2005

Childhood and Adolescent Neighborhood Effects on Adult Income: Using Siblings to Examine Differences in Ordinary Least Squares and Fixed-Effect Models

Thomas P. Vartanian
Bryn Mawr College, tvartani@brynmawr.edu

P. W. Buck

Custom Citation
Vartanian, Thomas P. and Page Walker Buck. "Childhood and Adolescent Neighborhood Effects on Adult Income: Using Siblings to Examine Differences in Ordinary Least Squares and Fixed-Effect Models." *Social Service Review* 79 (2005): 60-94.

Childhood and Adolescent Neighborhood Effects on Adult Income: Using Siblings to Examine Differences in Ordinary Least Squares and Fixed-Effect Models

Thomas P. Vartanian
Bryn Mawr College

Page Walker Buck
Bryn Mawr College

Using sibling data from the Panel Study of Income Dynamics, this article examines the effects of child and adolescent neighborhood conditions on adult income. Estimates from fixed-effect models and ordinary least squares regression (OLS) models are compared at four stages of childhood development, with three important findings. First, OLS models that include extensive control variables do not necessarily overstate the effects of neighborhoods. Second, neighborhoods have both linear and nonlinear relationships with adult economic well-being. Third, neighborhoods exert effects on even the youngest children.

The effects of urban poverty and neighborhood characteristics on children and adolescents have been the subject of increased interdisciplinary research since the publication of William Julius Wilson's *The Truly Disadvantaged* (1987). Many works test Wilson's hypothesis that growing up amid concentrated poverty has deleterious effects on children be-

Social Service Review (March 2005).

0037-7961/2005/7901-0004$10.00

cause of social isolation from role models, a lack of employment opportunities, and limited social networks. From a public policy perspective, the possible relations of neighborhood conditions to such individual outcomes as education, childbearing, income, and employment have implications for decisions on a range of public programs, including welfare, housing, education, and child care.

Empirical studies examining neighborhood effects vary greatly with respect to data, model specification, and findings. These variations make it difficult to draw broad conclusions about neighborhood effects. Donna Ginther, Robert Haveman, and Barbara Wolfe (2000) suggest that these disparities may result in part from differences in ways that studies address nonrandom selection of neighborhood and omitted variable bias. Families may move to neighborhoods for certain unobserved reasons, and this sorting process has the potential to bias results. The unobserved ways in which families both mediate and moderate neighborhood effects also have the potential to bias results. The question, therefore, is to what extent traditional regression analyses overestimate or underestimate neighborhood effects.

Although Tama Leventhal and Jeanne Brooks-Gunn's (2000) recent review of neighborhood literature proposes that neighborhood effects tend to account for 5–10 percent of the variance in child and adolescent developmental outcomes, the majority of the reviewed studies do not account for endogenous effects of neighborhood selection or unobserved parental characteristics. The literature also usually fails to address the timing of neighborhood effects across the developmental life span of children and adolescents (Ellen and Turner 1997). While most studies focus on the effect of neighborhood factors on adolescents, few look at the influence of neighborhoods in earlier stages of childhood.

This work studies a sample of siblings from the Panel Study of Income Dynamics (PSID), comparing estimates of neighborhood effects on adult income for ordinary least squares (OLS) and fixed-effect models. The fixed-effect models address issues of selection bias, endogenous membership, and omitted variable bias, minimizing the possibility that estimated long-term economic differences between individuals result merely from a prior sorting process or from unobserved sibling-invariant parental characteristics. This study examines the extent to which adult earnings are influenced by neighborhood factors at four different stages of development: early childhood, middle childhood, preadolescence, and adolescence.[1] The findings suggest that neighborhood effects are present even at the earliest stages of life.

Theoretical Issues of Neighborhood Studies

In considering the effects of neighborhoods on children and adolescents, this study examines three primary theoretical issues: the existing theories on the neighborhood effects, the factors that confound estimation, and the timing of neighborhood effects. Included in this discussion are issues of how the different neighborhood theories relate to statistical models, differences between OLS and other types of statistical models, and how neighborhoods may differentially affect children and adolescents.

Neighborhood Theories

Christopher Jencks and Susan Mayer (1990) extend Wilson's work with an influential review suggesting that there are six primary theoretical mechanisms to describe how neighborhoods may affect individual outcomes: the collective socialization theory, the social isolation theory, the epidemic theory, the competition theory, the relative deprivation theory, and the institutional resources theory. For more than a decade, these theories have been the bases for numerous studies on children and youth (Crane 1991; Brooks-Gunn et al. 1993; Aaronson 1998; Plotnick and Hoffman 1999; Vartanian 1999).

Three neighborhood theories that combine aspects of those mentioned by Jencks and Mayer (1990) are primarily of interest here. The first of these, referred to in this study as the neighborhood advantage theory, suggests that the more advantaged the conditions in a neighborhood, the better the likelihood that children growing up in that neighborhood do well as adults. This theory combines elements of the collective socialization theory, the social isolation theory, and the neighborhood institutional resource theory. Those three theories posit that children and adolescents are influenced by neighborhood role models and institutional resources available to them (Jencks and Mayer 1990). The more positive role models and the more abundant the institutional resources, such as programming at schools, libraries, playgrounds, and churches, the more likely children will be exposed to, and learn from, those resources around them (Wilson 1987; Ellen and Turner 1997; Leventhal and Brooks-Gunn 2000). Conversely, children who are socially isolated from positive role models and community resources while living in disadvantaged neighborhoods will fare worse. Evidence for the neighborhood advantage theory will be found when the linear effects of living in advantaged neighborhoods lead to positive outcomes.

The second theory is the relative deprivation theory. While the neighborhood advantage theory predicts that gainfully employed neighbors will ultimately positively influence economic outcomes, the relative deprivation theory suggests the potential for an opposite effect. This theory suggests that, given the importance of the perception of disadvantage, the effects of living among neighbors with higher socioeconomic standing are negative (Jencks and Mayer 1990). Evidence for the relative deprivation theory will be found when the effects of living in advantaged neighborhoods lead to negative outcomes.

The third neighborhood theory considered here is the epidemic theory. Initially proposed by Wilson (1987), it is supported by Jonathan Crane's (1991) finding that a certain type of disadvantaged neighborhood, described as a ghetto, develops when a neighborhood experiences a high incidence, or epidemic, of social problems. Crane theorizes that neighborhood effects are spread in a contagious and volatile manner when critical levels of social problems are reached. This primarily results from a loss of beneficial social networks and jobs (Jencks and Mayer 1990; Crane 1991). To address the epidemic theory, neighborhood studies must include variables that allow for nonlinear neighborhood effects.

Greg Duncan, James Connell, and Pamela Klebanov (1997) use nonlinear spline models with a PSID sample to examine the effects of high socioeconomic status (SES) neighbors on adolescent outcomes.[2] They find evidence of significant threshold effects of high SES neighborhoods for young African American males and females and for white females. There is also support for the epidemic theory in subsequent studies (Vartanian 1999; Galster, Quercia, and Cortes 2000).

Factors That Confound Estimation

The estimation of neighborhood effects is confounded by three primary issues: simultaneity, omitted variable bias, and endogenous membership (Leventhal and Brooks-Gunn 2000; Duncan and Raudenbush 2001; Dietz 2002). Simultaneity refers to the exogenous and endogenous social interactions that presumably occur among individuals, families, and their neighborhoods: people influence their neighborhoods and vice versa (Duncan et al. 1997). These transactional relationships are difficult to estimate, presenting empirical challenges to any neighborhood research (Duncan and Raudenbush 2001).

Omitted variable bias occurs when a study lacks important information because of data set constraints (Leventhal and Brooks-Gunn 2000). Selection bias occurs when study participants, instead of being randomly assigned to neighborhoods, choose them for unmeasured reasons (Duncan et al. 1997). This type of bias becomes an endogenous membership problem when the unmeasured parental characteristics that influence neighborhood choice are correlated with the dependent variables, exerting either upward or downward bias on the neighborhood effects (Duncan and Raudenbush 2001).

Researchers argue that OLS regression models produce biased estimates because they cannot address omitted variable bias and endogenous membership problems, although the evidence is inconclusive. In a study using child development data, Duncan and colleagues (1997) show that models that include typically unmeasured parental characteristics, such as the level of home warmth, the level of depression, and the level of social support, do not show significantly different neighborhood effects from conventional models that include controls for family and individual characteristics. They further test neighborhood effects by using an instrumental variable with the PSID and again find that OLS estimates do not overstate neighborhood effects. Ginther and colleagues (2000) dispute this assumption. They demonstrate bias in a study that tests the robustness of estimates for youth outcomes in four different OLS models. Moving from a basic OLS model to a model that includes an extensive set of control variables, the researchers find that estimates of neighborhood effects change greatly. They suggest that to be truly confident of neighborhood effects, model specifications must be "comprehensive in describing the full range of family and individual background" factors (Ginther et al. 2000, 633). The presumption seems to be that even reasonably extensive multivariate OLS models cannot feasibly control for all correlated background characteristics.

To assess the potential bias in estimates of neighborhood effects, scholars suggest the use of instrumental variable and fixed-effect models (Ellen and Turner 1997; Leventhal and Brooks-Gunn 2000; Duncan and Raudenbush 2001). Instrumental variable models use a two-stage regression in which the endogenous variables, in this case neighborhood characteristics, are regressed on one or more predictor variables. These predictor variables are theoretically highly correlated with the neighborhood characteristics but uncorrelated with unobservable family factors. The predicted, or instrumented, values for the neighborhood characteristics are then used in second stage regressions to provide presumably unbiased estimates. However, because of the difficulty in identifying predictor variables that are uncorrelated with the error term, results are often questionable (Dietz 2002).

Fixed-effect models address issues of bias by using residential migration and changes in neighborhood conditions to compare siblings while holding sibling-invariant unobserved family characteristics constant, or fixed (Plotnick and Hoffman 1995, 1999; Aaronson 1998). However, studies that employ these methods show contradictory results. Robert Plotnick and Saul Hoffman (1999) use OLS and fixed-effect models to estimate the effect of neighborhood conditions on income, postsecondary education, and nonmarital births for sister pairs in the PSID. They find that neighborhood effects decline significantly when moving from zero-order to multivariate OLS models and become statistically insignificant in fixed-effect models. Daniel Aaronson (1998) disputes Plotnick and Hoffman's (1995) findings, citing the small size of their sample and the limited range of observation (ages 16–18). Aaronson's analysis of the PSID finds that effects of neighborhood characteristics on educational outcomes are statistically significant in both OLS and fixed-effect models and are sometimes even larger in the fixed-effect models than in the OLS models. Similarly, Dan Levy and Duncan (2000) find that the effects of family income on educational outcomes are robust in a fixed-effect sibling model.

