Income Inequality, Economic Segregation and Children's Educational Attainment

Susan E. Mayer
Harris Graduate School of Public Policy
University of Chicago
s-mayer@uchicago.edu

Abstract

Households became more geographically segregated by income in the United States between 1970 and 1990. Research shows that growing up in a poor neighborhood is associated with worse outcomes for children. This suggests that economic segregation may be harmful to children. Economic inequality also increased between 1970 and 1980. Theoretical arguments suggest that the increase in inequality led to the increase in segregation. Using 1970, 1980 and 1990 Census data, I find that an increase in income inequality at the state level is associated with an increased in economic segregation between census tracts in the state. However, economic inequality between households in the same census tract hardly changed between 1970 and 1990. I then combine Census data with data from the Panel Study of Income Dynamic to show that given a constant level of economic inequality in a state, an increase in economic segregation between tracts in the same state increases affluent children's educational attainment but reduces poor children's educational attainment. Therefore segregation between census tracts increases inequality in educational attainment and may therefore increase inequality in the next generation. Economic inequality within census tracts has little effect on high or low-income children's educational attainment.

Income Inequality, Economic Segregation, and Children's Educational Attainment*

Susan E. Mayer
Harris Graduate School of Public Policy
University of Chicago

Households became more geographically segregated by income in the United States between 1970 and 1990 (Jargowsky 1993, 1997). A large research literature shows that growing up in a poor neighborhood is associated with worse outcomes for children. Many researchers therefore conclude that the increase in economic segregation has been harmful to children.

Economic inequality also increased in the United States between 1970 and 1980 (Karoly 1993, Morris and Western 1999). Some researchers have suggested that the increase in inequality led to the increase in segregation (Durlauf 1996, Wilson 1987). I first test this hypothesis. Then I estimate the effect of both economic segregation and economic inequality on children's educational attainment. If rising economic inequality among adults has led to more economic segregation and if increased economic segregation led to more inequality in children's outcomes such as educational attainment, increases in economic inequality among parents are likely to be transmitted to the next generation perpetuating economic segregation. Conversely, if economic inequality hurts children but economic segregation does not, efforts to reduce segregation without reducing inequality could be misdirected.

I. Theoretical Issues

I denote the total variance of household income as σ_t^2. If we divide a geographic area such as a state, *s*, into mutually exclusive geographic areas such as neighborhoods, *n*, we can decompose the total variance of household income for *s* into two additive components: a between-neighborhood component (σ_{bn}^2) and a within-neighborhood component (σ_{wn}^2). This yields the identity:

$$\sigma_t^2 = \sigma_{bn}^2 + \sigma_{wn}^2 \qquad (1)$$

Equation 1 shows that there is often a trade-off between reducing income inequality *within* neighborhoods and reducing income inequality *between* neighborhoods. If the distribution of household income in a state or city is fixed, at least in the short run, factors that reduce the *between*-neighborhood variance (the variance of neighborhoods' mean income) will necessarily increase the *within*-neighborhood variance of household income. Thus if we assume any given overall level of inequality (σ_t^2), the claim that residential segregation by income hurts children's well-being must therefore be a claim that inequality within neighborhoods does less harm than inequality between neighborhoods.[1]

Most research on the social consequences of economic inequality estimates a model in which the level of inequality in a geographic area (such as a nation or state) predicts the area's mean outcome on some measure like mortality or crime. A common measure of inequality is the coefficient of variation (σ_{ts}^2 / X_s^2, where X_s is mean income for s).[2] Thus estimates of the effect of inequality generally are of the following form:

$$O_s = \alpha + \beta_t\, \sigma_{ts}^2 / X_s^2 + \varepsilon_s \qquad (2)$$

[1] Combining equation 1 and 2 yields:

$$O_s = \alpha + \beta_w \sigma_{wn}^2 / X_n^2 + \beta_b \sigma_{bn}^2 / X_s^2 + \varepsilon_s$$

This demonstrates that β_t in equation 1 is the weighted sum of β_w and β_b. By measuring inequality within a geographic unit, estimates based on models such as equation 2 make assumptions about the effect of economic segregation. Studies that analyze the effects of inequality within nations, for example, assume that inequality within nations is more important than inequality between nations. Yet more than half the variation in household income is between nations (Firebaugh 1999). Inequality within nations presumably has different consequences from inequality between nations. Studies that estimate the effect of inequality at the neighborhood level assume that inequality within neighborhoods is more important than inequality between neighborhoods.

[2] Of course, there are many other possible measures of economic inequality. But only those based directly on the variance of income are decomposable into within and between area inequality. The variance of log income is a preferred measure of inequality than could be decomposed in this way. However, with the data that I use I cannot estimate the variance of log income for neighborhoods.

where ε is a stochastic error term.

Models of neighborhood effects estimate the effect of a characteristic of a child's neighborhood (N), such as mean income or percent poor on some outcome. Thus they are generally of the following type:

$$O_{in} = \alpha + \beta_n N_{in} + \beta_f F_{in} + \varepsilon_{in} \qquad (3)$$

where F is a set of family background controls, and the subscript i denotes an individual. These models have many well-known estimation problems (Duncan et al. 1997, Tienda 1991, Mayer and Jencks 1990). For example, almost all studies still estimate neighborhood effects by comparing outcomes for children whose parents have the same measured characteristics but chose to live in different neighborhoods. If the unmeasured parental characteristics that lead apparently similar parents to choose different neighborhoods affect children, as seems likely, this methodology is likely to bias the estimate of neighborhoods' impact on children.

Several studies estimate the effect of the percent of neighborhood residents who are poor or who are affluent, and many estimate the effect of both characteristics together on various outcomes of children (Brooks-Gunn et al. 1993, Duncan et al. 1994, Clark 1992, Duncan 1994, Chase-Lansdale et al. 1997, Halpern-Felsher 1997).[3] These models are as follows:

$$O_{in} = \alpha + \beta_p P_n + \beta_r R_n + \beta_f F_{in} + \varepsilon_{in} \qquad (4)$$

Most studies that estimate a model like this find that β_p is less than β_r. This is usually interpreted to mean that the absence of affluent neighbors is more important than the presence of low-income neighbors to children's outcomes. Sometimes this evidence is used to support a resource

[3] Other studies include in their models both mean or median family income and a measure of low income, such as the percent of residents who get welfare (Corcoran et al. 1992) or neighborhood poverty rate (Ensminger et al. 1996).

theory of neighborhood effects (Chase Lansdale et al. 1997), which emphases the quality of public and private institutions and amenities in the neighborhood. Sometimes the evidence that β_r is greater than β_p is used to support collective socialization theories, which hold that role models and neighborhood monitoring are important for children (Brooks-Gunn et al. 1993, Halpern-Felsher et al. 1997). This evidence is also used to dispel contagion theories (Brooks-Gunn et al. 1993), which focus on the ability of peers to spread problem behavior Crane 1991b).

Although suggestive, models like equation 4 cannot provide clear evidence about these theories. Theories that emphasize neighborhood resources hold that mean neighborhood income is important. The distinction between collective socialization and contagion depends on the positive externalities of high-income neighbors being greater than the negative externalities of low-income neighbors. In equation 4, with R_n constant, as P_n increases mean neighborhood income declines and vice versa. If mean income is all that matters and if mean income increases more when R_n increases than when P_n increases, β_p would be greater than β_r even when the externalities of rich and poor neighbors are the same.

