NEIGHBORHOOD EFFECTS ON HIGH-SCHOOL DROP-OUT RATES AND TEENAGE CHILDBEARING:

TESTS FOR NON-LINEARITIES, RACE-SPECIFIC EFFECTS, INTERACTIONS WITH FAMILY CHARACTERISTICS, AND ENDOGENOUS CAUSATION USING GEOCODED CALIFORNIA CENSUS MICRODATA

by

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Abstract

This paper examines the relationship between neighborhood characteristics and the likelihood that a youth will drop out of high school or have a child during the teenage years. Using a dataset that is uniquely wellsuited to the study of neighborhood effects, the impact of the neighborhood poverty rate and the percentageof professionals in the local labor force on youth outcomes in California is examined. The first section of the paper tests for non-linearities in the relationship between indicators of neighborhood distress and youth outcomes. Some evidence is found for a break-point at low levels of poverty. Suggestive but inconclusive evidence is also found for a second breakpoint, at very high levels of poverty, for African-American youth only. The second part of the paper examines interactions between family background characteristics and neighborhood effects, and finds that White youth are most sensitive to neighborhood effects, while the effect of parental education depends on the neighborhood measure in question. Among White youth, those from single-parent households are more vulnerable to neighborhood conditions. The third section of the paper finds that for White youth and Hispanic youth, the relevant neighborhood variables appear to be the own-race poverty rates and the percentage of professionals of youths' own race. The final section of the paper estimates a tract-fixed effects model, using the results from the third section to define multiple relevant poverty rates within each tract. The fixed-effects specification suggests that for White and Hispanic youth in California, neighborhood effects remain significant, even with the inclusion of controls for any unobserved family and neighborhood characteristics that are constant within tracts.

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1. Introduction

In recent years there has been an increase in academic interest in the study of neighborhood effects[1], a topic that was also the focus of considerable attention in the 1960s[2]. While racial segregation declined slightly over the 1970s and 1980s, economic segregation has been increasing, particularly in the 1980s (Jargowsky 1995); as a result, the percentage of poor persons living in high-poverty census tracts[3] increased from 12% to 18% between the 1970 and 1990 censuses, and the number of persons living in such tracts has increased from 4.1 to 8.0 million (Jargowsky 1997.) Economic segregation has increased among all ethnic groups, but the increase has been largest among Blacks and Hispanics. This increase in the concentration of urban poverty, particularly among ethnic minority populations, lends urgency to the concern that there may be significant spillover effects associated with residential clustering.

The isolation of poor families in high poverty communities is thought to restrict possibilities for economic mobility among parents, and contribute to the intergenerational transmission of poverty. Proposed reasons for these effects include reduced access to informational networks about jobs and to middle-class role models, physical distance from employment opportunities, and weak social support for work (Wilson 1987; Kain 1968; Kain 1992; Holzer 1991; Wilson 1996.) Borjas (1992, 1995) presents a formalization of the hypothesis that neighborhood and/or ethnic human capital generates spillover effects that interact with parental education and skills in forming children's skills, hence contributing to ethnic differences in intergenerational mobility.

Policy analysts are concerned with neighborhood effects, in part, because public housing policy has contributed significantly to the growth of concentrated poverty. Over the past fifty years, a total of 1.1 million units have been added to the public housing stock in the United States (Quigley 1999.) While these investments in public housing were designed to improve the housing conditions of low income American families, much of the new construction was clustered together in central city neighborhoods, contributing to the creation of very high poverty communities.

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[111] For example: Case and Katz (1991); Clark (1992); Corcoran *et al.* (1992); Crane (1991); Cutler *et al.* (1997); Duncan (1994); Evans *et al.* (1992); Jencks and Mayers (1990); Manski (1993); Glaeser *et al.* (1996); Kremer (1997); Moffitt (1999); Solon *et al.* (1999).

[2] Lewis (1966); Schelling (1971); Coleman (1966); Davis and Whinston (1961); all cited in Moffitt (1999).

[3] High-poverty tracts are defined as tracts where 40% or more of the population is poor.

Despite considerable interest in this area of research, the findings to date have been ambiguous. The literature that attempts to identify the existence, magnitude, and form of the relationship between neighborhood conditions and individual outcomes is limited by problems of identification, due to the nearly complete absence of exogenous sources of variation in neighborhood conditions. The concern is that the choice of residential neighborhood reflects families' (unobservable) preferences and constraints, which in turn can affect the outcome under study. For example, irrespective of observable characteristics such as household income and parental education, families who have stronger (unobserved) commitment to educational attainment may choose to live in neighborhoods where the local public schools have low drop-out rates. Such sorting would generate an inflated, if not altogether spurious, correlation between the drop-out rate of peers and an individual youth's risk of dropping out.

There is some quasi-experimental evidence from the Gautreaux program in Chicago[4] that supports the hypothesis that neighborhood conditions have causal effects upon the educational and labor market outcomes of youth (Rosenbaum 1992, 1995.) As HUD replicates this program in the five-city Moving to Opportunity experiment[5], even stronger tests of the relationship between neighborhood conditions and individual outcomes will become available. However, the majority of the literature on neighborhood effects uses non-experimental data, in which endogenous determination of neighborhoods and individual outcomes invalidates conclusions about causality. Two recent studies (Aaronson 1998; Plotnick and Hoffman 1996) have used the longitudinal information from the PSID to obtain within-family variation in neighborhood characteristics, primarily using information on siblings in families who moved during the siblings' childhood years. These two studies provide perhaps the most convincing non-experimental evidence about the relationship between neighborhood characteristics and youth outcomes; however, the

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[4] As described in Katz *et al.* (1999), page 2:

> "The Gautreaux program resulted from a Supreme Court consent decree in a racial discrimination lawsuit against the Chicago Housing Authority and the U.S. Department of Housing and Urban Development (HUD) filed on behalf of Chicago public housing residents. It provides low-income blacks originally residing in Chicago public housing (primarily single female-headed households on AFDC) with special housing certificates and assistance to move to neighborhoods in which the black population has a share of less than 30 percent, both in the suburbs and in other parts of the city of Chicago."

[5] The Moving to Opportunity program has been operated by the department of Housing and Urban Development since 1994. This program, which operates in five cities (Baltimore, Boston, Chicago, Los Angeles, and New York) relocates residents of subsidized housing projects in high-poverty areas into low-poverty communities. The program seeks genuine random assignment. From eligible families who volunteer for the program, an experiment group is assigned restricted vouchers which require residence in low-poverty communities, a comparison group is assigned vouchers to relocate anywhere in the city, and a control group does not receive relocation vouchers. For more detail on the MTO design, see Katz *et al.* (1999) and Ludwig *et al.* (1998.) Preliminary findings from the Boston MTO experiment suggest that relocation into suburban communities reduced the rates of injuries, asthma attacks, and criminal victimization among youth (Katz *et al.* 1999.) Early findings from the Baltimore MTO experiment demonstrate a reduction in participation in criminal activity among the youth relocated into middle-class suburban communities. (Ludwig *et al.* 1998)

sample sizes are small, and the studies come to somewhat inconsistent conclusions, with Aaronson (1998) but not Plotnick and Hoffman (1996) finding evidence of causal links.

While panel data provides better information about household characteristics than cross-sectional data, panels typically do not have enough information to identify the functional form of the relationship between neighborhood effects and the outcome variable. Typically the researchers simply compare the effects of "good" and "bad" neighborhoods, or assume a linear relationship between the neighborhood characteristic and the outcome variable (for example, Duncan (1994); Corcoran *et al.* (1992).) However, there is considerable interest in the possibility that social interactions generate non-linear relationships between neighborhood characteristics and individual outcomes. Jonathan Crane's "epidemic" model of neighborhood effects (Crane 1991) brought attention to the hypothesis that once indicators of neighborhood distress reach critical threshold levels, negative outcomes among youth begin to increase dramatically. While this model has generated significant interest, the one attempt to replicate it using comparable data from the 1980 decennial census did not produce comparable findings (Clarke 1992).

In this paper I address several outstanding problems in the literature on neighborhood effects. I examine the relationship between two indicators of neighborhood quality, the poverty rate and the percentage of professionals in the labor force, with two youth outcomes: dropping out of high-school, and teenage childbearing. Using a dataset that provides unusually rich cross-sectional information on families and their residential neighborhoods, I am able to test for the importance of interactions between various family and neighborhood variables; to examine the data for evidence of non-linearities; to test the claim that relevant neighborhood characteristics may be defined within racial groups; and finally, to develop a fixed-effects model that controls for the problem of endogenous sorting.

The remainder of the paper is organized as follows. Section 2 presents an economic motivation for the statistical relationships examined in this paper, and describes the econometric model. Section 3 describes the dataset. Section 4 describes the characteristics of the sample youth and their neighborhoods, and discusses the selection criteria for inclusion in the sample. Section 5 presents the results from the basic models predicting drop-out rates and teenage pregnancy as a function of the youths' family and neighborhood characteristics. Section 6 examines the topic of non-linearities in the relationship between the neighborhood variables and youth outcomes. In Section 7, I test for interactions between family and neighborhood variables, to determine what family background characteristics make youth most vulnerable to neighborhood conditions. Section 8 examines the hypothesis that the relevant neighborhood characteristics may be defined within racial groups: here I test whether the characteristics of same-race neighbors have a larger effect on youth's behavior than the characteristics of other-race neighbors. In Section 9, I attempt to address the problem of the self-selection of families into residential neighborhoods, and the resulting endogeneity bias in neighborhood effects parameters. This section estimates a tract fixed-effects model, where within-tract variation in the neighborhood variables are obtained by making the assumption that youth are primarily influenced by neighbors of their own race. Section 10 concludes.

2. Economic Motivation and Econometric Model

2.1. Economic Motivation

In this section, I present the outline of a basic economic model that explains the statistical relationships presented in this paper[6].

We can assume that youth make their decisions about how much education to acquire based on the perceived returns to education, at least in part. Suppose that youth form their expectations about the returns to education, in part, from observing the labor market outcomes adults in their local community. It is easy to see that in economically segregated neighborhoods, adults in poor communities will, on average, have received a lower return to education than adults in wealthy communities. The model of locally-inferred returns to education shows that youth in poor communities will, on average, under-estimate the true returns to education, and hence will under-invest in their own education. The findings of the basic model rest on two assumptions:

1. Since most high-school youth have little first-hand information about the high-skill labor market, we assume that youth will obtain most of their information about wages conditional on high levels of education based on observing neighborhood adults.

2. We assume, in addition, that most youth have some first-hand information (through their own work experience or that of their friends) about the wages obtainable through low-skill work; therefore, the estimated wage conditional on having low levels of educational attainment is assumed to be accurately observed by most youth.

[6] See Patterson (1996) for a formal presentation of this model and extensions.

Given these two assumptions, it is easy to show that the perceived returns to education will be lower in low-income communities, when there is residential sorting based on family income. (And correspondingly, the perceived returns to education will be over-estimated among youth who live in wealthy communities.) The implications of this model are that youth from poor communities will under-invest in education, while youth in wealthy communities will over-invest in education. It can be shown, in addition, that there is a net loss in social welfare from this state, compared to a state in which all youth correctly estimate the returns to education; for some high-ability / low-cost youth will not obtain enough education, while some low-ability / high-cost youth obtain too much education, thus raising the average social costs of educating the society's youth.

Extensions of this model show that when there is endogenous sorting of individuals into educational groupings based on unobserved ability, the neighborhood information bias is larger, and the corresponding level of under-investment in education among poor youth will be greater, as will the negative impact on social welfare. Similarly, if there are externalities in the production of human capital, the effects of residential economic segregation on youth outcomes are again exaggerated. However, the basic predictions for educational attainment are obtained in the simplest model.

The basic model predicts that youth in poor neighborhoods perceive the returns to education to be lower than they actually are, and hence acquire less education than they would with complete information. Both dropping out of high-school and teenage childbearing can be seen as strong indicators that youth perceive the returns to education to be low. These are the two dependent variables in this paper.

2.2. Econometric Model

The probability that an individual youth drops out of high school [or bears a child] is assumed to be a function of the youth's personal characteristics, such as age and gender, the youth's family background characteristics, and the youth's neighborhood characteristics.

Let Y^*_{ij} be an unobserved latent variable measuring the incentives of youth *i* in neighborhood *j* to complete high school: Y^* captures the youth's perception of the returns to education, as well as family resources that might constrain the youth's educational choices. The statistical model identifying the relationship of family characteristics and neighborhood characteristics to the youth's educational attainment decision is given by:

(1) $Y^*_{ij} = \gamma_0 + \gamma_1{*}X_{ij} + \gamma_2{*}Zj + \varepsilon_{ij}$

Where Z is a vector of neighborhood characteristics, and X is a vector of family characteristics; *i* indicates the individual, and *j* indicates the neighborhood.

Y* is not observed in the data; however, the indicator variable P is observed, which takes on the value of 1 if the youth has dropped out of high-school, and zero otherwise. The variable P_{ij} is defined by:

$P_{ij} = 1$ if $Y_{ij} > 0$

$P_{ij} = 0$ if $Y_{ij} \leq 0$

ε_{ij} is assumed to be distributed normally; therefore

(2) $P_{ij} = \theta(\gamma_0 + \gamma_1{*}X_{ij} + \gamma_2{*}Zj)$

where θ is the standard normal cumulative distribution function.

However, ε_{ij} is not independently and identically distributed across observations; observations within a given census tract will have correlated error terms. Because of the grouped structure of the data, the estimated standard errors on the tract-level variables will be underestimated if within-tract correlation in the variance-covariance matrix is not allowed (Moulton 1990.) Furthermore, due to the self-selection issues discussed in the introduction, we can assume that individuals within tracts are similar to each other along unobserved characteristics. Therefore, in equation 1, the error structure can be decomposed as:

$\varepsilon_{ij} = v_j + u_{ij}$,

where v_j is a tract-specific component, and u_{ij} is an individual random shock..

In the final section of this paper, v_j is estimated with tract fixed-effects. However, for most of the analysis in this paper, there is no within-tract variation in the neighborhood characteristics, so a fixed-effects specification is not possible. While a random-effects probit would be one approach to this issue, the random-effects specification unnecessarily imposes a normal distribution on the mean and variance of the tract-specific error term. Rather than imposing this structure, I use an approximation of the Huber-White estimation of the variance-covariance matrix adapted for non-linear models. This robust estimator allows the error terms to be correlated within tracts.

In the section on race-specific neighborhood effects, linear probability models are estimated in addition to probit models. These models are run with corrections for measurement error, and are discussed where they are used.

