can be used to analyze the weighted data. For continuous outcomes, we estimate a linear model

$$E[A|\ N_P, N_O] = \alpha^W + N_P\beta_1^W + N_o\beta_2^W\ , \qquad (4)$$

and for binary outcomes we estimate a logistic model,

$$P(A)/(1\text{- } P(A)) = \exp[\alpha^W + N_P\beta_1^W + N_o\beta_2^W]. \qquad (5)$$

Equations (4) and (5) are marginal structural models for the multigenerational effect of neighborhood disadvantage on child health. The models are "marginal" because they recover the marginal distributions of the potential outcomes, and they are "structural" because the coefficients represent causal effects (rather than associations) if sequential ignorability holds (Robins 1999b). In the linear MSM of Equation (4), the intercept, α^W, estimates children's mean health score if all parents and children had grown up in advantaged neighborhoods, and the sum of $\alpha^W + \beta_1^W + \beta_2^W$ estimates children's mean health score if all parents and children had grown up in disadvantaged neighborhoods. The sum of the two slopes $\beta_1^W + \beta_2^W$ thus gives the estimated causal effect of multigenerational neighborhood disadvantage on child health. The coefficient β_1^W by itself estimates the direct causal effect of parental exposure to neighborhood poverty regardless of the type of neighborhood to which the child is assigned. The coefficient β_2^W by itself estimates the causal effect of child's exposure to neighborhood poverty regardless of the type of neighborhood to which her parents were assigned. Interpretation of the coefficients in the logistic MSM are analogous.

Results

Sample Characteristics

Table 1 displays sample characteristics across generations for all variables used to model treatment status in the parent and the child generations, respectively, by residential history.

Living in a poor neighborhood is not an uncommon event—36 percent of parents and 28 percent of children grew up in a poor neighborhood. Whereas 56 percent of families in the sample grew up in non-poor neighborhoods in both generations, 20 percent of all families were exposed to neighborhood poverty across two successive generations.

Not surprisingly, families that lived in non-poor neighborhoods in both generations (Column 2) were also advantaged in several other respects compared to families in which either parents or children (or both) grew up in a poor neighborhood (Columns 3-5). Parents and grandparents in families of multigenerational advantage were considerably more likely to be married, in better health, have more schooling, higher income, and greater occupational status, among other factors. As potentially confounding factors for the relationship between neighborhood of residence and child cognitive outcomes, the analysis needs to account for these differences across treatment groups.

Weight construction

Stabilized inverse probability of treatment weights (Equation 3) are designed to capture selection into parents' and children's neighborhoods. They are estimated from flexible logistic regression models containing all predictors of neighborhood status listed in Table 1 as well as numerous interactions between predictors and race. Experimentation revealed the weights to be remarkably stable across several regression specifications.[6] Table 2 shows descriptive statistics for the final stabilized weights (Equation 3). The stabilized weights and their generation-specific components are well behaved—the observed means of the final weights and their components are close to 1, as they should be in expectation. The weights are skewed to the left but center

[6] The logistic models predicting parents' and children's neighborhood poverty are ancillary and serve no purpose beyond predicting treatment status. Results from these models are available from the authors. While noting that the coefficients from these models do (and need) not have a causal interpretation, we observe that race is the strongest predictor of residence in a poor neighborhood in both generations.

quite closely about the mean (standard deviations not exceeding 2.25). To prevent disproportionate influence from a small number of outlying cases, we drop 9 cases with extreme final weighs (>14) from the analysis. (See Appendix Table A for the results of the neighborhood selection models in Generations One and Two.)

Outcome Models

For each outcome, we first report completely unadjusted (associational) estimates and next estimates from a marginal structural model that accounts for observed selection into treatment status in both generations through IPT weighting. Conditional on the assumption of sequential unconfoundedness, these estimates can be interpreted as causal effects.