Fixed-effect models with sibling samples, however, are not a panacea for dealing with endogeneity. First, they may produce another type of selection bias, as they require analyzing families with more than one child. This may sort families by cultural and class backgrounds. These models also do not account for unobserved sibling heterogeneity, such as individual ability and ambition, or the effect of age differentials on the experience within the family (Ellen and Turner 1997; Aaronson 1998). In addition, fixed-effect models are vulnerable to endogenous effects, in the sense that the reasons that a family chooses a neighborhood may be related to factors that affect their children's development (Duncan and Raudenbush 2001). Also, fixed-effect models do not control for unobservable, varying parental characteristics (Levy and Duncan 2000). For example, many data sets do not contain information on parental emotional states. Such states may change over time and, therefore, may differentially affect child outcomes or neighborhood choice. More simply, parents may treat children differently for unobserved reasons, and fixed-effect models do not control for these differences.

Timing of Neighborhood Effects

Another issue to consider is the potential that neighborhoods have differential effects on children at each stage of development. While there are differing opinions as to exactly when these stages begin and end, the child development literature supports the theory that children undergo different stages of cognitive, emotional, and behavioral growth (Berk 2003). During these stages, the influences of parents, peers, and neighborhoods vary. The general presumption is that parental influence is greatest during early childhood, while other influences, such as neighborhoods, peers, and schools, have a greater effect on children as they grow older and are involved in schools and community activities (Erikson 1997). However, it is also plausible that neighborhoods exert indirect effects on young children through the experiences of their parents in the neighborhood (Wheaton and Clarke 2003). For example, research shows that the level of community resources available to parents is significantly and positively related to the quality of the home environment for children (Voydanoff and Donnelly 1998). Quality home environment, in turn, is an important factor in the overall well-being of children (Parcel and Menaghan 1994). These community resources exist in both formal and informal ways, constituting a form of parenting capital that is typically more available in advantaged neighborhoods. Parents in middle-class neighborhoods tend to have better access to community resources for everything from children's health care and nutritional needs to library reading programs and informal playground networks. Parents in disadvantaged neighborhoods may lack access to such parenting capital. They may also often suffer from the physical and emotional stresses that result from high crime rates and neighborhood blight. Moreover, the children of parents in disadvantaged neighborhoods may be more susceptible to parental stress at younger ages, given a lack of other mediating factors such as peers and school (Wheaton and Clarke 2003).

Studies that explore the timing of neighborhood effects have focused primarily on adolescents, apparently assuming that teenagers are more likely to be directly influenced by the world around them than are younger children (Plotnick and Hoffman 1999; Vartanian 1999). The bulk of this literature suggests that teenagers' decisions about schooling, employment, childbearing, and crime are significantly influenced by neighborhood factors. There are surprisingly few studies of elementary school-age children, despite the rich social dynamics that occur in this stage of a child's life with the introduction of friends, teachers, and classmates (Ellen and Turner 1997). Even less research examines the effects of residential choice on infants and preschoolers. This is due, in part, to the theory that neighborhood effects are either lagged or cumulative and, thus, do not appear in children until early adolescence (Wheaton and Clarke 2003).

Two recent studies examine the timing effects of family income (Duncan et al. 1998; Levy and Duncan 2000). Findings from Duncan and colleagues (1998) suggest that in predicting educational outcomes and fertility rates, family income in the earliest stages of childhood is more significant than income in other stages, and more so for children of low-income families. The authors argue that children who are in poverty in early childhood are more likely to perform poorly in school from the start and are thus at early risk for poor academic performance later in childhood. These results are robust across specifications, including sibling models.

In a study of the impact of stage-specific family income on completed years of schooling, Levy and Duncan (2000) also examine different stages of childhood. Using a fixed-effect model with four stages of childhood (ages 0–4, 5–8, 9–12, and 13–16 years), they are also able to show that family income has a statistically significant positive effect on educational outcomes during the first stage. Levy and Duncan posit that while family income during the earliest years of life may have a greater effect on adult outcomes than does family income at other stages of development; other factors, such as schools, peer groups, and neighborhoods, may have a greater influence on adult outcomes during later stages of childhood.

In sum, the current work follows the work of Levy and Duncan (2000) in examining childhood factors that may affect adult outcomes at different stages of children's lives. It predicts the adult family income-to-needs ratio using both OLS and fixed-effect siblings models and takes into account the potential nonlinearities of neighborhood effects through the use of spline models.

Methods

In this work, OLS and fixed-effect models are compared. Statistically speaking, the general form for determining neighborhood effects in OLS models is

$$Y_i = \alpha + \beta_1 \mathrm{FP}_i + \beta_2 \mathrm{FIV}_i + \gamma N_i + \mu_i,$$

where FP is the set of permanent family variables; FIV is the set of varying family and individual variables; N is the set of neighborhood variables; μ is the error term; β_1, β_2, and γ are the coefficients for the permanent family, varying family and individual, and neighborhood variables, respectively; and α is the intercept.

A fixed-effect model is better able to control for differences among families than OLS models. The fixed-effect model takes on the following form:

$$Y_{ij} = \alpha_j + \beta_1 \mathrm{FP}_j + \beta_2 \mathrm{FIV}_{ij} + \gamma N_{ij} + \mu_{ij},$$

where i denotes the individual child and j denotes the child's family. The constant now takes on family-specific value. Having a different constant value for each family provides a control for those factors that are permanent features of families or that are present in the family for each of the children being examined but are not explicitly examined in the statistical model. Such uncontrolled factors in the models may include family values or aspirations for the children of the family, parental skills not captured by educational variables included in the models, or the emotional well-being of the parents.

As Levy and Duncan (2000) and others (Aaronson 1998; Plotnick and Hoffman 1999) note, there are permanent components and variable components to family characteristics. The family fixed effect gets differenced out (i.e., held constant) in fixed-effect models. One example is the effect of parental intelligence. Varying family effects (such as those of income) remain because such effects will be different for each child. Thus, the fixed-effect model does not allow control of unobserved family variables that vary over children but does allow control for variables that are unobserved and are more permanent or the same across children. These unobserved permanent family variables may bias the comparable OLS estimates.

In fixed-effect models, sibling differences in unobserved family characteristics bias the key coefficients only if such differences affect the dependent variable (in this case, the log of the family income-to-needs ratio as an adult) and are correlated with sibling differences in the characteristics of the neighborhood. These unobserved variables among siblings include ability, ambition, and parental expectations (Aaronson 1998). As Aaronson points out, parents may learn how to parent better in caring for subsequent children and, thus, may choose better neighborhoods (e.g., for better schools) with each additional child. Thus, younger children may benefit from this parental learning, biasing the estimates. Also, if parents favor one child over another, the family may move to a neighborhood with better schools and other such characteristics when the favored child starts attending school. If parents favor that child in other ways (hiring tutors, giving more homework help) that are unobserved, the effects of all of these factors will be attributed to the neighborhood conditions. Like Aaronson (1998), the current article includes controls for birth order of children and, thus, explicitly controls for possible better parenting for subsequent children. However, other unobserved variables may still affect children differently and may be reflected in the neighborhoods where they live. In addition, the PSID does not contain enough information to distinguish between biological and nonbiological siblings in all cases. Thus, fixed-effect models cannot control for these differential and unobservable family factors. Accordingly, caution must be used in interpreting the estimates from the fixed-effect models.

The fixed-effect model takes the following form:

$$Y_{ij} - Y_{.j} = (\alpha_j - \alpha_j) + \beta_1(\mathrm{FP}_j - \mathrm{FP}_{.j}) + B_2(\mathrm{FIV}_{ij} - \mathrm{FIV}_{.j}) + \gamma(N_{ij} - N_{.j}) + (\mu_{ij} - \mu_{.j}).$$

The constant and the permanent family factors drop out of the equation. Also in this equation, the term $(\mathrm{FIV}_{ij} - \mathrm{FIV}_{.j})$, as well as the other subtractions of $.j$, indicate that overall mean family values are subtracted from individual values for both independent and dependent variables. In the current model, the dependent variable is the log of the average family income-to-needs ratio when the child becomes an adult and is at least 25 years old. The family income-to-needs ratio is a measure of income relative to the poverty line that adjusts for family size. The value of this variable is averaged over all years when the individual is 25 years or older. This fixed-effect model is estimated by regressing the differences in sibling outcomes on the differences in their observed family, neighborhood, and other variables.

Both OLS regression analysis and the fixed-effect models are used to examine the dependent variable: the log of family income-to-needs as an adult.[3] Ordinary least squares models are used as comparisons to the fixed-effect models to determine whether using OLS modeling produces large differences in the coefficient estimates for the neighborhood and other variables relative to the fixed-effect models. Bivariate and multivariate models that control for a number of family and individual factors during childhood are used to determine whether the independent effects of family-varying variables affect the relationship between neighborhood variables and the dependent variable. A set of models also controls for a number of adult factors, such as marital status, area of residence, and family size. The multivariate fixed-effect models do not explicitly control for permanent parental variables, such as level of education for the head of household, race, and region of residence, because only variables that vary across siblings can have nonzero values.[4]

Data and Variables

The data stem from the PSID, a nationally representative data set that began with interviews of approximately 5,000 families in 1968. The heads of the original households have been interviewed every year since 1968, as have the heads of households containing members who were part of one of the original households (in 1968) and who have since left those households to join others or to start ones of their own. Among the original households, the poor and African Americans were oversampled.[5] This work uses sample waves through 2001.

A secondary source of data is the PSID Geocode File, which allows for the linking of census data with PSID respondents. Census data are the source of information on the characteristics of PSID respondents' neighborhoods, operationally defined as their census tracts.[6] This file contains 1970, 1980, and 1990 census data on factors such as the poverty rate, the proportion of female-headed households, and the proportion of households receiving public assistance income, for the census tract in which each PSID respondent lived during each year of the survey.