Except for the sections of the paper which use race-specific neighborhood effects, the neighborhood effects included are the percentage of professionals in the labor force and the neighborhood poverty rate. For ease of interpretation, the marginal values of the estimated probit function ($d\theta/dX$) evaluated at independent variable means are presented, rather than the underlying coefficients[7].

3. Data

I analyze a dataset that is uniquely well-suited to the detailed study of neighborhood effects. With permission of the Bureau of the Census, I have obtained access to the 1990 decennial census micro-data files with geocoding available down to the block-group level. The census micro-data files (similar to the publicly available Public Use Micro Data Files) provide detailed information on current year earnings, transfer program income, labor force participation, occupation and industry of employment, and educational attainment, as well as fertility history, ethnicity and language, length of residency in the United States, and other demographic variables, for each member of a surveyed household. For youth living at home, this data provides excellent information on both youth fertility and educational outcomes and family of origin characteristics. This dataset is similar in structure to the special release of the 1970 Census analyzed by Jonathan Crane. The geocoded micro-data used here, however, has the additional advantage that it permits the construction of neighborhood-level variables not available in the Census Summary Tract Files. This allows certain hypotheses to be tested directly for the first time: for example, the hypothesis that black male youth are sensitive to the percentage of black professionals in their neighborhood, but not to the overall percentage of professionals (Duncan, 1994).

4. Sample Characteristics

4.1. Selection Criteria

[7] All models were initially run with linear probability specifications. None of the results were qualitatively different in the two specifications.

In order to identify the impact of neighborhood characteristics on youth outcomes, it is essential to include a comprehensive set of controls for individual and family characteristics. The decennial census collects data from households, providing information on all members of a residential household; however, this information is not available for youth who no longer live with their family of origin. The sample used in this analysis, therefore, is restricted to youth who live with their parents[8]. This restriction is significant, as the sample youth do differ in important characteristics from the excluded youth. In particular, the drop-out rate and the teen child-bearing rate are both much lower in the included sample (8% and 4%, respectively) than in the excluded sample[9] (33% and 36%, respectively.) Clearly, many of the youth exhibiting the behaviors of interest are excluded from this study. While this restriction limits the extent to which results may be generalized, it is arguable that the resulting parameter estimates on the neighborhood variables, at least in linear specifications, are conservative[10].

An additional restriction on the sample is that I drop observations for whom the Census Bureau has imputed either the race of the youth, or one of the two outcome variables (childbearing and educational attainment.) Race of youth is a particular concern, as Census imputation techniques use neighborhood characteristics.

I include youth ages 15 – 19 years old who are either the natural child or the step-child of the head of the household. Drop-outs are defined as youth who are not in school and have not-completed high-school at the time of the survey. Teenage mothers are defined as girls who have given birth to a child, whether or not that child currently lives with the teenager. The analysis is limited to households residing in one of California's 23 Metropolitan Statistical Areas.

4.2. Characteristics of Sample Youth and their Families of Origin

Table 1 and Appendix Table 1 show demographic characteristics of the sample youth and their families. The sample youth have an overall drop-out rate of 8%, and, among the girls, an overall rate of teenage childbirth of 4% (see Appendix Table 1). 47% of the youth are White, 7% are African-American, 32%

[8] This restriction is common in studies that analyze youth outcomes using versions of the decennial census. See, for example: O'Regan and Quigley (1996), Clark (1992), Crane (1991).
[9] See Appendix Table 1 for summary statistics comparing included and excluded youth.
[10] If youth who are most responsive to the effects of poor neighborhoods are most likely to leave the sample, linear estimates of neighborhood effects will be biased downward ("flattened.") Estimates that allow non-linear relationships will show a flatter relationship between neighborhood conditions and youth outcomes in the lowest quality segment of the neighborhood distribution than actually exists, while estimates over the higher-quality end of the distribution will be less affected.

are Hispanic, 10% are Asian, 4% list their ethnicity as “Other”, and 0.1% are Native American. The average age in the sample overall is just under 17 years. Only 2% of the youth live with their parents in a subfamily containing the youth’s own child, and less than 1% of the youth live in a subfamily made up of the youth and his or her spouse. Similarly, only 1% of the youth are married, and 2% receive welfare income.

Hispanic youth are the most likely to have dropped out (12.2%), while African-American girls are the most likely to have had a child (9.7%.) (See Table 1) Asian youth are least likely to have dropped-out (3.7%) or had a child (1.4%.) Age is a strong predictor of both outcomes, with 19 year olds having dropout rates and teen pregnancy rates more than twice the size of comparable rates for 17 year olds.

Parental education, family structure, and welfare recipiency are all strong correlates with the drop-out rate and the teen childbearing rate. (See Table 1) Parental education is a particularly important determinant of youth drop-out rates; youth in families where the household head has not completed high-school have a much higher drop-out rate (15%) than all other youth, even those in families where the household head has no more than a high-school degree (9% drop-out rate.) While girls in families where the head has less than a high-school degree are at elevated risk for teen childbearing (8%), the strongest family correlate with teen childbearing is residence in a family which has received welfare income in the past year (10% teen birth rate.) Residence in a family where there are more than three children and residence in single parent families are also strongly correlated with higher drop-out rates and teen childbearing rates.

4.3. Neighborhood Characteristics

The "typical" tract in which the sample youth reside is 69% White, 25% Hispanic, 7% African-American and 10% Asian (Table 2). The average tract-level poverty rate is 13%, and 27% of the labor force is in professional occupations. In the average tract, the poverty rate among African-Americans (16%) and Hispanics (17%) is nearly double that among Whites (9%), while the Asian poverty rate is also notably higher (12%). The percentage of the labor force in professional occupations is lowest among Hispanics (17%), followed by African-Americans (27%), Asians (30%), and Whites (32%).

Not surprisingly, the drop-outs and teenage mothers lived in neighborhoods with notably fewer professionals, and with higher rates of poverty and single-parent households, compared with the neighborhood characteristics of the average sample youth (Appendix Table 1). Drop-outs and teenage mothers also lived in neighborhoods with notably different racial compositions than those faced by the average sample youth.

5. Basic Model

Table 3 shows the result of the basic models. Models 1 - 3 show marginal probability estimates[11] from probit models of the drop-out rate on individual and family characteristics, and a set of MSA fixed effects. Model 1 does not include any neighborhood characteristics. Model 2 includes the neighborhood poverty rate, as well as the covariates included in model 1. Model 3 includes the percentage of professionals in the neighborhood (but excludes the neighborhood poverty rate), as well as the covariates included in model 1.

Consistent with the existing literature on determinants of youth educational attainment, the most significant family covariates in Model 1 are parental education and family structure. The predicted probability of dropping out among youth is significantly lower at each additional level of educational attainment of the parent[12]. Compared to a youth whose parent has a college degree, a youth whose parent has not graduated from high school has an 8 percentage point higher predicted probability of dropping-out. Youth from households headed by single mothers have a 4 percentage point higher predicted probability of dropping out than youth from two parent households, holding constant other family

[11] The marginal probability estimates are evaluated at the mean of all independent variables. For dummy variables the predicted change in probability when the dummy is "switched on", evaluated at means, is reported.

covariates.   Family size is important, with the predicted probability of dropping out rising by 0.6 percentage points with each additional child in the family. Family income, parental unemployment, and parental employment in low status occupations are all significant predictors of dropping out, with coefficients of the expected sign[13]. Race becomes notably less important as a predictor of dropping-out when other family characteristics are held constant. Table 1 showed that Hispanics, overall, had about a 6 percentage point higher drop-out rate than Whites; in the adjusted model, Hispanic ethnicity predicts just a 1.1 percentage point higher drop-out rate than White ethnicity. African-American youth have about a 3 percentage point higher drop-out rate than Whites, overall; but in the adjusted model, African-American ethnicity is not associated with a significantly higher drop-out rate. Interestingly, controlling for other family characteristics, youth whose primary language is not English have *lower* drop-out rates than others; this difference probably reflects lower rates of dropping out among first-generation immigrants.

Model 4 shows the results of a probit model of teenage childbearing on the same set of covariates as model 1. All of the important predictors of dropping-out are also important predictors of teenage childbearing. One interesting difference is that race is a much stronger predictor of teenage childbearing than of dropping-out in the adjusted models. In particular, African-American youth have a predicted probability of teenage childbearing 3 percentage points higher than White youth, a large increase over the White mean of 2.6%. Thus, controlling for family socioeconomic characteristics does not eliminate the differences in teen childbearing rates between African-American and White youth, even though it does eliminate the differences in the drop-out rate. As with the drop-out rate, Hispanic ethnicity predicts a significantly higher probability of teenage childbearing, and Asian ethnicity predicts a lower probability of teenage childbearing, relative to Whites.

Model 2 includes the neighborhood poverty rate as a regressor, and model 3 includes the percentage of professionals in the neighborhood as a regressor. The effect of living in a higher poverty neighborhood is clearly smaller than the effects of the more important family variables; however it is significant and large enough to be of economic interest. The estimates predict that a 10 percentage point increase in the neighborhood poverty rate increases the predicted probability of dropping out by 1 percentage point. Similarly, the estimates predict that a 10 percentage point increase in the percentage of the local labor force in professional occupations decreases the predicted probability of a youth dropping out by 1

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[12] The person listed as the head of household in two-parent families is usually the father. Specifications which defined the "education of head" based on the most educated of the two parents yielded nearly identical results.
[13] Family poverty is not significant. This is unsurprising given that family income is an included covariate. The family poverty indicator is included because the neighborhood poverty level is one of the key variables of interest.

percentage point. Compared to a baseline 8 percent dropout rate, these neighborhood effects are significant.

With the exception of the indicators for race, the family and individual effects on both the drop-out rate and the teen childbearing rate remain largely unchanged in magnitude by the inclusion of the neighborhood variables, and none change sign. The inclusion of neighborhood characteristics notably decreases the estimated importance of African-American and Hispanic ethnicity on the drop-out rate, however. The estimated effect of Hispanic ethnicity on the probability of dropping out falls by 1/3 with the inclusion of the poverty rate, and falls to under ½ it's original size with the inclusion of the percentage of professionals in the local labor force. The estimated effect of African-American ethnicity on the probability of dropping out changes even more dramatically: it reverses sign, and becomes statistically significant, with the inclusion of neighborhood characteristics . No such change is found in the teenage childbearing models, however. While the inclusion of neighborhood characteristics decreases the magnitude of the African-American effect somewhat, it is still large and significant in all models, as is the Hispanic effect. The Asian effect is very stable across all specifications.

Model 5 shows that a 10 percentage point increase in the neighborhood poverty rate is associated with an 0.4 percentage point increase in the probability of teenage childbearing, controlling for family characteristics. Similarly, a 10 percentage point increase in the percentage of professionals in the local labor force is associated with an 0.5 percentage point *decrease* in the probability of teenage childbearing. While these effects may sound small, they are fairly large compared to the baseline teenage childbearing rate in this sample, which is only 4%. A 10 percentage point change in neighborhood poverty is thus associated with a 10% increase in the probability of dropping out.

Having found significant neighborhood effects, controlling for family covariates and MSA fixed effects, the natural next question is whether there are interactions between family / individual characteristics and neighborhood characteristics in predicting youth outcomes. Before testing these interactions, the next section tests whether the assumption of linearity employed above is a reasonable one.

6. Non-Linearities: A Test of the "Epidemic" Model of Neighborhood Effects

This section examines whether a linear specification provides an adequate representation of the relationship between neighborhood characteristics and youth outcomes. The issue of whether neighborhood effects become stronger after neighborhood poverty / disadvantage reaches some threshold level is of fundamental policy interest. If causal, the finding of significant threshold effects in the relationship between neighborhood conditions and youth outcomes justifies the focus of greater policy attention and resources on families in neighborhoods above such thresholds. Non-linearities or threshold effects imply that policies which allow families to move out of poor neighborhoods benefit the recipient families more than they hurt the middle-class families in the neighborhoods into which the poor families move. Non-linearities also imply that policies that attempt to integrate poor neighborhoods by attracting middle-class residents, such as the construction of mixed-income housing units in former project sites, will again benefit the poor residents of the (formerly) poor neighborhood more than they hurt the new middle-class residents of the (formerly) poor neighborhood, assuming that enough middle-class people are brought in to move the neighborhood below the threshold poverty level. In contrast, a linear relationship between poverty rates and individual outcomes implies that the net social gains from, for example, providing housing vouchers to poor families from the poorest neighborhoods will be comparable to the gains from providing such a policy for poor families from a broader range of communities. Similarly, a linear relationship suggests that policies which integrate poor neighborhoods through the construction of mixed-income housing developments will hurt the new middle-class neighbors as much as they benefit the poor neighbors.

To test for non-linearities in the relationship between the neighborhood variables and the outcome variable, I transform the neighborhood variables into piece-wise linear splines. Let N be the original neighborhood variable, S_i, i = 1,..t be the spline variables to be created, and T_i, i = 1, … t-1 be the "tipping-points" or knots. If there are tipping points postulated at 10% poverty and 20% poverty, there would be three spline segments (S_1 - S_3) and two knots, where T_1 = 10% and T_2 = 20%. The spline variables are then:

$S_1 = N$

$S_i = \max(\min(N, T_i), T_{i-1})$ for i = 2, … t.

The coefficient on each spline segment represents the slope of the line between the relevant knots.

Four sets of models were tested. The two dependent variables examined were the drop-out rate and the teen childbearing rate, and the two neighborhood variables examined were the poverty rate and the percentage of professionals in the labor force. I first tested for significant breakpoints using the neighborhood spline variables as the only independent variables. I started by testing for breakpoints at every 10 percentage points intervals in the neighborhood variables, and I eliminated insignificant breakpoints until only significant breakpoints remain in the model. I also test for finer breakpoints at the tail ends of the neighborhood variable distribution, which are of particular interest[14]. Once significant breakpoints were located in the unadjusted model, I reestimated each model using the identified breakpoints and including the full set of family covariates[15]. The final models reported in Tables 4 - 7 include only those breakpoints found significant in at least one of the ethnic group regressions or in the full sample regression.

6.1. The Percentage of the Labor Force in Professional Occupations

In the unadjusted model run on the entire sample (Table 6, model 1), there is some suggestion of an increasing slope in the relationship between the percentage of professionals and the probability of dropping-out, as one moves from high to low quality neighborhoods. With no covariates in the model, significant breakpoints were detected at 20% and 40% professional in the model run on the entire sample. However, this relationship disappears when family covariates are included in the model (model 2); not only are the changes in slope no longer significant, but the point estimates no longer reveal steeper slopes in lower quality neighborhoods.

