Effects of Household and Neighborhood Characteristics on Racial Inequality in the Duration of Children's Exposure to Neighborhood Poverty and Affluence*

Jeffrey M. Timberlake

University of Cincinnati

Abstract

In this paper I construct covariate-adjusted increment-decrement life tables to estimate racial differences in the duration of children's exposure to neighborhood poverty and affluence. Using geocoded data from the 1999 and 2001 waves of the Panel Study of Income Dynamics, I estimate that black children born in 1999 can expect to spend about 9 of their first 18 years in poor neighborhoods, compared to less than 2 years for white children. Bivariate inequality in childhood exposure is reduced by 22% after controlling for racial differences in household characteristics, compared to a reduction of about 64% after controlling for racial differences in the racial composition and spatial location of children's neighborhoods. These findings indicate that household and especially urban ecological factors strongly affect the amount of time that black and white children can expect to spend in poor and nonpoor neighborhoods throughout childhood. I conclude by discussing some policy implications of the findings.

---

* Direct correspondence to Jeff Timberlake, University of Cincinnati Department of Sociology, PO Box 210378, Cincinnati, OH 45221-0378 (jeffrey.timberlake@uc.edu). Thanks to Patrick Heuveline for comments on an earlier draft.

Exposure to risk is a core concept in demography. At the population level, it constitutes the denominator (person-years) in the calculation of demographic rates, capturing the fact that the number of occurrences of an event (such as the number of births or deaths) depends on population size (Preston, Heuveline, and Guillot 2001:3). At the individual level, the concept captures the idea that the probability of experiencing an event is greater the longer one is exposed to the chances of that event occurring. Although sociologists focus less explicitly on the duration of exposure to risk, much sociological research implicitly accepts the idea that exposure in a binary sense to some event can be irrelevant or at least trivial; what matters is the accumulation of exposure to the constraints and opportunities associated with particular life states.

In the case of the present study, recent research has stressed the importance of exposure to risk for sociological studies of neighborhood effects on children's development (Quillian 2003; Timberlake 2007). For example, Timberlake (2007) argues that researchers have not paid sufficient empirical attention to the duration of children's exposure to neighborhood poverty, instead relying almost exclusively on point-in-time measures of neighborhood characteristics. He argues that the theory of neighborhood effects implies that in order for neighborhoods to exert their effects, children must experience relatively substantial durations of exposure to neighborhood-based milieux and events. Similarly, Quillian (2003) notes that "[m]ost of the mechanisms through which neighborhood poverty is believed to be linked to child and adolescent development… are likely to have effects that require at least moderately long exposure" (p. 222). Finally, empirical research has shown that the structuring (or lack thereof) of children's time and therefore exposure to neighborhood-based influences is a central pathway through which parents affect their children's development (Furstenberg et al. 1999; Lareau 2003).

In a recent article, Timberlake (2007) sought to draw attention to duration of exposure to neighborhood poverty and affluence by using increment-decrement life table (IDLT) methods to estimate racial and ethnic inequality in the amount of time children can expect to live neighborhoods with varying levels of poverty. He found that, at rates prevailing in the early- to mid-1990s, the average black child could expect to spend about 9 of her first 18 years in neighborhoods with poverty rates in excess of 20%. The corresponding figures for Latino and white children were about 8 years and 10 months, respectively. Timberlake also found that black/white differences in childhood exposure to neighborhood poverty were largely accounted for by inequality in the probability of being born into a poor neighborhood, and to a lesser degree by racial differences in rates of upward and downward neighborhood mobility during childhood.

This article contributed valuable empirical evidence on an important dimension of racial inequality among children; however, it was limited in one important way. Namely, Timberlake did not assess the impact of racial differences in children's household and neighborhood characteristics. Thus, although that article provided a baseline estimate of racial inequality in children's exposure to neighborhood poverty and affluence, it could not address the likely sources of that inequality. Yet, for scholars and policy makers interested in understanding and ameliorating inequality in children's neighborhood contexts, disentangling the effects of household and neighborhood characteristics is crucial because they imply starkly different policy responses, at least in the short term.

Explanations of Racial Inequality in Locational Attainment

Prior research has identified two basic sets of causal mechanisms that account for racial inequality in "locational attainment," or the socioeconomic status (SES) of individuals' and families' neighborhoods. The first points to distributional differences between blacks and whites in household-level causes of residence in poor or nonpoor neighborhoods. Such differences include (1) tastes for neighborhood locations, environments, and amenities and, more importantly, (2) ability to pay for residence in low-poverty neighborhoods. This model has intellectual roots in the human ecological and status attainment traditions in sociology and economics, respectively, and currently has been receiving much attention under the "spatial assimilation" label (see, e.g., South and Crowder 1997; Crowder and South 2005; South, Crowder, and Chavez 2005; Timberlake 2007). In short, the spatial assimilation model implies that blacks tend to live in poorer neighborhoods than whites because of group-level inequality in the characteristics that predict residence in nonpoor neighborhoods.

A second, complementary model of racial differences in locational attainment stresses the effects of historical and ongoing factors that have led blacks to be concentrated in central city neighborhoods with, on average, very high proportions of black residents, and whites to be concentrated in suburban neighborhoods with very high proportions of white residents. This mechanism has been discussed by Massey and colleagues (Massey and Denton 1993; Massey and Fischer 2000) and is often labeled in the locational attainment literature as the "place stratification" model (South and Crowder 1997; Crowder and South 2005; South et al. 2005; Timberlake 2007). In short, this model argues that whites exclude blacks from neighborhoods with high proportions of white residents via mechanisms ranging from interpersonal intimidation and terrorism to the ostensibly "color-blind" machinations of real estate, mortgage lending, and insurance markets and institutions. Because black poverty rates have historically been two to three times higher than white rates (U.S. Bureau of the Census 2006), the combination of these two factors (high poverty and residential segregation) has led to higher levels of poverty in neighborhoods dominated by blacks.

Of course, these two mechanisms are not unrelated; indeed, a core assumption of the neighborhood effects literature is that long-term residence in neighborhoods with high levels of poverty negatively affects children's performance in school and the labor market, which in turn leaves them with few resources with which to purchase residence in nonpoor neighborhoods upon reaching adulthood. Nevertheless, for the purposes of this paper I keep the two sets of explanations analytically distinct because doing so highlights the differences in short-term policy responses implied by the two models. If, according to the spatial assimilation model, racial differences in neighborhood SES are largely due to household-level differences in important predictors of residence in low-poverty neighborhoods, then it follows that public policy ought to be focused on reducing racial disparities in those factors. If, according to the place stratification model, racial differences are largely due to differences in the location and racial composition of black and white children's neighborhoods, then public policy ought to be directed at continuing to reduce the high levels of racial segregation in most American cities.

In this paper, I contribute to this academic and policy discussion by estimating the effects of household and neighborhood characteristics on racial inequality in the duration of children's exposure to neighborhood poverty and affluence. I analyze data from the 1999 and 2001 waves of the Panel Study of Income Dynamics, merged to tract-level data from the 2000 U.S. Census. I adapt the methods described in Land, Guralnik, and Blazer (1994) to estimate covariate-adjusted IDLTs, enabling me to assess the effects of important determinants of children's exposure to neighborhood poverty and affluence, namely parental family structure, household socioeconomic status, and the spatial location and racial distribution of children's neighborhoods. In the sections that follow I describe the data and measures I use to perform the analyses. I then describe the method at some length because, to the best of my knowledge, it has not appeared previously in published research (but cf. Land et al. 1994). Finally, I present findings and discuss some implications for public policy.

Data

Panel Study of Income Dynamics

The primary source of data for this research is the 1999 and 2001 waves of the Panel Study of Income Dynamics (PSID) (PSID 2007). The PSID was first administered in 1968 to 4,800 families (comprising about 18,000 individuals), and then annually until 1997 (thereafter, biennially). Children leaving the households of the original sample were followed and interviewed along with any new family members. The PSID has been an invaluable source of data for researchers interested in examining the changes over time in individuals' and families' economic well-being. I used individual-level weighted data to perform all analyses (Heeringa and Connor 1999).[1]

U.S. Census Data

Recently, the University of Michigan's Institute for Social Research released the 2000 Geocode Match Files (GMFs), which enables researchers to append tract-level information from the 2000 U.S. census to PSID data. I used the 2000 GMF to link PSID data with summary tape file data from the 2000 U.S. Census (GeoLytics, Inc. 2003). I used census data to construct the neighborhood poverty rates of the PSID children. The addition of census data to the PSID results in a singular source of data on children and the neighborhoods in which they live, operationalized in this research as census tracts. Although tracts may not perfectly replicate the subjective definitions residents have of their neighborhoods (Lee and Campbell 1997), many

[1] I used PSID cross-sectional weights for all analyses, as described in PSID documentation (Heeringa and Connor 1999). These weights adjust for sample selection probabilities and nonresponse attrition, and poststratify the sample to Current Population Survey data for "major demographic groups and geographic subclasses of the survey population" (Heeringa and Connor 1999:3), ensuring that the estimates I report are broadly representative of the population of black and white children in 1999 and 2001.

researchers have used tracts as the best available proxy (e.g., Jargowsky 1997; South and Crowder 1997; Quillian 2003; Harding 2003).

Measures

Dependent Variables

To estimate the duration of children's exposure to neighborhood poverty and affluence, I adapted a typology widely used in urban sociological and demographic research. Jargowsky and Bane (1991) developed a categorical measure of neighborhood poverty by defining neighborhoods with poverty rates of less than 20% as "nonpoor," 20% to 40% as "poor," and greater than 40% as "extremely poor." The authors and local census officials confirmed the validity of these categories by visiting neighborhoods in several cities, finding that neighborhoods in poorer categories appeared more distressed on several subjective indicators.