To determine whether high-income or low-income neighbors are more important for children's outcomes, one would have to control mean income. With mean income constant, an increase in the number of rich or poor neighbors will increase inequality. Thus such a model would approximately estimate the effect of the dispersion of neighborhood income on children's outcomes. We know from equation 1 that neighborhood economic inequality can be a function of economic inequality at higher levels of aggregation, say the MSA or state. With mean income constant, if P_n or R_n changes neighborhood inequality will change. But because neighborhood inequality depends on inequality at a higher level of aggregation, the apparent effect of neighborhood inequality could be due to inequality at the MSA or state level.

Thus when β_p is less than β_r in equation 4, it could mean that the externalities of rich neighbors are greater than the externalities of poor neighbors, that mean neighborhood income is important, that neighborhood inequality is important, or all three. The distinctions are important. If inequality at, say the state level is all that matters, attempts to reduce economic segregation without reducing state level inequality could be both costly and futile. Below I discuss several plausible arguments why inequality between neighborhoods could affect children's outcomes.

To test the claim that economic inequality within neighborhoods is less harmful than inequality between neighborhoods, one must estimate models that include the effect of both within and between neighborhood inequality. Such a model can also separate the effect of economic segregation from the effect of economic inequality at higher levels of aggregation. In this paper I test such a model to see whether growing economic segregation lowered poor children's educational attainment.

Theories about Economic Segregation and Economic Inequality. Wilson (1987) argued that deindustrialization and occupational bifurcation resulted in greater economic inequality and that this combined with the suburbanization of jobs led to a greater economic segregation. Jargowsky (1997) shows that economic segregation between census tracts in MSAs did in fact increase for blacks, whites and Hispanics during the 1970s and 1980s.

In this section I describe three circumstances under which an increase in economic inequality could increase economic segregation: 1) the rich believe that affluent neighbors are a net benefit, 2) the quality of housing units in any given neighborhood changes less rapidly than the distribution of income, and 3) income has a nonlinear effect on demand for costly neighborhood amenities.

Theories about economic segregation often begin with the idea proposed by Tiebout (1956) that families with the same income sort into different neighborhoods according to their distinctive preferences for local amenities. To some people good schools are very important while others care more about access to public transportation. As a result, people with the same income choose different neighborhoods. Although Tiebout focused on families with the same income but different tastes, his model can easily be extended to families with different incomes. Such families can also afford different levels of total amenities, which leads to sorting by income as well as taste.

If the demand for any given neighborhood amenity is a linear function of income, then when inequality within neighborhoods increases and mean neighborhood income remains unchanged, the rich will demand more of the amenity, the poor will demand less, and there will be no net change in demand. Under these circumstances the supply of amenities such as parks and public transportation would be unchanged.

If the relationship between income and demand for amenities is concave downward, then when the rich get another $1,000 they will demand a bit more, but when the poor lose $1,000 they will demand a lot less. Thus all else equal when inequality increases overall demand will fall. Assuming the supply drops in response, the neighborhood may attract fewer affluent residents. For example, as bus ridership in an area declines, the transportation department may eliminate the line. When it does, people who had high demand for public transportation (employed people) will move to a neighborhood where it is offered. Those with low demand (unemployed people) will remain where they are. Thus there will be more neighborhood sorting on availability of public transportation. Because need for transportation is correlated with income, there will also be more sorting by income.

Other models of economic segregation add the idea that affluent residents generate positive externalities for their neighbors. As a result, families will pay more to have affluent neighbors, independent of the level of publicly provided goods. Such these benefits of affluent neighbors could derive from a higher tax base that allows lower tax rates, from better role models, or from more effective neighborhood monitoring (Wilson 1987, Jencks and Mayer 1990, Sampson and Laub 1994).

If everyone saw advantaged neighbors as an advantage and if families cared only about having the most affluent neighbors, neighborhoods would be perfectly sorted by income because the only way that everyone can avoid having neighbors poorer than themselves is for everyone to have neighbors exactly like themselves. However, some families may see advantaged neighbors as a disadvantage. When disadvantaged children must compete with advantaged children for good grades, good jobs, or social status they are more likely to lose out (Davis 1966, Jencks and Mayer 1990).[4] In addition, the relative deprivation model holds that when the poor compare themselves to the rich, it can lead to unhappiness, stress, and alienation (Merton and Kitt 1950, Davis 1959, Runciman 1966, Williams 1975). Both the relative deprivation and competition models suggest that if all else is equal and neighbors are a relevant reference group, families will avoid having richer neighbors. If everyone chose neighbors exclusively in this way, we would again observe perfect sorting by income, because the only way everyone can avoid having neighbors richer than themselves is for everyone to have neighbors exactly like themselves.

On the other hand, if relative deprivation were so important that the psychological benefits of having poorer neighbors exceeded the costs of having such neighbors, poorer

[4] For example, when a state university accepts all state residents whose grades place them in the top 10 percent of their graduating class, a student's chances of getting in are better if he or she goes to a disadvantaged rather than an advantaged school (Attwell 1999).

neighbors would be a scarce resource and rich families would seek them out. If this were the case all neighborhoods would under plausible assumptions be a microcosm of larger society.[5] This is not what we observe. As I show below, neighborhoods are on average quite economically heterogeneous but they are not as heterogeneous as the states in which they are located. This is partly because different families make different trade-offs between the quality of the housing unit and the cost of neighborhood amenities, including neighbors with different incomes. In addition, families value proximity to work, and employees in the same work site have highly variable earnings, so perfect sorting by income is unlikely. Finally, not all families have always been able to freely choose among neighborhoods. Current and historical racial and ethic segregation can affect the current level of economic segregation (Massey and Denton 1993, Jargowsky 1997). In this paper I focus exclusively on economic segregation. The rise in economic inequality may affect economic segregation differently from racial or ethic segregation and racial and ethnic segregation may have a different effect than economic segregation on children's outcomes.[6]

If the externalities of neighbors are a linear function of their income, increasing one neighbor's income by $1,000 while reducing another's by the same amount will leave the mean externality unchanged. Increases in income inequality within neighborhoods will thus give no one a reason to move. If the externalities generated by neighbors are a nonlinear function of their income, such that raising the incomes of the rich by $1,000 generates more benefit than raising the income of the poor by $1,000, increases in inequality within a neighborhood will

[5] If poor neighbors were desirable, the rich would bid up the price of housing in poorer neighborhoods, driving out the poor. This process would continue until all neighborhoods had equal numbers of poor residents and were equally costly.

[6] Several studies show that there is more racial segregation than economic segregation among neighborhoods in metropolitan areas (Farley 1977, Massey and Eggers 1990, Jargowsky 1996)

make it more attractive. Then as the rich get richer they will bid up the price of rich neighbors. As the poor get poorer, they will be less able to afford affluent neighbors. In this case neighborhood segregation would increase.