When the sample is disaggregated by race, only White youth show evidence of a non-linear relationship between the percentage of professionals in the neighborhood and the drop-out rate (models 3 & 4.) In both the unadjusted and adjusted models, there is a significant change in slope between the 0% - 20% professional segment and the 20% - 40% professional segment, with a much steeper slope in the 0% - 20% professional segment. While this finding is consistent with the idea that neighborhood effects are stronger in worse neighborhood, it is not consistent with the "epidemic" model described by Jonathan Crane, which posited dramatic increases in negative outcomes at the very tail end of the distribution of neighborhoods. The breakpoint found among the White youth in this model is, in contrast, fairly close to the mean of the neighborhood distribution.

[14] I test for one additional breakpoint at each percentage point between 2 and 8 percent poverty / professional, and similarly at the upper end of the tails.
[15] I also tested for breakpoints using percentiles of the population distribution over the neighborhood variables as my starting point. This approach yielded similar results.

Among the Hispanic, African-American, and Asian youth (models 4 – 10) there are no significant changes in slope in the relationship between the percentage of professionals and the drop-out rate over the distribution of neighborhoods, and the hypothesis that all segments are equal cannot be rejected. For these youth, a linear relationship between the percentage of professionals and the drop-out rate appears to fit the data well.

A somewhat different pattern is seen for the teenage childbearing rate. In the combined sample, one significant breakpoint is found, at 20% professional (Table 5, models 1 and 2). No change in slope is found between the 20% - 40% professional neighborhoods and the 40% + professional neighborhoods. In contrast to the drop-out rate models, the slope of the relationship between teenage childbearing and the percentage of professionals is flatter in the poorest quality neighborhoods. Disaggregating the sample by race, this relationship is significant only in the Hispanic sample (models 5 & 6), although the same pattern is seen in the White sample (models 3 & 4). The data suggests that the risk of teenage childbearing increases steadily as the percentage of professionals declines over the range of high quality neighborhoods (above 20% professional), but once the percentage of professionals in the tract reaches the low-average level, the effect of further changes in neighborhood quality are less pronounced. This pattern is statistically significant in the Hispanic sample, but is also suggested by the point estimates in the White sample (model 4).

6.2. The Poverty Rate

Stronger evidence of non-linearities are found in the relationship between the neighborhood poverty rate and the drop-out (Table 4). This is perhaps because high rates of neighborhood poverty rate are a more precise indicator of neighborhood distress than are low rates of the percentage of professionals, while at the other end of the neighborhood quality distribution, the percentage of professionals allows a more precise measure of neighborhood affluence. In the model estimated on the entire sample with covariates, significant breakpoints are found at 10% poverty, 30% poverty, and 50% poverty. Disaggregating the sample by race, this aggregate pattern is seen to result from two fairly distinct patterns across different racial groups. Among Whites and Hispanics, the predicted probability of dropping out increases dramatically over the 0% - 10% poverty range, as one moves from the very best neighborhoods to neighborhoods closer to average (models 4 and 6). After this breakpoint at 10% poverty, the relationship between neighborhood poverty and youth drop-out rates flattens out, though it remains positive and significant. In contrast, among African-American youth, there is not a significant change in slope between the 0% - 10% poverty range and the next higher poverty range (model 8). However, there is a significant increase in the relationship between neighborhood poverty and the drop-out rate, among African-Americans, in very low quality neighborhoods – those with a 50% poverty rate or higher. There is some evidence that White youth show this second breakpoint at 50% poverty too: the point estimate on this segment is much larger than the point estimate on the previous segment (model 4). However, the change in slope is not statistically significant among White youth. For White youth, African-American youth, and Hispanic youth, the hypothesis that all spline segments are of equal slope comes close to being rejected in most models.

In the teenage childbearing models, the combined sample shows a significant breakpoint at 10% poverty (Table 5, models 1 and 2.) As in the drop-out models, the estimated slope on the neighborhood poverty spline is largest in the 0% - 10% poverty segment, and flattens out thereafter. Disaggregated by race, however, the hypothesis that all spline segments have equal slope can be rejected only for the White sample (models 3 and 4.) The point estimates in the Hispanic and African-American models are suggestive of a similar breakpoint (models 6 and 8), although the changes in slope are not statistically significant.

6.3. Summary: Non-Linearities

The percentage of professionals in the neighborhood reveals a non-linear relationship with the drop-out rate for White youth only: the largest impact of the neighborhood variable on the drop-out rate occurs as one moves from the lowest quality neighborhoods to just below the mean, between 0% and 20% professionals. For Hispanics, African-Americans, and Asians, this relationship seems well-described by a linear form. There appears to be a non-linear relationship between the percentage of professionals and the teenage childbearing rate for Hispanics only, with a different pattern: the strongest neighborhood effects on teenage childbearing occur as one moves from very high quality neighborhoods to average quality neighborhoods (above 20% professionals.) Thereafter – in neighborhoods with 20% professionals or less – the relationship between further changes in neighborhood quality and teenage childbearing is no longer as strong.

The relationship between neighborhood poverty and youth outcomes shows a more consistent pattern across models. A linear relationship between the poverty rate and the teenage childbearing rate cannot be rejected for Hispanics, African-Americans, and Asians. For Whites, however, there is a significant breakpoint at 10% poverty, with the strongest neighborhood effects occurring as one moves from very high quality neighborhoods to those closer to average (0% - 10% poverty.) Thereafter, neighborhood effects become weaker, though they remain significant.

In the relationship between the neighborhood poverty rate and the drop-out rate, two breakpoints were detected. The finding that the largest increase in the drop-out rate comes when neighborhood quality declines from very high (0% poverty) to moderate (10% poverty) is consistent with Clarke's findings using the 1980 census (Clarke 1992). However, there is quite suggestive evidence of a second threshold, with a dramatic increase in drop-out rates at very high levels of poverty. This finding among African-American youth, and possibly among White youth, is consistent with the "epidemic" model of tipping points at very low levels of neighborhood quality. It should be noted that the line segment estimated above 50% poverty is based on extremely few data points (see Appendix Tables 3 and 4.) For African-American youth, for example, this segment is estimated based on less than 2% of the sample; for White youth, this segment consists of less than 1/10 of 1 percent of the sample. These youth reside in less than 20 tracts.

Given these sizes, the slope estimates should be treated as merely suggestive, despite the narrow confidence intervals in the African-American model (model 8.) Nevertheless, these findings should not be dismissed because of their small numbers, as these are the very tracts of most interest to many policy-makers. For example, HUD's Moving to Opportunity program in Baltimore is targeting families in the 5 poorest census tracts in the city – those with poverty rates above 60%. A more definitive examination of youth behavior in the very highest poverty tracts will require more observations at this extreme tail of the distribution, which I expect to obtain when I expand this analysis to a national sample.

7. Interactions between neighborhood and family characteristics

7.1. Race and Neighborhood Characteristics

In this section I examine whether youth with different individual and family characteristics respond differently to neighborhood conditions. Despite the evidence above suggesting some non-linearities in the relationship, this and subsequent sections specify a linear relationship between the neighborhood variables and the outcomes. I test for interactions between neighborhood characteristics and ethnicity, parental education, and family structure[16].

Consistent with the existing literature, I find that non-White youth are significantly less responsive to neighborhood conditions than White youth[17] (see Table 8.) A 10 percentage point increase in the poverty rate is associated with a 1.8 percentage point increase in the predicted probability of dropping-out among White youth, a 1.0 percentage point increase among African-American youth, an 0.8 percentage point increase among Hispanic youth, and an 0.7 percentage point increase among Asian youth (model 1). Relative to the baseline drop-out rates, which are significantly lower among Whites than among African-Americans and Hispanics, these differences are even larger. Very similar racial differences are seen in the effect of the percentage of professionals on drop-out rates (model 3). A 10 percentage point increase in the percentage of professionals in the local labor force decreases the predicted probability of dropping-out among White youth by 1.2 percentage points; among Hispanic and African-American youth, by 0.8 percentage points; and among Asians, by 0.6 percentage points. Similar patterns are apparent in the teenage childbearing outcome s (Table 8, models 2 and 4.)

Larger estimated effects of neighborhood characteristics on White youth outcomes could reflect greater residential sorting among White families. If a substantial portion of estimated neighborhood effects are actually picking up unmeasured family characteristics such as commitment to educational attainment, this effect will be greater in populations with greater ability to sort into residential communities that match their preferences. If non-White families are more constrained in their residential location than White families, due to differential access to home mortgage lending, voluntary residential segregation, or other reasons, neighborhood effects will be larger among Whites.

Another explanation for weaker neighborhood effects on non-White youth is that an overall neighborhood quality indicator may not be the relevant neighborhood variable. Several authors have suggested that African-American youth may be less responsive than Whites to the overall percentage of professionals in their neighborhood, because the reference group that influences the youth's outcome is the African-American community: thus the relevant neighborhood variable is the percentage of the *African-American* labor force who are in professional occupations. This hypothesis is tested later in the paper; while the

[16] All models in this paper were run with linear probability specifications, as well as probit specifications. Estimated interaction effects were close to identical.
[17] This is consistent with the findings of Mayer (1991), Clarke (1992), and Duncan (1994).

theory does not seem to explain the Black-White differences in the neighborhood effect parameters in this sample, it does appear to explain some of the Hispanic-White differences.

7.2. Parental Education and Neighborhood Characteristics

Youth from families where the head of household has a high-school degree or less are much more sensitive to the neighborhood poverty rate than are youth from families where the head has more education. This finding is true across racial groups, although the cross-education group differences are least striking among Asians. Among African-American youth, for example, a 10 percentage point increase in the poverty rate is associated with a 2.3 percentage point increase in the drop-out rate, among families where the household head has not graduated from high school (Table 9, model 3.) Among families where the household head has some college, a similar increase in the poverty rate is associated with a 1.0 percentage point increase in the predicted probability of dropping out; and among families where the household head has a college degree or more, changing the neighborhood poverty rate generates an estimated effect not significantly different from zero (the point estimate predicts an 0.5 percentage point increase in the predicted probability of dropping out.) Similar patterns are seen among Whites (model 2), Hispanics (model3), and Asians. For Hispanics, in fact, a higher neighborhood poverty rate is associated with a significantly *lower* probability of dropping out, among youth from families where the household head has a college degree[18]. This interaction between the poverty rate and parental education is very similar in the teenage childbearing models (Table 10), and the pattern again is consistent across racial groups. Among African-American youth, for example, a 10 percentage point increase in the poverty rate is associated with a 1.6 percentage point increase in the teenage childbearing rate, for youth from families where the household head has not completed high-school (model 4.) The same increase in the poverty rate is associated with an 0.4 percentage point increase in the predicted probability of teenage childbearing among youth where the head of household has a college degree or more, and the estimated increase is not statistically significant.

A parallel finding obtains for the relationship between the percentage of professionals and youth outcomes. The percentage of professionals in the local labor force has a much stronger association with youth outcomes among youth from families where the household head has a college degree or higher (Tables 9 & 10, lower panels). Indeed, for youth from families where the household head does not have

[18] This may reflect immigrant history differences. If the majority of college-educated Hispanics who live in poor communities are recent immigrants, then poor neighborhoods are also an indicator for recent immigrant status,

even a high school degree, the percentage of professionals in the census tract is not significant in three of the four ethnic groups for the drop-out equations (Table 9, models 7, 8 & 9). Among families where the head of household has a college degree or more, the percentage of professionals is strongly associated with the drop-out rate: for Hispanics in this group, for instance, a 10 percentage point increase in the percentage of professionals is associated with a 3.6 percentage point decrease in the predicted probability of dropping-out (model 9). This finding of increasing sensitivity to the percentage of professionals as parental education increases is also seen in the teenage childbearing models, among all race groups (Table 10, models 6 – 10.) For example, among African-American girls in families where the household head has a college degree, a 10 percentage point increase in the percentage of professionals is associated with a 2.5 percentage point decrease in the predicted teenage childbearing rate. In contrast, among African-American girls in families where the head has less than a high school degree, a 10 percentage point increase in the percentage of professionals is associated with just an 0.1 percentage point decrease in the predicted teenage childbearing rate, and the association is not statistically significant.

There are several possible explanations for the finding that less parental education is associated with stronger neighborhood poverty effects, while more parental education is associated with stronger effects of the percentage of professionals.

First, families where the household head has some college or more may be clustered over a narrow (and low) range of neighborhood poverty, so that there is less variation in the neighborhood poverty rate for this group. In contrast, families where the household head has a high school degree or less may be spread out over a much wider range of neighborhood poverty. Similarly, families where the household head has a high-school degree or less may be clustered over a narrow (and low) range of percent professionals, while families where the parents have some college or more may be spread out over a wide range of neighborhoods with respect to the percentage of professionals. This lack of variation in the neighborhood variable for certain groups of families could generate the findings of insignificant neighborhood effect estimates for these families. However, the evidence from the section on non-linearities, which shows that one of the most important segments of neighborhood poverty distribution is between very high quality and moderate quality neighborhoods (0% - 10% poverty,) suggests that highly educated families, who cluster in this range of the distribution, should have strong neighborhood effects.

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which, conditional on parental education, is associated with lower drop-out rates. At lower levels of education, the relationship between recent immigration and neighborhood quality is probably less pronounced.

A second possibility is that the neighborhood poverty rate is a good indicator of unobserved family characteristics for families where the parents have little education, and is *not* a good indicator among more educated families. Assuming that parental income constrains residential choice for less educated parents to a range of lower-income neighborhoods, those whose choose lower poverty neighborhoods may : 1) have lower levels of unobserved wealth or permanent income, or 2) have self-selected based on unobserved factors, which presumably might include commitment to their children's educational attainment. In contrast, families with high parental education may reside exclusively in extremely low poverty neighborhoods, so that neighborhood poverty is effectively not a choice variable for these families. Among more educated families, while neighborhood poverty may be consistently very low, the percentage of professionals in the neighborhood represents a neighborhood quality indicator which *does* vary for these families. Thus, in more educated families, self-selection into different quality neighborhoods is over the percentage of professionals rather than over the poverty rate. For such families, residence in a predominantly professional neighborhood may indicate a higher level of unobserved wealth or personal income, and / or may indicate a preference for "good" neighborhoods resulting from interest in their children's educational outcomes. This argument suggests that there is an underlying issue of selection along unobserved family characteristics, in addition to lack of identifying variation, for certain family / neighborhood combinations.

A final possibility is that the patterns represent youth responding to the size and behavior of a group perceived as a relevant reference group. It may be that youth from educated families identify with professionals; therefore they are sensitive to the percentage of professionals in their community. Similarly, youth from less educated families identify more with the poor; therefore they are more sensitive to the poverty rate in their community. This hypothesis is similar to the finding, discussed in Section 8, that youth respond more to the characteristics of neighbors of their own race than to the characteristics of other-race neighbors.