I followed Jargowsky and Bane by defining "high poverty" neighborhoods as those with between 20% and 40% of their residents in poverty, and "extreme poverty" neighborhoods as those with poverty rates in excess of 40%. I also extended their typology by disaggregating the "nonpoor" neighborhood type into three components: "affluent" neighborhoods have 3% or less of their residents in poverty,[2] "low poverty" neighborhoods are those with poverty rates of between 3% and 10%, and "moderate poverty" neighborhoods are defined as having poverty rates of 10% to 20%. This extension obviously yields more detailed information on inequality in children's exposure to neighborhood poverty and affluence; however, I find that this extended typology also reveals substantively important findings. This is because there are much higher

---

[2] This neighborhood type might be more precisely labeled "extremely nonpoor," since it is not necessarily true that neighborhoods with low poverty rates are affluent in other respects. My analysis of 2000 census data reveals that the average 1999 median family income in "affluent" neighborhoods fell between the 91st and 92nd percentiles of the entire family income distribution. Although there is obviously variation around that average (i.e., not all "extremely nonpoor" neighborhoods also have high median family incomes), this fact suggests that this neighborhood type corresponds well to a reasonable definition of "affluent."

levels of inequality at the upper end of the distribution than in the middle, inequality that an aggregated “less than 20%” category would obscure.[3]

Independent variables

Child- and household-level. The PSID contains measures of many household-level predictors of neighborhood socioeconomic status (SES). Following Gramlich et al. (1992), I measured permanent family income as the average of family income from the 1997, 1999, and 2001 PSID interviews, with each year adjusted to 2001 dollars. I measured education level of a child’s caregivers with dummy variables indicating the highest number of years of schooling attained by either the householder or his or her partner. I measured whether there were none, one, or two employed caregivers in the household. Because the reasons for and outcomes of moving change throughout the life course, I measured the age of the householder. I also measured the householder’s current marital status, distinguishing married and cohabiting couples from single adults. Finally, because homeownership is correlated with household wealth and is an important deterrent to residential mobility, I measured whether the household owns or rents the home in which they live. Controlling for these factors allows me to assess the extent to which racial inequality in the duration of children’s exposure to neighborhood poverty is due to racial differences in household SES and family structure.

Neighborhood-level. Much research has shown that high-poverty neighborhoods are clustered in central cities and low-poverty neighborhoods are predominantly located in suburbs of metropolitan areas (Timberlake and Michael 2007). Furthermore, Massey and colleagues (Massey and Denton 1993; Massey and Fischer 2000) have shown that residential segregation

---

[3] Any conversion of a quasi-continuous variable into categories requires choosing somewhat arbitrary cut points. In 2000, the cut points for the typology I use in this paper (3%, 10%, 20%, and 40%) corresponded to the 13.6th, 55th, 78.9th, and 95.7th percentiles, respectively. As noted in the text, the three-category “nonpoor (0% to 20%), poor (20% to 40%), very poor (greater than 40%)” division has been both widely used and validated in the field (Jargowsky and Bane 1991). The 10% cut point between low and moderate poverty neighborhoods has also been used in the literature (Harding 2003), though less frequently than the 20% and 40% cut points. Finally, as noted in note 2, the 3% cutoff for “affluent” corresponds to the top decile of the tract median family income distribution.

between two or more groups mathematically concentrates poverty in the neighborhoods of the poorer group. Thus, in this research I control for whether a child lived in a central city of a metropolitan area or a non-metropolitan area, with suburban neighborhoods as the reference category. I also control for percent black and percent white in the neighborhood. Controlling for these characteristics allows me to ask the following counterfactual: how much racial inequality in children's exposure to neighborhood poverty would there be if black and white children were equally likely to live in a central city (or a suburb or a non-metropolitan area), and if there were no racial residential segregation?

Methods

A Brief Introduction to Period Life Tables

Period life tables are a general class of demographic models that describe the transition over time of a cohort of individuals from one life state to another. In its most classic form, a mortality life table forecasts the dying out of a birth cohort. However, life tables can be extended to other types of transitions. For example, in studying adolescent mortality, a multiple decrement life table might be used to account for multiple causes of death (e.g., suicide, homicide, motor vehicle accident, and so on). The increment-decrement life table (IDLT) is an extension of these methods in that some destination states are "non-absorbing;" that is, flows to (increments) and from (decrements) various states are possible (Palloni 2001:256).

In contrast to cohort life tables, which simply record what happens to a cohort as it ages, period life tables estimate what *would* happen to a cohort if it were to experience, in the case of the present study, the age-specific neighborhood transition probabilities that exist during the period in which the cohort is defined (here, 1999 to 2001). Because the future experiences of such cohorts are not observed, but rather estimated with period conditions, demographers refer to them as "synthetic" cohorts (Preston et al. 2001:42). The benefit of period life tables is that they generate predictions, without having to wait until children's experiences have already happened. However, it is important to remember that the estimates presented here are only forecasts of children's future experiences. If children's neighborhood conditions or transition probabilities change substantially in the coming years, then my estimates will be inaccurate.

Conventional IDLT Estimation

There are two principal methods to construct an IDLT—one based on rates, and another on probabilities of transition between life states. With repeated cross-sectional data, transitions are not directly observed, so researchers must use the former method (see Palloni 2001). With panel or retrospective data, however, transition probabilities (and therefore person-years spent in various states) can be estimated directly, as shown in Heuveline, Timberlake, and Furstenberg (2003) and Timberlake (2007). The core equation used in calculating these probability-based life tables is shown below:

$$\frac{{}_{n}^{i}L_{x}^{j}\left[t-n,t\right]}{{}_{n}L_{x-n}^{i}\left[t-n,t\right]}=\frac{{}_{n}^{i}N_{x}^{j}(t)}{{}_{n}N_{x-n}^{i}(t-n)}, \tag{1}$$

The right-hand side of equation (1) is simply a conditional transition probability, where the numerator ${}_{n}^{i}N_{x}^{j}(t)$ is the number of persons aged x to $x + n$ who ended an interval of observation (t) in state j, conditional on their having been in state i at the beginning of the interval of observation ($t - n$). The denominator ${}_{n}N_{x-n}^{i}(t-n)$ is the number of persons aged $x - n$ to x who began the interval of observation in state i. With a time interval of one year (i.e., $n = 1$), this transition probability is also the number of person-years expected to be spent in state j from ages x to $x + n$, conditional on having begun the interval in state i, shown in the left-hand side of equation (1). With a time interval of longer than one year (i.e., $n > 1$), person-years are estimated by multiplying the right-hand side by the length of the interval.

The chief benefit of the probability-based method is its simplicity—no matrix inversion is required, as is true of the rate-based method described in Palloni (2001). The limitation of both methods, however, is their inability to account for more than a few covariates, due to the problem of shrinking sample sizes when even a few covariates are added. Of course, with very large sample sizes, life tables can be estimated for groups defined by several characteristics simultaneously. Nevertheless, the combination of even two fairly rare characteristics can result in very small cell sizes and therefore poor reliability of estimation (Land et al. 1994:299-301).

As I argued above, for describing baseline racial inequality in childhood exposure to neighborhood violence, Timberlake's (2007) analysis was adequate. However, social scientific models of locational attainment contend that SES and other household-level variables strongly affect the chances that children will experience upward or downward neighborhood mobility during childhood (South and Crowder 1997; Crowder and South 2005; South et al. 2005). Furthermore, research has shown that most families do not move in a given year, and those that do tend to move between similar types of neighborhoods (South and Crowder 1997; Timberlake 2007). Because black children are more likely to live in central city neighborhoods with high proportions of black residents, then these factors, along with racial differences in household characteristics, may account for a large share of the observed racial inequality in children's neighborhood transition probabilities, and ultimately in the durations of their exposure to poor and nonpoor neighborhoods.

Covariate-Adjusted IDLT Estimation

In order to estimate racial inequality in children's exposure to neighborhood poverty while simultaneously accounting for racial differences in a relatively large number of household and neighborhood characteristics, I adapted methods detailed in Land et al. (1994), in which the authors estimate IDLTs with multiple covariates. My approach predicts group-specific probabilities of birth in one of the five neighborhood poverty types defined in this study, as well as transition probabilities from each type to all others. These predicted probabilities then become inputs into the probability-based IDLT estimation procedure noted above (Heuveline et al. 2003; Timberlake 2007). The resulting life tables provide information on children's expected duration in the five neighborhood poverty types, controlling for differences in household and neighborhood characteristics.

Step 1: predicted birth distributions. I first predicted the probability of birth into one of the five neighborhood poverty types by estimating logistic regressions of each of the five types (where $y_i = 1$ if a child lives in neighborhood type *i* in wave 1, 0 otherwise) on child age in 1999, race/ethnicity, and the interaction of the two independent variables. The models are specified as follows:

$$\ln\left[\frac{\Pr(y_i = 1)}{1 - \Pr(y_i = 1)}\right] = \beta_0 + \beta_1(Age_{1999}) + \beta_2(Black) + \beta_4(Age_{1999} \times Black) + \varepsilon, \tag{2}$$

where *i* indexes neighborhood types 1 through 5 in 1999. The constant β_0 in equation (2) is interpreted as the log odds of a white child's being born in neighborhood type *i* (i.e., in neighborhood type *i* at age 0). The associated probabilities q_0^i are derived from the following formula:

$$q_0^i = \Pr(y_i = 1 \mid Age_{1999} = 0) = \frac{\exp(\beta_0)}{[1 + \exp(\beta_0)]}. \tag{3}$$

For black children, the equivalent birth probabilities are derived by adding the β_2 coefficients from equation (1) above to the constants and exponentiating as in equation (3).