An increase in inequality could also increase economic segregation if housing quality within neighborhoods does not change as quickly as the distribution of income. If the income of the richest neighborhood residents increases and want they want better housing as a result, they can either improve their current residence or move to a better one. If improving existing units is relatively expensive, richer residents will move to richer neighborhoods. As aggregate demand for expensive housing grows, developers will create new neighborhoods composed of exclusive units. As a result, the variance of household income within existing neighborhoods will stay constant and the increase in total variance will be expressed as an increase in the variance of neighborhood mean income.

I know of no other studies that estimate the effect of inequality on economic segregation. Jargowsky (1997) finds that holding constant MSA mean income, an increase in MSA economic inequality between 1980 and 1990 was associated with a decline in neighborhood poverty levels for African Americans. But an increase in economic inequality among African Americans was associated with an increase in neighborhood poverty. I also know of no data that could be used to test these hypotheses about how inequality affects economic segregation. Therefore in this paper, I estimate the effect of a change in inequality on a change in economic segregation. But I do not try to explain why such a relationship exists.

Theories about Economic Segregation and Educational Attainment. When schooling is locally financed, economic segregation can affect school spending and school quality, which in turn affects educational outcomes (Benabou 1996, Fernandez and Rogerson 1996, de Bartolome

1990).[7] Of course, this sorting could benefit high-income children as much as it hurts low-income children. Only if additional school spending increases rich children's educational attainment less than it increases poor children's educational attainment would income-related disparities in school spending hurt poor children more than it helps rich children.[8]

Sociologists who study neighborhood effects have been less interested in school finance and more interested in the way role models, social networks, and neighborhood monitoring influence children's schooling.[9] Recent research tends to find that growing up with advantaged neighbors or classmates modestly improves children's educational attainment (Halpern-Felsher 1997, Connell and Halpern-Felcher 1997, Brooks-Gunn et al. 1993, Clark 1992, Crane 1991a, and Mayer 1991).[10] This finding, if correct, implies that economic segregation harms poor children. But it does not follow that economic segregation lowers overall educational attainment. That depends on whether advantaged students gain enough from segregation to offset poor students' losses. In a study that focuses mainly on racial segregation, Cutler and Glaeser (1997) find that economic segregation has little effect on white MSA residents' chances of graduating from high school or college. I am not aware of any other studies that address this issue directly.

---

[7] The effect of school spending on educational outcomes is still hotly debated. Some reviews claim that neither school spending nor other school resources affect school achievement or other educational outcomes (Hanushek 1997). Other studies find that per pupil spending has a small positive effect on educational outcomes (Hedges et al. 1992, Ferguson and Ladd 1996) and future earnings (Card and Krueger 1996).

[8] If school quality were a linear function of school spending and returns to schooling were identical for rich and poor children, economic segregation (and the resulting disparities in school spending) would lead to an increase in educational attainment among the rich that would exactly off set the decrease among the poor.

[9] See Jencks and Mayer (1990), Ellen and Turner (1997), and Gephart (1997) for reviews of this research.

[10] An exception is Evans et al. (1992) who find that the effect of school social composition on schooling outcomes is largely spurious.

Section 2 estimates the effect of changes in state-level economic inequality on economic segregation between census tracts from 1970 to 1990. Section 3 estimates the effect of economic segregation on children's educational attainment.

II. Effect of Inequality on Segregation.

Data and Measures. In order to measure economic segregation, one must decide what geographic units to compare. Ideally one would select the geographic units that were theoretically relevant to the outcome of interest. I estimate the effect of inequality in states on segregation between census tracts in the state. In the next section of this paper I estimate the effect of inequality and segregation on children's years of schooling. Unlike neighborhoods or MSAs, states are relevant political jurisdictions for educational outcomes. A typical American state provides about half the funding for its public schools, while local school districts provide most of the rest. If one were mainly interested in school financing, one might want to assess the effect of economic segregation between school districts within the same state. But if interpersonal comparisons involving relative deprivation or role models influence children's educational attainment, and if children are more likely to make such comparisons with people in their immediate neighborhoods, it makes more sense to compare elementary school attendance areas or census tracts (which typically contain about 4,000 people). I estimated the level of economic segregation both between school districts and between census tracts within states. I then estimated the effect of both segregation between school districts and segregation between census tracts on children's educational attainment. Because there was little substantive difference in the estimates, I report only the estimates for census tracts. Geographic units other than those used in this paper also may be relevant ad that is an important issue for future research.

My measures of state characteristics come from the 1970 1 percent Public Use Micro Sample (PUMS) of census data and from the 1980 and 1990 5 percent PUMS. I use the PUMS data to estimate the dispersion of household income in each state in 1970, 1980 and 1990. I then estimate the level of economic segregation between census tracts in each state for these same years. The appendix gives a full explanation of the data and variables that I use and descriptive statistics for these variables.

To estimate the components of variance in equation 1, I calculate the total variance of household income for each state from PUMS data and calculate mean income for each census tract in the state using the STF4 and STF5 Census files.[11] I weight each tract mean by the population of the tract. The variance of the weighted means is the variance of household income between census tracts. To get the within tract variance I subtract the between tract variance from the total variance of household income in the state.

The ratio of the between-tract variance to the total variance (σ_b^2/σ_t^2) is a measure of economic segregation (Jargowsky, 1996). In the absence of economic segregation, all areas have the same mean income and $\sigma_b^2/\sigma_t^2 = 0$. With complete economic segregation, there is no income variation within geographic areas and $\sigma_b^2/\sigma_t^2 = 1$.

Sociologists have developed many other possible measures of economic segregation.[12] Most of these were developed to measure racial or ethnic segregation. The most commonly used measures are the "exposure index," which gives the average probability that members of one group live in the same neighborhood as members of another group, and the "index of dissimilarity," which gives the percent of residents with a particular characteristic who would

---

[11] Not all the geographic area states fall into census tracts. See the Appendix for a description of how I handle areas that were untracted in a year.

[12] See White (1987) and James (1986) for reviews of measures of segregation.

have to move for the group to be equally represented in all neighborhoods. Because these measures were developed to estimate racial segregation, they require classifying people into discrete categories. Some research has measured economic segregation in the same way (Massey and Eggers 1990), but because income is continuous, by breaking income into discrete categories this approach throws away potentially valuable information (Jargowsky, 1996).

Trends in Economic Inequality and Economic Segregation. The first row in Table 1 shows that mean household income in the United States increased between 1970 and 1980 and again between 1980 and 1990. The total variance of household income in the United States also increased over this period. The next set of rows shows that by far most of the income variance in the United States is within states, and within states most of it is within census tracts. Even in 1990 on average two-thirds of the variance in state household income was within census tracts.[13] Row 5 shows that economic segregation between census tracts within states declined slightly between 1970 and 1980, but increased quite a lot between 1980 and 1990.[14]

States vary quite a bit in both the level of economic segregation and in the change in economic segregation between 1970 and 1990. In 1990 the most economically segregated state was Illinois, where 52 percent of the income variance was between census tracts. It was followed by Texas and Virginia, where 42 percent of the variance was between census tracts. The least economically segregated states tend to be in the South. In both Arkansas and Mississippi less than 15 percent of the income variance was between tracts in 1990. The increase in segregation between 1980 and 1990 was not confined to one particular region.