Which hypothesis is correct is quite important. If the differences in neighborhood effects by parental education result from the fact that unobserved family characteristics are the primary source of observed neighborhood effects, then the role of neighborhood conditions as an exogenous influence on youth outcomes is clearly minimal. I attempt to control for common unobserved family characteristics within neighborhoods in Section 9.

7.3. Family Structure and Neighborhood Effects

For non-White youth, there are no significant interactions between living in a single parent household and neighborhood characteristics.[19] However, White youth showed a significant interaction between family structure and the percentage of professionals in the neighborhood, for both the drop-out and teenage childbearing outcomes (Table 11, models 2 & 7.) The size of the interaction is modest: a 10 percentage point increase in the percentage of professionals is associated with a 1.1 percentage point decline in the drop-out rate for White youth from two-parent households, compared with a 1.5 percentage point decline for White youth from single-parent households. A similar interaction is seen in the teenage childbearing model (model 7.) For non-White youth, the interaction terms are insignificant, and are not uniformly in the same direction as the White youth interaction terms.

Of the interactions examined in this Section, this finding for White families is most suggestive of a plausibly causal interaction. It seems unlikely that single-parent households engage in more neighborhood sorting along unobservable characteristics than do two-parent households; on the contrary, given that we do not have indicators of wealth or permanent income, it seems likely that the single parent households in this sample have unobservable characteristics that make them *less* able to sort into neighborhoods on the basis of commitment to their children's outcomes than are the two-parent households. Therefore, the finding that White youth from single-parent households are more influenced by neighborhood characteristics than youth from two-parent households seems likely to be causal. One reason youth from single parent households may be more influenced by neighborhood conditions is greater exposure; because single parents have less time to spend monitoring and interacting with their teenage children, the youth presumably spend more time in the community beyond the family. Furthermore, single parents may have less ability than partnered parents to neutralize community influences on their children, due to either lack of time for supervision, or reduced authority in the eyes of the youth.

7.4. Summary: Interactions between Family and Neighborhood Characteristics

The findings that White youth are more responsive to neighborhood effects than non-White youth suggest that endogenous sorting of families into residential neighborhoods may be a significant cause of observed neighborhood effects. Because White families presumably have greater residential constraints on

[19] I also tested whether the drop-out rate among girls is more sensitive to the percent of professionals in the female labor force than the percent of professionals in the male labor force. Preliminary findings do not support this hypothesis.

residential mobility than non-White families, we expect endogenous sorting to be a more significant factor in the White community.

In the section on interactions with parental education, I found that youth from families where the household head has some college or higher are much more responsive to the percentage of professionals than youth with less educated parents, while at the same time, youth from families where parental education is low (a high school degree or less) are more sensitive to the neighborhood poverty rate. As discussed above, these findings are also consistent with the hypothesis that unobserved family characteristics generate a large part of estimated neighborhood effects.

The one interaction which reasonably can be viewed as an exogenous influence on the relationship between neighborhood characteristics and youth outcomes is family structure. Under the assumption that neighborhood effects are driven entirely by endogenous sorting of families with similar unobserved characteristics into neighborhoods, one would expect that youth from single parent families would show *weaker* neighborhood effects, because their families have fewer resources to allow for effective residential sorting. The fact that such youth show significantly *stronger* neighborhood effects, at least in the White community, is suggestive that the single parent family structure actually makes youth more vulnerable to neighborhood quality.

8. The Effects of Own-Race and Other-Race Neighbors

This section of the paper tests whether the characteristics of own-race neighbors are stronger correlates with youth outcomes than are the characteristics of neighbors of other races. As mentioned above, it has been suggested that one explanation for the lower sensitivity of non-White youth to neighborhood conditions may be an incorrect definition of the relevant neighborhood effect. For example, if African-American youth form their labor market expectations on the basis of outcomes they observe in the local African-American community, then the relevant neighborhood variable for this group are the African-American poverty rate, and the percentage of professionals in the African-American community. Two types of models are tested in this section, and all models are run stratified by race of youth. First, models are run that include each of the four race-specific neighborhood effects as regressors; thus, the White poverty rate, the Hispanic poverty rate, the Asian poverty rate, and the Latino poverty rate are included in each regression of the outcome variables on neighborhood poverty. Second, models are run that include only the youth's own-race poverty rate, and the poverty rate among all other races combined.

8.1. Correcting for Measurement Error

An issue of particular concern in this section, and indeed in much of the literature on neighborhood effects, is that the key variables of interest are measured with error; for the tract-level variables are themselves estimates. In previous sections, most of the discussion has focussed on parameter estimates of one neighborhood variable. In situations where only one variable is measured with error, the parameter estimate is known to be biased downward, and we can therefore regard the findings as conservative estimates of the parameters of interest.

In this section, however, we are explicitly interested in comparing the parameter estimates on several different neighborhood variables. Because more than one variable is measured with error, we do not know *a priori* the direction of the bias. In addition, there is reason for concern that the measurement error bias might be in favor of our hypotheses, leading us to falsely accept the theory that own-race neighborhood effects are more significant than other-race neighborhood effects. The logic is as follows: due to residential segregation, most youth will live in tracts where their own race makes up the majority of the population. Thus for the typical youth, the estimated own-race poverty rate will be based on a larger sample, and hence measured with less error, than the estimated other-race poverty rates. As a result, there may be more attenuation bias in the parameter estimates on other-race poverty rates than on own-race poverty rates, and such a pattern would bias our results in favor of the hypothesis that own-race neighbors are more.

Of course, we do not *know* the direction of the bias in our models. Even if residential segregation is extensive enough that every youth lived in a tract where their own race made up the majority of the tract population, we would not know the direction of the measurement error bias on any given coefficient, as there is more than one variable measured with error in every model.

Fortunately, we are in the privileged position of having information on the amount of measurement error associated with each tract level variable, as we have constructed these tract level estimates. Every tract-level estimate has an estimated standard error, which is a measure of the standard deviation of the population estimate around its true mean; this standard error squared provides an estimate of the variance of the error associated with each tract variable.

Consider the standard errors-in-variables regression model[20]:

$$y = \mathbf{X^*}\beta^*_0 + \mathbf{u}$$

$$\mathbf{X} = \mathbf{X^*} + \mathbf{V}$$

Where y is a *T*-vector of observed dependent variables, **X*** and **X** are *T x k* matrices of the true unobserved explanatory variables and their observed measurements, respectively, u is a *T*-vector of disturbance terms, **V** is a *T x k* matrix of unobservable measurement errors, and β_0 is a k-vector of unknown parameters. Let y and **X** be centered at their sample means, and E(**X***) = 0. If the variance of **V** is consistently estimated by an estimator $\mathbf{\Omega}$, then β^*_0 can be consistently estimated by:

$\beta_0 = [\mathbf{X'X} - \mathbf{\Omega}]^{-1}\mathbf{X}'y$; this is the estimator corrected for attenuation.

In our case, a natural estimate of **Ω**, the variance of **V**, is simply a diagonal matrix with elements consisting of the square of the standard error of each tract level variable. The amount of measurement error associated with each tract level variable (or reliability) is a function of the signal to noise ratio in each estimate: the ratio of the "noise" variance (**Ω)**, to the "total" ("signal + noise") variance, or the variance of observed **X**.

Because of software requirements, the models presented in this section do not in fact use an estimate of the complete matrix **Ω**. Rather than using the standard error on every tract-level observation as the "noise" measure, I have averaged these values to obtain one estimate (across all observations) of the within-tract measurement error variance, for each tract-level variable. However, in order to keep more of the information that would have been provided by the individual tract standard errors, I have constructed the average within-tract standard errors separately by race of youth. This allows the signal-to-noise ratio on the various tract level
variables to differ for youth of different race groups, which is important, given that our concern about measurement error biases revolves around the impact of the bias on the estimated race-specific neighborhood parameters (see above.) Furthermore, in sections where I have estimated the models on different subsets of the data (defined by the level of tract integration,) reliability estimates are recomputed on the relevant subset of tracts.

8.2. The Problem of Homogeneous Neighborhoods

Another issue of particular concern in this section is the extent to which results may be driven by residential segregation. We are particularly interested in testing the hypothesis that the behavior of

[20] This discussion follows Iwata (1992), but the results presented are well known.

neighbors of one's own racial group have a larger impact on youth outcomes than the behavior of neighbors of different racial groups. This hypothesis has little meaning in environments where youth are exposed almost exclusively to neighbors of one racial group.

Furthermore, youth living in homogenous neighborhoods could generate a spurious finding in favor of our hypothesis that own-race neighbors have a larger effect than other-race neighbors. Suppose that the true relationship between neighborhood variables and youth outcomes is such that youth simply respond to the overall neighborhood poverty rate, regardless of the race of the neighbor. In highly homogenous neighborhoods, the parameter estimates could show a large coefficient on "own-race poverty" and a small or insignificant coefficient on "other-race poverty", simply because the overall poverty rate is dominated by and nearly identical to the own-race poverty rate. (In addition, of course, this situation would produce the possibility of larger measurement error in the other-race poverty rate, as discussed above.)

In order to assess the sensitivity of the own-other parameter differences to residential segregation, these models were estimated on three different samples. Models were first estimated on all tracts. Then models were estimated only on youth who live in highly integrated tracts; tracts where members of the youth's own race are between 40% and 60% of the total population. This restriction, while guaranteeing that results are based on youth living in highly integrated environments, significantly reduces the number of tracts and youth available for analysis. This restriction can also be seen as peculiar in some contexts. While the restriction seems reasonable for Hispanic youth – with the average Hispanic youth living in a tract that is 46% Hispanic – it seems arbitrary for other groups. For example, Black youth make up less than 10% of the sample, and live in tracts that are on average about 25% Black. Thus, excluding Black youth who live in tracts that are less than 40% Black appears arbitrary and will generate a somewhat peculiar sample.

A final set of models is estimated on tracts where members of the youth's own race are between 20% and 80% of the total population. This restriction provides some balance between the need to exclude youth in highly homogenous tracts, and the need to include youth that are fairly representative of the sample population.

8.3. Results: Own-Race and Other-Race Neighbors

There is evidence that youth do respond more strongly to the characteristics of own-race neighbors than to the characteristics of other-race neighbors, particularly for the youth drop-out rate. Table 12, models 1

– 4, shows the result of probit models of the drop-out rate on family characteristics, MSA dummies, and four neighborhood variables: the White poverty rate, the African-American poverty rate, the Hispanic poverty rate, and the Asian poverty rate. Models are run separately for youth of each racial group. Table 12, models 5 – 10, shows the results of similar models, but with the following four neighborhood variables: the percentage of professionals in the White community, the percentage of professionals in the African-American community, the percentage of professionals in the Hispanic community, and the percentage of professionals in the Asian community[21].

Models 1 – 3 of Table 12 show that for Whites, Hispanics, and African-Americans, the poverty race in a youth's own race group has a much larger effect on the drop-out rate than does the poverty rate of other-race groups. Furthermore, the own-race poverty rate is the only significant poverty rate in each of these cases. The largest effects of own-race poverty are seen among Whites and Hispanics, with smaller effects for Blacks. Among Hispanics, for example, a 10 percentage point increase in the Hispanic poverty rate is associated with a 1.0 percentage point increase in the drop-out rate; a 10 percentage point increase in the White poverty rate, in contrast, is associated with an 0.1 percentage point increase in the drop-out rate, and the predicted value is not significantly different from zero. For Asians, none of the race-specific poverty measures are statistically significant.

When the percentage of professionals in the neighborhood is used instead, the own-race neighborhood variable is again a much larger and more significant predictor of the drop-out rate than any other-race neighborhood characteristics for Whites and Hispanics, and is also significant for Asians. (Table 12, models 5 – 10.) For African-Americans, however, the own-race poverty rate is not significant in this model (model 2.)

The teenage childbearing models do not yield as consistent results as the drop-out models. While the percentage of professionals of a youth's own race is the most important neighborhood variable for Whites and Hispanics (Table 13, models 5 and 7), this relationship does not obtain for African-Americans or for Asians (models 6 and 8.) Furthermore, the poverty rate variable does not show this pattern; for African-Americans, Hispanics, and Asians, the race-specific poverty rates are not significantly associated with teenage childbearing (models 2 – 4), while for Whites, other-race poverty rates appear equally as important as own-race poverty rates (model 1.)

[21] The reported models also include a control for overall tract racial composition, measured by the percentage of the tract population of the youth's own race. This variable is included because the race-specific poverty rate

8.4. *Alternative Model Specifications*

In order to test the sensitivity of the results to functional form, measurement error, and neighborhood integration, several alternative models were run to test the relationship between the dropping-out and race-specific poverty rates.

Table 14 replicates the results of shown in Table 12, using two alternative model specifications. Models labeled "OLS" are linear probability models, with standard errors robust to heteroscedasticity and tract-level clustering in the standard errors. Models labeled "ME" are also linear probability models, but in these models the estimated reliability of the tract-level variables are used to correct for measurement error biases in the coefficients. Standard errors in the measurement error correction models are not adjusted to correct for heteroscedasticity or tract-level clustering. The top panel of Table 14 shows results run on the entire sample on youth. The bottom panel of Table 14 shows results run on a sample restricted to youth who live in highly integrated census tracts. Highly integrated tracts are defined as those where the population of a youth's own race group makes up no more than 60% and no less than 40% of the total tract population.

The first observation to note about the parameter estimates from Table 14 is that they are largely comparable to the marginal effects generated from the probit models. The OLS estimates are consistently a bit larger than the probit estimates; but the difference in the estimates is only substantial for the White youth. In the White sample, the probit estimates predict that a 10 percentage point increase in the White poverty rate is associated with a 1.2 percentage point increase in the drop-out rate; the OLS estimates predict that a 10 percentage point increase in the White poverty rate is associated with a 2.5 percentage point increase in the drop-out rate. Because the probit estimate is derived from one marginal coefficient evaluated at the mean of sample characteristics, rather than the mean over all probit estimates for White youth, perhaps the linear model predictions should be considered more reliable.

The second observation to note about Table 14 is the remarkable similarity between the OLS estimates and the measurement-error adjusted estimates, as well as their standard errors. The measurement-error adjustments (described above) have the effect of consistently increasing the magnitude of the own-race coefficient. Most often, the adjustment decreases the size of the other-race coefficients, although not

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presumably is more important in tracts where there are many members of a youth's own racial group. Results are similar when this variable is omitted.

consistently. However, the coefficients do not change very much, and our assessment of tthe relative importance of own-race and other-race poverty rates is unchanged by these adjustments. Equally interesting is the fact that the standard errors in the measurement error models, which do not include any corrections for tract-level clustering, are nearly identical to the standard errors in the OLS models.