Four separate samples are used to examine the effects of neighborhood and other variables at different stages of children's lives. Following Levy and Duncan (2000), age categories are split into four groups. Here, the age categories used are 0–4, 5–8, 9–13, and 14–18 years.[7] These categories correspond with rough estimates of early childhood, middle childhood, preadolescence, and adolescence (Levy and Duncan 2000). In order to be considered siblings, children were required to pass through the same stage of development during the sample period.[8] For example, if two children enter the sample at ages 9 and 14, they will only be treated as siblings in the 14–18-year-old category, assuming that they both pass through this adolescent period. Like Plotnick and Hoffman (1999), the current study uses childhood information up to age 18. Unlike the categories of Levy and Duncan (2000) and Ginther and colleagues (2000), each of these categories is used as a separate sample, instead of including variables that indicate conditions of the child during each of these periods within a single sample. While using separate samples for the different age categories provides less information on the effects of neighborhoods and other variables throughout childhood, this approach allows for larger sample sizes (and thus more precise measurement) in the older age categories than those approaches using a single sample.[9] To the degree that neighborhood conditions at different age categories are correlated with one another, standard errors are lower in these models compared with those that use a single model that examines neighborhood conditions over these different age categories. However, the shorter time frame for examining childhood conditions may mean less variation of these childhood conditions within families for families that do not move or whose neighborhood conditions change little over time. Also, for those in the older age categories, the models will determine stage-specific neighborhood effects that may include indirect neighborhood effects from previous periods because of the high correlation with neighborhood conditions in previous stages.

The analyzed samples consist of all PSID respondents who were born in any year between 1968 and 1976, were age 5 between 1968 and 1981, were age 9 between 1968 and 1985, and were age 14 between 1968 and 1990. The sample consists of 1,660 observations for the 0–4 age group, with 831 of these observations coming from families with at least one sibling in the sample. There are 2,683 observations and 1,723 siblings in the 5–8 age group. There are 3,818 total children and 2,795 siblings in the 9–13 age group. There are 4,949 observations and 3,961 observations with siblings in this sample in the 14–18 age group.[10]

These children are examined for either 4 or 5 years to identify individual, family, and neighborhood characteristics. The characteristics over these time periods are averaged. These children are also examined when they become adults and are at least 25 years old to determine their average family income relative to the poverty line and a number of other adult characteristics. These adult characteristics are averaged over the entire span of their adult lives.

Models essentially predict average adult family income-to-needs ratios by childhood neighborhood characteristics. To account for differences in the time span for earnings and for greater ability to gain experience in the workforce, there is a control for the maximum age of the individual. A quadratic age variable is also used. In subsequent models, there are controls for other adult variables, such as education level, area of residence, marital status, and family size.

A number of neighborhood variables are included in the analysis. Because of the high level of collinearity among them, only single neighborhood variables, or sets of neighborhood variables, are included in separate models.[11] These variables include the percentage in poverty, the percentage of households receiving public assistance income, the percentage of households headed by females, the percentage of households with income below $15,000 (in 2001 dollars), the percentage of households with income above $60,000 (in 2001 dollars), the percentage of households with income above the respondent's average family income, and the percentage of households with income at the same level as the respondent's average family income.[12] These types of neighborhood variables have been used by previous researchers to reflect the conditions of the neighborhood (Plotnick and Hoffman 1999; Ginther et al. 2000).

To serve as summary indicators of neighborhood quality, two composite variables are created through principal components analysis. These are a neighborhood quality index and an index of the proportion of residents in the neighborhood with higher, lower, or the same levels of income as the respondent. Each of the variables takes into account information from the seven neighborhood variables. Details of the construction of the neighborhood quality index are shown in appendix table A1. High-quality neighborhoods have a high proportion of residents with high income, a low proportion of residents with low income, a low poverty rate, and primarily two-parent households.

Nonlinear neighborhood effects are examined through regressions that include splines for the first neighborhood index variable. Spline regressions fit a regression equation into a series of linear segments. Each segment may have a different slope (Galster et al. 2000; Marsh and Cormier 2001). The significance levels for the spline variable coefficients indicate whether the slope for the particular segment is different from the previous segment. The somewhat arbitrary cutoff points are set at the top 10 percent of neighborhoods, the 11th–25th percentiles, the 26th–50th percentiles, the 51st–75th percentiles, the 76th–90th percentiles, and the 90th–100th percentiles. Splines are also tested using cutoffs at the top 25th percentile, the 26th–75th percentiles, and the 76th–100th percentiles. There is evidence for the epidemic theory if the poorest neighborhoods (i.e., 90th–100th percentiles or the 76th–100th percentiles, respectively) have the most detrimental effects on future income.

Multivariate models include controls for factors such as area of residence, marital status, and birth order. In the first set of multivariate models, only childhood variables are included. In a second set of multivariate regressions, variables from the respondents' adult years are included in order to control for a number of personal, educational, and economic factors that are likely to affect the family income-to-needs ratio. See appendix table A2 for a complete list of control variables and the models in which they are used.

Childhood neighborhood characteristics might influence adult income directly or might influence adult outcomes indirectly through a preliminary impact on such outcomes as education or work experience (i.e., bad neighborhood characteristics lead to fewer years of education, which leads to lower income). Some models exclude adult variables to estimate the overall effects—direct and indirect—of neighborhood characteristics on adult income. Others include adult variables to estimate only the direct effects.

The dependent variable is the natural log of the respondent's average family income-to-needs ratio at age 25 and beyond.[13] This is a comprehensive measure of economic status that is equally applicable to men and women. In contrast, wage rates, labor income, and hours of work can be difficult to model for women, who sometimes have inconsistent work patterns when rearing young children.

The number of adult years of data varies across respondents. For example, if a child entered the 0–4 age sample in 1975, there are at most only 1 or 2 years of adult data. For those who were age 14 in 1968 and, thus, turned age 25 in 1979, there are potentially 22 years of adult data, depending on how long the person stays in the sample.

Results

Table 1 shows the within-family variation in the neighborhood and adult income variables for members of each of the age groups. The first column for each age group indicates the percentage of siblings that had within-family differences in each variable. The second column indicates the variables' mean differences and standard deviations for siblings. The third column indicates what percentage of the variance in the variable is accounted for by differences within the family.

Results show that the majority of families report some variation in their neighborhood variables but that the difference generally is not large. These differences tend to increase slightly with the age of the sample members. For example, the within-family difference in the percentage of families in poverty increases from 6.07 percent in the 0–4 age category to 6.98 percent in the 5–8 age category to 7.79 percent in the 9–13 age category and, finally, to 8.97 percent in the 14–18 age category.

Likewise, results suggest that only a small proportion of the total variance in any of the neighborhood conditions is explained by within-family differences. For example, in the 0–4 age group, only 5–13 percent of the total variance is explained by within-family differences. Results also show that within-family differences explain from 33–38 percent of the total variance in the log of the family income-to-needs ratio.

Regression Results

Table 2 shows the results of bivariate models for both the OLS and fixed-effect models. The top section of table 2 shows that all of the neighborhood variables are related to the log of the family income-to-needs ratio, all in the expected direction. The estimated relations stay about

Table 1

WITHIN-FAMILY VARIATION IN NEIGHBORHOOD CHARACTERISTICS AND INCOME AS AN ADULT

Neighborhood Characteristic and Adult Income	Ages 0–4			Ages 5–8		
	Within-Family Differences (%)	Mean Within-Family Differences (SD) for Those with Differences	Total Variance Explained by Within Variance (%)	Within-Family Differences (%)	Mean Within-Family Difference (SD) for Those with Differences	Total Variance Explained by Within Variance (%)
Female-headed families	83.2	1.64 (1.88)	5.79	79.2	2.02 (2.54)	7.26
In poverty	82.8	2.06 (2.46)	6.07	77.5	2.32 (3.05)	6.98
Households receiving public assistance	78.2	1.37 (1.68)	7.90	75.3	1.67 (2.62)	10.03
Household income < $15,000[a]	85.7	1.48 (1.83)	6.87	80.6	1.80 (2.58)	9.24
Household income > $60,000[a]	85.9	2.59 (2.88)	5.33	80.7	2.95 (3.44)	6.28
Income above respondent's	93.9	5.67 (5.64)	13.37	93.7	5.75 (5.60)	11.24
Income same as respondent's	93.5	1.15 (1.43)	12.15	93.7	1.33 (1.75)	14.19
Neighborhood index 1	93.9	.27 (.33)	4.97	93.8	.30 (.42)	6.26
Neighborhood index 2	93.9	.29 (.28)	11.21	93.8	.29 (.29)	12.58
Income as an adult[a,b]	100.0	13.20 (15.68)	36.37	100.0	13.42 (14.41)	35.41
Family income-to-needs ratio as an adult	100.0	.80 (1.04)	34.47	100.0	.79 (.88)	31.14
Log of family income-to-needs ratio as an adult	100.0	.33 (.42)	36.84	100.0	.35 (.38)	33.03
N	831			1,723		
	Ages 9–13			Ages 14–18		
Female-headed families	85.4	2.36 (3.19)	9.14	87.4	2.66 (3.35)	8.61
In poverty	84.4	2.50 (3.08)	7.79	86.9	2.66 (3.45)	8.97
Households receiving public assistance	81.0	1.87 (2.38)	10.09	83.9	2.03 (2.72)	10.68
Household income < $15,000[a]	88.3	1.93 (2.55)	9.94	90.7	2.07 (2.77)	11.03
Household income > $60,000[a]	88.3	3.12 (3.64)	7.00	90.7	3.38 (3.90)	7.79
Income above respondent's	96.2	6.14 (6.19)	13.07	98.0	6.69 (6.47)	14.71
Income same as respondent's	96.5	1.50 (1.85)	15.82	98.5	1.64 (2.01)	23.73
Neighborhood index 1	96.7	.33 (.43)	6.98	98.6	.34 (.46)	7.61
Neighborhood index 2	96.6	.29 (.31)	14.93	98.6	.32 (.35)	20.54
Income as an adult[a,b]	100.0	13.89 (14.53)	37.79	100.0	14.70 (15.58)	39.21
Family income-to-needs ratio as an adult	100.0	.79 (.85)	33.33	100.0	.83 (.88)	35.83
Log of family income-to-needs ratio as an adult	100.0	.35 (.39)	35.05	100.0	.36 (.39)	37.64
N	2,795			3,961		

[a] Income expressed in 2001 dollars.
[b] In thousands of dollars.