Education-Related Outcomes

Table 3 shows unadjusted and IPT weighted MSM results for the effect of multigenerational exposure to neighborhood poverty on child education-related outcomes. The completely unadjusted (associational) model demonstrates that both parental neighborhood poverty and child neighborhood poverty are strongly associated with parents' expectations that their child will not complete a four-year degree. Parents of children who come from multigenerationally disadvantaged families have exp(.4 + .95) = 3.86 greater log odds of expecting that their child will not graduate from college than parents of children from multigenerationally advantaged families. These results, however, lack a causal interpretation because they do not take into account the dynamic selection of families into neighborhoors across generations. Results from the marginal structural models show that much of this association is due to selection. Point estimates for the contribution of each generation's contribution are reduced. Nevertheless, the direct effect of child's own neighborhood remains statistically significant, as does the multigenerational effect of exposure to neighborhood poverty in both generations. The multigenerational effect of coming from a family residing in poor neighborhoods in two successive generations compared to a family living in non-poor neighborhoods is an increase of 0.88 in the log odds of low expectations for the child's schooling. This multigenerational effect of neighborhood disadvantage on parents' expectations is is substantively large and statistically significant at α=0.01. Living in poor neighborhoods over two consecutive generations multiplies the odds of parents' expecting the child *not* to complete a four-year degree by exp(.88) = 2.41 relative to never living in a poor neighborhood.

Results are similar when parents are asked whether they would like their child to complete a four-year degree. The unadjusted association is large and statistically significant. Again, taking account of selection reduces the point estimates of each generation's neighborhood context to statistical insignificance. However, the multigenerational effect of exposure to neighborhood poverty on parents' aspirations remains statistically significant at α=0.05; living in a poor neighborhood over consecutive generations roughly doubles (exp.[.68] = 1.97) the odds of parents' reporting that they would not like their child to complete a four-year degree.

The second half of Table 3 restates the estimates of multigenerational neighborhood poverty on children's cognitive test scores, previously estimated in Sharkey and Elwert (2010). In these specifications, neighborhood poverty in the parents' generation has a strong effect on the child's cognitive skills. First considering broad reading scores, the direct causal effect of parental neighborhood poverty on its own – while fixing child neighborhood poverty – reduces child broad reading scores by 5.07 points, or a third of a standard deviation. The causal effect of child's own neighborhood poverty – while fixing parental treatment status – reduces child's broad reading scores by 4.20 points, more than one fourth of a standard deviation. Both coefficients are significant at the α=0.05 level. The multigenerational effect of coming from a family residing in poor neighborhoods in two successive generations compared to a family living in non-poor neighborhoods is a reduction of b_1+b_2 = -9.27 points in child's broad reading scores. This multigenerational effect of neighborhood disadvantage on reading scores is substantively large (more than half a standard deviation in broad readings scores) and statistically significant at the α=0.01 percent level.

Results for applied problem solving scores are similar to results for broad reading scores. The direct causal effect of parent's neighborhood poverty on child applied problem scores – while fixing child neighborhood poverty – is -5.97 points, or more than one third of a standard deviation, and statistically significant at α=0.01. The estimated causal effect of child's own neighborhood poverty – while fixing parent's neighborhood status – is also negative, but substantively smaller (-2.39 points) and not statistically significant. The joint causal effect of multigenerational exposure to neighborhood poverty is substantively large and statistically significant, reducing child's applied problem scores by 8.36 points, more than half a standard deviation.

Child Health Outcomes

Table 4 shows unadjusted and IPT weighted MSM results for the effect of multigenerational neighborhood exposure on child health outcomes. Overall, the results for the effects of multigenerational exposure to neighborhood poverty on child health outcomes are much weaker than the results for education-related outcomes. Indeed, for none of the investigated outcomes do we find a statistically significant association (unadjusted or adjusted for selection) with children's own neighborhood of residence. None of the multigenerational effects rise to the conventional 5 percent level of statistical significance either, although all point estimates are in the expected direction.

Specifically, we find that neighborhood poverty in each generation is positively associated with BMI, but the estimated effect is non-significant in the selection-adusted MSM. The multigenerational effect of living in poor neighborhoods in consecutive generations is also in the expected direction but not statistically significant. Wide confidence intervals strongly discourage a substantive interpretation.

Analyzing the dichotomous measure of obesity, we find that parental neighborhood poverty – while fixing child neighborhood poverty – increases the log odds of child obesity by 0.39, a marginally significant effect (p-value =.07). The multigenerational effect of neighborhood poverty in consecutive generations is also positive and marginally significant (p-value =.09). Living in poor neighborhoods compared to living in non-poor neighborhoods over two generations is estimated to multiply the odds of child obesity by exp(.59) = 1.66.