Step 2: predicted transition probabilities. To predict transition probabilities from neighborhood type *i* to neighborhood type *j* between ages $x - n$ and x from 1999 to 2001, I estimated five logistic regression models where the five dependent variables y_j denote that a child lived in neighborhood type *j* in 2001. These models are specified as follows:

$$\ln\left[\frac{\Pr(y_j=1)}{1-\Pr(y_j=1)}\right]=\beta_0+\beta_1(Age_{1999})+\beta_2(Black)+\sum_{i=1}^{5}\beta_{(2+i)}(y_i)$$

$$+\beta_8(Age_{1999}\times Black)+\sum_{i=1}^{5}\beta_{(8+i)}(Age_{1999}\times y_i)+\sum_{i=1}^{5}\beta_{(13+i)}(Black\times y_i) \quad (4)$$

$$+\sum_{i=1}^{5}\beta_{(18+i)}(Age_{1999}\times Black\times y_i)+\varepsilon.$$

In this model, the constant β_0 is interpreted as the log odds of a white child's transitioning to neighborhood type *j* in 2001, given that she was in neighborhood type 1 (the omitted category) and age 0 in 1999. The associated predicted probability is derived from the following formula:

$${}_2q_0^{1j}=\Pr(y_j=1\mid y_{i=1}=1, Age_{1999}=0)=\frac{\exp(\beta_0)}{[1+\exp(\beta_0)]} \quad (5)$$

For black children, the equivalent predicted probability would again be derived by adding the β_2 coefficient from equation (4) above to the constant and exponentiating as in equation (5).

A more complicated example would be, for instance, the predicted probability of a 10 year-old child's transitioning from neighborhood type 2 in 1999 to neighborhood type *j* in 2001. Here, using the coefficients from equation (4) above, the predicted probabilities for white children would be calculated as:

$${}_2q_{10}^{2j}=\Pr(y_j=1\mid y_{i=2}=1, Age_{1999}=10)=\frac{\exp(\beta_0+\beta_1(10)+\beta_4+\beta_{10}(10))}{[1+\exp(\beta_0+\beta_1(10)+\beta_4+\beta_{10}(10))]}. \quad (6)$$

For black children, the equivalent predicted probabilities would be:

$${}_2q_{10}^{2j}=\frac{\exp(\beta_0+\beta_1(10)+\beta_2+\beta_4+\beta_8(10)+\beta_{10}(10)+\beta_{15}+\beta_{20}(10))}{[1+\exp(\beta_0+\beta_1(10)+\beta_2+\beta_4+\beta_8(10)+\beta_{10}(10)+\beta_{15}+\beta_{20}(10))]}. \quad (7)$$

Step 3: life table construction. Results from equation (2) above yield a starting distribution of q_0^i (the predicted race-specific probabilities of birth (i.e., age *x* = 0) into the five neighborhood poverty types in 1999), which can be written in matrix form as follows:

$$\mathbf{Q_0^i}=\begin{bmatrix} q_0^1 & q_0^2 & q_0^3 & q_0^4 & q_0^5 \end{bmatrix} \quad (8)$$

Results from equation (4) above yield two sets (one each for white and black children) of nine predicted transition probability matrices from age x to $x + 2$, where $x = 0, 2, 4\ldots16$. I denote birth type probabilities and transition probabilities with the letter q to conform to standard IDLT notation (e.g., Palloni 2001). Thus, ${}_2q_x^{ij}$ refers to the conditional probability of transitioning from origin state i into destination state j from age x to $x + 2$. These matrices take the following form:

$$
{}_2\mathbf{Q}_\mathbf{x}^\mathbf{ij} = \begin{bmatrix} {}_2q_x^{11} & {}_2q_x^{12} & {}_2q_x^{13} & {}_2q_x^{14} & {}_2q_x^{15} & {}_2q_x^{1LTF} \\ {}_2q_x^{21} & {}_2q_x^{22} & {}_2q_x^{23} & {}_2q_x^{24} & {}_2q_x^{25} & {}_2q_x^{2LTF} \\ {}_2q_x^{31} & {}_2q_x^{32} & {}_2q_x^{33} & {}_2q_x^{34} & {}_2q_x^{35} & {}_2q_x^{3LTF} \\ {}_2q_x^{41} & {}_2q_x^{42} & {}_2q_x^{43} & {}_2q_x^{44} & {}_2q_x^{45} & {}_2q_x^{4LTF} \\ {}_2q_x^{51} & {}_2q_x^{52} & {}_2q_x^{53} & {}_2q_x^{54} & {}_2q_x^{55} & {}_2q_x^{5LTF} \end{bmatrix}, \tag{9}
$$

where LTF indicates that an observation was “lost to follow-up,” either due to child death or attrition from the PSID.[4]

I then generated three sets of nine ${}_2\mathbf{L}_\mathbf{x}^\mathbf{j}$, which are 1 × 5 vectors of expected durations in neighborhood type j from age x to $x + 2$. The first such vector ${}_2\mathbf{L}_\mathbf{0}^\mathbf{j}$ is calculated by pre-multiplying the first transition matrix ${}_2\mathbf{Q}_\mathbf{0}^\mathbf{ij}$ by the birth distribution vector $\mathbf{Q}_\mathbf{0}^\mathbf{i}$ and then post-multiplying by the scalar 2 (because the average duration from the 1999 to 2001 PSID interviews was two years), as shown below:

$$
{}_2\mathbf{L}_\mathbf{0}^\mathbf{j} = \mathbf{Q}_\mathbf{0}^\mathbf{i} \times {}_2\mathbf{Q}_\mathbf{0}^\mathbf{ij} \times 2 \tag{10}
$$

Subsequent ${}_2\mathbf{L}_\mathbf{x}^\mathbf{j}$ vectors were derived by pre-multiplying each transition probability matrix ${}_2\mathbf{Q}_\mathbf{x}^\mathbf{ij}$ by the preceding ${}_2\mathbf{L}_\mathbf{x}^\mathbf{j}$ vector, as shown below:

$$
{}_2\mathbf{L}_\mathbf{x}^\mathbf{j} = {}_\mathbf{x}\mathbf{L}_{\mathbf{x-2}}^\mathbf{j} \times {}_2\mathbf{Q}_\mathbf{x}^\mathbf{ij} \tag{11}
$$

[4] The q^{ij} in these matrices sum to 1.0 within rows, but because LTF is an absorbing state, I constructed the life tables by excluding children transitioning into the LTF state. The dimensions of the resulting matrices are therefore 5 × 5. I apportioned the LTF children into the 5 observed neighborhood types by multiplying the LTF predicted probabilities by the share of each predicted transition probability into the five non-absorbing states (i.e., destination states 1 through 5). This approach makes the assumption that, conditioning on origin neighborhood type, the destination neighborhood type for a LTF child would be the same as the destination type if they had not been LTF.

The final step is to sum the nine ${}_{2}\mathbf{L}_{\mathbf{x}}^{\mathbf{j}}$ vectors, which yields $\mathbf{E}_{\mathbf{0}}^{\mathbf{j}}$, a 1 × 5 vector of elements e_0^j, representing the group-specific number of years children can expect to spend in the five neighborhood poverty types *j* from birth to exact age 18. Hence,

$$\mathbf{E}_{\mathbf{0}}^{\mathbf{j}} = \sum_{x=0}^{16} {}_{2}\mathbf{L}_{\mathbf{x}}^{\mathbf{j}} \tag{12}$$

Multiplying each element in $\mathbf{E}_{\mathbf{0}}^{\mathbf{j}}$ by $18/e_0^j$ (to apportion LTF child-years–see note 4) and then multiplying by 100 yields quantities to which I will refer as "childhood expectancy" (Heuveline et al. 2003). Analogous to life expectancy at birth in a conventional mortality life table, the term "childhood expectancy" refers to the percentage of childhood (again, birth to exact age 18) that the average child from a given life table can expect to spend in each of the five neighborhood types, if she were to experience the period age-specific neighborhood transition probabilities throughout childhood.

Covariate-adjusted IDLTs. The methods I have described thus far represent an improvement over conventional IDLT estimation procedures (Palloni 2001; Heuveline et al. 2003; Timberlake 2007) because they are likely to provide more stable estimates of group- and age-specific transition probabilities than those computed directly from sample data (Land et al. 1994). This is because, whereas the sample sizes within any observed transition matrix would range from about 50 to 100 PSID children, the predicted transition matrices are derived from logistic regression estimates on over 5,000 cases. A related, but even greater benefit of this method is its ability to include multiple covariates in the models shown in equations (2) and (4) above.

To do this, I recoded all household and neighborhood covariates so that they are expressed in deviation units, (i.e., each control variable X_c is centered around its mean $[X_{ci} - \overline{X}_c]$). The resulting constants and coefficients on race, age, origin neighborhood type, and their interactions are then be interpreted as effects on the log odds of transitioning from neighborhood type *i* to *j* for children whose household and neighborhood characteristics are average for the whole sample. I then re-estimated the IDLTs with covariate-adjusted predicted transition matrices, as shown in equations (10) and (11).

This analysis enables me to assess the extent to which racial inequality in the duration of exposure to neighborhood poverty is due to group-level differences in children's household-level characteristics and in the locational and compositional characteristics of children's neighborhoods. I present these findings in the following section.