Comparing the top panel of Table 14 to the bottom panel shows the effect of restricting the analysis to youth who live in highly integrated tracts. The main effect of this restriction is that the estimated coefficients on own-race poverty rates become slightly smaller. There is also a larger difference between the OLS models and the measurement adjusted models, reflecting the fact that the own-race poverty rate is typically measured with more error in less homogenous tracts. However, the parameter estimates from the top panel and the bottom panel are generally consistent. The one exception to this consistency is in the Asian sample. Among Asians, in models run on the full sample, the effect of own-race poverty is estimated to be *negative* (albeit insignificant.) Once the sample is restricted to those living in integrated neighborhoods, however, the effect of own-race poverty becomes large, of the expected sign, and highly significant. Apparently the finding that Asian youth are insensitive to the own-race poverty rate was simply driven by the fact that many of them live in tracts with very few other Asians.

Finally, Table 15 shows the results of including as regressors in the drop-out model a youth's own-race poverty rate and the poverty rate among all other races in the tract combined. This is perhaps a simpler and more direct means of testing the relative importance of the youth's own-race poverty rate than models where each race-specific poverty rate is included. Models are run both with and without measurement error adjustments, as in Table 14.

The top panel of Table 15 shows the full set of models run on the entire sample. Not surprisingly, the parameter estimates on own-race poverty are little different from the estimates generated in the models of Table 14. We find that for Whites, Blacks, and Hispanics the own-race poverty rate is much larger and more significant than the other-race poverty rate. However, tests for whether the own-race poverty rates and other-race poverty rates differ in slope are significant only for Whites. For Asians, while the slopes differ, we obtain the interesting result that the own-race poverty rate is insignificant, while the other-race poverty rate is large and highly significant. As observed above, this finding results from the fact that Asians tend to live in neighborhoods with relatively few other Asians. As we will see, this result for Asians disappears when we restrict the sample to more integrated neighborhoods.

The lower panels of Table 15 show the results of re-estimating the first set of models on increasingly restricted samples. The middle panel shows the results re-estimated on youth who live in tracts where their own-race population makes up no less than 20% and no more than 80% of the total population. The bottom panel shows the results re-estimated on youth who live in tracts where their own-race population makes up no less than 40% and no more than 60% of the total population.

For Whites and Hispanics, restricting the sample to more integrated tracts generally has the result of decreasing the significance, but not the size, of the parameter estimates on the own-race poverty rate, while the size of the parameter estimates on other-race poverty rates increases slightly. Thus, the estimated effects of own-race poverty rates seem fairly robust to changes in the level of tract integration. For Blacks, however, the estimated effects of own-race poverty rates become do very small when the sample is at it's most restrictive. The Asian sample shows the same interesting change in parameter estimates that we observed in Table 14. In the sample restricted to highly integrated tracts, the own-race poverty coefficient is larger than the other-race poverty coefficient, while in the unrestricted and less restricted samples, the reverse is true.

8.5. Conclusions: The Relative Importance of Own-Race Neighbors

These models suggest that at least in predicting youth drop-out rates, own-race poverty rates and the percentage of professionals of a youth's own race are more significant than the characteristics of other-race neighbors. This finding is consistently strong for Whites and Hispanics, but is less stable for African-Americans and Asians.

I suspect that the instability of the finding for African-Americans – and in particular, the tendency of the Hispanic neighborhood conditions to matter for African-American youth – reflects the considerable residential overlap and similar income distributions of the African-American and Hispanic communities in this California sample, where the African-American sample is substantially smaller than the Hispanic sample.

The finding of mostly insignificant results for Asians is consistent with the much smaller neighborhood effects estimated for Asians in almost all model specifications. Overall rates of teenage pregnancy and dropping-out are extremely low in this community, and do not appear to be very sensitive to neighborhood conditions.

At least for the drop-out rate, these findings suggest that neighborhood effects appear to be influencing youth through racially-defined social networks. This finding is strongest for White youth and Hispanic youth in the California sample. The fact that such race-specific effects exists provides some evidence that neighborhood effects are capturing more than just correlated unobserved family characteristics or unobserved neighborhood characteristics. To the extent that residential neighborhoods appeal to parents for reasons orthogonal to race, there is no reason that unobserved family or neighborhood characteristics that determine residential selection should generate a finding of race-specific neighborhood effects on youth.[22] Of course, the results of this section are suggestive, but not overwhelming: for Asian youth and African-American youth, the own-race neighborhood effects were not consistently stronger than the other-race neighborhood effects.

In the next section, I attempt to test for the existence of neighborhood effects while controlling for parental sorting into residential neighborhoods. To do this, I build on the findings of the current section, which suggest that own-race neighbors are the relevant source of neighborhood effects in many cases.

[22] Another possibility, of course, is that the census tract is too large a level of aggregation to accurately capture neighborhoods, and there are actually multiple neighborhoods within each tract. If these “true” neighborhoods are more racially homogenous than the census tract, the own-race poverty rate is then simply a better measure of the poverty rate in the “true”, sub-tract neighborhood.

9. A Neighborhood Fixed-Effects Model

In this section, I make the assumption that the relevant neighborhood variable for any given youth is defined by the characteristics of neighbors of the youth's own race. Effectively constraining the cross-race effects to be zero, I redefine the poverty rate as the own-race poverty rate for each youth, and I redefine the percentage of professionals as the percentage of professionals of the youth's own race. There are thus, effectively, four poverty rates and four professional rates in each census tract, one for each race group.

This redefinition of the relevant neighborhood variables means that there is now within-tract variation in the relevant poverty rates and the professional rates, which permits the estimation of a tract fixed-effects model. Tables 14 and 15 show the results of these fixed effects model. Each model includes the own-race poverty /professional rate, interactions between each race group and the own-race poverty/professional rate[23], the standard set of family covariates, and tract fixed effects.

Table 16, model 1, shows the fixed effects parameter estimates from the drop-out rate regression on the poverty rate. Row 1, the first coefficient, shows that for White youth the effect of own-race poverty is still highly significant, even with tract-level fixed effects. A 10 percentage point

increase in the own-race poverty rate, in this model, is associated with an estimated 1.7 percentage point increase in the White drop-out rate, an effect similar to that estimated in the
basic model with race interactions (Table 8, model 1.)

The second coefficient shows the interaction between "Black" and own-race poverty, which is large and negative. The net effect of own-race poverty on African-Americans is small, once tract-fixed effects are included: a 10 percentage point increase in own-race poverty is associated with only an 0.2 percentage point increase in the drop-out rate, and the association is not statistically significant.

[23] It might appear confusing to allow an interaction term between youth's race and the own-race poverty rate, since the effect of the own-race poverty rate is identified off within-tract variation, *across races*, in the poverty rate. However, because there are more tracts than race groups and the race * own-race poverty interactions are constrained to be constant across tracts, there is enough variation in the data to identify the tract fixed effect, the own-race poverty effect, and an interaction between race of youth and the own-race poverty rate.

For Hispanics, the effects of own-rate poverty are notably smaller than for Whites, but are still significant. The net effect of poverty on Hispanics is .047, so that a 10 percentage point increase in the poverty rate is associated with an 0.5 percentage point increase in the drop-out rate. This effect is fairly similar in size to that estimated in the model using aggregate poverty rates (Table 8, model 1.)

Finally, for Asians, the fixed-effects model yields estimates of an unexpected sign. This is not tremendously surprising: there was no reason to expect that own-race poverty is a good measure of neighborhood effects for Asians, given the results from Section 8 above.

The fixed effects model of drop-out rates on the percentage of professionals yields quite similar findings (Table 17, model 1.) Once again, own-race neighborhood effects are large and highly significant for Whites and Hispanics, and are not significant for African-Americans. Asians again show own-race neighborhood effects of the wrong sign.

The teenage pregnancy models yield far less consistent findings. The own-race poverty rate is marginally significant only for African-Americans (at $p<.10$), and again the estimates yield results of unexpected sign for the Asians, reminding us, as we saw in Section 8, that own-race poverty rates are not the relevant neighborhood measure for this group. The percentage of professionals in a youths' own race is insignificant in the teenage childbearing fixed-effects model.

The results of this section, then, strongly suggest that there are some important neighborhood effects operating within racially-defined social networks for White and Hispanic youth in California. The fact that own-race poverty rates are large and significant, controlling for neighborhood fixed effects, is important: for the fixed effects model controls for all common observed and unobserved characteristics of the neighborhood and it's residents, including unobserved institutional features, the overall poverty rate, and any common preferences for educational outcomes among resident families.

10. Conclusions

This paper has addressed several questions about the relationship between neighborhood characteristics and youth outcomes. The first finding of this paper is that there do appear to be interesting non-linearities in the relationship between the neighborhood poverty rate and youth outcomes. The strongest evidence suggests not a threshold poverty level in extremely poor neighborhoods, but rather a threshold at fairly low poverty (10%), implying that the largest change in youth outcomes occurs as one compares outcomes in extremely high quality neighborhoods to neighborhoods that are closer to the mean. This finding is broadly consistent with those of Clark (1992.) There is, in addition, some interesting evidence of a threshold effect at high levels of poverty – above 50% – for African-American youth. At this point, the relationship between neighborhood poverty and the drop-out rate increases dramatically, consistent with the "epidemic" model described by Crane (1991.) While this breakpoint is statistically significant, it is based on very few observations, and hence cannot be considered conclusive at this point. I intend to explore further the evidence for a breakpoint at very high levels of poverty in a national analysis, which will include a larger number of youth in very high poverty neighborhoods.

Significant interactions were detected between neighborhood characteristics and parental education, race of youth, and family structure. Consistent with other studies, White youth were found to be much more sensitive to neighborhood conditions than non-White youth, for both the drop-out rates and teenage pregnancy outcomes. Youth whose parents had little education (a high school degree or less) were found to be most sensitive to the neighborhood poverty rate, while youth whose parents had some college or more were found to be most sensitive to the percentage of professionals in the neighborhood. All of these finds are consistent with the hypothesis that a large portion of estimated neighborhood effects consist of unobserved family characteristics that are common within neighborhoods. White families are presumed to have more ability to engage in residential sorting than non-White families, and the differences by parental education are consistent with the hypothesis that neighborhood poverty is a good indicator for unobserved family characteristics among less educated families, while the percentage of professionals in a neighborhood is a good indicator of unobserved family characteristics in more educated families.

The one family interaction which is not consistent with the hypothesis that neighborhood effects result primarily from endogenous sorting is the family structure interaction term. The finding that, among White youth, youth from single-parent families are more sensitive to neighborhood characteristics seems likely to be causal.

The next finding in this paper is that for White youth and Hispanic youth in California, the own-race poverty rate is the relevant neighborhood characteristics[24]. There is some evidence that this relationship may obtain for African-Americans as well, but the findings are notably weaker. This finding suggests

[24] It is perhaps not surprising that same-race neighborhood effects are found to be strongest among Whites and Hispanics in California. Hispanics are by far the most prevalent minority group in this sample, and the difference between the African-American and Hispanic poverty rates in the majority of tracts is very small not statistically significant, in contrast to the difference between White and Hispanic poverty rates. I expect to find stronger results among African-Americans when I expand the analysis to a national sample of cities.

that neighborhood effects appear to be operating through race-specific social networks – a finding at odds with the hypothesis that neighborhood effects are entirely driven by common family and neighborhood unobserved characteristics in a tract.

The final section of the paper tests for neighborhood effects in a tract fixed-effects model, which controls for any common unobserved family characteristics in the neighborhood. This section uses the finding that own-race neighborhood characteristics are the most significant neighborhood variable in many cases, and makes the assumption that the relevant neighborhood variable for each youth is the race-specific poverty/professional rate. The tract fixed-effects model shows that for White youth and Hispanic youth own-race poverty rates and professional rates remain significant, even after controlling for all common tract-level unobserved characteristics of families. The point estimates on neighborhood poverty for these groups are only slightly smaller than in the model without controls for tract-fixed effects. These findings provide evidence that neighborhood effects persist in the presence of strong controls for the presence of omitted and unobservable family and neighborhood level variables

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Table 1
Sample Sizes and Means: Drop-Out Rates and Teen Childbearing Rates by Race, Education of Head, and Family Structure

	Drop-Out Rate		**Teen Childbearing Rate**	
Race	**N**	**mean**	**N**	**mean**
White	88,333	5.7%	42,128	2.6%
Black	12,608	8.7%	6,243	9.7%
Hispanic	61,766	12.2%	29,365	6.7%
Hispanic: English Speakers	*16,928*	*9.4%*	*7,982*	*6.5%*
Hispanic: Spanish Speakers	*44,838*	*13.3%*	*21,383*	*6.8%*
Asian	19,424	3.7%	9,335	1.4%
Age	**N**	**mean**	**N**	**mean**
15 years	40,288	3.8%	19,618	1.2%
16 years	38,926	4.4%	18,916	2.3%
17 years	38,389	7.1%	18,337	4.1%
18 years	33,715	11.9%	15,820	6.7%
19 years	30,813	14.5%	14,380	9.5%
Education of Head	**N**	**mean**	**N**	**mean**
Less than High School	43,466	15.4%	20,559	7.8%
High School	30,595	8.9%	14,719	6.1%
Some College	59,505	6.0%	28,488	3.7%
BA or higher	48,565	3.0%	23,305	1.3%
Family Type	**N**	**mean**	**N**	**mean**
Both parents	135,137	6.8%	64,430	3.3%
Single Father	9,515	12.9%	3,886	6.0%
Single Mother	37,479	10.8%	18,755	7.8%
Family Size	**N**	**mean**	**N**	**mean**
1 - 3 children	130,991	6.5%	62,170	2.9%
More than three children	51,140	11.8%	24,901	8.3%
Family Receives Welfare Income	**N**	**mean**	**N**	**mean**
Yes	14,582	12.0%	7042	9.6%
No	167,549	7.6%	80,029	4.0%

Notes: Means weighted by population weights. Number of observations = unweighted count.

Table 2

Tract Characteristics: Average Values

Variable	Obs	Mean	Std. Dev.
Percent White	5620	69.05	23.19
Percent Hispanic	5619	25.40	23.02
Percent Black	5620	7.39	13.83
Percent Asian	5620	9.57	10.70
Percent Female Headed Households w/ Children	5563	9.51	6.25
Percent Unemployed	5595	7.09	4.47
Percent Poor	5595	12.57	10.14
Percent Professional	5594	26.88	13.20
Percent Professional: White	5562	31.64	13.47
Percent Professional: Hispanic	5549	16.92	12.65
Percent Professional: Black	4792	27.34	23.76
Percent Professional: Asian	5217	29.79	20.90
Percent Poor: White	5590	8.93	9.19
Percent Poor: Hispanic	5539	16.98	12.46
Percent Poor: Black	5007	16.42	20.46
Percent Poor: Asian	5313	11.66	15.79

Notes: Means weighted by population size in census tract.