Parent-reported assessments of the child's overall health reveal only weak, effects of neighborhood poverty on child health. Parental neighborhood poverty has a marginally significant positive effect on the child's health being reported as "fair" or "poor" (p-value = .08) Parental neighborhood poverty – while fixing child neighborhood poverty – increases the log odds of poor/fair child health, according to parents, by a factor of 0.47. The coefficient for child neighborhood poverty, and the multigenerational effect, however, are smaller and not statistically significant.

Finally, Table 3 reports on estimated neighborhood effects on children's self-report of any depressive symptoms. Neither the purely associational model, nor the fully adjusted MSM pick up any association between parental or child's own exposure to neighborhood poverty. Point estimates are substantively small, and not statistically significant.

Discussion

This paper responds to growing evidence that neighborhood inequality cannot be fully captured at a single point in a child's life, or even in a single generation in a family's history. A large majority of African-American families living in today's most disadvantaged residential areas are the same families that occupied the most disadvantaged neighborhoods in the 1970s, suggesting that neighborhood inequality should be conceptualized and studied as a multigenerational process (Sharkey 2008; Sharkey and Elwert 2010). Parents' neighborhood environments may have lasting impacts that extend into adulthood, creating the potential for cross-generational effects. Children's own neighborhood environments may impact their outcomes as well, through mechanisms ranging from local institutions to peers.

The evidence presented here suggests that a multigenerational perspective is important for understanding how neighborhood impact outcomes related to schooling and the development of cognitive skills. Neighborhood poverty over consecutive generations roughly doubles the odds that parents' report no expectations or aspirations for their child to complete a four-year degree. This result conforms with previous findings showing that a family's exposure to neighborhood poverty over two consecutive generations reduces children's cognitive skills by more than half a standard deviation (Sharkey and Elwert 2010).

One of the most interesting findings is that parents' neighborhood poverty appears to have strong effects on children's education/cognitive outcomes, a generation later. This finding is consistent with the idea that the parent's own childhood environment may influence the parent's child through its impact on the parent's educational attainment, occupational choices, income, marriage partner, and mental health. Through these and any number of additional pathways, it is plausible that the effect of the neighborhood environment on adult outcomes may linger on to impact the next generation.

While multigenerational neighborhood effects appear to be important for schooling plans and cognitive outcomes, we find minimal or no effects on child health outcomes. This divergence in findings reinforces the idea that it is a mistake to think about the potential impact of neighborhoods as an "either/or" question—that is, they affect kids' outcome or they do not. Evidence from recent experimental programs, the most notable being Moving to Opportunity, shows very different impacts of moving to low-poverty neighborhoods depending on the outcome under study. Our study reaches a similar conclusion, showing minimal effects on health outcomes and substantial effects on educational plans and cognitive outcomes.

Before discussing the implications of these findings, we must acknowledge several limitations. Most importantly, causal inference about multigenerational neighborhood effects from observational data necessarily relies on strong assumptions about the absence of unobserved selection bias, specifically the assumption of sequential ignorability. This includes the assumption that respondents select into neighborhoods only on the basis of factors observed by the analyst, or factors strongly correlated with these observed factors. We estimate marginal structural models that rely on assumptions of sequential uncounfoundedness that are weaker than the assumptions necessary in the corresponding conventional regression models, but our methods rely on these assumptions nonetheless.

A second limitation is that the structure of the PSID data forced us to make decisions in the analysis design that are less than ideal. Because parents give birth at different ages, there is substantial variation in the duration of the gap between measurement of neighborhood conditions in each generation. Further, in an effort to retain as many cases as possible, our specifications include children from a wide age range. Retaining most children assessed in the CDS allows us to estimate multigenerational neighborhood effects more precisely, but it compromises our ability to make any claims about the developmental timing of neighborhood effects.