[13] Appendix table 2 shows the absolute variance for states and census tracts in each year.

[14] Jargowsky's (1996) finds that economic segregation between census tracts increased between 1970 and 1980 for blacks, whites, and Hispanics in MSAs. The trend in economic segregation in states need not be the same as the trend in MSAs. In addition, differences between the way Jargowsky and I calculate economic segregation may affect the trend in segregation.

California, Illinois, and Texas all experienced a large increase in segregation while several southern and mid-western states had small increases.

Table 1 shows that the CV of household income in the United States hardly changed between 1970 and 1980, but increased a lot between 1980 and 1990. Thus inequality increased over this period.[15] Rows 8 and 9 shows that both the CV for income within tracts and the CV for income between tracts increased between 1970 and 1980. Thus census tracts became slightly more economically heterogeneous during the 1970s when segregation declined. This trend was reversed in the 1980s, when the CV for income within census tracts declined. By 1990 tracts were only slightly less economically heterogeneous than they had been in 1970, at least by this measure of inequality, even though economic segregation between tracts increased a lot over this period.

The degree of economic heterogeneity within a typical census tract varies substantially by state. In 1990 southern states had the most economically heterogeneous census tracts. This was because, as we have seen, southern states tend to be less economically segregated than other states. In Arkansas, Louisiana, Mississippi, and West Virginia the CV for income within a census tract exceeded .80. In Connecticut, Illinois, Maryland, New Jersey and Virginia the mean was less than .60. Other upper Midwest and northeastern states including New York, Michigan, and Pennsylvania had CVs for income within census tracts around .63.

Changes in Inequality and Segregation. To test the hypothesis that the level of state economic inequality (I) in state *s* affects economic segregation between census tracts within states one could estimate:

[15] Other measures of inequality yield a similar trend for 1980 to 1990. But some other measures show more growth in inequality between 1970 and 1990. The Gini coefficient of household income increased from .361 in 1970 to .368 in 1980 to .381 in 1990. The standard deviation of log income in creased from .789 in 1970 to .822 in 1980 to .856 in 1990.

$$\sigma_{bn}^2 / \sigma_{ts}^2 = \alpha + \beta_I I_s + \varepsilon_s \qquad (7)$$

where $\sigma_{bn}^2 / \sigma_{ts}^2$ measures segregation. This model has several drawbacks. First, it confounds the effect of inequality on the numerator and the denominator of the dependent variable. Second, because σ_{ts}^2 / X_s^2 is a measure of inequality, σ_{ts}^2 appears on both sides of equation 2. This is a problem if σ_{ts}^2 is measured with error. To address these issues, I control $1/X^2$ and predict the income variance between census tracts.[16] With a $1/X^2$ controlled, the total variance of income in a state (σ_{ts}^2) is itself a measure of inequality. I therefore estimate:

$$\sigma_{bs}^2 = \beta_0 + \beta_t \sigma_{ts}^2 + \beta_x\, 1/X^2 + \varepsilon_s \qquad (8)$$

The main problem with this equation is that the level of economic inequality is correlated with many other state characteristics that could affect segregation. To estimate the effect of a change in inequality on economic segregation, one would have to control all factors that influence both inequality and segregation. We do not have measures of all the possible state factors that might meet this requirement and there may well be more possible candidates than there are states.

To reduce omitted variable bias I include state dummy variables. This controls all characteristics of a state that remain unchanged over the period of observation. I also include year dummies to account for the fact that there was a secular trend in both economic segregation and inequality. I also control state mean income because mean income is correlated with inequality and it could affect the level of segregation in a state. With state (γ_s) and year (γ_t) dummy variables and state mean income, I estimate the effect of changes in state economic inequality on a change in between census tract income variance:

[16] Expanding equation 8 yields $\sigma_{bn}^2/\sigma_{ts}^2 = \alpha + \beta_t \sigma_{ts}^2 / X_s^2 + \varepsilon_s$. In this model β_t is the combined effect of the variance of income and mean income in the state. Thus I separate these effects and remove the total variance from the denominator of the right side to yield equation 8.

$$\sigma_{bs}^2 = \alpha + \beta_t \sigma_{ts}^2 + \beta_x 1/X^2 + \beta_2 X^2 + \gamma_s + \gamma_t + \varepsilon_{st} \qquad (9)$$

This model tells us whether an increase in the total variance of income (net of mean income) is associated with an increase in the variance of income between census tracts, and if so how large the effect is. If β_t is greater than 1, the increase in σ_{bs}^2 is greater than the increase in σ_{ts}^2, indicating that the within-tract variance fell and that tracts became more economically homogeneous. If β_{ts} equals 1, inequality between tracts increased by the same amount as overall inequality, leaving within tract inequality unchanged.

This model relies on data for states measured in 1970, 1980 and 1990. Vermont and Wyoming were omitted in 1970 because Census data did not include census tract income for these states for that year. This leaves a sample of 148 state-year data points. The means for these 148 state-year data points are shown in the last column of Table 2.

The first column in Table 2 shows that a one point increase in the total variance of a state's household income leads to a .871 point increase in between-tract variance, leaving a .129 point increase in the within-tract variance. The racial composition of a state may affect both economic inequality and economic segregation in a state. Thus I control the percent of state residents who are African American and the percent who are Hispanic. But *changes* in states' racial composition cannot have much effect on *changes* in economic inequality, because percent African American in 1980 correlates .98 with the percent African American in both 1970 and 1990. The inter-year correlations for Hispanics are equally high. This is demonstrated in the second column in Table 2 where neither percent African American nor percent Hispanic has a large or statistically significant effect on the between census tract variance of income. β_t is less than 1 in both models suggesting that an increase in the total variance of income makes census tracts more internally heterogeneous, but because the coefficient is greater than .5, most of the increase in inequality is between census tracts.

An increase in inequality in a state is associated with both an increase in the heterogeneity of census tracts and an increase in economic segregation between census tracts. The increase in segregation could occur either because income increases near the top of the distribution lead families to move to richer tracts or because income increases were especially common among families already living in such tracts.

III. Effect of Segregation on Educational Attainment.

Data and Measures. Because many adults no longer live in the state where they were raised, using economic segregation in a state to predict the educational attainment of the adults in the state could lead to serious errors. I therefore use data from the Panel Study of Income Dynamics (PSID) to estimate the effect of state economic segregation measured when childen were fourteen years old on children's eventual years of schooling. I estimate the effect of segregation on overall educational attainment and on the educational attainment of high and low-income children.

As noted above, many models of neighborhood effects fail to distinguish the effect of the dispersion of income within neighborhoods from the effect of neighborhood mean income, or from the effect of inequality at higher levels of aggregation. To overcome these problems one could predict a child's eventual years of schooling from economic inequality with the neighborhood, economic inequality between neighborhoods in the state, and family background.