Table 2

Coefficient Estimates for OLS and Fixed-Effect Bivariate Models for the Natural Log of Family Income-to-Needs Ratio as an Adult

	Ages 0–4	Ages 5–8	Ages 9–13	Ages 14–18
OLS models:				
Female-headed families (%)	−.021 (.002)***	−.022 (.002)***	−.022 (.001)***	−.022 (.001)***
Households receiving public assistance income (%)	−.031 (.004)***	−.031 (.002)***	−.031 (.002)***	−.031 (.002)***
In poverty (%)	−.020 (.002)***	−.022 (.001)***	−.022 (.001)***	−.023 (.001)***
Household income < $15,000 (%)[a]	−2.667 (.279)***	−2.957 (.206)***	−2.832 (.171)***	−2.876 (.152)***
Household income > $60,000 (%)[a]	1.595 (.138)***	1.722 (.111)***	1.712 (.089)***	1.787 (.079)***
Income above respondent's income (%)	−.550 (.097)***	−1.001 (.084)***	−1.051 (.070)***	−1.136 (.060)***
Income same as respondent's (%)	1.536 (.390)***	1.768 (.318)***	1.677 (.234)***	1.159 (.229)***
Neighborhood index 1	.136 (.012)***	.154 (.009)***	.157 (.007)***	.164 (.007)***
Neighborhood index 2	−.087 (.015)***	−.163 (.017)***	−.169 (.015)***	−.158 (.013)***
Splines (% of neighborhood):				
Top 10	−.328 (.132)**	−.265 (.114)**	−.098 (.107)	−.109 (.120)
Top 11–25	−.195 (.068)**	−.228 (.049)***	−.351 (.042)***	−.347 (.036)***
Top 26–50	−.164 (.052)**	−.304 (.042)***	−.215 (.032)***	−.248 (.032)***
Top 51–75	−.111 (.048)*	.014 (.047)	−.068 (.035)*	−.008 (.031)
Top 76–90	−.187 (.119)	−.015 (.108)	−.222 (.101)*	−.242 (.090)**
Bottom 10	−.067 (.044)	−.096 (.031)**	−.031 (.028)	−.058 (.024)*
Log of family income-to-needs ratio	.514 (.033)***	.569 (.027)***	.549 (.023)***	.535 (.019)***
N	1,660	2,683	3,818	4,949
No. of groups	1,199	1,660	2,043	2,319
R^2 for neighborhood index models	.126	.179	.189	.200

Fixed-effect models:				
Female-headed families (%)	−.006 (.011)	−.001 (.006)	−.010 (.003)**	−.010 (.003)***
Households receiving public assistance income (%)	−.029 (.013)*	.001 (.007)	−.011 (.005)**	−.012 (.003)***
In poverty (%)	−.005 (.009)	.001 (.005)	−.006 (.003)+	−.008 (.003)**
Household income < $15,000 (%)[a]	−.745 (1.142)	−.555 (.571)	−.665 (.415)	−.576 (.313)+
Household income > $60,000 (%)[a]	1.084 (.691)	.543 (.396)	.224 (.277)	.622 (.209)**
Income above respondent's income (%)	.806 (.320)**	−.421 (.208)*	−.312 (.146)*	−.028 (.113)
Income same as respondent's (%)	1.470 (1.395)	1.663 (.759)*	.600 (.534)	.496 (.404)
Neighborhood index 1	.072 (.062)	.057 (.033)+	.074 (.024)**	.071 (.018)***
Neighborhood index 2	.067 (.066)	−.135 (.042)***	−.073 (.031)*	−.026 (.022)
Splines (% of neighborhood):				
Top 10	.091 (.719)	−.135 (.323)	−.230 (.261)	−.061 (.281)
Top 11–25	−.234 (.239)	−.251 (.168)	−.038 (.121)	−.181 (.091)*
Top 26–50	−.092 (.140)	−.149 (.094)	−.027 (.068)	.005 (.055)
Top 51–75	.105 (.101)	.010 (.063)	−.076 (.044)+	−.018 (.034)
Top 76–90	.467 (.337)	.100 (.188)	−.060 (.137)	−.145 (.110)
Bottom 10	−.468 (.166)**	.022 (.065)	−.079 (.049)	−.094 (.038)**
Log of family income-to-needs ratio	−.298 (.171)	.281 (.099)**	.079 (.066)	−.105 (.045)*
N	831	1,723	2,795	3,961
No. of groups	370	700	1,020	1,331
Average no. of observations per group	2.2	2.5	2.7	3.0
Within R^2 for neighborhood index models	.007	.012	.007	.006

NOTE.—OLS = ordinary least squares. Neighborhood index variables are determined through principal components analysis (see app. table A1). Generally, each coefficient and standard error in the table comes from a separate regression model. Neighborhood variables run in the same models include the two neighborhood index variables, income above respondent's income (%) and same income as respondent's (%), and the spline variables.

[a] Income expressed in 2001 dollars.

+ $p \leq .10$; all for two-tailed tests.

* $p \leq .05$.

** $p \leq .01$.

*** $p \leq .001$.

the same throughout childhood, except for the relations involving the percentage of neighbors with higher income levels; that percentage increases over the childhood years. The nonlinear splines show negative relations for those living in the bottom 10 percent of neighborhoods in the 5–8 and 14–18 age groups, and in the top 76–90 percentile for the 14–18 age group.

The results involving fixed-effect models generally are similar to those of the OLS models in terms of direction. However, standard errors typically are at least twice the level. Further, the size of the relations is smaller in the bivariate fixed-effect models. In the fixed-effect, but not OLS, model, there is no relation between the percentage in poverty and the percentage of households with household income under $15,000 in the neighborhood for the first two age categories. One variable that shows a larger relation to adult outcomes is the percentage of residents in the neighborhood with higher levels of income in the 0–4 age category. Yet, the coefficient estimate changes from positive in the 0–4 age category to negative in the 5–8 and 9–13 age categories.

Results involving the neighborhood index variables indicate that living in more prosperous neighborhoods (neighborhood index 1) increases the family income-to-needs ratio in all but the 0–4 age category, although the coefficient estimates are smaller than in the OLS model. In general, fixed-effect estimates for neighborhood index 1 are about half that for the OLS model for all of the age groups.

Multivariate Models

Table 3, which reports the multivariate analyses that control for a host of individual, family, and other factors, shows fewer statistically significant coefficients for neighborhood variables in the OLS models. This is in line with previous research (e.g., Ginther et al. 2000). However, the neighborhood coefficients in the fixed-effect models are now sometimes larger than in the OLS models. For example, the percentage of households with incomes below $15,000 in a neighborhood has a larger estimated effect for all the age categories (although the coefficients are not statistically significant for the first two age categories). The coefficient for the percentage of residents with higher incomes than the respondent's is especially large and positive in the 0–4 age category. It is statistically significant (at the .10 level) in the 9–13 age category, but negative. It is not statistically significant in the other age categories. These results suggest that living in neighborhoods with higher income residents has a positive effect on the income-to-needs ratio for the first 4 years of life and then has a negative effect later. Perhaps children cannot perceive their own disadvantage relative to that of neighbors until they reach a certain age. The estimated income-to-needs ratio advantage for parents of young children living among higher income neighbors may reflect the amount of parenting support they receive or the amount of parenting capital that is available in the neighborhood.

The table suggests that, in the fixed-effect models, the coefficient for the first neighborhood index variable is statistically significant for all age groups. In the 0–4 age category, a one-standard-deviation increase in neighborhood index 1 (indicating a higher economic status neighborhood) is modeled to increase the family income-to-needs ratio by approximately 18 percent. For the 9–13 age group, a one-standard-deviation increase in the first neighborhood index is modeled to lead to a 11 percent increase in the family income-to-needs ratio. A one-standard-deviation increase in the 14–18 age category is modeled to lead to a 9 percent increase in the family income-to-needs ratio (for means and standard deviations, see app. tables A3 and A4). While the relations are statistically significant over each of the models, the size of the effects decreases from the youngest group to the older age groups.

As shown in the spline regression results, there is some evidence for the epidemic theory in the fixed-effect models for the 9–13 and 14–18 age groups. For the bottom 10 percent category, the coefficient is negative and statistically significant at the .01 and .10 levels in the 0–4 and 14–18 age groups, respectively. In results not shown in the table, a three category spline model with cutoffs at the bottom and top 25th percentiles (0–25th percentiles, 25th–75th percentiles, and 75th–100th percentiles) shows that the coefficient for the segment living in the bottom 25th percentile is negative and statistically significant at the 5 percent level in both the 0–4 age group and the 14–18 age group.

Results in table 4, which reports models that add controls for adult characteristics, are similar to those in table 3. However, the coefficient estimates are again somewhat smaller. Similar to the results reported above, the coefficients for the first neighborhood index are larger in the fixed-effect than the OLS models in all of the age categories. They only are statistically significant in the last two age categories. While the coefficient estimates are less likely to be statistically significant in the fixed-effect models than in the OLS models, this is mainly because of the higher standard errors.

Given the linear and positive relationship between some of these neighborhood coefficients and adult income, results again provide some support for the neighborhood advantage theory. There is also some evidence supporting the epidemic theory. Table 4 shows that in the 0–4 age group, the spline coefficient for the bottom 10 percent on the first neighborhood index is statistically significant at the .01 level. This coefficient estimate is far larger than those in the OLS model. In results not shown in the table, spline models with cutoffs for the bottom 25 percent indicate negative and statistically significant coefficient estimates (at the .05 level for the 0–4 age group and at the .10 level for the 14–18 age group).