Findings

Descriptive Statistics

Table 1 below shows the distributions of PSID children in the five neighborhood types, as well as the means of the predictors I used to estimate the covariate-adjusted life tables. I present these means by child racial group, as well as the *t*-statistics from tests for differences between black and white children on each variable. All data are weighted, and the standard errors used for the *t*-tests account for the clustering of multiple children within families.[5]

(Table 1 about here)

Table 1 shows that in 1999, white children were much more likely to live in affluent and low-poverty neighborhoods, and black children were much more likely to live in high- and extreme-poverty neighborhoods. A nearly identical percentage (about 26%) lived in the moderate poverty type, or neighborhoods with poverty rates between 10% and 20%. Table 1 also reveals substantial white/black inequality in measures of household-level SES and family structure. White children lived in households with higher family incomes, more educated heads or partners, and more two-income couples. They were also much more likely to live in an owner-occupied

[5] The clustering of multiple PSID families within tracts is not as much of a concern, given that about 90% of tracts in this sample had only one PSID family in them.

home and have two married or cohabiting caregivers. Finally, at the neighborhood level, white children on average lived in neighborhoods that were about 7% black and 86% white, compared to black children, who lived in neighborhoods that were an average of 55% black and 37% white. Black children were much more likely than white children to live in central cities compared to suburbs and non-metropolitan areas.

In the analysis that follows I estimate racial inequality in childhood exposure to the five neighborhood types discussed above. I first estimate bivariate inequality, that is, without controls for household and neighborhood characteristics. I then add such characteristics to subsequent analyses and calculate the percentage of inequality explained by these variables.

Analysis of Childhood Durations of Exposure

Table 2 shows estimates of childhood expectancy in the five neighborhood poverty types, derived from the IDLT procedures described above. The far left-hand panel (Model 1) shows the findings from bivariate analyses, that is, analyses of racial differences unadjusted by household- or neighborhood-level characteristics. The middle left-hand panel (Model 2) shows the findings after controlling for household characteristics, the middle-right hand panel (Model 3) substitutes neighborhood characteristics, and the far right-hand panel (Model 4) shows the results when both sets of characteristics are included. The data used to calculate the childhood expectancies can be found in appendix Tables A1 through A5. In each panel, I subtract the black figure from the white figure and then square (the "$(W - B)^2$" columns) and sum the differences (the "Sum of squares" row).

These sums of squared deviations become inputs into equation (13) below, which estimates π, the percentage of the racial inequality in childhood expectancy in the five neighborhood types, indexed by j, that is due to racial differences in the distributions of the household and neighborhood covariates:

$$\hat{\pi} = \left(1 - \frac{\sum_{j=1}^{5} \left(L_j^{W^m} - L_j^{B^m} \right)^2}{\sum_{i=1}^{5} \left(L_j^{W^1} - L_j^{B^1} \right)^2} \right) \times 100, \tag{13}$$

where the L_j^W and L_j^B are childhood expectancies for black and white children, respectively. The superscript "*m*" in the numerator indicates a higher-order model than Model 1 (the "bivariate" or "baseline" model) in the denominator. For example, if $m = 2$, then the estimate of π would be the inequality explained by the household model (Model 2) relative to the bivariate model. Note that if, in one limiting case, the only difference between black and white children were their distributions on the included covariates, then controlling for these factors would make the numerator of equation (13) zero, and thus 100% of the inequality in childhood expectancies would be explained by differences in the covariates. In the other limiting case, if the group-specific numerators and denominators were equal (i.e., $L_j^{W^m} = L_j^{W^1}$ and $L_j^{B^m} = L_j^{B^1}$ for all *j*), this would mean that none of the inequality could be explained by inequalities in the predictors of neighborhood at birth and neighborhood transitions during childhood.

(Table 2 about here)

Bivariate racial inequality. The figures from Model 1 show that black children born in 1999 can expect to spend about 50% (9 of their first 18 years) in poor neighborhoods, those with poverty rates of at least 20%. This 50% comprises childhood expectances of 34.3% in high and 16.1% in extreme poverty neighborhoods. White children, by contrast, can expect to spend only about 10% of childhood in poor neighborhoods, including only about 1% (about two months) in extreme poverty neighborhoods. Both black and white children can expect to spend about 29% of childhood in moderately poor neighborhoods. At the affluent end of the spectrum, black children can expect to spend only about 20% of childhood in the two least poor types, compared to fully 60% for white children. Figure 1 shows these expectancies in graphical form, facilitating comparisons across neighborhood types between the two groups.

(Figure 1 about here)

Not surprisingly, these findings correspond well to those appearing in Timberlake's (2007) analysis of childhood expectancies in the mid-1990s. As I have mentioned, however, a limitation of the methodology used in that article was its inability to estimate covariate-adjusted childhood expectancies. That is, the analyses could not assess the extent to which black children's greater exposure to poor neighborhoods derives from household factors such as low income, which may result in black families' disproportionate residence in poor neighborhoods. Nor could that analysis determine the extent to which racial inequality is due to factors such as residential segregation, which would lead to a greater concentration of poverty in neighborhoods dominated by black families (Massey and Denton 1993; Massey and Fischer 2000).

Inequality controlling for household and neighborhood characteristics. The data from Model 2 of Table 2 displays covariate-adjusted childhood expectancies, derived from the coefficients shown in Tables A1 ("Model 2" panel) and A3, in which I included household-level controls for SES and family structure. Recall that these covariates were expressed in deviation units, so the resulting childhood expectancies can be interpreted as the expected exposure to the five neighborhood poverty types for children from families who are average for the whole sample. Because about 83% of the weighted sample was white, this technique has the effect of slightly reducing the advantage of white children and dramatically increasing the advantage of black children in the calculation of the resulting life tables. For example, about 81% of white children lived with a married or cohabiting head of household, compared to only 38% for black children (see Table 1). The total sample average, 73%, is a weighted average of the two, where the weights are the proportions of black and white children.

Controlling for household-level factors reduces black/white inequality largely at the tails of the distribution. Note that, relative to the bivariate model, in the "Model 2" panel of Table 2, white childhood expectancy in affluent neighborhoods decreased from 16.8% to 13.4%, while black childhood expectancy increased from 3.4% to 5.7%. Similarly, black children's expected duration in extremely poor neighborhoods declined from 16.1% of childhood to 7.1%, a relative decline of 56%. Overall, bivariate inequality in childhood expectancies was reduced by 22% after accounting for racial differences in household characteristics (see explanation of equation [13] above). Figure 2 shows in graphic form these adjusted expectancies, compared to the bivariate results from Figure 1 and the far left-hand panel of Table 2. Figure 2 also shows adjusted childhood expectances after controlling for neighborhood characteristics only (Model 3 of Table 2) and both household and neighborhood characteristics (Model 4 of Table 2).

(Figure 2 about here)

Model 3 of Table 2 displays covariate-adjusted childhood expectancies, derived from the coefficients shown in Tables A1 ("Model 3" panel) and A4, in which I included controls for the urban ecological location and racial composition of children's neighborhoods. Again, because these covariates have been centered around their means, the resulting childhood expectancies should be interpreted as expected durations in the five neighborhood poverty types for children who have identical (and average) neighborhood racial distributions and likelihoods of living in central cities versus suburbs or non-metropolitan areas. Controlling for neighborhood characteristics has some of the same effect as shown in the analysis of household characteristics. This is not surprising, of course, since household characteristics to some degree predict residence in central city versus suburban or largely white versus largely black neighborhoods. Again relative to the bivariate model, controlling for neighborhood characteristics reduces inequality somewhat at the tails; however it has far larger effects in the second-most and second-least poor neighborhoods. Note that black children's predicted childhood expectancy in low poverty neighborhoods (between 3% and 10% poor) increased from 17% of childhood in the bivariate model to 28% in Model 3, a relative increase of 65%. Similarly, black childhood expectancy in high poverty neighborhoods (between 20% and 40% poor) decreased from 34% of childhood in the bivariate model to 22% in Model 3, a relative decrease of 36%. Overall, the inclusion of neighborhood characteristics accounts for 64% of bivariate racial inequality. This suggests that if racial segregation between blacks and whites and the spatial concentration of blacks in central cities were eliminated (and sustained over time), white/black inequality in childhood exposure to neighborhood poverty and affluence would decline by almost two-thirds. Importantly, *this decline would be achieved without changing the household characteristics of blacks or whites*.

Finally, Model 4 of Table 2 displays covariate-adjusted childhood expectancies, derived from the models shown in Tables A1 (bottom panel) and A5, in which I included household and neighborhood covariates. Relative to any of the previous models, Model 4 yields the lowest level of inequality at the tails of the distribution. Note that the difference between white and black childhood expectancies in extreme poverty neighborhoods is quite small (about 0.5% for whites and 6% for blacks, compared to bivariate expectancies of 1% and 16%, respectively). Furthermore, there is effectively no difference between white and black children in their predicted duration of exposure to the most affluent neighborhood type (about 11% for each group). Slightly more inequality is apparent in the low poverty neighborhood relative to Model 3, yielding a slightly lower percentage of inequality explained (61%) relative to Model 3 (64%). Again, Figure 2 above shows the dramatic differences in the childhood expectancy distributions compared to the bivariate model.

Conclusions

The primary goal of this research was to assess the extent to which racial inequality in the duration of childhood exposure to neighborhood poverty and affluence could be explained by two sets of factors: racial differences in important household-level predictors of neighborhood SES and neighborhood-level ecological factors such as the racial distribution and spatial location of children's neighborhoods. I found that racial differences in household characteristics account for about 22% of bivariate racial inequality, and nearly two-thirds are accounted for by racial differences in the spatial location and racial composition of children's neighborhoods. The combination of both sets of effects account for about 61% of the bivariate level of racial inequality in children's exposure to neighborhood poverty and affluence. These findings indicate that household and especially urban ecological factors strongly affect the amount of time that black and white children can expect to spend in poor and nonpoor neighborhoods throughout childhood.