As noted above, the effect of economic inequality within neighborhoods is likely to be biased in such a model because the characteristics that cause parents with the same income to select neighborhoods with different levels of inequality can also affect children's educational attainment. This creates a correlation between neighborhood inequality and the error term. One strategy for reducing this correlation is to aggregate across neighborhoods in the same state and regress a child's years of schooling on a state-level measure of neighborhood segregation. Since the unmeasured characteristics of state residents are subsumed in the state-wide disturbance term, any correlation between ε_{in} and σ_{iwn}^2 is due to intra-state neighborhood selection is eliminated. Inter-state selection is not eliminated, but this bias is less serious. This I estimate:

$$E_{ist} = \alpha + \beta_w \sigma_{wst\text{-}k}^2 + \beta_n 1/X_{nst\text{-}k}^2 + \beta_b \sigma_{bst\text{-}k}^2 + \beta_x 1/X_{st\text{-}k}^2 + \beta_f F_{ist} + \varepsilon_{ist} \qquad (10)$$

Where the subscript *t-k* indicates the year the child was fourteen years old. In this model, β_w is the effect of living in a state with more economically heterogeneous census tracts, controlling inequality between tracts. Similarly, β_b is the effect of living in a state with more inequality between census tracts controlling economic inequality within tracts. If economic segregation affects educational attainment, β_b will differ from β_w. If only the overall level of inequality in a state matters, β_b will not differ significantly from β_w.

I measure state characteristics when a child was fourteen years old using the 1970, 1980, and 1990 PUMS data described in the previous section. I use linear interpolation to estimate state characteristics in years between 1970, 1980, and 1990.[17] I measure years of schooling when respondents were twenty-three years old. I measure family background characteristics (described below) when children were twelve to fourteen years old. My PSID sample, therefore, includes all respondents who were in the data set both when they were twelve to fourteen years old and when they were twenty-three years old (N = 3240). A full description of the data and the variables appears in the Appendix.

---

[17] When I use weighted PSID data to replicate model 1 in Table 2, the coefficient for the effect of the total income variance on between census tract variance was .734, which is similar to the .871 using aggregate census data.

I control dummy variables for the Northeast, South, and Midwest. This controls characteristics of the region that remain unchanged over the period of observation. An alternative would be to control state dummy variables as I did when I estimated the effect of inequality on segregation. This strategy has the advantage of controlling all invariant characteristics of states. However, it has three important disadvantages. First, it can magnify measurement error in independent variables, including the measure of segregation, which would downwardly bias the estimated effects. Second, if the lag structure of the model is not correctly specified, this too can result in downwardly biased estimates of the effect of segregation. This is less a problem in estimates of the effect of inequality on segregation because inequality increased before segregation increased making the direction of causality clear. Third, including state dummy variables greatly reduces the degrees of freedom available to estimate the model, which in turn increases the standard errors of the estimates. Nonetheless I report below the sensitivity of my conclusions to controlling state rather than region dummy variables.

I control year dummy variables to account for the secular national trend in educational attainment. With both region and year dummy variables, variation in inequality derives from a combination of changes in inequality within states over time and differences in equality among states in the same region.

I also control a set of exogenous state-level determinants of inequality that are also likely to affect children's yeas of schooling. These include the percent of state residents who are African American, the percent who are Hispanic, state mean income, the state unemployment rate and the state returns to schooling. These are all measured in the year a child was fourteen years old. Fluctuations in the unemployment rate are mainly attributable to short-term fluctuations in the business cycle and do not contribute much to the level of inequality in the state. However, among states with the same mean income, those with high levels of unemployment are likely to have more inequality because unemployment reduces the income of some state residents.

Returns to schooling are likely to affect educational attainment because higher returns provide a greater incentive to stay in school. My measure of returns to schooling is the average effect of an extra year of schooling on log wages in a given state and year, estimated for workers aged 18 to 65. I estimate the effect of state returns to schooling when a child was fourteen years old on his or her eventual educational attainment. I use returns when a child was age fourteen rather than returns at a later age for two reasons. First, the decision about how much schooling to get is intertwined with decisions about what to study: a student who does not expect to attend college often makes decisions about what to study in high school that make college attendance very difficult. Second, I assume that the rate of return to school often affects individual enrollment decisions indirectly, by affecting the way "significant others" value education. These indirect influences are likely to mean that current attitudes reflect past as well as current returns.

If parental characteristics that affect children's schooling also affect their choice of a state within a region, omitting controls for these characteristics could bias the estimated effect of economic segregation. I control the logarithm of family income when a child was twelve to fourteen years old, parental education, and the child's race.

Table 3 shows these results. For reference, the first row shows the effect of the total variance of income in a state on children's years of schooling. To make the coefficients readable, the variance of income/1,000 is itself divided by 1,000. Children who live in economically unequal states get more years of schooling than children who live in economically homogeneous states. This is consistent with other evidence showing that inequality has a positive effect on average educational attainment (Mayer 1999).

Model 2 in Table 3 shows that the effect of the between-tract income variance on years of schooling is positive but not statistically significant at the .10 level. The effect of the within tract variance of income is also positive but not statistically significant. Given a constant level of inequality in a state, a shift to more between district variation in income decreases the within district variation. Consequently, Table 3 suggests that holding constant the state-wide level of economic inequality, an increase in the average economic heterogeneity of census tracts would increase years of schooling. But, because the difference between β_b and β_w is not statistically significant at even the .10 level, we cannot have much confidence in this difference.[18] These results suggest instead that overall inequality and not residential economic segregation affects educational attainment. Economic heterogeneity within neighborhoods might improve children's educational attainment, but no more than economic heterogeneity between neighborhoods.

Poor Children. Table 3 describes the average effect of economic segregation for all children, rich and poor. Since the overall effect is small we can conclude either that neighbor's income does not matter or that the benefits to rich children from living near other rich children roughly offset the costs to poor children of living near other poor children. To distinguish between these possibilities, I estimate separate models for high and low-income children.

"High-income" children are those in the top half of the income distribution. "Low-income" children are those in the bottom half of the income distribution. Dividing the sample at the mid-point allows all variables to interact with household income in a way that is easy to interpret and preserves enough high and low-income cases for a meaningful analysis. Other

---

[18] I test the statistical significance of the difference between coefficients using a Wald test.

divisions of the sample, such as quartiles, provide qualitatively similar results but with larger standard errors. A model that interacts household income with all the relevant variables is difficult to interpret and also results in very large standard errors. Dividing the sample in half is instructive even though it may not capture all the nuances of the effect of inequality at different parts of the income distribution.

Table 4 shows that among high-income children β_b is greater than β_w and the difference is statistically significant at the .05 level. This implies that economic segregation increases the educational attainment of high-income children.

Among children in the bottom half of the income distribution, β_b is large, negative and statistically significant. The effect of the within tract variance is smaller and not statistically significant. The difference between the coefficients is statistically significant. Thus economic segregation reduces the educational attainment of low-income children.

If state economic inequality is unchanged, an increase in between-tract variance will lead to the same increase in within-tract variance. Thus Table 4 suggests that a one standard deviation increase in between census tract income variance increases high-income children's schooling by [3.891 (.118) – 1.344(.118)] = .300 years. The same increase reduces low-income children's schooling by [-3.045(.118) – (-1.167) (.118)] = -.221 years. These effects roughly cancel one another.