Table 3

Coefficient Estimates and Standard Errors for Multivariate Models for the Natural Log of Family Income-to-Needs Ratio as an Adult

	Ages 0–4	Ages 5–8	Ages 9–13	Ages 14–18
OLS models:				
Female-headed families (%)	−.002 (.003)	−.001 (.002)	−.003 (.002)+	−.005 (.001)***
Households receiving public assistance income (%)	−.009 (.004)*	−.005 (.003)+	−.004 (.002)	−.006 (.002)***
In poverty (%)	−.003 (.003)	−.003 (.002)+	−.004 (.001)**	−.005 (.001)***
Household income < $15,000 (%)[a]	−.643 (.342)+	−.646 (.246)**	−.444 (.187)*	−.555 (.166)***
Household income > $60,000 (%)[a]	.378 (.170)*	.335 (.137)**	.311 (.112)**	.442 (.098)***
Income above respondent's income (%)	.214 (.114)+	−.103 (.100)	−.222 (.083)**	−.255 (.070)***
Income same as respondent's (%)	−.102 (.397)	.591 (.311)+	.581 (.244)*	.184 (.228)
Neighborhood index 1	.023 (.016)	.038 (.012)***	.042 (.010)***	.049 (.009)***
Neighborhood index 2	.024 (.019)	−.046 (.017)**	−.064 (.016)***	−.049 (.013)***
Splines (% of neighborhood):				
Top 10	−.163 (.130)	−.098 (.111)	.004 (.115)	.033 (.128)
Top 11–25	−.021 (.062)	−.050 (.049)	−.137 (.041)***	−.096 (.036)**
Top 26–50	.008 (.054)	−.078 (.041)+	−.013 (.033)	−.069 (.029)*
Top 51–75	−.082 (.044)+	.018 (.041)	−.052 (.031)+	.018 (.028)
Top 76–90	.056 (.119)	.101 (.101)	−.085 (.091)	−.049 (.083)
Bottom 10	−.059 (.045)	−.048 (.031)	.015 (.027)	−.032 (.023)
Log of family income-to-needs ratio	.177 (.073)**	.296 (.043)***	.259 (.034)***	.292 (.029)***
N	1,660	2,683	3,818	4,949
No. of groups	1,199	1,660	2,043	2,319
R^2 for neighborhood index models	.242	.281	.284	.299

Fixed-effect models:				
Female-headed families (%)	−.004 (.013)	.001 (.006)	−.007 (.004)+	−.006 (.003)*
Households receiving public assistance income (%)	−.030 (.015)*	.002 (.007)	−.006 (.005)	−.008 (.004)*
In poverty (%)	−.010 (.009)	.001 (.005)	−.007 (.004)*	−.008 (.003)***
Household income < $15,000 (%)[a]	−1.912 (1.244)	−.810 (.615)	−.903 (.437)*	−.768 (.326)*
Household income > $60,000 (%)[a]	1.124 (.738)	.483 (.416)	.061 (.296)	.399 (.219)+
Income above respondent's income (%)	1.103 (.517)*	−.269 (.292)	−.332 (.193)+	−.063 (.132)
Income same as respondent's (%)	1.656 (1.639)	1.671 (.875)+	.412 (.613)	−.018 (.461)
Neighborhood index 1	.109 (.066)+	.059 (.036)+	.064 (.026)*	.054 (.019)**
Neighborhood index 2	.018 (.078)	−.118 (.044)**	−.066 (.033)*	−.010 (.023)
Splines (% of neighborhood):				
Top 10	.333 (.728)	−.215 (.331)	−.280 (.266)	.058 (.288)
Top 11–25	−.141 (.250)	−.183 (.172)	−.013 (.124)	−.121 (.093)
Top 26–50	−.111 (.146)	−.124 (.096)	−.011 (.069)	.015 (.055)
Top 51–75	.136 (.102)	.018 (.064)	−.082 (.044)+	−.019 (.034)
Top 76–90	.461 (.360)	.121 (.191)	−.040 (.139)	−.162 (.110)
Bottom 10	−.541 (.177)**	−.007 (.066)	−.068 (.051)	−.068 (.040)+
Log of family income-to-needs ratio	−.379 (.202)+	.284 (.120)*	.170 (.081)*	.008 (.060)
N	831	1,723	2,795	3,961
No. of groups	370	700	1,020	1,331
Average no. of observations per group	2.2	2.5	2.7	3.0
Within R^2 for neighborhood index models	.078	.052	.031	.027

Source.—Panel Study of Income Dynamics and the 1970, 1980, and 1990 censuses.

Note.—OLS = ordinary least squares. All models control for the full set of control variables (see the first two cols. of app. table A2 for a full list of variables included in each of the models). Neighborhood index variables are determined through principal components analysis (see app. table A1). Generally, each coefficient and standard error in the table comes from a separate regression model. Neighborhood variables run in the same models include the two neighborhood index variables, income above respondent's income (%) and same income as respondent's (%), and the spline variables.

[a] Income expressed in 2001 dollars.

+ $p \leq .10$; all for two-tailed tests.

* $p \leq .05$.

** $p \leq .01$.

*** $p \leq .001$.

Table 4

Coefficient Estimates and Standard Errors for Multivariate Models for the Natural Log of Family Income-to-Needs Ratio as an Adult, with Adult Variables Included

	Ages 0–4	Ages 5–8	Ages 9–13	Ages 14–18
OLS models:				
Female-headed families (%)	−.001 (.003)	.001 (.002)	−.002 (.001)	−.004 (.001)***
Households receiving public assistance income (%)	−.008 (.003)*	−.002 (.002)	−.001 (.002)	−.004 (.002)*
In poverty (%)	−.002 (.002)	−.002 (.002)	−.003 (.001)*	−.004 (.001)***
Household income < $15,000 (%)[a]	−.494 (.303)+	−.341 (.212)	−.320 (.155)*	−.409 (.143)**
Household income > $60,000 (%)[a]	.336 (.149)*	.195 (.117)+	.233 (.093)**	.334 (.082)***
Income above respondent's income (%)	.170 (.102)+	−.081 (.084)	−.157 (.068)*	−.178 (.057)**
Income same as respondent's (%)	−.183 (.355)	.289 (.266)	.292 (.203)	−.009 (.190)
Neighborhood index 1	.018 (.014)	.018 (.010)+	.028 (.008)***	.034 (.007)***
Neighborhood index 2	.023 (.017)	−.027 (.015)+	−.040 (.013)**	−.028 (.011)**
Splines (% of neighborhood):				
Top 10	−.175 (.108)+	−.027 (.093)	.039 (.092)	.025 (.102)
Top 11–25	−.003 (.056)	−.035 (.041)	−.087 (.034)**	−.050 (.030)+
Top 26–50	.005 (.051)	−.060 (.036)+	−.013 (.028)	−.062 (.025)**
Top 51–75	−.043 (.040)	.036 (.035)	−.027 (.027)	.005 (.024)
Top 76–90	.070 (.101)	.132 (.084)	−.067 (.077)	−.033 (.070)
Bottom 10	−.067 (.040)+	−.042 (.025)+	.012 (.022)	−.017 (.019)
Log of family income-to-needs ratio	.152 (.068)*	.231 (.037)***	.192 (.030)***	.224 (.024)***
N	1,660	2,683	3,818	4,949
No. of groups	1,199	1,660	2,043	2,319
R^2 for neighborhood index models	.380	.437	.444	.467

Fixed-effect models:				
Female-headed families (%)	−.005 (.012)	.004 (.006)	−.008 (.004)*	−.006 (.003)*
Households receiving public assistance income (%)	−.031 (.014)*	.004 (.007)	−.007 (.005)	−.005 (.003)
In poverty (%)	−.009 (.009)	.002 (.005)	−.008 (.003)**	−.006 (.002)**
Household income < $15,000 (%)[a]	−1.098 (1.187)	−.503 (.566)	−1.003 (.395)**	−.515 (.295)+
Household income > $60,000 (%)[a]	.920 (.701)	.347 (.383)	.244 (.268)	.321 (.198)+
Income above respondent's income (%)	.795 (.500)	−.160 (.268)	−.078 (.175)	−.037 (.120)
Income same as respondent's (%)	.513 (1.574)	.970 (.809)	.530 (.555)	.062 (.416)
Neighborhood index 1	.069 (.063)	.027 (.033)	.064 (.024)**	.040 (.018)*
Neighborhood index 2	.067 (.070)	−.071 (.041)+	−.039 (.030)	−.010 (.021)
Splines (% of neighborhood):				
Top 10	.518 (.696)	−.114 (.303)	−.257 (.240)	.050 (.260)
Top 11–25	−.079 (.238)	−.081 (.159)	−.036 (.112)	−.121 (.084)
Top 26–50	−.086 (.138)	−.141 (.088)	−.021 (.063)	−.001 (.050)
Top 51–75	.119 (.097)	.028 (.059)	−.060 (.040)	−.028 (.031)
Top 76–90	.577 (.341)+	.250 (.177)	−.147 (.125)	−.164 (.100)+
Bottom 10	−.556 (.168)***	−.017 (.061)	−.044 (.046)	−.023 (.036)
Log of family income-to-needs ratio	−.292 (.193)	.217 (.111)*	.132 (.073)+	−.015 (.055)
N	831	1,723	2,795	3,961
No. of groups	370	700	1,020	1,331
Average no. of observations per group	2.2	2.5	2.7	3.0
Within R^2 for neighborhood index models	.194	.214	.217	.209

Source.—Panel Study of Income Dynamics and the 1970, 1980, and 1990 censuses.

Note.—OLS = ordinary least squares. All models control for the full set of control variables (see the last two cols. of app. table A2 for a full list of variables included in each of the models). Neighborhood index variables are determined through principal components analysis (see app. table 1). Generally, each coefficient and standard error in the table comes from a separate regression model. Neighborhood variables run in the same models include the two neighborhood index variables, income above respondent's income (%) and same income as respondent's (%), and the spline variables.

[a] Income expressed in 2001 dollars.

+ $p \leq .10$; all for two-tailed tests.

* $p \leq .05$.

** $p \leq .01$.

*** $p \leq .001$.

In models that only examine those children who lived in families with income at or below 150 percent of the poverty line (not shown in the tables), there is no evidence for the relative deprivation theory. Most of the coefficient estimates for the neighborhood variables are similar to those shown in tables 3 and 4.

Conclusions

This study has three main findings. First, OLS models that include extensive control variables do not substantially overstate the effects of neighborhood conditions. In fact, many fixed-effect models show neighborhood coefficients that are larger than in the OLS models. Second, neighborhoods have both linear and nonlinear relationships with adult economic well-being. Third, this study suggests that neighborhoods exert an effect, and sometimes a strong effect, on young children, an important new finding. In addition, support was found for the neighborhood advantage theory, which suggests that there is a positive, linear relationship between childhood and adolescent neighborhood advantage and adult economic well-being. There is also some support for the epidemic theory, especially for the youngest children, although there is no support for the relative deprivation theory.

Not surprisingly, the bivariate OLS models, which fail to take into account important family differences between children, are found to overestimate neighborhood effects. Once observed controls are introduced in multivariate OLS models, the estimated effects of neighborhoods decline and are similar to estimates from the multivariate fixed-effect models. In most cases, the difference between these models stems from the larger sample sizes and lower standard errors in the OLS models (as shown in tables 3 and 4). Aaronson (1998) similarly suggests that fixed-effect models do not differ greatly from OLS models and that fixed-effect models sometimes indicate larger neighborhood effects relative to OLS models.