With these limitations in mind, we believe that the notion of multigenerational neighborhood effects points to a revised, broader, conceptualization of how the neighborhood environment influences child developmental and health outcomes. The vast majority of research on “neighborhood effects” attempts to estimate the causal effect of *contemporary* neighborhood poverty. By design these studies do not capture the *lagged or cumulative* effects of previous neighborhood environments. This focus on contemporary neighborhood circumstances has been questioned in recent research on youth in Chicago, which shows that the impact of living in severely disadvantaged neighborhoods continues to be felt years later (Sampson et al. 2008). The challenge is strengthened considerably when one considers the possibility of generation-lagged effects or cumulative, multigenerational effects. A change in a family’s neighborhood may bring about an abrupt and radical change in the social environment surrounding children, but this change may be a short-term departure from a familial history of life in disadvantaged environments. The shift in context may improve the opportunities available to adults and children, the child’s peers and school environment, and the parent’s mental health, but it may not undo the lingering influence of the parent’s childhood environment. In short, a temporary change of scenery may not disrupt the effects of a family history of disadvantage.

For outcomes related to child health, it may not be essential to consider the environments of family members over multiple generations. Evidence from Moving to Opportunity suggests that a point-in-time move to a low-poverty neighborhood may bring about some health benefits for families and for female children, suggesting that the child’s own environment may be most important for understanding children's health outcomes (Kling et al 2007; but see Leventhal and Brooks-Gunn 2004 for results suggesting that neighborhoods matter for the mental health of boys but not of girls). The same is not true for children's educational trajectories and cognitive development. To understand how parents think about a child's educational future, a multigenerational perspective contributes valuable information. Living in poor neighborhoods over consecutive generations appears to substantially reduce parents' expectations about what is possible for their child's educational attainment. The effects are even more pronounced for children's cognitive skills. Here, living in poor neighborhoods over consecutive generations reduces children's cognitive skills by more than one half standard deviation. In each case, a multigenerational perspective appears essential to uncovering the total impact of a family's neighborhood environment.

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Table 1. Sample Characteristics

	All	Parent not poor Child not poor	Parent not poor Child poor	Parent poor Child not poor	Parent poor Child poor
Grandparent characteristics predicting neighborhood poverty parent generation[1]					
African-American	0.47	0.15	0.69	0.90	0.93
Disability	0.34	0.28	0.26	0.46	0.44
Welfare receipt	0.22	0.08	0.29	0.34	0.47
Vocabulary score (0 to 13)	9.15	9.90	9.12	7.99	7.98
Married	0.69	0.81	0.67	0.53	0.48
Occupational status	-148.20	-101.94	-174.43	-213.46	-216.19
Number of children	3.56	3.18	3.77	3.87	4.32
Income (log)	10.64	10.98	10.53	10.18	10.11
Education (yrs schooling)	12.02	13.05	11.03	10.68	10.58
Age (centered around age 40)	-1.89	-1.13	-3.88	-2.16	-3.06
Own home	0.59	0.75	0.51	0.41	0.30
Annual hours worked (log)	7.43	7.66	7.57	7.20	6.94
Efficacy scale	3.50	3.84	3.45	3.09	2.88
Aspirations scale	3.49	3.39	3.77	3.48	3.69
Time horizons scale	5.06	5.30	4.96	4.68	4.74
Grandparent male	0.74	0.87	0.72	0.59	0.50
Parent (and child) characteristics predicting neighborhood poverty in child generation[2]					
First child	0.30	0.32	0.32	0.28	0.25
Disability	0.29	0.25	0.31	0.35	0.35
Welfare receipt	0.25	0.10	0.38	0.30	0.56
Self-reported health	2.22	2.03	2.30	2.42	2.56
Married	0.32	0.40	0.29	0.30	0.14
Occupational status	-132.57	-93.90	-169.46	-171.01	-196.19
Number of children	1.43	1.17	1.77	1.57	1.90
Income (log)	10.37	10.72	9.99	10.20	9.65
Education (yrs schooling)	13.34	13.88	12.71	13.04	12.33
Age (centered around age 40)	-12.06	-11.94	-12.91	-11.77	-12.27
Own home	0.38	0.49	0.20	0.33	0.17
Annual hours worked (log)	7.35	7.59	7.09	7.24	6.86
Parent male	0.36	0.40	0.31	0.32	0.29
Child characteristics					
Child male	0.51	0.49	0.55	0.54	0.51
Age in 2001	10.65	10.52	10.32	10.63	11.15
N	1556 (100%)	877 (56%)	118 (8%)	243 (16%)	318 (20%)

[1] These measures represent characteristics of the household head in the parent's childhood family.