I repeated the estimates shown in Tables 3 and 4 substituting state dummy variables for region dummy variables. For the top half of the income distribution the effect of between neighborhood income variance is 3.477 in the model with state dummy variables and 3.891 with region dummy variables. For the bottom half of the income distribution, the effect of between neighborhood income variance is –3.161 in the model with state dummy variables compared to -3.045 in the model with region dummy variables. The effect of within neighborhood variance is not statistically significant in either model for the top half or the bottom half of the income distribution.

Between 1970 and 1990, economic inequality increased prior to the increase in economic segregation suggesting that the segregation is the result of inequality and not vice versa. However, because returns to a college education have increased over the last twenty-five years, economic segregation may eventually increase economic inequality.

IV. Conclusions

The results in this paper support four conclusions. First, the increase in economic inequality between 1970 and 1990 resulted in increased economic segregation between census tracts. Second, the increase in economic segregation did not mainly come about because tracts became more economically homogeneous. Economic inequality within tracts was roughly the same in 1990 and in 1970, but inequality between tracts grew. Third, growing economic segregation increased years of schooling among high-income children. Fourth, growing segregation reduced the years of schooling among low-income children. The effects on rich and poor children roughly off-set one another.

If economic segregation improves the well-being of affluent children, the rich are likely to segregate as they get richer. If advantaged neighbors improve advantaged but not disadvantaged children's educational attainment, economic segregation in one generation will also contribute to economic inequality in the next generation.

Because economic inequality is associated with economic segregation, studies that try to estimate the effect of one without accounting for the other could be misleading. They will attribute some of the effect of inequality to segregation. Because the fraction of the poor in neighborhoods depends in part to the degree of economic segregation, studies of the effect of neighborhood poverty rates may be biased because none controls economic inequality of the neighborhood.

I do not try to explain why economic segregation has different affects on the educational attainment of rich and poor children. The effect of segregation is not mainly due to decreasing within neighborhood economic heterogeneity. Instead it is mainly due to an increase in the between neighborhood economic inequality. This implies that the effect of economic segregation on educational attainment may have less to do with interpersonal comparisons and more to do with school financing and other factors that can be influenced by competition between low-income and high-income neighborhoods. Understanding these effects is an important topic for future research. Because economic and racial segregation are collinear, some of what I attribute to economic segregation could also be due to racial and ethnic segregation. That too is an important topic for future research.

References

Attwell, 1999. "The Winner Take-All High School: Organizational Adaptions to Educational Stratification." Unpublished manuscript. Department of Sociology, City University of New York.

Benabou, Roland. 1996. "Heterogeneity, Stratification, and Growth: Macroeconomic Implications of Community Structure and School Finance." *American Economic Review*, June: 584-609.

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

Card, David and Alan Krueger. 1996. "Labor Market Effects of School Quality: Theory and Evidence" in Gary Burtless (ed.) *Does Money Matter? The Effect of School Resources on Student Achievement and Adult Success.* Washington, D.C.: Brookings Institution Press.

Ceci, Stephen J. 1991. "How Much Does Schooling Influence General Intelligence and Its Cognitive Components? A Reassessment of the Evidence." *Developmental Psychology,* 27(5):703-722.

Chase-Lansdale, Lindsay, Rachel Gordon, Jeanne Brooks-Gunn and Pamela Klebanov. 1997. "Neighborhood and Family Influences on the Intellectual and Behavioral Competence of Preschool and Early School-Age Children" in Jeanne Brooks-Gunn, Greg Duncan and J. Lawrence Aber (eds) *Neighborhood Poverty: Context and Consequences*. New York, Russell Sage Foundation Press.

Clark, R. L. 1992. "Neighborhood Effects on Dropping Out of High School Among Teenage Boys" Washington, D.C.: Urban Institute, Unpublished manuscript.

Connell, James and Bonnie Halpern-Felsher. 1997. "How Neighborhoods Affect Educational Outcomes in Middle Childhood and Adolescence: Conceptual Issues and an Empirical Example" in Jeanne Brooks-Gunn, Greg Duncan and J. Lawrence Aber (eds) *Neighborhood Poverty: Context and Consequences*. New York, Russell Sage Foundation Press.

Crane, Jonathan. 1991a. "Effects of Neighborhood on Dropping Out of School and Teenage Childbearing." in Christopher Jencks and Paul Peterson, eds. *The Urban Underclass*. Washington D.C.: Brookings Institution Press.

Crane, Jonathon. 1991b. "The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing." *American Journal of Sociology* 96(5):1226-1259.

Cutler, David and Edward Glaeser. 1997. "Are Ghettos Good Or Bad?" *Quarterly Journal of Economics*, 112 (August): 827-72.

Davis, James A. 1959. “A Formal Interpretation of the Theory of Relative Deprivation” *Sociometry* 22: 280-296.

Davis, James. 1966. “The Campus as a Frog Pond: An Application of the Theory of Relative Deprivation to Career Decisions of College Men.” *American Journal of Sociology* 72:17-31.

de Bartolome, Charles. 1990. “Equilibrium and Inefficiency in a Community Model with Peer Effects.” *Journal of Political Economy*, 98(11):110-133.

Duncan, Greg and Jeanne Brooks-Gunn and Pamela Klebanov. 1994. “Economic Deprivation and Early Childhood Development.” *Child Development* 65(2): 296-318.

Duncan, Greg and James Connell and Pamela Klebanov. 1997. “Conceptual and Methodological Issues in Estimating Causal Effects of Neighborhoods and Family Conditions on Individual Development” in Jeanne Brooks-Gunn, Greg Duncan and J. Lawrence Aber (eds) *Neighborhood Poverty: Context and Consequences*. New York, Russell Sage Foundation Press.

Durlauf, Steven N. 1996. “A Theory of Persistent Income Inequality.” *Journal of Economic Growth* 1: 75-93.

Ellen, Ingrid Gould and Margery Austin Turner. 1997. “Does Neighborhood Matter: Assessing Recent Evidence.” *Housing Policy Debate* 8: 833-866.

Evan, William, William Oates and R.M. Schwab. 1992. “Measuring Peer Group Effects: A Study of Teenage Behavior.” *Journal of Political Economy* 100: 966-91.

Ferguson, Ronald and Helen Ladd. 1996. “How and Why Money Matters: An Analysis of Alabama Schools.” in Helen Ladd (ed.) *Holding Schools Accountable,* Washington, D.C.” Brookings Institution Press.

Fernandez, Raquel and Richard Rogerson. 1996. “Income Distribution, Communities, and the Quality of Public Education.” *Quarterly Journal of Economics,* 135-164

Firebaugh, Glenn. 1999. “Empirics of World Income Inequality.” *American Journal of Sociology.* 104(6):1597-1630.

Halpern-Flesher, Bonnie, James P. Connell, Margaret Beale Spencer, J. Lawrence Aber, Greg Duncan, Elizabeth Clifford, Warren Crichlow, Peter Usinger, Steven Cole, La Rue Allen, and Edward, Seidman. 1997. “Neighborhood and Family Factors Predicting Educational Risk and Attainment in African-American and White Children and Adolescence” in Jeanne Brooks-Gunn, Greg Duncan and J. Lawrence Aber (eds) *Neighborhood Poverty: Context and Consequences*. New York, Russell Sage Foundation Press.