As I argued above, these two sets of factors imply two distinct mechanisms by which children are exposed to greater or lesser degrees of neighborhood poverty, and suggest two different types of policy responses. First, policy could attempt to change the families in the neighborhoods in which children currently live. According to Jargowsky (2003), the 1990s saw a dramatic decline in the number of extremely poor neighborhoods, and he attributes this largely to the strong economic recovery during that period. This suggests that neighborhood conditions for children are dramatically affected by the health of the national, regional, state, and local economies. As such, the findings of the present analysis would prescribe prolonged and robust economic development for improving the neighborhood conditions of minority children. Of course, such development is not entirely subject to the whims of policy makers, given normal business cycle fluctuations over time. In fact, it is likely that many of the economic gains for African Americans achieved during the latter half of the 1990s were eroded during the first half of the 2000s, which suggests that concentrated poverty has likely increased since Jargowsky's (2003) analysis and since the period under consideration in this paper.

Of course, policy makers do have more control over the provision and funding of anti-poverty policies such as targeted investment in education and employment opportunities. Such policies collectively could change long-run racial inequality in poverty rates, thereby reducing black children's exposure to neighborhood poverty, even absent dramatic changes in residential segregation.

A second set of policy prescriptions would target this very point—reducing further the spatial concentration of African Americans in central cities and still-high levels of residential segregation. For example, financial incentives could be applied to induce families to change neighborhoods. White families could be given tax incentives to reward them for exiting segregated White neighborhoods and entering more integrated neighborhoods. Conversely, policies could be enacted to increase the mobility of minority families from poor to nonpoor neighborhoods (the focus of the Gautreaux and Moving to Opportunity residential mobility programs). Examples of such policies would include an increase in the Section 8 housing voucher program, or low interest mortgage loans to minority families making integrating moves. Assuming that such incentives would actually result in those families' attempting to move into largely white neighborhoods, increased oversight of fair housing laws would also likely be necessary, given the findings from research on housing discrimination (Yinger 1995).

Neither of these policy types is particularly novel; indeed, they appear repeatedly in the urban sociological literature (e.g., Pattillo-McCoy 1999:217-218; Greenbaum 2006). Moreover, they echo much older debates between, for example, Booker T. Washington and W. E. B. DuBois regarding the extent to which African Americans should push for racial uplift within the black community versus increased integration with whites. Put bluntly, scholarly understanding of the causes and consequences of concentrated poverty is not lacking; what is lacking is the political will necessary to allocate public resources to ameliorate the problem. Clearly, any serious engagement of either type of policy outlined above would cost a great deal of money. At least in the current political and fiscal climate, the chances of such expenditures being allocated seem slim. Absent such expenditures, the slow but steady decline in at least black/white residential segregation appears to be the best hope for reducing the stark levels of inequality in children's neighborhood conditions demonstrated in this research.

References

Crowder, Kyle and Scott J. South. 2005. "Race, Class, and Changing Patterns of Migration between Poor and Nonpoor Neighborhoods." *American Journal of Sociology* 110:1715-63.

Furstenberg, Frank F., Jr., Thomas D. Cook, Jacquelynne Eccles, Glen H. Elder, Jr., and Arnold Sameroff. 1999. *Managing to Make It: Urban Families and Adolescent Success*. Chicago: University of Chicago Press.

GeoLytics, Inc. 2003. *CensusCD Neighborhood Change Database 1970-2000 Tract Data* [MRDF]. East Brunswick, NJ.

Gramlich, Edward, Deborah Laren, and Naomi Sealand. 1992. "Moving into and out of Poor Urban Areas." *Journal of Policy Analysis and Management* 11:273-87.

Greenbaum, S. (2006). "Comments on Katrina." *City & Community* 5: 109-113.

Harding, David J. 2003. "Counterfactual Models of Neighborhood Effects: The Effect of Neighborhood Poverty on Dropping Out and Teenage Pregnancy." *American Journal of Sociology* 109:676-719.

Heeringa, Steven G. and Judith H. Connor. 1999. "1997 Panel Study of Income Dynamics Analysis Weights for Sample Families and Individuals." Ann Arbor, MI: Survey Research Center, Institute for Social Research, University of Michigan.

Heuveline, Patrick, Jeffrey M. Timberlake, and Frank F. Furstenberg, Jr. 2003. "Shifting Child Rearing to Single Mothers: Results from 17 Western Nations." *Population and Development Review* 19:47-71.

Jargowsky, Paul A. and Mary Jo Bane. 1991. "Ghetto Poverty in the United States, 1970-1980." In *The Urban Underclass*, edited by Christopher Jencks and Paul Peterson. Washington, DC: The Brookings Institution.

Land, Kenneth C., Jack M. Guralnik, and Dan G. Blazer. 1994. Estimating Increment-Decrement Life Tables with Multiple Covariates from Panel Data: The Case of Active Life Expectancy. *Demography* 31: 297-319.

Lareau, Annette. 2003. *Unequal Childhoods: Class, Race, and Family Life*. Berkeley, CA: University of California Press.

Lee, Barrett and Karen Campbell. 1997. "Common Ground? Urban Neighborhoods as Survey Respondents See Them." *Social Science Quarterly* 78:922-936.

Massey, Douglas S. and Nancy A. Denton. 1993. *American Apartheid: Segregation and the Making of the Underclass*. Cambridge, MA: Harvard University Press.

Massey, Douglas S. and Mary J. Fischer. 2000. "How Segregation Concentrates Poverty." *Ethnic and Racial Studies* 23:670-691.

Palloni, Alberto. 2001. "Increment-Decrement Life Tables." In *Demography: Measuring and Modeling Population Processes*, by S. H. Preston, P. Heuveline, and M. Guillot. Oxford, UK: Blackwell Publishers.

Panel Study of Income Dynamics (PSID). 2007. *Panel Study of Income Dynamics, Waves 1991 to 2001* [MRDF]. Ann Arbor MI: Institute for Social Research [producer]. Survey Research Center [distributor].

Pattillo-McCoy, M. 1999. *Black Picket Fences: Privilege and Peril Among the Black Middle Class*. Chicago: University of Chicago Press.

Preston, Samuel H., Patrick Heuveline, and Michel Guillot. 2001. *Demography: Measuring and Modeling Population Processes*. Oxford, UK: Blackwell Publishers.

Quillian, Lincoln. 2003. "How Long Are Exposures to Poor Neighborhoods? The Long-Term Dynamics of Entry and Exit from Poor Neighborhoods." *Population Research and Policy Review* 22:221-49.

South, Scott J. and Kyle D. Crowder. 1997. “Escaping Distressed Neighborhoods: Individual, Community, and Metropolitan Influences.” *American Journal of Sociology* 102:1040-84.

South, Scott J., Kyle D. Crowder, and Erick Chavez. 2005. “Exiting and Entering High-Poverty Neighborhoods: Latinos, Blacks, and Anglos Compared.” *Social Forces* 84:873-900.

Timberlake, Jeffrey M. 2007. “Racial and Ethnic Inequality in the Duration of Children’s Exposure to Neighborhood Poverty and Affluence.” *Social Problems* 54:319-42.

Timberlake, Jeffrey M. and Joseph Michael. 2007. “Children’s Exposure to Neighborhood Poverty and Affluence in the United States, 1990 to 2000.” Pp. 136-162 in B. Arrighi and D. J. Maume, Jr. (Eds.), *Child Poverty in America Today: Vol. 1, Families and Children*. Westport, CT: Greenwood Publishing Group.

U.S. Bureau of the Census. 2006. “Historical Poverty Tables,” accessed May 10, 2006, <http://www.census.gov/hhes/www/poverty/histpov/hstpov2.html>.

Yinger, John. 1995. *Closed Doors, Opportunities Lost: The Continuing Costs of Housing Discrimination*. New York: Russell Sage Foundation.

Table 1. Means of Variables Used in the Analysis, by Child Race: PSID Children, 1999

	Child race		
	White	Black	*t* Δ
Dependent variable (neighborhood poverty type)			
"Nonpoor" neighborhoods			
Affluent (less than 3%)	0.178	0.039	*4.9* ***
Low (3% to 10%)	0.463	0.143	*9.0* ***
Moderate (10% to 20%)	0.260	0.265	*0.2*
"Poor neighborhoods"			
High (20% to 40%)	0.087	0.447	*11.1* ***
Extreme (40% or greater)	0.012	0.106	*5.7* ***
Independent variables			
Child race	0.826	0.174	—
Household characteristics			
1996 to 1999 average family income ($)	58,403	24,150	*13.8* ***
Head/partner highest years of schooling	13.9	12.4	*7.7* ***
Head/partner employment			
No one employed	0.068	0.244	*7.0* ***
One caregiver employed	0.440	0.498	*1.5*
Two caregivers employed	0.492	0.258	*5.9* ***
Owns home	0.755	0.382	*10.5* ***
Head married/cohabiting	0.805	0.382	*11.6* ***
Head age	38.8	38.6	*0.2*
Neighborhood characteristics			
Tract percent black	6.9	54.8	*21.2* ***
Tract percent white	85.7	36.7	*26.1* ***
Tract location			
Central city of metropolitan area	0.159	0.501	*9.4* ***
Suburb of metropolitan area	0.601	0.374	*9.4* ***
Non-metropolitan area	0.239	0.125	*4.3* ***

Notes: Data are weighted and *t*-test standard errors adjusted for the clustering of children in families. N = 3,171 for white and 2,335 for black children. *** white - black difference in means significant at α = .001, two-tailed tests.