More basically, even after controlling childhood and adult variables, neighborhood effects persist in this analysis. In the fixed-effect models without adult controls, relations are largest for the youngest age group (although standard errors are three times as large as in the OLS models). In testing the direct and indirect effects of neighborhood factors on adult family income-to-needs (table 3), a one-standard-deviation increase in neighborhood advantage is estimated to increase adult income for the 0–4 age group by 18 percent. This figure is 10 percent for the 5–8 age group (not statistically significant), 11 percent for the 9–13 age group, and 9 percent for the 14–18 age group. The finding that even young children are affected by neighborhood conditions may suggest that neighborhoods influence young children through the experiences of their parents.

The second set of multivariate regressions, which examines only the direct effects of neighborhoods on adult income, suggests that a one-standard-deviation increase in neighborhood quality (neighborhood index 1) increases adult income by roughly 11 percent for the 9–13 age group and 7 percent for the 14–18 age group. If coefficient estimates for the 0–4 age group and the 5–8 age group were statistically significant, they would have fallen slightly above (for the 0–4 age group) or slightly below (for the 5–8 age group) these two estimates.

It may be the case, however, that neither the OLS nor the fixed-effect model adequately captures differences between individuals. For example, if the models do not control for differences between individuals that are correlated with neighborhood characteristics, coefficient estimates will be biased. The direction of this potential bias, however, is unclear.

Results from this study suggest that poverty might be reduced or, at least, income-to-needs ratios might be increased by improving the quality of disadvantaged neighborhoods. But that is a daunting task. To address this issue more realistically, further research should investigate the mechanisms by which neighborhoods affect even the youngest children, such that policies, programs, and families could focus on factors more tangible than neighborhood quality.

Appendix

Table A1

Principal Components Analysis (%)

	Eigenvector 1	Eigenvector 2	Correlation with Principal Component 1	Correlation with Principal Component 2
Ages 0–4:				
Female-headed families	−.397	−.080	−.811	−.093
Households with public assistance income	−.425	−.088	−.868	−.101
In poverty	−.467	−.054	−.953	−.062
Household income < $15,000[a]	−.457	−.068	−.934	−.078
Household income > $60,000[a]	.456	.005	.931	.006
Income above respondent's income	−.030	.733	−.061	.845
Income same as respondent's	.159	−.664	.324	−.767
Variation explained	59.5	19.0		
Ages 5–8:				
Female-headed families	−.403	−.097	−.826	−.108
Households with public assistance income	−.423	−.101	−.867	−.112
In poverty	−.462	−.066	−.948	−.073
Household income < $15,000[a]	−.454	−.104	−.931	−.116
Household income > $60,000[a]	.455	.007	.932	.008
Income above respondent's income	−.079	.727	−.161	.806
Income same as respondent's	.160	−.661	.327	−.734
Variation explained	60.0	17.6		
Ages 9–13:				
Female-headed families	−.407	−.094	−.843	−.101

Table A1 (*Continued*)

	Eigenvector 1	Eigenvector 2	Correlation with Principal Component 1	Correlation with Principal Component 2
Households with public assistance income	−.429	−.106	−.890	−.115
In poverty	−.459	−.079	−.950	−.086
Household income < $15,000[a]	−.453	−.114	−.940	−.123
Household income > $60,000[a]	.451	−.016	.935	−.018
Income above respondent's income	−.087	.719	−.181	.779
Income same as respondent's	.152	−.666	.315	−.722
Variation explained	61.3	16.8		
Ages 14–18:				
Female-headed families	−.418	−.103	−.869	−.109
Households with public assistance income	−.436	−.106	−.907	−.112
In poverty	−.459	−.065	−.955	−.068
Household income < $15,000[a]	−.455	−.092	−.946	−.097
Household income > $60,000[a]	.447	−.065	.930	−.069
Income above respondent's income	−.086	.667	−.179	.703
Income same as respondent's	.103	−.719	.214	−.758
Variation explained	61.8	15.9		

[a] Income expressed in 2001 dollars.

Table A2

Control Variables Used in Tables 3 and 4

	Table 3: No Adult Variables		Table 4: Adult Variables Included	
Variable	OLS	Fixed Effect	OLS	Fixed Effect
Childhood or adolescent characteristics:				
No. of household moves	✓	✓	✓	✓
Child order	✓	✓	✓	✓
Income variance	✓	✓	✓	✓
Head of household or wife before age 18	✓	✓	✓	✓
Family income-to-needs ratio	✓	✓	✓	✓
Years receiving AFDC (%)	✓	✓	✓	✓
Age of the head of household	✓	✓	✓	✓
Area unemployment rate	✓	✓	✓	✓
Any physical or emotional limitations for the head of household	✓	✓	✓	✓
Does the family own their home	✓	✓	✓	✓
Separated or divorced	✓	✓	✓	✓
Widowed	✓	✓	✓	✓
Married	✓	✓	✓	✓
Never married (all years)	✓	✓	✓	✓
Separated or divorced (all years)	✓	✓	✓	✓
Widowed (all years)	✓	✓	✓	✓
No. of children	✓	✓	✓	✓
Children under 6 (dummy)	✓	✓	✓	✓
Maximum age of respondent	✓	✓	✓	✓
Maximum age of respondent squared	✓	✓	✓	✓
Female	✓	✓	✓	✓
High school dropout	✓	…	✓	…
High school graduate	✓	…	✓	…
Some college	✓	…	✓	…
African American	✓	…	✓	…
Races other than white or African American	✓	…	✓	…

Table A2 (*Continued*)

Variable	Table 3: No Adult Variables		Table 4: Adult Variables Included	
	OLS	Fixed Effect	OLS	Fixed Effect
Region of South	✔	…	✔	…
Big city (population of 500,00+)	✔	✔	✔	✔
City 2 (population of 100,000–499,999)	✔	✔	✔	✔
City 3 (population of 50,000–99,999)	✔	✔	✔	✔
City 4 (population of 25,000–49,999)	✔	✔	✔	✔
Adult characteristics:				
Started a household as a wife	…	…	✔	✔
Years married (%)	…	…	✔	✔
Family size	…	…	✔	✔
High school dropout	…	…	✔	✔
High school graduate	…	…	✔	✔
Some college	…	…	✔	✔
Student after age 25	…	…	✔	✔
Area unemployment rate	…	…	✔	✔
Live in the South	…	…	✔	✔
Live in a SMSA	…	…	✔	✔
Other characteristics:				
Entered the sample in 1968–72	✔	✔	✔	✔
Entered the sample in 1973–77	✔	✔	✔	✔
Entered the sample in 1978–82	✔	✔	✔	✔
Entered the sample in 1983–87	✔	✔	✔	✔

Note.—A ✔ indicates that the variable is included in the model. Each model also contains a single or a set of neighborhood characteristics. For the variables for year entering the sample, only 1968–72 is used in the 0–4 years age category; 1968–72 and 1973–77 are used in the 5–8 years age category; 1968–72, 1973–77, and 1978–82 are used in the 9–13 years age category; and all years in the 14–18 years age category (with entering the sample after 1987 used as the excluded category). SMSA = standard statistical metropolitan area; AFDC = Aid to Families with Dependent Children.

Table A3

Weighted Mean Values (SD)

Variable	Ages 0–4		Ages 5–8	
	Siblings	All	Siblings	All
Childhood neighborhood variables:				
Households with public assistance income (%)	5.834 (5.584)	6.317 (6.142)	6.749 (6.167)	6.934 (6.453)
In poverty (%)	12.989 (10.131)	13.601 (10.682)	13.349 (10.538)	13.490 (10.758)
Household income < $15,000 (%)[a]	9.250 (7.215)	9.768 (7.670)	9.466 (7.745)	9.448 (7.689)
Household income > $60,000 (%)[a]	37.295 (9.142)	37.433 (8.694)	35.756 (8.993)	35.611 (8.942)
Income above respondent's income (%)	48.083 (22.605)	46.820 (22.862)	42.295 (24.163)	42.026 (23.984)
Income same as respondent's (%)	10.412 (5.870)	10.636 (6.098)	10.699 (6.530)	10.670 (6.359)
Neighborhood index 1	.798 (1.596)	.688 (1.698)	.729 (1.679)	.701 (1.700)
Neighborhood index 2	−.026 (1.292)	−.113 (1.319)	−.089 (1.229)	−.095 (1.212)
Female-headed families (%)	11.621 (7.303)	12.175 (7.912)	12.933 (8.176)	13.064 (8.464)
Family variables:				
No. of children	2.862 (1.604)	2.685 (1.601)	3.567 (1.741)	3.180 (1.680)
Any children under age 6	…	…	…	.928 (.258)
Child order	2.252 (1.467)	2.095 (1.443)	2.538 (1.617)	2.265 (1.507)
Maximum age of respondent	29.578 (2.988)	29.475 (2.962)	31.654 (3.985)	31.430 (4.069)
Female	.491 (.512)	.502 (.500)	.520 (.505)	.514 (.500)
No. of household moves	1.356 (1.342)	1.285 (1.294)	.967 (1.203)	.928 (1.163)
Family income-to-needs ratio	2.671 (1.766)	2.623 (1.543)	2.447 (1.757)	2.558 (1.719)
Income variance	3.9e+8 (2.0e+9)	3.7e+8 (1.8e+9)	3.7e+8 (1.5e+9)	3.8e+8 (1.5e+9)
Proportion of years receiving AFDC	.064 (.198)	.072 (.213)	.088 (.236)	.082 (.228)
Age of the head of household	28.648 (6.172)	29.624 (7.259)	33.783 (6.677)	34.109 (7.304)
Any physical or emotional limitations for the head of household	.245 (.440)	5.592 (1.771)	.270 (.449)	.291 (.454)
Does the family own their home	.879 (.334)	.313 (.464)	.866 (.345)	.854 (.353)