Hanushek, Eric. 1997. “Assessing the Effects of School Resources on Student Performance: An Update.” *Educational Evaluation and Policy Analysis,* 19(2):141-64.

Hedges, Larry, Richard Laine and Rob Greenwald. 1992. "Does Money Matter? Meta-Analysis of Studies of the Effect of Differential School Inputs on Student Outcomes." *Educational Researcher* 23(3):5-14

James, Franklin. 1986. "A New Generalized 'Exposure-Based' Segregation Index: Demonstration in Denver and Houston." *Sociological Methods and Research* 14(3):301-316.

Jargowsky, Paul. 1997. *Poverty and Place: Ghettos, Barrios, and the American City.* New York: Russell Sage Foundation.

Jargowsky, Paul A. 1996. "Take the Money and Run: Economic Segregation in U.S. Metropolitan Areas." *American Sociological Review*. 61: 984-998.

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

Karoly, Lynn A. 1993. "The Trend in Inequality among Families, Individuals, and Workers in the United States: A Twenty-Five Year Perspective." In Sheldon Danziger and Peter Gottschalk (eds.) *Uneven Tides: Rising Inequality in America*. New York: Russell Sage Foundation.

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

Massey, Douglas and Mitchell Eggers. 1990. "The Ecology of Inequality: Minorities and the Concentration of Poverty" *American Journal of Sociology* 95:1153-88.

Mayer, Susan E. 1991. "How Much Does a High School's Racial Socioeconomic Mix Affect Graduation and Teenage Fertility Rates?" in Christopher Jencks and Paul Peterson, eds. *The Urban Underclass*. Washington D.C.: Brookings Institution Press.

Mayer, Susan E. and David Knutson. 1999. "Does the Timing of Schooling Affect How Much Children Learn?" in *Earning and Learning: How Schools Matter*, edited by Susan E. Mayer and Paul Peterson. Washington, D.C.: Brookings Institution Press.

Morris, Martina and Bruce Western, 1999. "Inequality in Earnings at the Close of the Twentieth Century." *American Sociological Review*. 25:623-57.

Merton, Robert and Alice Kitt. 1950. "Contributions to the Theory of Reference Group Behavior" in *Studies in the Scope and Method of "The American Soldier"* edited by Robert Merton and Paul Lazarsfeld. Glencoe, IL: The Free Press.

Runciman, W.G. 1966. *Relative Deprivation and Social Justice: A Study of Attitudes to Social Inequality in Twentieth Century England*. Berkeley: University of California Press.

Sampson, Robert and John Laub. 1994. “Urban Poverty and the Family Context of Delinquency: A New Look aat Structure and Process in a Classic Study” *Child Development* 65:523-540.

Tiebout, C. 1956. “A Pure Theory of Local Expenditure.” *Journal of Political Economy*, 64:416-424.

White, Michael. 1987. *American Neighborhoods and Residential Differentiation.* New York: Russell Sage Foundation.

Williams, Robin Jr. 1975. “Relative Deprivation” in *The Idea of Social Structure: Papers in Honor of Robert K. Merton* edited by Lewis A. Coser. New York: Harcourt Brace Jovanovich.

Wilson, William J. 1987. *The Truly Disadvantaged: The Inner City, the Urban Underclass and Public Policy*. Chicago: University of Chicago Press.

Winship, Christopher and Sanders Korenman. 1999. “Economic Success and the Evolution of Schooling and Mental Ability” in *Earning and Learning: How Schools Matter*, edited by Susan E. Mayer and Paul Peterson. Washington, D.C.: Brookings Institution Press.

Appendix

Description of the Data and Variables

Appendix
Description of the Data and Variables

PSID Data

I use data from the 1993 wave of the PSID. The sample includes all respondents who were ages 23 through 37 in 1993 and who are not missing data on independent variables. I weighted the observations to account for the PSID sample design.

PSID variables were constructed by pooling across the 26 currently available waves of the PSID Family File (years 1968 through 1993). I assigned values to each individual based on that individual's age rather than a particular year. For example, I average family income when children were aged twelve to fourteen. Thus it was averaged over 1985 to 1987 for children born in 1973 and over 1990 to 1992 for children born in 1978. Following is the description of the variables created with PSID data. The means and standard deviations of all variables are in Table A1.

Years of Schooling is the number of years of schooling that a respondent reported when he or she was twenty-three years old.

Log Family Income is cash income averaged over the three years when the child was age twelve through fourteen. All income values are in 1998 dollars using the CPI-U-X1 price adjustment. I use the natural logarithm of the averaged value.

Parental Education is the highest year of schooling completed by the mother when the child was aged fourteen. If this was missing, I use the mother's education when the child was age thirteen and so on until age eleven. If all of these values were missing, then I assigned the father's education when the child was age fourteen.

African American: A dummy variable set equal to 1 if the child was African American, 0 otherwise.

Census Data

Most of the state level variables used in this analysis come from the 1970, 1980, and 1990 Public Use Microdata Sample (PUMS) from the U.S. Census. In 1980 and 1990 we used the full 5 percent samples. In 1970 we use the 1 sample because that is what is available.

Because state-level data is attached to individual cases, the state-level means and standard deviations in tables are approximately weighted by the state population.

Mean Household Income was computed by summing the components of income for each person in a household. Using components of person's income rather than person's total income increases the detail available at the upper tail of the distribution by avoiding Census Bureau top-coding of person's total income. To limit the detrimental effect on comparability of changes in the Census Bureau's top-coding of income components, we created uniform income components and top-codes that we used in all years. Variables are top-coded by reassigning values above the lowest 99th percentile of positive values among the years to the median of all values across years that lie above that lowest 99th percentile. The same was done for negative values using the highest 1st percentile as the cutoff. All dollars are adjusted to1998 dollars using CPI-U-X1.

The resulting components are then summed to get household income. The state-level measures of income, including income inequality, were then calculated from the resulting household incomes, both at the household level and the person level. Persons in group quarters were excluded from all calculations.

Percent African American and Percent Hispanic. I estimate these variables using 1970, 1980, and 1990 PUMS data and then use linear interpolation to assign values for the state in the year when the child was fourteen years old.

Returns to Schooling. My measure of returns to schooling is the average effect of an extra year of schooling on log wages for individual *i* in state *s* and year *y*,(W_{isy}) estimated for workers aged 18 to 65 using the following model:

$$\ln W_{isy} = \beta_0 + \beta_s S_{is} + \varepsilon_{is}$$

where *S* is the individual's schooling. β_s is the percentage increase in wages due to an additional year of schooling. I experimented with over 12 different measures of returns to schooling, using different age groups, different functional forms and separating returns for men and women. I selected the measure that increased R^2 the most when added to the estimation model. The measure I use also corresponds best to economic theory about the functional form of returns to schooling and produces an estimated return to a year of schooling that is consistent with previous research on the returns to schooling (Winship and Korenman 1999, Mayer and Knutson, Ceci 1991).