[2] These measures represent characteristics of the parent or household head in the child's family (see text).

Table 2. Stabilized Inverse Probability of Treatment Weights for Epxosure to Neighborhood Poverty (≥20% Poor Residents) in Generations 1 and 2

	Median	Mean	Std. dev.	Minimum	Maximum
Generation-specific components					
Generation 1	0.65	1.02	2.25	0.36	49.75
Generation 2	0.90	1.00	0.61	0.13	7.73
Final Weights	0.59	0.98	1.98	0.16	40.99

Note: Table includes 9 outlying cases with weights > 14, which are omitted from the marginal structural models presented in Table 4.

Table 3. Estimated Neighborhood Effects on Educational Outcomes

	Parent-reported:[1]				Child Test Scores:[2]			
	Child will not complete 4 yr college				Broad reading score		Applied problems score	
	Aspirations		Expectations					
	Unadjusted	MSM	Unadjusted	MSM	Unadjusted	MSM	Unadjusted	MSM
Parent neighborhood poverty only, β_1	.51***	0.41	.40**	0.37	-8.83***	-5.07**	-9.68***	-5.97***
	(.20)	(0.26)	(.14)	(0.23)	(1.16)	(2.38)	(0.97)	(1.85)
Child neighborhood poverty only, β_2	.80***	0.27	.95***	0.51**	-5.98***	-4.20**	-5.66***	-2.39
	(.20)	(0.25)	(.15)	(0.23)	(1.23)	(2.00)	(1.00)	(1.79)
Multigenerational exposure, $\beta_1+\beta_2$	-	0.68**	-	0.88***	-	-9.27***	-	-8.36***
	-	(0.31)	-	(0.23)	-	(1.68)	-	(1.69)

Notes: *** = significant at p<.01; ** = significant at p<.05; * = significant at p<.10
Standard errors account for clustering at the family level.
[1] Reports coefficients from logit models.
[2] Reports coefficients from linear models, restated from Sharkey and Elwert (2010)

Table 4. Estimated Neighborhood Effects on Child Health Outcomes

	BMI		Obese (CDC)[1]		Poor health[1]		Any depressive symptoms[1]	
	Unadjusted	MSM	Unadjusted	MSM	Unadjusted	MSM	Unadjusted	MSM
Parent neighborhood poverty only, β_1	1.52***	0.51	.51**	0.39*	.61***	0.47*	.06	0.06
	(.41)	0.58	(.17)	0.22	(.18)	0.27	(.13)	0.21
Child neighborhood poverty only, β_2	0.06	0.43	-.24	0.12	.08	-0.11	-.01	-0.37
	(.45)	0.63	(.19)	0.24	(.19)	0.26	(.14)	0.22
Multigenerational exposure, $\beta_1+\beta_2$	-	0.95	-	0.51*	-	0.36	-	-0.31
	-	(.60)	-	(.30)	-	(.27)	-	(.23)

Notes: *** = significant at p<.01; ** = significant at p<.05; * = significant at p<.10

Standard errors account for clustering at the family level.

[1] Reports coefficients from logit models.

Table A. Logit Models for Selection Into Treatment (Neighborhood Poverty >=20%)

	Generation 1		Generation 2	
Grandparent characteristics				
Treatment: Neighborhood poverty	-		19.25	***
Race: 1=African-American	0.00	**	0.00	
Disability	1.25		0.75	*
Welfare receipt	0.34	*	0.50	
Vocabulary score (0 to 13)	0.85	*	1.00	
Married	1.39		1.25	
Occupational status	1.00		1.00	**
Number of children	1.00		1.03	
Income (log)	0.00	**	0.02	
Education (yrs schooling)	1.25		1.72	**
Age (centered around age 40)	1.04	***	0.99	
Own home	0.16	***	0.77	
Annual hours worked (log)	0.85		1.09	
Efficacy scale	0.92		1.01	
Aspirations scale	0.91		1.11	
Time horizons scale	0.95		1.00	
Gender: 1=male	0.65	*	0.77	
Race x vocab score	1.08		1.05	
Race x education	1.08		0.83	
Race x occupation	1.00		1.00	
Race x income	3.06	**	3.35	**
Race x home ownership	4.24	***	1.89	
Race x welfare	1.91		3.25	
Income (log) squared	1.46	*	1.14	
Education (yrs schooling) squared	0.99		0.98	***