Marital status of head over the childhood or adolescent years:				
Separated or divorced	.123 (.337)	.116 (.320)	.099 (.301)	.100 (.300)
Widowed	.001 (.033)	.010 (.099)	.012 (.112)	.013 (.112)
Married	.167 (.382)	.185 (.388)	.192 (.398)	.200 (.400)
Never married (all years)	.012 (.112)	.012 (.110)	.009 (.096)	.013 (.112)
Separated or divorced (all years)	.023 (.152)	.031 (.173)	.067 (.253)	.067 (.250)
Widowed (all years)	.001 (.024)	.005 (.073)	.014 (.120)	.013 (.111)
Married (all years)	.807 (.404)	.784 (.411)	.762 (.430)	.756 (.430)
Head of household's education:				
High school dropout	.215 (.421)	.241 (.428)	.287 (.457)	.284 (.451)
High school graduate	.195 (.406)	.207 (.405)	.204 (.408)	.200 (.400)
Some college	.125 (.338)	.119 (.324)	.135 (.346)	.137 (.344)
College graduate	.465 (.510)	.431 (.495)	.371 (.488)	.377 (.485)
Race of head of household:				
White	.817 (.396)	.808 (.393)	.775 (.422)	.787 (.410)
African American	.145 (.360)	.154 (.361)	.185 (.393)	.175 (.380)
Races other than white or African American	.038 (.196)	.037 (.189)	.040 (.198)	.039 (.193)
Area and region of residence:				
South	.319 (.477)	.331 (.470)	.324 (.473)	.328 (.470)
Big city (population of 500,000+)	.249 (.442)	.280 (.449)	.333 (.476)	.327 (.469)
City 2 (population of 100,000–499,999)	.318 (.476)	.293 (.455)	.251 (.438)	.253 (.435)
City 3 (population of 50,000–99,999)	.137 (.352)	.126 (.332)	.126 (.336)	.128 (.334)
City 4 (population of 25,000–49,999)	.080 (.278)	.069 (.254)	.071 (.259)	.071 (.257)
City 5 (population of 10,000–24,999)	.085 (.285)	.085 (.279)	.083 (.278)	.081 (.274)
City 6 (population under 10,000)	.132 (.346)	.146 (.353)	.137 (.347)	.140 (.347)
Area unemployment rate	5.637 (1.873)	5.592 (1.771)	6.077 (1.938)	6.087 (1.995)
Year entering the sample:				
1968–72	.707 (.466)	.714 (.452)	.536 (.504)	.521 (.500)
1973–77	.293 (.466)	.286 (.451)	.330 (.476)	.318 (.466)
1978–82	…	…	.134 (.344)	.161 (.367)
1983–87	…	…	…	…
1988–92	…	…	…	…

Table A3 (*Continued*)

Variable	Ages 0–4		Ages 5–8	
	Siblings	All	Siblings	All
Adult variables:				
Wife	.209 (.416)	.240 (.427)	.244 (.434)	.248 (.432)
Proportion of years married	.473 (.455)	.495 (.447)	.501 (.436)	.510 (.437)
Family size	2.272 (1.190)	2.332 (1.184)	2.456 (1.244)	2.452 (1.220)
High school dropout	.464 (.510)	.467 (.499)	.349 (.482)	.366 (.482)
High school graduate	.191 (.403)	.198 (.398)	.234 (.428)	.224 (.417)
Some college	.179 (.393)	.165 (.371)	.164 (.375)	.157 (.363)
College graduate	.166 (.381)	.033 (.178)	.252 (.439)	.254 (.435)
Student after age 25	.036 (.190)	4.756 (1.136)	.035 (.186)	.035 (.183)
Head of household or wife before age 18	.023 (.154)	.388 (.487)	.026 (.160)	.023 (.149)
Area unemployment rate	4.683 (1.102)	.240 (.427)	5.120 (1.216)	5.072 (1.191)
Live in the South	.376 (.496)	.495 (.447)	.372 (.489)	.377 (.485)
Live in a standard metropolitan statistical area	.539 (.510)	.526 (.493)	.554 (.503)	.557 (.497)
Income outcome variables:				
Log of family income-to-needs ratio	.918 (.793)	.906 (.766)	.890 (.801)	.902 (.787)
Log of income as an adult	10.477 (1.183)	10.494 (.992)	10.504 (1.008)	10.517 (.953)
Income as an adult ($000)[a]	46.709 (34.749)	46.311 (31.083)	47.850 (34.748)	47.748 (32.693)
Family income-to-needs ratio	3.143 (2.300)	3.086 (2.053)	3.122 (2.257)	3.118 (2.104)
N	831	1,660	1,723	2,683

Note.—AFDC = Aid to Families with Dependent Children.

[a] Income expressed in 2001 dollars.

Table A4

Weighted Mean Values (SD)

Variable	Ages 9–13 Siblings	Ages 9–13 All	Ages 14–18 Siblings	Ages 14–18 All
Childhood neighborhood variables:				
Households with public assistance income (%)	7.261 (6.844)	7.348 (6.878)	7.874 (7.625)	7.896 (7.631)
In poverty (%)	13.184 (10.870)	13.286 (10.868)	13.313 (11.087)	13.465 (11.223)
Household income < $15,000 (%)[a]	9.211 (7.872)	9.241 (7.824)	9.162 (8.086)	9.321 (8.228)
Household income > $60,000 (%)[a]	33.959 (8.978)	33.828 (8.972)	31.801 (9.257)	31.628 (9.273)
Income above respondent's income (%)	38.790 (24.137)	39.443 (24.397)	36.909 (24.168)	37.821 (24.505)
Income same as respondent's (%)	11.039 (6.677)	10.733 (6.487)	9.886 (6.060)	9.790 (6.004)
Neighborhood index 1	.773 (1.700)	.733 (1.695)	.756 (1.707)	.723 (1.715)
Neighborhood index 2	−.148 (1.157)	−.095 (1.155)	−.136 (1.120)	−.097 (1.130)
Female-headed families (%)	13.267 (8.948)	13.554 (9.132)	14.510 (10.270)	14.603 (10.267)
Family variables:				
No. of children	3.590 (1.671)	3.223 (1.653)	2.677 (1.658)	2.474 (1.605)
Any children under age 6	.419 (.496)	.383 (.486)	.206 (.406)	.196 (.397)
Child order	2.500 (1.469)	2.220 (1.390)	2.222 (1.347)	2.000 (1.299)
Maximum age of respondent	33.683 (4.904)	33.325 (5.081)	35.671 (5.809)	35.311 (6.077)
Female	.512 (.502)	.515 (.500)	.506 (.501)	.512 (.500)
No. of household moves	.776 (1.089)	.760 (1.063)	.506 (.857)	.532 (.888)
Family income-to-needs ratio	2.427 (1.869)	2.539 (1.874)	2.730 (2.408)	2.769 (2.314)
Income variance	5.0e+8 (3.7e+9)	4.9e+8 (3.3e+9)	9.3e+8 (1.6e+10)	8.3e+8 (1.4e+10)
Proportion of years receiving AFDC	.080 (.223)	.082 (.227)	.073 (.220)	.071 (.216)
Age of the head of household	38.093 (6.685)	38.210 (7.210)	42.923 (7.255)	42.974 (7.645)
Any physical or emotional limitations for the head of household	.300 (.460)	.307 (.461)	.268 (.444)	.285 (.451)
Does the family own their home	.882 (.324)	.866 (.341)	.851 (.356)	.846 (.361)

Table A4 (*Continued*)

Variable	Ages 9–13		Ages 14–18	
	Siblings	All	Siblings	All
Marital status of the head of household:				
Separated or divorced	.080 (.273)	.086 (.280)	.068 (.252)	.069 (.254)
Widowed	.012 (.109)	.014 (.118)	.017 (.129)	.021 (.142)
Married	.201 (.403)	.215 (.411)	.201 (.402)	.215 (.411)
Never married (all years)	.007 (.087)	.011 (.103)	.008 (.091)	.010 (.101)
Separated or divorced (all years)	.076 (.267)	.083 (.276)	.097 (.296)	.104 (.306)
Widowed (all years)	.024 (.152)	.023 (.150)	.037 (.190)	.037 (.189)
Married (all years)	.753 (.433)	.735 (.441)	.730 (.445)	.713 (.452)
Head of household's education:				
High school dropout	.312 (.466)	.309 (.462)	.333 (.472)	.333 (.471)
High school graduate	.183 (.389)	.183 (.387)	.178 (.383)	.176 (.381)
Some college	.159 (.368)	.150 (.357)	.146 (.354)	.142 (.349)
College graduate	.344 (.477)	.357 (.479)	.339 (.475)	.346 (.476)
Race of head of household:				
White	.766 (.426)	.770 (.421)	.763 (.426)	.768 (.422)
African American	.184 (.389)	.181 (.385)	.182 (.387)	.181 (.385)
Races other than white or African American	.051 (.220)	.048 (.214)	.055 (.228)	.051 (.221)
Area and region variables:				
South	.302 (.461)	.313 (.464)	.308 (.463)	.317 (.466)
Big city (population of 500,000+)	.350 (.479)	.337 (.473)	.333 (.472)	.324 (.468)
City 2 (population of 100,000–499,999)	.236 (.427)	.244 (.429)	.254 (.436)	.252 (.434)
City 3 (population of 50,000–99,999)	.126 (.334)	.130 (.336)	.114 (.319)	.119 (.324)
City 4 (population of 25,000–49,999)	.070 (.256)	.070 (.255)	.074 (.262)	.074 (.262)
City 5 (population of 10,000–24,999)	.095 (.294)	.097 (.296)	.092 (.290)	.096 (.295)
City 6 (population under 10,000)	.124 (.331)	.123 (.328)	.132 (.340)	.134 (.341)
Area unemployment rate	6.326 (1.996)	6.297 (2.063)	6.427 (2.085)	6.379 (2.118)
Year entering the sample:				
1968–72	.436 (.498)	.425 (.494)	.294 (.457)	.296 (.456)
1973–77	.313 (.466)	.295 (.456)	.305 (.462)	.282 (.450)

1978–82	.195 (.398)	.199 (.400)	.228 (.421)	.215 (.411)
1983–87	.056 (.231)	.081 (.272)	.136 (.344)	.151 (.358)
1988–92	…	…	.036 (.187)	.056 (.231)
Adult variables:				
Wife	.255 (.438)	.256 (.437)	.260 (.440)	.261 (.439)
Proportion of years married	.537 (.423)	.540 (.425)	.560 (.415)	.554 (.417)
Family size	2.619 (1.278)	2.605 (1.256)	2.702 (1.285)	2.682 (1.274)
High school dropout	.284 (.453)	.303 (.459)	.241 (.429)	.260 (.439)
High school graduate	.247 (.434)	.234 (.423)	.248 (.433)	.236 (.425)
Some college	.158 (.366)	.152 (.359)	.149 (.357)	.149 (.357)
College graduate	.311 (.465)	.312 (.463)	.361 (.481)	.354 (.478)
Student after age 25	.042 (.202)	.039 (.195)	.042 (.200)	.040 (.197)
Head of household or wife before age 18	.028 (.165)	.026 (.159)	.025 (.156)	.024 (.153)
Area unemployment rate	5.303 (1.240)	5.267 (1.260)	5.561 (1.415)	5.525 (1.434)
Live in the South	.368 (.485)	.369 (.483)	.354 (.479)	.359 (.480)
Live in a standard metropolitan statistical area	.559 (.499)	.565 (.496)	.572 (.496)	.578 (.494)
Income outcome variables:				
Log of family income-to-needs ratio	.911 (.777)	.914 (.768)	.931 (.751)	.927 (.753)
Log of income as an adult	10.561 (.944)	10.562 (.897)	10.611 (.798)	10.602 (.794)
Income as an adult ($000)	49.702 (34.289)	49.484 (34.581)	51.371 (35.785)	50.838 (35.227)
Family income-to-needs ratio	3.132 (2.120)	3.136 (2.130)	3.173 (2.119)	3.162 (2.130)
N	2,795	3,818	3,910	4,949

Source.—Panel Study of Income Dynamics and the 1970, 1980, and 1990 censuses.