<u>Decomposition of Income between Census Tracts.</u> I begin with the variance of total household income in a state calculated from the PUMS data described above. Next I compute the mean household income of each census tract using data from the STF4 file in 1970 and the STF5 file in 1980 and 1990. In 1980 and 1990 I divide the aggregate household income of the tract by the number of households in the tract. I weight mean tract income by the number of households in the tract and calculate the variance of mean tract income. This is the *between tract variance of income*. The *within-tract variance of income* is the total variance of income less the between tract variance.

Not all the geographic areas of states are grouped into census tracts. The proportion of the population in census tracts in a state increased over time as states both increased population and as population becomes more concentrated. In 1970 62 percent of the population lived in a census tract. In 1980 71 percent lived in tracts and in 1990 77 percent did. The number of census tracts changed over time both because new tracts were created and because the boundaries of old tracts changed. The number of tracts increased from 34,026 in 1970, to 41,925 in 1980 to 48,187 in 1990.

I use all the tract data available in a year, rather than using a consistent definition of tracts. I do this because the growth in census tracts largely reflects growth and concentration of population. I estimate the mean income for the state population not living in census tracts and treat that area like a "super census tract." That is for the purpose of computing the between tract variance I treat the weighted mean of the untracted area as a census tract. This allows the within and the between tract variance of income to exactly sum to the total variance of income for the state. Because I weight by state population, states with higher proportions of their residence living in census tracts get high weights and those living in less populous states get lower weights. There was no tract level data available for Vermont or Wyoming in 1970 and these states are omitted from all analyses that involve census tracts.

Table A1 Correlations among Variables

	1	2	3	4	5	6	7	8	9
1. Years of Schooling	1.00								
2. Mean Household Income/$1,000	.106	1.00							
3. Percent African American	-.305	-.080	1.000						
4. Percent Hispanic	.369	.055	-.135	1.000					
5. Child’s Race is Black	-.982	-.144	.330	-.005	1.000				
6. Total Variance									
7. Returns to Schooling	.148	.046	.394	.334	.104	.447	1.000		
8. Log Household Income	.263	.359	-.208	.120	-.374	-.184	-.609	1.000	
9. Parent’s Education	.257	.346	-.213	.092	-.229	-.113	.030	.425	1.000
Mean	12.906	36.728	11.460	4.971	.155	.402	.062	10.759	11.431
Standard Deviation	2.121	4.526	7.744	6.170	.362	.018	.011	.657	2.661

Source: See date description in the Appendix.
Notes: These means and standard deviations are based on the 3,504 cases in the sample for models predicting high school graduation. The sample for college outcomes is 3,240 cases so the means differ slightly.

Appendix Table 2, Decomposition of Income Variance

Variable	1970	1980	1990
(1) Mean Household Income for the US in 1998 CPI-U-X1 dollars	39,715	43,569	45,482
(2) Variance of Household Income for the US/10,000	103,188	128,773	174,482
(3) Between State Variance of Household Income for the United States	3,333	3,219	6,211
(4) Within State Variance of Household Income for the United States	99,855	125,553	168,270
(5) Within State but between Census Tract Variance of Income	25,758	27,408	59,585
(6) Within Census Tract Variance of Household Income/1,000	74,097	98,000	108,685

Table 1, Household Income Characteristics by Year

Variable	1970	1980	1990
(1) Mean Household Income for the US in 1998 CPI-U-X1 dollars	39,715	43,569	45,482
(2) Variance of Household Income for the US/10,000	103,188	128,773	174,482
(3) Percent of US Variance of Household Income between States	3.2	2.5	3.6
(4) Percent of US Variance of Household Income within States	96.8	97.5	96.4
(5) Percent of State Variance between Census Tracts	24.8	21.0	33.6
(6) Percent of State Variance within Census Tracts	75.2	79.0	66.4
(7) Coefficient of Variation for Household Income	.783	.785	.825
(8) Coefficient of Variation for Within Census Tract Income	.678	.696	.668
(9) Coefficient of Variation for between Census Tract Income	.384	.355	.470

Source: 1970, 1980, and 1990 Census data weighted by state population. Means are means of state characteristics. See the Appendix for details on the computation of these variables

Table 2, Effect of the Change in the Total Variance of Income on
the Change in between Census Tract Variance of Income in States, 1970 to 1990

Variable	Model 1	Model 2	Mean (Standard Deviation)
Total Variance of Income/1,000	.869 (10.599)	.867 (7.793)	1,233.769 (367.222)
State Mean Income	-22.991 (-5.298)	-24.396 (-3.131)	43.749 (6.556)
Percent Hispanic		-3.356 (-.939)	6.793 (7.789)
Percent African American		1.796 (.317)	11.438 (7.489)
R^2	.939	.938	

Source: 1970, 1980 and 1990 Census data for states weighted by population size as described in the Appendix. Number of cases is 148.
Notes. Both models control year and state dummy variables, and $1/X^2$ where X^2 is state mean income. T-statistics are in parentheses.

Table 4 OLS Regression Coefficients for the Effect of within Census Tract Variance of Income and between Census Tract Variance of Income on Years of Schooling

Model and Variables	Model 1	Model 2	Mean (SD)
Total Variance of (Income/1,000)/1,000	1.789 (2.256)		1.093 (.205)
Between Tract Variance/1,000		1.360 (1.421)	.256 (.118)
Within Tract Variance/1,000		.833 (.878)	.837 (.113)
State Mean Income/1,000	-.060 (-1.892)	-.046 (-.921)	36.334 (4.279)
Percent African American	-.020 (-1.985)	.008 (.878)	11.422 (7.696)
Percent Hispanic	-.020 (-1.233)	-.010 (-.737)	4.731 (5.713)
Returns to Schooling	24.846 (2.338)	9.426 (.884)	.060 (.009)
Unemployment Rate	-.045 (-2.230)	-.022 (-1.175)	8.788 (2.341)
Log Household Income in 1998 dollars		.788 (10.728)	10.809 (.630)
Parents' Years of Schooling		.202 (10.433)	11.452 (2.806)
Child is African American		.016 (.138)	.150 (.357)
R^2	.038	.193	

Source: PSID sample described in Appendix.
Note: Models control region and year dummy variables, and $1/X^2$ where X^2 is state mean income. T-statistics are in parentheses.

Table 4 Effect of within Census Tract Variance of Income and between Census Tract Variance of Income on Educational Outcomes by Parental Income

Sample and Variables	Greater than Median	Less than Median
Between Tract Variance/1,000	3.891 (3.049)	-3.045 (-2.163)
Within Tract Variance/1,000	1.344 (1.095)	-1.167 (-.730)
State Mean Income	-.182 (-2.491)	.160 (2.095)
Percent African American	-.006 (-.422)	.009 (.651)
Percent Hispanic	-.026 (-1.506)	.001 (.047)
Returns to Schooling	3.198 (.218)	18.941 (1.241)
Unemployment Rate	-.002 (-.065)	-.055 (-1.998)
Log Household Income in 1998 dollars	1.053 (6.458)	.084 (.583)
Parents' Years of Schooling	.221 (9.063)	.179 (6.862)
Child is African American	-.489 (-2.684)	.230 (1.675)
R^2	.154	.105

Source: PSID sample described in Appendix.
Note: Models control region and year dummy variables, and $1/X^2$ where X^2 is state mean income. T-statistics are in parentheses.