Number of observations = unweighted number of tracts with non-missing values for variable in sample

Table 3
Regressions of Drop-Out and Teen Childbearing on Family and Neighborhood Characteristics

	Outcome: Dropping-Out			Outcome: Teenage Childbearing		
Independent Variables	**dP/dX**	**dP/dX**	**dP/dX**	**dP/dX**	**dP/dX**	**dP/dX**
percent poor	--	0.10 ***	--	--	0.04 ***	--
	--	(0.01)	--	--	(0.01)	--
percent professional	--	--	-0.10 ***	--	--	-0.05 ***
	--	--	(0.01)	--	--	(0.01)
female	-1.53 ***	-1.62 ***	-1.61 ***	--	--	--
	(0.12)	(0.13)	(0.13)	--	--	--
black	0.26	-0.79 **	-0.57 *	3.00 ***	2.54 ***	2.43 ***
	(0.28)	(0.27)	(0.27)	(0.34)	(0.35)	(0.33)
hispanic	1.12 ***	0.75 ***	0.54 *	1.27 ***	1.22 ***	1.03 ***
	(0.21)	(0.22)	(0.21)	(0.19)	(0.20)	(0.19)
asian	-2.58 ***	-2.65 ***	-2.76 ***	-1.27 ***	-1.21 ***	-1.24 ***
	(0.21)	(0.22)	(0.22)	(0.17)	(0.19)	(0.18)
age 16	0.99 ***	1.10 ***	1.10 ***	2.09 ***	2.14 ***	2.12 ***
	(0.24)	(0.25)	(0.25)	(0.31)	(0.33)	(0.32)
age 17	4.37 ***	4.51 ***	4.49 ***	4.87 ***	4.96 ***	4.89 ***
	(0.28)	(0.29)	(0.29)	(0.39)	(0.41)	(0.41)
age 18	9.89 ***	10.18 ***	10.14 ***	8.41 ***	8.47 ***	8.37 ***
	(0.35)	(0.36)	(0.36)	(0.51)	(0.53)	(0.52)
age 19	12.80 ***	13.26 ***	13.21 ***	12.05 ***	0.68 ***	12.08 ***
	(0.39)	(0.41)	(0.41)	(0.61)	(0.03)	(0.63)
number of children in family	0.64 ***	0.61 ***	0.58 ***	0.69 ***	-1.22 ***	0.65 ***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.15)	(0.03)
English not primary language	-1.00 ***	-1.23 **	-1.10 **	-1.08 ***	12.21 ***	-1.20 ***
	(0.18)	(0.19)	(0.19)	(0.14)	(0.64)	(0.15)
Head: Less than High School	8.17 ***	7.30 ***	6.75 ***	2.67 ***	2.46 ***	2.03 ***
	0.40	0.41	0.40	0.34	0.35	0.33
Head: High School Degree	4.56 ***	4.20 ***	3.58 ***	2.94 ***	2.86 ***	2.39 ***
	0.33	0.35	0.34	0.34	0.35	0.34
Head: Some College	2.28 ***	2.18 ***	1.73 ***	1.64 ***	1.59 ***	1.30 ***
	0.24	0.25	0.25	0.22	0.24	0.23
single mother household	3.75 ***	3.70 ***	3.75 ***	1.83 ***	1.87 ***	1.84 ***
	(0.37)	(0.38)	(0.38)	(0.38)	(0.40)	(0.39)
single father household	1.37 ***	1.31 ***	1.38 ***	1.83 ***	1.84 ***	1.83 ***
	(0.20)	(0.21)	(0.21)	(0.20)	(0.21)	(0.21)

Continued on next page

Notes. See notes on next page.

Continued from previous page

log(family income)	-0.44 ***	-0.38 ***	-0.36 ***	-0.10 **	-0.08 *	-0.07
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
head: unemployed	0.80 *	0.64	0.55	0.85 **	0.82 **	0.69 *
	(0.36)	(0.37)	(0.36)	(0.32)	(0.33)	(0.32)
no parent works	1.39 ***	1.25 *	1.34 ***	0.72 **	0.64 **	0.65 **
	(0.30)	(0.31)	(0.31)	(0.25)	(0.26)	(0.26)
one parent works	0.61 ***	0.61 ***	0.65 ***	-0.07	-0.11	-0.11
	(0.16)	(0.17)	(0.17)	(0.13)	(0.14)	(0.14)
family poverty indicator	0.20	-0.06	0.28	0.43 *	0.28	0.38 *
	(0.23)	(0.23)	(0.24)	(0.19)	(0.20)	(0.20)
head:service	1.59 ***	1.38 ***	1.25 ***	0.75 ***	0.61 **	0.48 *
	(0.30)	(0.30)	(0.30)	(0.25)	(0.25)	(0.24)
head: technical	0.55 **	0.49 *	0.33	0.61 ***	0.57 **	0.46 *
	(0.22)	(0.23)	(0.22)	(0.19)	(0.20)	(0.20)
head: agricultural	1.60 **	1.45 ***	1.18 **	-0.13	-0.10	-0.23
	(0.42)	(0.43)	(0.42)	(0.29)	(0.30)	(0.28)
head: craft	0.74 ***	0.63 *	0.36	1.09 ***	0.98 ***	0.78 ***
	(0.26)	(0.27)	(0.26)	(0.25)	(0.26)	(0.25)
head: laborer	1.49 ***	1.29 ***	1.00 ***	0.91 ***	0.87 ***	0.66 **
	(0.27)	(0.28)	(0.27)	(0.24)	(0.25)	(0.24)
MSA dummies	yes	yes	yes	yes	yes	yes

Notes. Reported coefficients are the change in the predicted probability of the outcome associated with a discrete change from 0 to 1 for dummy variables, and the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable. "Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering. Vector X includes individual and family coefficients (see Table X for complete list) and MSA fixed effects.
***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05.

TABLE 4
Piece-Wise Linear Splines in the Poverty Rate. Outcome: Probability of Dropping-Out of High-School

	Entire Sample (N=168,425)		Whites (N = 80,544)		Hispanics (N = 58,400)		Black (N = 11,933)		Asian (N=17,533)	
model:	1	2	3	4	5	6	7	8	9	10
Variable	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX
Poverty Rate: 0% - 10%	0.723 ***	0.282 ***	0.492 ***	0.221 ***	0.870 ***	0.324 ***	0.227	0.017	0.307 ***	--
	(0.037)	(0.035)	(0.038)	(0.037)	(0.102)	(0.094)	(0.176)	(0.161)	(0.070)	--
Poverty Rate: 10% - 30%	0.245 ***	0.096 ***	0.171 ***	0.095 ***	0.227 ***	0.136 ***	0.297 ***	0.192 ***	0.088 **	--
	(0.017)	(0.015)	(0.028)	(0.026)	(0.032)	(0.030)	(0.052)	(0.049)	(0.034)	--
Change in slope	yes ***	yes ***	yes ***	yes *	yes ***	yes +	no	no	yes *	
Poverty Rate: 30% - 50%	0.038	0.044	0.090	0.102	0.066	0.080	0.079	0.016	0.024	--
	(0.036)	(0.031)	(0.110)	(0.087)	(0.058) *	(0.052)	(0.085) +	(0.077)	(0.101)	--
Change in slope	yes ***	no	no	no	no	no	no	no	no	
Poverty Rate: > 50%	0.262 ***	0.234 **	0.340	0.303	0.034	0.099	0.454 ***	0.361 ***	--	--
	(0.087)	(0.082)	(0.633)	(0.487)	(0.197)	(0.202)	(0.102)	(0.096)	--	--
Change in slope	yes *	yes *	no	no	no	no	no *	no *		
Poverty Rate 0% - 100%	--	--	--	--	--	--	--	--	--	0.089
	--	--	--	--	--	--	--	--	--	(0.018)
Test, all segments equal:	0.000	0.000	0.000	0.075	0.000	0.099	0.118	0.100	0.014	n/a
Controls for X	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo-R2	0.03	0.11	0.02	0.11	0.01	0.11	0.03	0.11	0.02	0.11

See table notes at end of table section.

TABLE 5
Piece-Wise Linear Splines in the Poverty Rate. Outcome: Probability of Teenage Childbearing

	Entire Sample (N=80,468)		Whites (N =38,383)		Hispanics (N =27,725)		African-American (N =5.911)		Asian (N=8,443)	
model:	1	2	3	4	5	6	7	8	9	10
Variable	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX
Poverty Rate: 0% - 10%	0.562 ***	0.220 ***	0.354 ***	0.151 ***	0.469 ***	0.254 **	0.785 **	0.472 *	0.143 *	--
	(0.037)	(0.030)	(0.035)	(0.028)	(0.104)	(0.090)	(0.265)	(0.229)	(0.059)	--
Poverty Rate: 10% - 30%	0.116 ***	0.018	0.053 *	0.006	0.090 **	0.057 *	0.186 *	0.046	-0.010	--
	(0.015)	(0.012)	(0.024)	(0.018)	(0.030)	(0.028)	(0.077)	(0.069)	(0.028)	--
Change in slope	yes ***	yes ***	yes ***	yes ***	yes **	yes +	yes +	no	yes +	
Poverty Rate: 30% - 50%	0.116 ***	0.056 *	0.032	0.016	0.094	0.082	0.288 *	0.190 +	0.059	--
	(0.035)	(0.024)	(0.075)	(0.054)	(0.064)	(0.052)	(0.131)	(0.108)	(0.091)	--
Change in slope	no	no	no	no	no	no	no	no	no	
Poverty Rate: > 50%	-0.037	-0.050	0.756 +	0.431	-0.289	-0.294	-0.130	-0.165	--	--
	(0.141)	(0.097)	(0.440)	(0.322)	(0.294)	(0.300)	(0.318)	(0.269)	--	--
Change in slope	no	no	no	no	no	no	no	no		
Poverty Rate 0% - 100%	--	--	--	--	--	--	--	--	--	0.018
	--	--	--	--	--	--	--	--	--	(0.012)
Test, all segments equal:	0.000	0.000	0.000	0.000	0.003	0.139	0.132	0.330	0.149	n/a
Controls for X	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Psuedo R-2	0.04	0.14	0.03	0.13	0.01	0.10	0.02	0.12	0.01	0.11

See table notes at end of table section.

TABLE 6
Piece-Wise Linear Splines in the Percent Professional. Outcome: Probability of Dropping-Out of High-School

	Entire Sample (N=168,425)				Whites (N = 80,544)				Hispanics (N = 58,400)				Black (N = 11,933)				Asian (N=17,533)		
model:	1		2		3		4		5		6		7		8		9		10
Variable	dP/dX		dP/dX		dP/dX		dP/dX		dP/dX		dP/dX		dP/dX		dP/dX		dP/dX		dP/dX
Percent Professional: 0% - 20%	-0.347	***	-0.108	***	-0.323	***	-0.193	***	-0.285	***	-0.134	***	-0.330	***	-0.149	*	-0.064		--
	(0.020)		(0.019)		(0.041)		(0.037)		(0.037)		(0.035)		(0.074)		(0.069)		(0.051)		--
Percent Professional: 20% - 40%	-0.275		-0.120	***	-0.182	***	-0.084	***	-0.336	***	-0.155	***	-0.147	*	-0.076		-0.123	***	--
	(0.016)	***	(0.015)		(0.017)		(0.016)		(0.043)		(0.040)		(0.068)		(0.060)		(0.028)		--
Change in slope	yes	*	no		yes	**	yes	*	no		no		no		no		no		
Percent Professional: > 40%	-0.183	***	-0.076	***	-0.135	***	-0.057	*	-0.252	*	-0.147		-0.339	+	-0.271	+	-0.088		--
	(0.029)		(0.026)		(0.025)		(0.024)		(0.136)		(0.127)		(0.177)		(0.147)		(0.059)		--
Change in slope	yes	*	no		no		no		no		no		no		no		no		
Percent Professional: 0% - 100%	--		--		--		--		--		--		--		--		--		-0.069
	--		--		--		--		--		--		--		--		--		(0.014)
Test, all segments equal:	0.000		0.443		0.000		0.004		0.756		0.937		0.324		0.557		0.695		n/a
Controls for X	No		Yes		No		Yes		No		Yes		No		Yes		No		Yes
Pseudo R2	0.03		0.11		0.02		0.08		0.01		0.10		0.01		0.10		0.01		0.04

See table notes at end of table section.

TABLE 7
Piece-Wise Linear Splines in the Percent Professional. Outcome: Probability of Teenage Childbirth

	Entire Sample (N=80,468)		Whites (N =38,383)		Hispanics (N =27,725)		Black (N =5.911)		Asian (N=8,443)	
model:	1	2	3	4	5	6	7	8	9	10
Variable	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX	dP/dX
Percent Professional: 0% - 20%	-0.144 ***	-0.023	-0.093 **	-0.019	-0.075 *	-0.032	-0.409 ***	-0.156 +	-0.033	--
	(0.018)	(0.015)	(0.032)	(0.024)	(0.037)	(0.033)	(0.107)	(0.092)	(0.047)	--
Percent Professional: 20% - 40%	-0.217 ***	-0.086 ***	-0.135 ***	-0.063 ***	-0.221 ***	-0.144 ***	-0.188 *	-0.091	-0.016	--
	(0.015)	(0.012)	(0.014)	(0.011)	(0.046)	(0.040)	(0.093)	(0.083)	(0.021)	--
Change in slope	yes *	yes ***	no	no	yes *	yes *	no	no	no	
Percent Professional: > 40%	-0.243 ***	-0.131 ***	-0.124	-0.060 *	-0.435 *	-0.285 *	-0.716 *	-0.547 *	-0.132 *	--
	(0.042)	(0.032)	(0.031)	(0.024)	(0.188)	(0.159)	(0.317)	(0.245)	(0.063)	--
Change in slope	no	no	no	no	no	no	no	no	no	
Percent Professional: 0% - 100%	--	--	--	--	--	--	--	--	--	-0.017
	--	--	--	--	--	--	--	--	--	(0.009)
Test, all segments equal:										
	0.005	0.003	0.559	0.267	0.008	0.032	0.285	0.273	0.307	n/a
Controls for X	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R2	0.04	0.14	0.04	0.13	0.01	0.10	0.02	0.12	0.01	0.11

See table notes at end of table section.