Note.—AFDC = Aid to Families with Dependent Children.

[a] Income expressed in 2001 dollars.

References

Aaronson, Daniel. 1998. "Using Sibling Data to Estimate the Impact of Neighborhoods on Children's Educational Outcomes." *Journal of Human Resources* 33 (4): 915–46.

Berk, Laura E. 2003. *Child Development.* 6th ed. Boston: Allyn & Bacon.

Brooks-Gunn, Jeanne, Greg J. Duncan, Pamela K. Klebanov, and Naomi Sealand. 1993. "Do Neighborhoods Influence Child and Adolescent Development?" *American Journal of Sociology* 99 (2): 353–95.

Crane, Jonathan. 1991. "The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing." *American Journal of Sociology* 96 (5): 1226–59.

Dietz, Robert D. 2002. "The Estimation of Neighborhood Effects in the Social Sciences: An Interdisciplinary Approach." *Social Science Research* 31 (4): 539–75.

Duncan, Greg J., James P. Connell, and Pamela K. Klebanov. 1997. "Conceptual and Methodological Issues in Estimating Causal Effects of Neighborhoods and Family Conditions on Individual Development." 219–50 in *Neighborhood Poverty*, vol. 1, *Context and Consequences for Children*, edited by Jeanne Brooks-Gunn, Greg J. Duncan, and J. Lawrence Aber. New York: Russell Sage.

Duncan, Greg J., and Stephen W. Raudenbush. 2001. "Neighborhoods and Adolescent Development: How Can We Determine the Links?" 105–36 in *Does It Take a Village? Community Effects on Children, Adolescents, and Families*, edited by Alan Booth and Ann C. Crouter. Mahwah, NJ: Erlbaum.

Duncan, Greg J., Jean W. Yeung, Jeanne Brooks-Gunn, and Judith R. Smith. 1998. "How Much Does Childhood Poverty Affect the Life Chances of Children?" *American Sociological Review* 63 (3): 406–23.

Ellen, Ingrid Gould, and Margery A. Turner. 1997. "Does Neighborhood Matter? Assessing Recent Evidence." *Housing Policy Debate* 8 (4): 833–66.

Erikson, Erik H. 1997. *The Life Cycle Completed.* Extended version. New York: Norton.

Galster, George C., Roberto G. Quercia, and Alvaro Cortes. 2000. "Identifying Neighborhood Thresholds: An Empirical Exploration." *Housing Policy Debate* 11 (3): 701–32.

Ginther, Donna, Robert Haveman, and Barbara Wolfe. 2000. "Neighborhood Attributes as Determinants of Children's Outcomes: How Robust Are the Relationships?" *Journal of Human Resources* 35 (4): 603–42.

Jencks, Christopher, and Susan E. Mayer. 1990. "The Social Consequences of Growing Up in a Poor Neighborhood." 111–86 in *Inner-City Poverty in the United States*, edited by Laurence E. Lynn and Michael G. H. McGeary. Washington, DC: National Academy Press.

Leventhal, Tama, and Jeanne Brooks-Gunn. 2000. "The Neighborhoods They Live In: The Effects of Neighborhood Residence on Child and Adolescent Outcomes." *Psychological Bulletin* 126 (2): 309–37.

Levy, Dan, and Greg J. Duncan. 2000. "Using Sibling Samples to Assess the Effect of Childhood Family Income on Completed Schooling." Working Paper no. 168. Joint Center for Poverty Research, Northwestern University and University of Chicago, Chicago.

Marsh, Lawrence C., and David R. Cormier. 2001. "Spline Regression Models." Sage University Papers Series: Quantitative Applications in the Social Sciences no. 07-137. Sage, Thousand Oaks, CA.

Page, Marianne E., and Gary Solon. 2003. "Correlations between Sisters and Neighboring Girls in Their Subsequent Income as Adults." *Journal of Applied Econometrics* 18 (5): 545–62.

Parcel, Toby L., and Elizabeth G. Menaghan. 1994. "Early Parental Work, Family Social Capital, and Early Childhood Outcomes." *American Journal of Sociology* 99 (4): 972–1009.

Plotnick, Robert D., and Saul D. Hoffman. 1995. "Fixed Effect Estimates of Neighborhood Effects." Working Paper no. 95-2. Center for Studies in Demography and Ecology, University of Washington, Seattle.

———. 1999. "The Effect of Neighborhood Characteristics on Young Adult Outcomes: Alternative Estimates." *Social Science Quarterly* 80 (1): 1–18.

Vartanian, Thomas P. 1999. "Adolescent Neighborhood Effects on Labor Market and Economic Outcomes." *Social Service Review* 73 (2): 142–67.

Voydanoff, Patricia, and Brenda W. Donnelly. 1998. “Parents’ Risk and Protective Factors as Predictors of Parental Well-Being and Behavior.” *Journal of Marriage and the Family* 60 (2): 344–55.
Weinberg, Bruce A., Patricia B. Reagan, and Jeffrey J. Yankow. 2004. “Do Neighborhoods Affect Hours Worked? Evidence from the Longitudinal Data.” *Journal of Labor Economics* 22 (4): 891–924.
Wheaton, Blair, and Philippa Clarke. 2003. “Space Meets Time: Integrating Temporal and Contextual Influences on Mental Health in Early Adulthood.” *American Sociological Review* 68 (5): 680–706.
Wilson, William Julius. 1987. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago: University of Chicago Press.

Notes

An earlier version of this article was presented at a meeting of the Association for Public Policy Analysis and Management (APPAM), Washington, DC, November 2003. The authors would like to thank Philip Gleason, our discussants, and other session participants at APPAM, and also our three anonymous referees for their excellent comments and advice on the article.

1. Other studies examining the effects of childhood neighborhood conditions on adult economic outcomes include Vartanian (1999), Page and Solon (2003), and Weinberg, Reagan, and Yankow (2004).

2. Spline regressions estimate slopes for different linear segments of an independent variable in order to test for nonlinearities.

3. The OLS models use robust standard errors for coefficient estimates to account for the nonindependence of the observations (e.g., siblings).

4. There was little difference in region of residence among siblings.

5. Weights adjust for this oversampling and for differential rates of attrition in reported mean values and standard deviations.

6. Although census tracts are not necessarily synonymous with neighborhoods, they are generally regarded as the best available proxy for neighborhoods. Neighborhoods have been defined as census tracts in a number of previous studies (Brooks-Gunn et al. 1993; Plotnick and Hoffman 1999; Ginther et al. 2000). The average number of people living in a census tract is approximately 4,000. To the extent that census tracts do not correspond to true neighborhoods, the resulting measurement error will lead to a downward bias in the estimate of neighborhood effects. When census tract data are not available, the neighborhood is defined as the next lowest level of geography. Minor civil divisions are first examined for valid data, and, if missing, zip code data are used. Neighborhood characteristics from the 1970 census are used for the years 1968–75. Those from the 1980 census are used for the years 1976–85. Those from the 1990 census are used for the years 1986–92.

7. Levy and Duncan (2000) use slightly different age groups: 0–4, 5–8, 9–12, and 13–16.

8. Following Levy and Duncan (2000), this article only classifies children as siblings when they live in the same family household during all overlapping childhood years and allows for more than two siblings per family. For the OLS models in this analysis, children who do not have siblings are also included; OLS models using the sibling samples (as were used in the fixed-effect models) were also examined. The results from these models did not substantially differ from the OLS results presented here.

9. Given that not all years of a child’s life must be available in the data to use the observation in the analysis, the sample sizes for older children are larger than they would be if all years of childhood were required. For example, children who entered the sample at age 14 in 1968 are included in the adolescent sample but are not included in the younger samples.

10. Several other models examine different specifications. A first model examines a sample that included all childhood and adolescent years with separate variables for conditions of the child at ages 0–4, 5–8, 9–13, and 14–18. The total sample size decreased to 1,445 observations, with 986 observations coming from families with siblings in the sample (589 families). The results indicate that neighborhood variables from the different childhood stages are highly correlated. The lowest correlation coefficient between any two of

the neighborhood index variables (see app. table A1) for the different age groups was .70, and the highest was .9 (for the neighborhood indices between ages 9 and 13 and ages 14 and 18). The relative deprivation theory is tested by examining only those whose family income-to-needs ratio was at or below 150 percent of the poverty line.

11. Two neighborhood index variables created by principal components, which are uncorrelated with one another, are included in the same regression model. A set of neighborhood variables is included in the spline regressions, and two neighborhood variables, one for the percentage of residents in the same income category as the respondent and the other for the percentage of residents with higher incomes relative to the respondent, are included in the same regression model. All other regression models include a single neighborhood variable.

12. Each variable is measured as the average value of the characteristic over the 4 or 5 years when the sample member was in the particular age group. Among those who moved away from their parents, however, only the years that they lived with their parents are used in this calculation.

13. Results were similar for a number of other dependent variables, such as adult income, the log of adult income, and adult family income-to-needs.