Table 2. Childhood Expectancy in Five Neighborhood Poverty Types, By Child Race and Model Covariates: PSID Children, 1999 to 2001

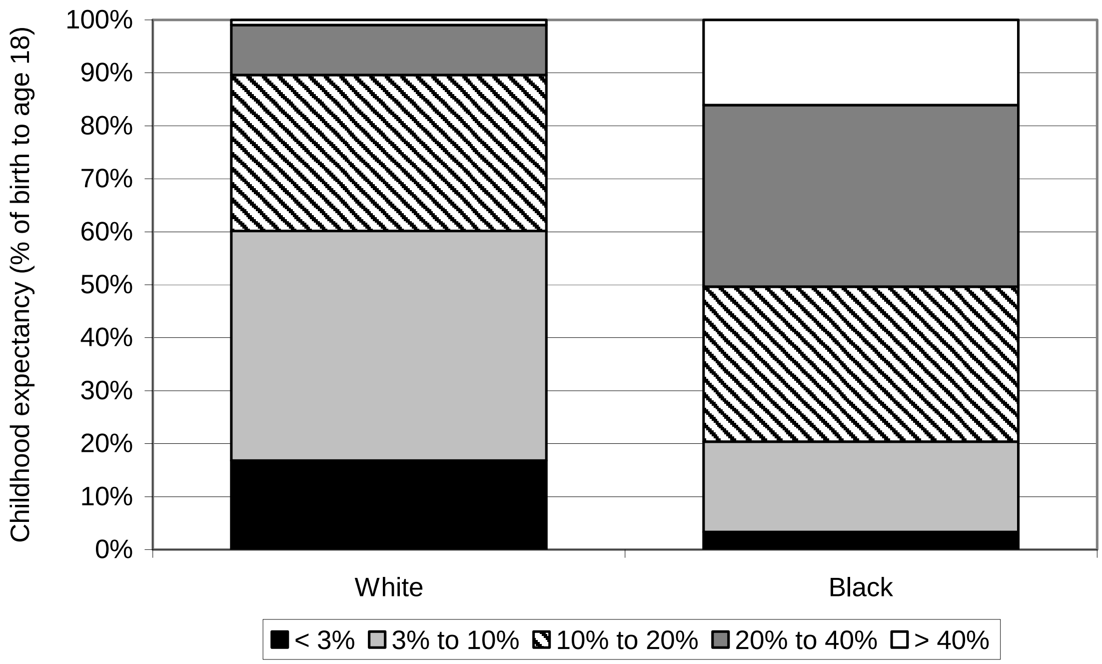
	Model											
	(1) Bivariate			(2) Household characteristics[a] only			(3) Neighborhood characteristics[a] only			(4) Household and neighborhood characteristics[a]		
	White	Black	$(W - B)^2$	White	Black	$(W - B)^2$	White	Black	$(W - B)^2$	White	Black	$(W - B)^2$
"Nonpoor" neighborhoods												
Affluent (less than 3%)	16.8	3.4	181.5	13.4	5.7	60.1	14.1	7.5	43.2	10.7	10.5	0.0
Low (3% to 10%)	43.3	17.0	692.8	48.1	22.6	649.3	46.0	28.1	322.2	50.6	29.1	462.7
Moderate (10% to 20%)	29.4	29.3	0.0	28.4	30.8	6.2	30.3	32.9	6.5	28.9	31.9	9.1
"Poor" neighborhoods												
High (20% to 40%)	9.4	34.3	619.2	9.7	33.7	576.4	8.8	22.0	174.7	9.4	22.8	178.5
Extreme (40% or greater)	1.0	16.1	227.5	0.4	7.1	45.4	0.8	9.5	76.6	0.4	5.7	28.4
Sum of squares[b]			1,721.0			1,337.5			623.2			678.7
% explained vs. model 1[b]			—			22.3			63.8			60.6

Notes: Data are weighted. N = 3,171 for white and 2,335 for black children. Figures in "White" and "Black" columns derived from coefficients in Tables A1 to A5, as described in text, "Methods" section.

[a] See Table 1 or A1 to A5 for a list of covariates.

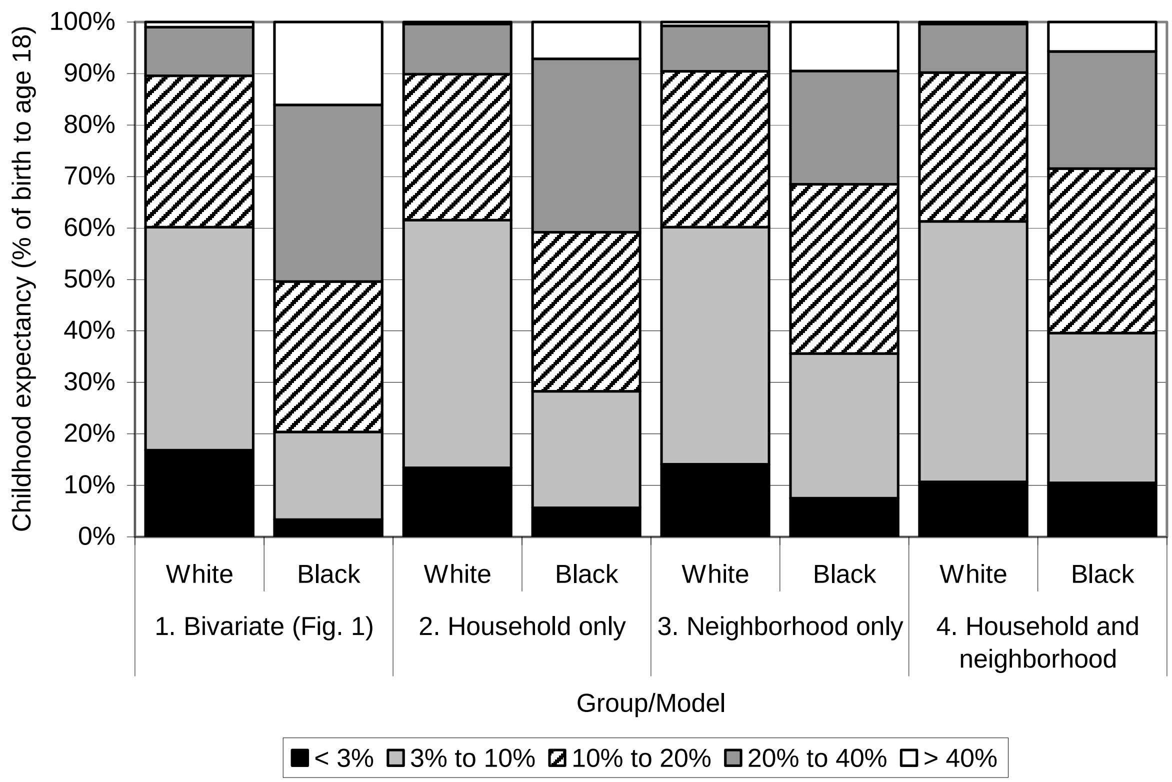
[b] See discussion of equation (13) in text.

Figure 1. Childhood Expectancy in 5 Neighborhood Poverty Types, by Child Race Only: PSID Children, 1999 to 2001



Notes : Figures from synthetic birth cohorts estimated for the 1999 to 2001 period (see Table 2). Data are weighted. n = 3,171 for Whites and 2,335 for Blacks.

Figure 2. Childhood Expectancy in Five Neighborhood Poverty Types, By Child Race and Model Covariates: PSID Children, 1999 to 2001



Notes : Figures from synthetic birth cohorts estimated for the 1999 to 2001 period (see Table 2). Data are weighted. n = 3,171 for Whites and 2,335 for Blacks.

Table A1. Coefficients and Standard Errors from Logistic Regressions of Neighborhood Poverty Type in 1999 on Race, Child Age, and Household and Neighborhood Covariates: PSID Children, 1999

	Neighborhood poverty type									
	Affluent (less than 3%)		Low poverty (3% to 10%)		Moderate poverty (10% to 20%)		High poverty (20% to 40%)		Extreme poverty (40% or greater)	
Model/parameters	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Model 1: Race and child age										
Constant	-1.730 ***	0.145	-0.188	0.108	-0.954 ***	0.115	-2.204 ***	0.188	-3.770 ***	0.448
Black	-0.926 *	0.435	-2.026 ***	0.300	0.312	0.225	1.835 ***	0.271	1.486 **	0.537
Child age	0.023	0.013	0.005	0.010	-0.011	0.011	-0.019	0.017	-0.090 *	0.037
Black × age	-0.094 *	0.040	0.041	0.032	-0.034	0.022	0.036	0.026	0.107 *	0.048
Model 2: Household characteristics										
Constant	-2.189 ***	0.236	-0.124	0.122	-1.113 ***	0.133	-2.361 ***	0.194	-4.827 ***	0.428
Black	0.050	0.461	-1.838 ***	0.311	0.267	0.243	1.439 ***	0.292	0.773	0.595
Child age	0.007	0.017	-0.009	0.012	0.006	0.013	-0.003	0.019	-0.043	0.040
Black × age	-0.097 *	0.042	0.044	0.032	-0.038	0.023	0.032	0.028	0.092	0.052
Log family income	0.423 *	0.212	0.073	0.049	-0.014	0.038	-0.087	0.050	-0.129 *	0.062
Schooling	0.191 ***	0.052	0.030	0.026	-0.095 ***	0.025	-0.054	0.035	-0.100 *	0.044
One worker	0.084	0.540	0.699 *	0.306	-0.059	0.272	-0.289	0.297	-0.328	0.530
Two workers	-0.165	0.555	0.681 *	0.339	0.113	0.309	-0.588	0.381	-0.528	0.775
Owns home	0.569 *	0.287	-0.093	0.160	0.167	0.168	-0.315	0.229	-1.665 ***	0.481
Married/cohabiting	0.420	0.334	0.053	0.199	-0.007	0.200	-0.190	0.298	-0.244	0.546
Head age	0.015	0.015	0.016	0.008	-0.024 **	0.009	-0.006	0.012	-0.022	0.023