Table 8
Interactions: Race by Neighborhood Characteristics

Variable	Model 1 **Drop-Out** dP/dX	Model 2 **Teen Childbearing** dP/dX
Percent Poor	0.184 ***	0.087 ***
	(0.016)	(0.012)
Black * Percent Poor	-0.080 ***	-0.055 ***
	(0.024)	(0.017)
Net Effect, Blacks	0.104 ***	0.033 **
Hispanic * Percent Poor	-0.106 ***	-0.064 ***
	(0.017)	(0.013)
Net Effect, Hispanics	0.078 ***	0.024 **
Asian * Percent Poor	-0.117 ***	-0.091 ***
	(0.032)	(0.030)
Net Effect, Asians	0.067 *	-0.003
X	yes	yes

Variable	Model 3 **Drop-Out** dP/dX	Model 4 **Teen Childbearing** dP/dX
Percent Professional	-0.123 ***	-0.088 ***
	(0.010)	(0.009)
Black * Percent Professional	0.044	0.046 **
	(0.027)	(0.017)
Net Effect, Blacks	-0.078 **	-0.042 **
Hispanic * Percent Professional	0.045 **	0.062 ***
	(0.014)	(0.012)
Net Effect, Hispanics	-0.078 ***	-0.026 **
Asian * Percent Professional	0.067 **	0.082 ***
	(0.025)	(0.021)
Net Effect, Asians	-0.056 *	-0.006
X	yes	yes

See notes at end of table section.

Table 9
Interactions: Neighborhood Characteristics by Education of Household Head

Outcome: Drop-Out rate Variable	All dP/dX	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Poor	0.191 ***	0.308 ***	0.227 ***	0.222 ***	0.105 ***
	(0.009)	(0.020)	(0.028)	(0.016)	(0.022)
Head: High School Degree * % Poor	-0.067 ***	-0.103 ***	-0.100 ***	-0.168 ***	0.057 *
	(0.010)	(0.021)	(0.025)	(0.021)	(0.025)
net effect	*0.123* ***	*0.205* ***	*0.127* ***	*0.054* *	*0.161* ***
Head: Some College * % Poor	-0.119 ***	-0.193 ***	-0.123 ***	-0.225 ***	-0.008
	(0.011)	(0.021)	(0.027)	(0.026)	(0.025)
net effect	*0.072* ***	*0.115* ***	*0.104* ***	*-0.002*	*0.097* ***
Head: BA or higher * % Poor	-0.218 ***	-0.316 ***	-0.168 ***	-0.366 ***	-0.066 *
	(0.022)	(0.031)	(0.050)	(0.056)	(0.032)
net effect	*-0.028*	*-0.008*	*0.059*	*-0.144* **	*0.038*
X	yes	yes	yes	yes	yes

Outcome: Drop-Out rate Variable	All dP/dX	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Professional	-0.007	0.017	0.049	-0.036	-0.058 **
	(0.010)	(0.014)	(0.042)	(0.020)	(0.019)
Head: High School Degree * % Prof.	-0.110 ***	-0.087 ***	-0.174 ***	-0.195 ***	0.027
	(0.009)	(0.012)	(0.042)	(0.023)	(0.019)
net effect	*-0.117* ***	*-0.071* ***	*-0.124* **	*-0.231* ***	*-0.031*
Head: Some College * % Prof.	-0.157 ***	-0.125 ***	-0.199 ***	-0.289 ***	-0.015
	(0.009)	(0.011)	(0.039)	(0.022)	(0.018)
net effect	*-0.164* ***	*-0.108* ***	*-0.149* ***	*-0.324* ***	*-0.073* ***
Head: BA or higher * % Prof.	-0.185 ***	-0.155 ***	-0.253 ***	-0.326 ***	-0.036 *
	(0.010)	(0.012)	(0.043)	(0.031)	(0.018)
net effect	*-0.191* ***	*-0.138* ***	*-0.203* ***	*-0.361* ***	*-0.094* ***
X	yes	yes	yes	yes	yes

Notes. Reported coefficients are the change in the predicted probability of the outcome associated with a discrete change from 0 to 1 for dummy variables, and the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable.
"Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering.
Vector X includes individual and family coefficients (see Table X for complete list) and MSA fixed effects.
***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05.

Table 10
Interactions: Neighborhood Characteristics by Education of Household Head

Outcome: Teen Childbear Variable	All dP/dX	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Poor	0.061 ***	0.095 ***	0.155 ***	0.082 ***	0.013
	(0.007)	(0.014)	(0.044)	(0.015)	(0.017)
Head: High School Degree * % Poor	0.011	-0.024	-0.033	0.017	0.039 *
	(0.008)	(0.014)	(0.040)	(0.019)	(0.017)
net effect	*0.072 ****	*0.071 ****	*0.122 ***	*0.099 ****	*0.052 ****
Head: Some College * % Poor	-0.011	-0.044 ***	-0.052	-0.035	-0.003
	(0.009)	(0.014)	(0.039)	(0.023)	(0.021)
net effect	*0.050 ****	*0.051 ****	*0.103 ***	*0.047*	*0.010*
Head: BA or higher * % Poor	-0.082 ***	-0.137 ***	-0.115	-0.103 *	-0.017
	(0.020)	(0.024)	(0.083)	(0.052)	(0.025)
net effect	*-0.021*	*-0.042*	*0.041*	*-0.021*	*-0.005*
X	yes	yes	yes	yes	yes

Outcome: Teen Childbear Variable	All dP/dX	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Professional	-0.034 ***	-0.021 *	-0.011	-0.053 *	-0.027
	(0.008)	(0.009)	(0.065)	(0.021)	(0.015)
Head: High School Degree * % Prof.	-0.015	-0.021 *	-0.097	-0.017	0.036 *
	(0.008)	(0.008)	(0.065)	(0.021)	(0.013)
net effect	*-0.049 ****	*-0.042 ****	*-0.108 **	*-0.069 ***	*0.009*
Head: Some College * % Prof.	-0.050 ***	-0.036 ***	-0.171 **	-0.102 ***	0.010
	(0.007)	(0.008)	(0.061)	(0.020)	(0.013)
net effect	*-0.084 ****	*-0.056 ****	*-0.182 ****	*-0.155 ****	*-0.017*
Head: BA or higher * % Prof.	-0.082 ***	-0.059 ***	-0.238 ***	-0.124 ***	0.001
	(0.009)	(0.008)	(0.073)	(0.028)	(0.014)
net effect	*-0.116 ****	*-0.080 ****	*-0.249 ****	*-0.177 ****	*-0.026 ***
X	yes	yes	yes	yes	yes

Notes. Reported coefficients are the change in the predicted probability of the outcome associated with a discrete change from 0 to 1 for dummy variables, and the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable. "Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering. Vector X includes individual and family coefficients (see Table X for complete list) and MSA fixed effects.
***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05.

Table 11
Interactions: Neighborhood Characteristics by Family Structure

Outcome: Drop-Out Rate Variable	All dP/dX	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Professional	-0.143 *** (0.008)	-0.113 *** (0.010)	-0.167 *** (0.043)	-0.216 *** (0.021)	-0.080 *** (0.016)
Single Parent Family * Percent Professional	-0.021 (0.012)	-0.034 * (0.016)	0.048 (0.051)	-0.007 (0.034)	0.002 (0.034)
Net Effect:	-0.164 ***	-0.147 ***	-0.119 ***	-0.223 ***	-0.078 *
X	yes	yes	yes	yes	yes

Outcome: Teen Childbearing Variable	All dP/dX	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Professional	-0.082 *** (0.007)	-0.061 *** (0.008)	-0.181 *** (0.056)	-0.114 *** (0.019)	-0.016 (0.011)
Single Parent Family * Percent Professional	-0.009 (0.010)	-0.025 * (0.012)	0.018 (0.072)	0.012 (0.030)	-0.014 (0.021)
Net Effect:	-0.091 ***	-0.086 ***	-0.164 ***	-0.102 ***	-0.030
X	yes	yes	yes	yes	yes

Notes. Reported coefficients are the change in the predicted probability of the outcome associated with a discrete change from 0 to 1 for dummy variables, and the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable.
"Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering.
Vector X includes individual and family coefficients (see Table X for complete list) and MSA fixed effects.
***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05.

Table 12
Neighborhood Characteristics: Own-Race vs. Other-Race Neighbors

Outcome: Drop-Out Rate Variable	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Poor: White	0.124 *** (0.024)	-0.007 (0.021)	0.010 (0.017)	0.055 (0.027)
Percent Poor: Black	0.003 (0.005)	0.055 * (0.025)	0.005 (0.008)	0.014 (0.009)
Percent Poor: Hispanic	0.016 (0.011)	0.021 (0.022)	0.102 *** (0.019)	0.046 (0.018)
Percent Poor: Asian	-0.011 (0.008)	-0.008 (0.015)	0.005 (0.010)	-0.017 (0.017)
X	yes	yes	yes	yes

Outcome: Drop-Out Rate Variable	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Professional: White	-0.072 *** (0.012)	-0.004 (0.014)	-0.014 (0.011)	0.000 (0.018)
Percent Professional: Black	0.004 (0.003)	-0.034 (0.026)	-0.001 (0.007)	-0.002 (0.007)
Percent Professional: Hispanic	-0.012 (0.010)	-0.081 * (0.038)	-0.207 *** (0.032)	-0.028 (0.021)
Percent Professional: Asian	0.001 (0.005)	-0.008 (0.015)	-0.012 (0.008)	-0.043 ** (0.015)
X	yes	yes	yes	yes

Notes. Reported coefficients are the change in the predicted probability of the outcome associated with a discrete change from 0 to 1 for dummy variables, and the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable. "Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering.
Vector X includes individual and family coefficients (see Table X for complete list) and MSA fixed effects.
These models include controls for the percentage of tract population of own race. Results are similar with this variable ommitted from the model.
***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05.

Table 13
Neighborhood Characteristics: Own-Race vs. Other-Race Neighbors

Outcome: Teenage Pregnancy Variable	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Poor: White	**-0.042** * (0.018)	0.050 (0.026)	0.011 (0.017)	-0.005 (0.017)
Percent Poor: Black	0.010 ** (0.003)	**0.033** (0.038)	0.010 (0.008)	0.006 (0.005)
Percent Poor: Hispanic	0.024 ** (0.008)	0.002 (0.031)	**0.027** (0.020)	0.014 (0.010)
Percent Poor: Asian	0.006 (0.005)	0.023 (0.019)	0.011 (0.008)	**-0.013** (0.010)
X	yes	yes	yes	yes

Outcome: Teenage Pregnancy Variable	Whites dP/dX	Blacks dP/dX	Hispanics dP/dX	Asians dP/dX
Percent Professional: White	**-0.040** *** (0.008)	-0.038 (0.022)	-0.025 * (0.011)	0.002 (0.012)
Percent Professional: Black	0.001 (0.002)	**-0.050** (0.041)	0.009 (0.007)	0.004 (0.004)
Percent Professional: Hispanic	-0.010 (0.007)	-0.115 * (0.053)	**-0.094** *** (0.027)	-0.001 (0.010)
Percent Professional: Asian	-0.002 (0.003)	-0.001 (0.020)	-0.022 ** (0.008)	**-0.018** (0.011)
X	yes	yes	yes	yes

Notes. Reported coefficients are the change in the predicted probability of the outcome associated with a discrete change from 0 to 1 for dummy variables, and the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable. "Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering.
Vector X includes individual and family coefficients (see Table X for complete list) and MSA fixed effects.

These models include controls for the percentage of tract population of own race. Results are similar with this variable ommitted from the model.

***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05.

Table 14

Impact of Own-Race Poverty Rates vs. Other Race Poverty Rates on Dropping Out
Corrections for Measurement Error, and Restrictions to Integrated Tracts

Outcome: Dropping Out. Models run on complete sample	Whites		Blacks		Hispanics		Asians	
	n=67,793		n=10,256		n=47,853		n=14,604	
	n(tracts)=4,202		n(tracts)=2,225		n(tracts)=4,264		n(tracts)=2,969	
	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)
White Poverty Rate	**0.248*** **	**0.313*** **	0.021	0.027	0.016	0.014	0.096*	0.117**
	(0.042)	(0.036)	(0.028)	(0.041)	(0.023)	(0.026)	(0.045)	(0.044)
Black Poverty Rate	0.007	0.007	**0.064***	**0.073***	0.010	0.011	0.019	0.023
	(0.006)	(0.007)	(0.033)	(0.035)	(0.010)	(0.011)	(0.013)	(0.014)
Hispanic Poverty Rate	0.029*	0.023	0.047*	0.047	**0.136*** **	**0.146*** **	0.042	0.042
	(0.013)	(0.015)	(0.026)	(0.031)	(0.023)	(0.023)	(0.024)	(0.025)
Asian Poverty Rate	-0.016	-0.031**	-0.002	-0.006	0.009	0.011	**-0.019**	**-0.032**
	(0.011)	(0.012)	(0.021)	(0.019)	(0.013)	(0.013)	(0.023)	(0.026)

Models run on sample restricted to diverse tracts (own race between 40% and 60% total population)	Whites		Blacks		Hispanics		Asians	
	n=4,690		n=1,453		n=8,055		n=2121	
	n(tracts)=566		n(tracts)=112		n(tracts)=407		n(tracts)=112	
	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)
White Poverty Rate	**0.203**	**0.237**	-0.001	-0.007	0.072	0.103	0.097	0.127
	(0.127)	(0.162)	(0.043)	(0.103)	(0.058)	(0.071)	(0.136)	(0.205)
Black Poverty Rate	0.020	0.030	**0.043**	**0.063**	-0.001	-0.005	0.048	0.081
	(0.030)	(0.045)	(0.120)	(0.192)	(0.024)	(0.030)	(0.046)	(0.071)
Hispanic Poverty Rate	0.103	0.133	-0.002	-0.012	**0.113***	**0.110**	-0.034	-0.111
	(0.071)	(0.095)	(0.088)	(0.123)	(0.056)	(0.059)	(0.069)	(0.123)
Asian Poverty Rate	-0.061	-0.115*	-0.002	-0.006	0.000	-0.003	**0.249***	**0.376** **
	(0.044)	(0.059)	(0.043)	(0.059)	(0.027)	(0.031)	(0.106)	(0.137)

Notes:(1) OLS models have standard errors corrected for heteroscedasticity and tract-level clustering. (2) ME model coefficients include adjustments for estimated measurement error, but there are no corrections for heteroscedasticity or clustering in the standard errors.
All models include the vector of covariates (X) listed in Table 3.
*** : underlying coefficient significant at p <= .001; **: significant at p<=.01; *: significant at p<=.05.