(continued on next page)

	Generation 1		Generation 2	
Parent characteristics				
First child	-		1.00	
Disability	-		0.91	
Welfare receipt	-		0.33	**
Self-reported health	-		1.07	
Married	-		0.89	
Occupational status	-		1.00	
Number of children	-		1.41	***
Income (log)	-		0.21	
Education (yrs schooling)	-		0.77	
Age (centered around age 40)	-		1.05	*
Own home	-		0.25	**
Annual hours worked (log)	-		1.15	
Gender: 1=male	-		1.27	
Race x gen 1 treatment	-		0.13	***
Race x education	-		0.94	
Race x occupation	-		1.00	
Race x income	-		0.91	
Race x home ownership	-		1.65	
Race x welfare	-		4.49	**
Income (log) squared	-		1.05	
Education (yrs schooling) squared	-		1.01	
Child characteristics				
Gender: 1=male	-		1.00	
Age as of 2001	-		0.98	

Notes: Figures in columns showing model results represent odds ratios, standard errors not shown.
*** = significant at p<.01; ** = significant at p<.05; * = significant at p<.10
[1] These measures represent characteristics of the household head in the parent's childhood family.
[2] These measures represent characteristics of the household head in the child's family.

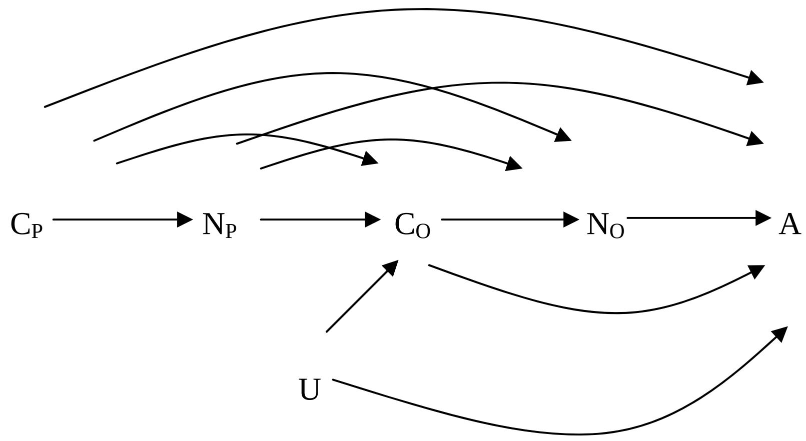

Figure 1. Directed acyclic graph displaying possible direct and indirect causal pathways linking neighborhood exposure (N) and confounding variables (C), which determine neighborhood of residence in the parent (P) and child (O) generations, to child outcomes (A). The vector U represents unobserved factors.

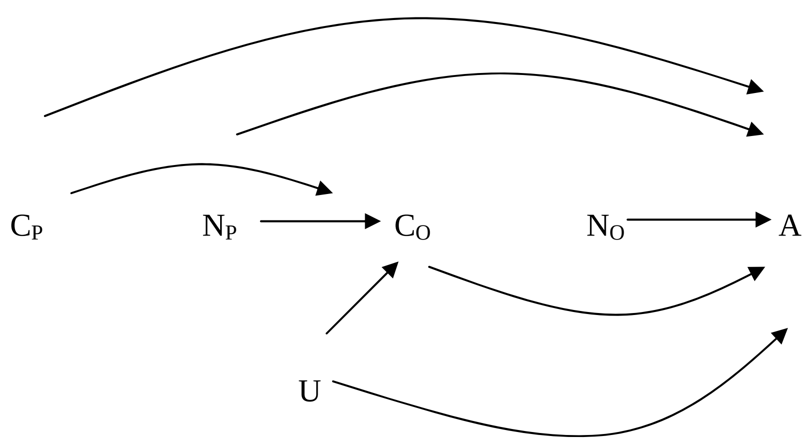

Figure 2. Directed acyclic graph representing the same data structure as Figure 1 reweighted with IPT weights to remove the association between neighborhood of residence and confounding variables while keeping causal pathways between neighborhood of residence and child outcomes unchanged.