Table A1. (cont'd) **Coefficients and Standard Errors from Logistic Regressions of Neighborhood Poverty Type in 1999 on Race, Child Age, and Household and Neighborhood Covariates: PSID Children, 1999**

	Neighborhood poverty type									
	Affluent (less than 3%)		Low poverty (3% to 10%)		Moderate poverty (10% to 20%)		High poverty (20% to 40%)		Extreme poverty (40% or greater)	
Model/parameters	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Model 3: Neighborhood characteristics										
Constant	-2.809 ***	0.2396	-0.448 ***	0.1213	-1.032 ***	0.1287	-2.483 ***	0.2369	-5.087 ***	0.6967
Black	1.1847 *	0.5332	-0.828 *	0.3318	0.3749	0.2969	0.0606	0.4028	-0.905	0.631
Child age	0.0253	0.0142	0.002	0.011	-0.015	0.0123	-0.01	0.0196	-0.091 *	0.0415
Black × age	-0.119 **	0.044	0.0429	0.0311	-0.027	0.023	0.0451	0.0299	0.1248 *	0.0508
% Black	-0.032 *	0.0159	0.0171 *	0.0074	-0.009	0.007	-0.033 ***	0.0086	-0.017	0.0106
% White	0.0252 *	0.01	0.0459 ***	0.0067	-0.011	0.0067	-0.069 ***	0.0094	-0.063 ***	0.0174
Central city	-0.991 ***	0.2601	-0.241	0.1682	0.0706	0.195	1.3855 ***	0.2625	3.0725 ***	0.8229
Nonmetro	-3.302 ***	0.4432	-0.978 ***	0.1577	1.6379 ***	0.1569	1.4731 ***	0.2931	3.771 ***	0.8673
Model 4: Household and neighborhood characteristics										
Constant	-3.127 ***	0.278	-0.379 **	0.136	-1.146 ***	0.146	-2.526 ***	0.228	-5.904 ***	0.677
Black	1.884 ***	0.572	-0.863 *	0.344	0.420	0.298	0.019	0.407	-1.003	0.623
Child age	0.019	0.019	-0.007	0.013	-0.003	0.014	-0.006	0.021	-0.062	0.039
Black × age	-0.132 **	0.048	0.044	0.031	-0.030	0.024	0.041	0.029	0.114 *	0.051
Log family income	0.257	0.156	0.049	0.046	0.003	0.044	-0.081	0.071	-0.131	0.069
Schooling	0.156 **	0.052	-0.002	0.026	-0.074 **	0.027	-0.010	0.040	-0.087	0.045
One worker	0.041	0.561	0.690 *	0.313	0.025	0.267	0.028	0.327	0.180	0.559
Two workers	-0.116	0.583	0.681	0.350	0.148	0.303	-0.361	0.414	0.275	0.819
Owns home	0.703 *	0.288	-0.197	0.167	0.133	0.177	-0.077	0.262	-1.636 ***	0.478
Married/cohabiting	0.263	0.350	-0.128	0.207	-0.043	0.210	0.155	0.319	-0.078	0.511
Head age	0.003	0.016	0.011	0.009	-0.017	0.009	0.004	0.014	-0.001	0.024
% Black	-0.038 *	0.017	0.019 *	0.008	-0.007	0.007	-0.031 ***	0.009	-0.005	0.012
% White	0.016	0.011	0.047 ***	0.007	-0.007	0.007	-0.065 ***	0.010	-0.045 *	0.018
Central city	-0.909 ***	0.256	-0.210	0.170	0.028	0.197	1.366 ***	0.259	3.000 ***	0.805
Nonmetro	-2.941 ***	0.447	-0.930 ***	0.159	1.528 ***	0.161	1.420 ***	0.300	3.761 ***	0.969

Note : N = 5,506. Variables in italics have been centered around their means. * $p < .01$; ** $p < .01$; *** $p < .001$, two-tailed tests.

Table A2. Coefficients and Standard Errors from Logistic Regressions of Neighborhood Poverty Type in 2001 on Race, Child Age, and Neighborhood Poverty Type in 1999: PSID Children, 1999 to 2001

	Neighborhood poverty type									
	Affluent (less than 3%)		Low poverty (3% to 10%)		Moderate poverty (10% to 20%)		High poverty (20% to 40%)		Extreme poverty (40% or greater)	
Model/parameters	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	1.023 **	0.379	-1.375 **	0.431	-2.680 ***	0.710	-4.885 ***	1.011	-18.556 ***	1.006
Black	-0.851	0.985	-10.408 **	3.208	-15.827 ***	1.640	4.819 ***	1.370	0.000	1.148
Child age	0.161 **	0.054	-0.192 **	0.064	-0.093	0.095	-0.078 ***	0.014	0.000	0.009
Low	-3.643 ***	0.544	2.831 ***	0.482	0.493	0.757	0.860	1.184	13.175	—
Moderate	-4.199 ***	0.676	-0.238	0.510	3.937 ***	0.750	1.004	1.153	0.000	1.659
High	-10.913 ***	1.177	-0.644	0.727	0.462	0.899	6.220 ***	1.095	13.843 ***	1.428
Extreme	—	—	-16.885 ***	3.373	-1.490	1.579	4.014 **	1.310	19.541 ***	1.324
Black × age	0.058	0.112	0.810 **	0.251	0.093	0.066	-0.207	0.108	0.000	0.080
Age × low	-0.247 ***	0.070	0.270 ***	0.068	0.022	0.099	0.041	0.065	-0.130	—
Age × moderate	-0.314 ***	0.087	0.114	0.071	0.172	0.099	0.075	0.061	0.000	—
Age × high	0.215 **	0.070	0.098	0.100	0.084	0.112	0.102 *	0.047	0.069 ***	0.020
Age × extreme	—	—	0.192	0.285	0.321 **	0.117	0.070	0.090	-0.077	0.086
Black × low	0.096	1.480	11.483 ***	3.274	14.570 ***	1.807	-4.910 **	1.836	—	—
Black × moderate	-1.575	1.522	9.538 **	3.306	15.272 ***	1.706	-2.330	1.585	15.907	—
Black × high	—	—	9.116 **	3.333	15.675 ***	1.802	-5.184 ***	1.474	3.144	—
Black × extreme	—	—	26.678	—	17.527	—	-5.371 **	1.729	-0.214	1.538
Black × age × low	-0.040	0.124	-0.936 ***	0.257	0.045	—	0.319 *	0.160	0.000	0.000
Black × age × moderate	-0.009	0.132	-0.788 **	0.263	-0.057	0.083	0.027	0.144	-0.042	0.092
Black × age × high	—	—	-0.803 **	0.273	-0.036	0.098	0.229	0.124	-0.296	—
Black × age × extreme	—	—	-1.467	—	-0.525 ***	0.106	0.185	0.149	0.154	0.129

Note : N = 5,506. — = parameter not estimated due to multicollinearity. * $p < .01$; ** $p < .01$; *** $p < .001$, two-tailed tests.

Table A3. Coefficients and Standard Errors from Logistic Regressions of Neighborhood Poverty Type in 2001 on Race, Child Age, Neighborhood Poverty Type in 1999, and Household Covariates: PSID Children, 1999 to 2001

	Neighborhood poverty type									
	Affluent (less than 3%)		Low poverty (3% to 10%)		Moderate poverty (10% to 20%)		High poverty (20% to 40%)		Extreme poverty (40% or greater)	
Model/parameters	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	0.953 *	0.440	-1.525 ***	0.451	-2.777 ***	0.677	-4.692 ***	1.015	-20.754 ***	1.283
Black	-0.462	0.960	-13.908 **	4.329	-16.835 ***	1.697	4.753 ***	1.414	1.416	1.062
Child age	0.128 *	0.056	-0.202 **	0.067	-0.064	0.092	-0.094 ***	0.020	0.018	0.023
Low	-3.879 ***	0.600	2.940 ***	0.489	0.461	0.729	0.818	1.192	14.618 ***	1.775
Moderate	-4.141 ***	0.727	-0.109	0.520	3.898 ***	0.719	0.939	1.167	-0.271	—
High	-10.862 ***	1.268	-0.226	0.727	-0.111	0.912	6.093 ***	1.140	14.721 ***	0.838
Extreme	—	—	-17.056 ***	4.585	-2.109	1.645	3.756 **	1.378	20.219 ***	1.540
Black × age	0.075	0.107	1.078 **	0.328	0.088	0.100	-0.232 *	0.118	-0.030	0.049
Age × low	-0.236 ***	0.070	0.283 ***	0.068	0.001	0.096	0.042	0.067	-0.097	—
Age × moderate	-0.308 ***	0.088	0.125	0.071	0.158	0.096	0.078	0.061	-0.012	—
Age × high	0.236 **	0.076	0.097	0.097	0.089	0.110	0.107 *	0.047	0.123 ***	0.036
Age × extreme	—	—	0.178	0.391	0.286 *	0.120	0.069	0.083	-0.041	0.109
Black × low	-0.044	1.545	15.294 ***	4.374	15.362 ***	1.879	-5.043 **	1.881	—	—
Black × moderate	-1.811	1.515	13.208 **	4.436	16.324 ***	1.744	-2.528	1.632	15.850	—
Black × high	—	—	12.454 **	4.447	17.182 ***	1.835	-5.274 ***	1.525	1.921	—
Black × extreme	—	—	30.597	—	18.962	—	-5.430 **	1.805	-0.972	1.408
Black × age × low	-0.043	0.117	-1.216 ***	0.332	0.054	0.122	0.355 *	0.169	—	—
Black × age × moderate	-0.028	0.129	-1.062 **	0.339	-0.058	0.110	0.056	0.153	0.038	—
Black × age × high	—	—	-1.062 **	0.344	-0.058	0.117	0.258 *	0.126	-0.295 **	0.104
Black × age × extreme	—	—	-1.714	—	-0.522	—	0.217	0.148	0.167	0.123
Log family income	0.305 **	0.098	0.128 *	0.055	-0.105	0.057	-0.051	0.070	0.053	0.121
Schooling	0.148 *	0.067	0.091 **	0.033	-0.139 ***	0.035	0.011	0.044	-0.020	0.084
One worker	-0.490	0.756	-0.236	0.541	0.625	0.447	-0.109	0.387	-0.265	0.602
Two workers	-0.090	0.829	-0.093	0.597	0.213	0.533	0.084	0.586	-1.699	1.207
Owns home	1.260 *	0.520	-0.503	0.274	0.031	0.287	0.224	0.390	-0.948	0.555
Married/cohabiting	-1.362 *	0.578	0.169	0.325	0.635	0.371	-0.577	0.443	0.523	0.699
Head age	0.005	0.022	0.010	0.015	-0.013	0.015	0.010	0.015	-0.043	0.023