Table 15

Impact of Own-Race Poverty Rates vs. Other Race Poverty Rates on Dropping Out
Corrections for Measurement Error, and Restrictions to Integrated Tracts

Outcome: Dropping Out. Models run on complete sample	Whites		Blacks		Hispanics		Asians	
	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)
Own Race Poverty Rate	0.225***	0.267***	0.085**	0.090*	0.109***	0.103***	-0.007	-0.022
	(0.039)	(0.032)	(0.031)	(0.040)	(0.024)	(0.029)	(0.022)	(0.026)
Other Race Poverty Rate	0.016	0.014	0.051	0.066	0.052**	0.076*	0.105***	0.132***
	(0.009)	(0.011)	(0.030)	(0.052)	(0.024)	(0.035)	(0.026)	(0.025)
Jointly significant?	yes***	yes***	yes***	yes***	yes***	yes***	yes***	yes***
Slopes differ?	yes***	yes***	no	no	no	no	yes**	yes**
Sample restricted to moderately diverse tracts (own race between 20% and 80% total population)	Whites		Blacks		Hispanics		Asians	
	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)
Own Race Poverty Rate	0.192***	0.234***	0.096	0.095	0.119***	0.103**	0.009	-0.004
	(0.054)	(0.053)	(0.052)	(0.063)	(0.032)	(0.040)	(0.042)	(0.049)
Other Race Poverty Rate	0.043**	0.042	0.034	0.044	0.060	0.093*	0.083*	0.103**
	(0.020)	(0.023)	(0.042)	(0.070)	(0.033)	(0.048)	(0.038)	(0.041)
Jointly significant?	yes***	yes***	yes*	yes**	yes***	yes***	yes*	yes**
Slopes differ?	yes*	yes***	no	no	no	no	no	no
Sample restricted to most diverse tracts (own race between 40% and 60% total population)	Whites		Blacks		Hispanics		Asians	
	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)	OLS(1)	ME(2)
Own Race Poverty Rate	0.222*	0.278*	0.003	0.016	0.093	0.070	0.211	0.238*
	(0.114)	(0.136)	(0.099)	(0.145)	(0.055)	(0.075)	(0.106)	(0.123)
Other Race Poverty Rate	0.067	0.065	-0.024	-0.041	0.066	0.105	0.091	0.112
	(0.053)	(0.065)	(0.089)	(0.159)	(0.061)	(0.088)	(0.077)	(0.117)
Jointly significant?	yes**	yes***	no	no	yes***	yes***	yes**	yes**
Slopes differ?	no	no	no	no	no	no	no	no

Notes:(1) OLS models have standard errors corrected for heteroscedasticity and tract-level clustering. (2) ME model coefficients include adjustments for estimated measurement error, but there are no corrections for heteroscedasticity or clustering in the standard errors.
All models include complete vector of covariates (X) listed in Table 3, as well as a variable "percent other race."
"Jointly significant": test whether the two poverty rates are jointly significant.
"Slopes differ": test for whether the two poverty rate coefficients are statistically different.
*** : Test statistic / underlying coefficient significant at p <= .001; **: significant at p<=.01; *: significant at p<=.05.

Table 16
Estimates of Neighborhood Effects from Tract Fixed - Effects Models

	Model 1 Drop-Out Coefficient	Model 2 Teen Birth Coefficient
Poverty Rate	0.1660 ***	-0.0210
	(0.0438)	(0.0434)
Black* Poverty Rate	-0.1430 ***	0.0747
	(0.0447)	(0.0487)
Net Effect	0.0230	0.0537 +
Hispanic * Poverty Rate	-0.1186 **	0.0001
	(0.0394)	(0.0398)
Net Effect	0.0475 *	-0.0209
Asian * Poverty Rate	-0.2803 ***	-0.0895 *
	(0.0432)	(0.0427)
Net Effect	-0.1143	-0.1105 ***
X	yes	yes
Tract Fixed Effects	yes	yes
R-squared	0.10	0.12
Adj. R-squared	0.07	0.06
N	182129	87071
N(tracts)	5249	5211

Notes. Reported coefficients from linear probability model. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable.
"Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity.
Vector X includes individual and family coefficients (see Table 3 for complete list) and census tract fixed effects.
***:coefficient significant at p <=.001; ** coefficient significant at p<=.01; * coefficient significant at p<=.05; + coefficient significant at p<=.10.

Table 17

Estimates of Neighborhood Effects from Tract Fixed - Effects Models

	Model 1 Drop-Out Coefficient	Model 2 Teen Birth Coefficient
% Professional	-0.0932 ***	-0.0473
	(0.0179)	(0.0194)
Black* % Professional	0.0955 ***	-0.0341
	(0.0236)	(0.0317)
Net Effect	0.0023	-0.0814
Hispanic * % Professional	0.0120	0.0263
	(0.0199)	(0.0206)
Net Effect	-0.0812 ***	-0.0211
Asian * % Professional	0.1368 ***	0.1056
	(0.0155)	(0.0162)
Net Effect	0.0437 **	0.0582
X	yes	yes
Tract Fixed Effects	yes	yes
R-squared	0.10	0.12
Adj. R-squared	0.07	0.06
N	182129	87071
N(tracts)	5249	5211

Notes. Reported coefficients from linear probability model. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable.

"Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity.

Vector X includes individual and family coefficients (see Table 3 for complete list) and census tract fixed effects.

***:coefficient significant at p <=.001; ** coefficient significant at p<=.01; * coefficient significant at p<=.05; + coefficient significant at p<=.10.

Appendix Table 1

Summary Statistics for Youth Included and Excluded from Sample

	Dependent Youth				Independent Youth		
	All	Dropouts	Has Child (Girls Only)	In Sub-families	All	Dropouts	Has Child (Girls Only)
Youth Characteristics							
Number of Observations*:	190,332	15,028	4,013	4798	17,212	5,747	3,751
Dropout?	8%	100%	35%	28%	33%	100%	53%
Female?	48%	41%	100%	83%	61%	59%	100%
Girls Only: Own Child?	4%	23%	100%	55%	36%	59%	100%
In husband/wife subfamily?	0.2%	1%	4%	8%	--	--	--
In parent/child subfamily?	2%	8%	51%	92%	--	--	--
Youth is Married?	1%	4%	12%	12%	26%	36%	53%
Youth on Welfare?	2%	5%	15%	10%	6%	11%	20%
White	47%	34%	28%	26%	45%	26%	35%
Black	7%	8%	17%	17%	6%	5%	10%
Latino	32%	50%	49%	50%	40%	65%	49%
Asian	10%	5%	3%	4%	6%	2%	2%
Average Age	16.9	17.6	17.8	17.5	18.3	18.2	18.3
Family of Origin Characteristics							
Education of Head:							
Less than High School Degree	24%	46%	41%	43%	--	--	--
High School Degree	17%	19%	23%	22%	--	--	--
Some College	33%	25%	28%	28%	--	--	--
BA Degree or Higher	26%	10%	8%	7%	--	--	--
Two Parent Family of Origin	74%	63%	56%	59%	--	--	--
Single Mother Family of Origin	21%	28%	38%	37%	--	--	--
Single Father Family of Origin	5%	9%	6%	5%	--	--	--
Family Received Welfare Income	9%	13%	19%	18%	--	--	--
Average Family Income	$54,360	$40,353	$36,911	$39,400	$12,744	$15,394	$17,204
Average Household Income	$55,591	$42,219	$38,813	$41,141	$25,743	$26,310	$21,600

continued on next page

* Includes youth not living in MSAs.

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Neighborhood Characteristics

Percent Professionals	26%	20%	19%	19%	23%	18%	19%
Percent Unemployed	7%	9%	10%	10%	8%	10%	10%
Percent Poor	13%	17%	18%	18%	19%	20%	19%
Percent Very Poor	5%	7%	7%	7%	9%	8%	8%
Percent FHH	10%	12%	13%	13%	12%	13%	14%
Percent Black	8%	10%	13%	13%	8%	9%	10%
Percent Hispanic	29%	38%	39%	40%	31%	42%	37%
Percent White	66%	59%	55%	54%	65%	58%	60%

Appendix Table 2

Sample Sizes: by Race and by Tract

Average Number of Sample Youth Per Tract

	Count, tracts	Mean Number of Sample Youth	Std. Dev.
Entire Sample	4391	36	22
White Sample	4125	19	16
Black Sample	2364	5	6
Latino Sample	4009	13	15
Asian Sample	3149	6	7

Average Number of Sample Employed Adults per Tract (denominator for Percent Professional)

	N (sample obs)	Mean Number of Adults in Employment Population Denominator	Std. Dev
Entire Sample	156375	404	211
White Sample	76366	419	214
Black Sample	10888	361	273
Latino Sample	50910	392	190
Asian Sample	18211	404	201

	N (tracts)	Mean Number of Adults in Employment Population Denominator	Std. Dev.
Entire Sample	4391	338	156

Total Population Size (Census Estimate) per Tract

	N (sample obs)	Estimated Tract Population Size	Std. Dev
Entire Sample	190332	6957	3882
White Sample	89456	6861	4070
Black Sample	13323	6844	4290
Latino Sample	60906	7217	3602
Asian Sample	19127	6679	3533

Appendix Table 3

Dropout Rates and Teen Childbearing Rates by Neighborhood Poverty Rates

	All Dropout			White Dropout			Black Dropout			Hispanic Dropout			Asian Dropout		
Poverty Rate	Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.	
0% - 10%	5.1%	[5.0%	5.2%]	4.5%	[4.4%	4.7%]	5.1%	[4.4%	5.8%]	8.4%	[8.0%	8.8%]	2.9%	[2.6%	3.2%]
10% - 30%	10.6%	[10.4%	10.8%]	8.4%	[8.1%	8.8%]	9.0%	[8.3%	9.8%]	13.2%	[12.9%	13.6%]	5.2%	[4.7%	5.8%]
30% - 50%	14.6%	[14.0%	15.2%]	11.1%	[9.3%	13.0%]	12.2%	[10.9%	13.6%]	16.5%	[15.7%	17.3%]	**D**		
50% - 100%	21.3%	[18.1%	24.8%]	**D**			**D**			**D**			**D**		
Overall Rate:	8.0%	[7.9%	8.1%]	5.6%	[5.5%	5.8%]	8.7%	[8.2%	9.2%]	12.4%	[12.1%	12.6%]	3.8%	[3.5%	4.1%]

	All Teen Births			White Teen Births			Black Teen Births			Hispanic Teen Births			Asian Teen Births		
Poverty Rate	Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.	
0% - 10%	2.6%	[2.4%	2.7%]	2.0%	[1.8%	2.1%]	5.7%	[4.7%	6.9%]	5.0%	[4.5%	5.5%]	**D**		
10% - 30%	5.9%	[5.7%	6.2%]	4.2%	[3.8%	4.6%]	10.2%	[9.1%	11.4%]	7.0%	[6.6%	7.4%]	**D**		
30% - 50%	9.6%	[8.9%	10.3%]	**D**			14.5%	[12.5%	16.7%]	9.4%	[8.5%	10.3%]	**D**		
50% - 100%	**D**			**D**			**D**			**D**			**D**		
Overall Rate:	4.4%	[4.3%	4.6%]	2.6%	[2.4%	2.7%]	9.9%	[9.2%	10.7%]	6.8%	[6.5%	7.1%]	1.4%	[1.1%	1.6%]

Exact binomial confidence intervals are calculated. D: not disclosed because sample size is less than 75 observations.

Appendix Table 4

Dropout Rates and Teen Childbearing Rates by Neighborhood Professional Rates

	All Dropout			White Dropout			Black Dropout			Hispanic Dropout			Asian Dropout		
% Professional	Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.	
0% - 20%	12.0%	[11.8%	12.3%]	9.4%	[8.9%	9.9%]	10.7%	[10.0%	11.5%]	14.3%	[13.9%	14.6%]	5.2%	[4.6%	5.8%]
20% - 40%	6.3%	[6.1%	6.4%]	5.5%	[5.3%	5.8%]	6.6%	[5.9%	7.4%]	9.3%	[8.9%	9.8%]	3.6%	[3.3%	4.1%]
40% - 100%	3.2%	[3.0%	3.4%]	3.2%	[2.9%	3.4%]	**D**			5.1%	[4.3%	6.0%]	**D**		
Overall Rate:	8.0%	[7.9%	8.1%]	5.6%	[5.5%	5.8%]	8.7%	[8.2%	9.2%]	12.4%	[12.1%	12.6%]	3.8%	[3.5%	4.1%]

	All Teen Births			White Teen Births			Black Teen Births			Hispanic Teen Births			Asian Teen Births		
% Professional	Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.		Mean	95 % C.I.	
0% - 20%	7.0%	[6.7%	7.3%]	5.1%	[4.6%	5.6%]	12.0%	[10.9%	13.2%]	7.7%	[7.3%	8.1%]	**D**		
20% - 40%	3.5%	[3.3%	3.7%]	2.6%	[2.4%	2.8%]	8.1%	[7.1%	9.3%]	5.5%	[5.1%	6.0%]	**D**		
40% - 100%	1.1%	[1.0%	1.3%]	0.9%	[0.7%	1.1%]	**D**			**D**			**D**		
Overall Rate:	4.4%	[4.3%	4.6%]	2.6%	[2.4%	2.7%]	9.9%	[9.2%	10.7%]	6.8%	[6.5%	7.1%]	1.4%	[1.1%	1.6%]

Exact binomial confidence intervals are calculated. D: not disclosed because sample size is less than 75 observations

Table Notes

Table 3 notes:

Reported coefficients are the change in the predicted probability of the outcome associated with a discrete change from 0 to 1 for dummy variables, and the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable.

Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering.

Baseline characteristics are: White, male, 15 year old, English speaking youth; head of household has a BA, is employed in a professional occupation, two parents, both parents work, living in MSA 4480 (Los Angeles.)

***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05.

Notes for Tables 4 - 7

Reported coefficients are the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable. Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering.

Vector X includes individual and family coefficients (see Table 3 for complete list) and MSA fixed effects.

The spline segment > 50% poverty dropped from the Asian model due to all negative outcomes.

***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05; + underlying coefficient significant at p<=.10

Notes for Tables 8 – 10:

Reported coefficients are the change in the predicted probability of the outcome associated with a discrete change from 0 to 1 for dummy variables, and the change in the predicted probability of the outcome due to a one percentage point change in the independent variable for continuous variables. Coefficients have been multiplied by 100. Thus, a coefficient of .19 means a one percentage point increase in the independent variable generates a predicted .19 percentage point increase in the outcome variable.

"Net effect" is the sum of the interaction term and the neighborhood variable coefficients; significance test based on the significance of the linear combination. Standard errors in parentheses; corrected for heteroscedasticity and tract-level clustering.

Vector X includes individual and family coefficients (see Table 3 for complete list) and MSA fixed effects.

***:underlying coefficient significant at p <=.001; ** underlying coefficient significant at p<=.01; * underlying coefficient significant at p<=.05.