Table A4. Coefficients and Standard Errors from Logistic Regressions of Neighborhood Poverty Type in 2001 on Race, Child Age, Neighborhood Poverty Type in 1999, and Neighborhood Covariates: PSID Children, 1999 to 2001

	Neighborhood poverty type									
	Affluent (less than 3%)		Low poverty (3% to 10%)		Moderate poverty (10% to 20%)		High poverty (20% to 40%)		Extreme poverty (40% or greater)	
Model/parameters	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	0.872*	0.441	-1.577***	0.455	-2.587***	0.736	-4.789***	1.058	-19.005***	1.016
Black	-0.871	1.038	2.940***	0.481	0.350	0.764	0.872	1.209	13.663	—
Child age	0.159**	0.053	-10.145**	3.147	-15.681***	1.695	4.532**	1.411	-0.117	1.177
Low	-3.599***	0.519	0.013	0.531	3.712***	0.773	0.887	1.218	-0.055	—
Moderate	-3.961***	0.696	-0.346	0.784	0.444	0.959	5.885***	1.171	14.276***	1.495
High	-10.951***	1.512	-16.542***	3.309	-1.720	1.572	3.690**	1.335	20.162***	1.475
Extreme	—	—	0.802**	0.246	0.083	0.067	-0.185	0.096	0.005	0.085
Black × age	0.049	0.108	0.273***	0.068	0.022	0.100	0.037	0.066	-0.132	0.092
Age × low	-0.244***	0.069	0.118	0.071	0.174	0.100	0.069	0.061	-0.004	—
Age × moderate	-0.306***	0.086	0.104	0.098	0.076	0.113	0.106*	0.048	0.069	0.091
Age × high	0.221**	0.079	0.197	0.282	0.337**	0.123	0.053	0.094	-0.077	0.127
Age × extreme	—	—	11.321***	3.190	14.682***	1.814	-4.920**	1.872	—	—
Black × low	0.010	1.515	9.422**	3.214	15.356***	1.706	-2.288	1.617	16.340	—
Black × moderate	-1.681	1.528	9.031**	3.258	15.672***	1.810	-5.033***	1.508	3.109	1.699
Black × high	—	—	26.662	—	17.700	—	-5.364**	1.723	-0.567	1.669
Black × extreme	—	—	-0.933***	0.254	0.064	—	0.294	0.153	—	—
Black × age × low	-0.030	0.126	-0.787**	0.260	-0.031	0.084	0.000	0.138	-0.045	—
Black × age × moderate	-0.014	0.135	-0.804**	0.268	-0.020	0.098	0.205	0.115	-0.299	—
Black × age × high	—	—	-1.459	—	-0.523***	0.113	0.179	0.144	0.152	0.133
Black × age × extreme	—	—	0.002	0.013	0.004	0.010	-0.014	0.010	0.007	0.021
% Black	-0.001	0.023	0.007	0.013	0.011	0.013	-0.025	0.013	0.001	0.022
% White	0.000	0.024	-0.125	0.323	0.420	0.299	-0.378	0.391	-0.282	0.920
Central city	0.236	0.477	-0.584*	0.241	0.603*	0.248	0.228	0.417	0.168	0.963
Nonmetro	-1.042	0.609	-1.577***	0.455	-2.587***	0.736	-4.789***	1.058	-19.005***	1.016

Notes : N = 5,506. Variables in italics have been centered around their means. — = parameter not estimated due to multicollinearity. * $p < .01$; ** $p < .01$; $^{\cdot}$ $p < .001$, two-tailed tests.

Table A5. Coefficients and Standard Errors from Logistic Regressions of Neighborhood Poverty Type in 2001 on Race, Child Age, Neighborhood Poverty Type in 1999, and Household and Neighborhood Covariates: PSID Children, 1999 to 2001

	Neighborhood poverty type									
	Affluent (less than 3%)		Low poverty (3% to 10%)		Moderate poverty (10% to 20%)		High poverty (20% to 40%)		Extreme poverty (40% or greater)	
Model/parameters	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	0.757	0.482	-1.687 ***	0.467	-2.700 ***	0.703	-4.641 ***	1.070	-21.501 ***	1.194
Black	-0.328	1.022	-13.751 **	4.429	-16.637 ***	1.845	4.456 **	1.428	1.391	1.397
Child age	0.131 *	0.055	-0.201 **	0.066	-0.067	0.094	-0.091 ***	0.022	0.015	0.022
Low	-3.847 ***	0.573	3.033 ***	0.486	0.337	0.738	0.849	1.220	15.338	—
Moderate	-3.947 ***	0.755	0.099	0.536	3.726 ***	0.742	0.848	1.235	-0.383	1.796
High	-10.876 ***	1.551	0.004	0.783	-0.069	0.958	5.849 ***	1.227	15.528 ***	1.520
Extreme	—	—	-16.817	—	-2.319	1.713	3.504 *	1.421	21.233 ***	1.614
Black × age	0.066	0.104	1.075 **	0.333	0.068	0.109	-0.191	0.100	0.047	0.046
Age × low	-0.235 ***	0.070	0.284 ***	0.068	-0.002	0.097	0.039	0.067	-0.099	—
Age × moderate	-0.303 ***	0.089	0.127	0.071	0.158	0.097	0.074	0.061	-0.010	—
Age × high	0.250 **	0.081	0.101	0.096	0.085	0.110	0.110 *	0.049	0.132 ***	0.037
Age × extreme	—	—	0.183	0.397	0.310 *	0.128	0.064	0.087	-0.037	0.100
Black × low	0.005	1.571	15.150 ***	4.431	15.390 ***	1.987	-4.988 **	1.895	—	—
Black × moderate	-1.811	1.530	13.120 **	4.487	16.325 ***	1.830	-2.426	1.639	16.622	—
Black × high	—	—	12.384 **	4.517	17.112 ***	1.914	-5.063 ***	1.533	2.001	—
Black × extreme	—	—	30.628 ***	4.633	19.097	—	-5.339 **	1.778	-1.276	1.251
Black × age × low	-0.040	0.120	-1.216 ***	0.338	0.084	0.131	0.308 *	0.156	—	—
Black × age × moderate	-0.025	0.132	-1.065 **	0.346	-0.017	0.120	0.009	0.142	-0.038	—
Black × age × high	—	—	-1.065 **	0.347	-0.035	0.123	0.214	0.116	-0.388 ***	0.104
Black × age × extreme	—	—	-1.716	—	-0.517	—	0.178	0.136	0.096	0.116

Table A5. (cont'd) **Coefficients and Standard Errors from Logistic Regressions of Neighborhood Poverty Type in 2001 on Race, Child Age, Neighborhood Poverty Type in 1999, and Household and Neighborhood Covariates: PSID Children, 1999 to 2001**

	Neighborhood poverty type									
	Affluent (less than 3%)		Low poverty (3% to 10%)		Moderate poverty (10% to 20%)		High poverty (20% to 40%)		Extreme poverty (40% or greater)	
Model/parameters	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Log family income	0.306 **	0.101	0.127 *	0.058	-0.093	0.058	-0.068	0.067	0.048	0.124
Schooling	0.131	0.068	0.085 *	0.034	-0.144 ***	0.036	0.031	0.047	-0.034	0.079
One worker	-0.479	0.781	-0.228	0.550	0.597	0.463	-0.013	0.375	-0.290	0.608
Two workers	-0.072	0.857	-0.064	0.611	0.121	0.551	0.252	0.554	-1.667	1.232
Owns home	1.285 *	0.529	-0.512	0.279	-0.033	0.286	0.231	0.379	-1.077	0.565
Married/cohabiting	-1.366 *	0.585	0.155	0.331	0.617	0.371	-0.602	0.456	0.495	0.652
Head age	0.001	0.023	0.008	0.015	-0.009	0.015	0.008	0.015	-0.042	0.024
% Black	-0.011	0.033	0.003	0.013	0.008	0.010	-0.015	0.010	0.012	0.022
% White	-0.003	0.034	0.006	0.014	0.016	0.013	-0.025 *	0.013	0.010	0.022
Central city	0.250	0.515	-0.095	0.332	0.473	0.300	-0.428	0.373	-0.425	0.832
Nonmetro	-0.829	0.626	-0.508 *	0.249	0.557 *	0.257	0.188	0.413	0.158	0.840

Notes : N = 5,506. Variables in italics have been centered around their means. — = parameter not estimated due to multicollinearity. * p < .01; ** p < .01; *** p < .001, two-tailed tests.