# How Did the Increase in Economic Inequality between 1970 and 1990 Affect Children's Educational Attainment?[1]

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This study estimates the effect of changes in economic inequality between 1970 and 1990 on children's educational attainment. Data on individual children from the Panel Study of Income Dynamics is combined with other data on state characteristics. Growing up in a state with widespread economic inequality increases educational attainment for high-income children and lowers it for low-income children. Most of the effect is due to factors unassociated with family income or economic segregation in the state. These other factors include state spending for schooling and the increase in the returns to schooling over this period.

Disparities in hourly wages, annual earnings, and household income have all increased over the past generation in the United States. A considerable amount of research has tried to determine why income inequality grew over this period (Morris, Bernhardt, and Handcock 1994; Morris and Western 1999). Much less research has been done on the consequences of inequality than on its causes. This article estimates the effect of changes in income inequality on mean educational attainment and on the disparity in educational attainment between rich and poor children. I also separate the effect of income inequality that is due to the nonlinear effect of a

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family's own income from other effects of inequality. If growing income inequality contributes to inequality in educational attainment between children from rich and poor families, inequality in one generation will be perpetuated in the next generation.

This article focuses entirely on changes in the overall dispersion of household income. Inequality of household income increased between 1970 and 1980 and increased even more between 1980 and 1990 (Karoly 1993; U.S. Bureau of the Census 1998). Inequality among families with children also grew (Lichter and Eggebeen 1993). Changes in inequality between groups, such as blacks and whites or men and women may or may not parallel changes in the level of overall economic inequality, and their effect on educational attainment may differ from the effect of overall economic inequality.

The proportion of 25–29 year olds who had graduated high school or earned a GED increased from 75.4% in 1970 to 85.4% in 1980, then did not change between 1980 and 1990 (U.S. Department of Education 1998, table 8), when inequality increased.[2] The percentage of 25–29 year olds who had enrolled in college declined from 44% in 1970 to 52% in 1980, and the percentage who had graduated college increased from 16.4% in 1970 to 22.5% in 1980. Neither college enrollment nor college graduation increased between 1980 and 1990 (U.S. Department of Health and Human Services 1998).

Ellwood and Kane (1999) show that between the early 1980s and 1992 the proportion of children in the poorest income quartile who went on to some postsecondary schooling increased from 57% to 60%. But the proportion of children in the top income quartile getting some postsecondary schooling increased from 81% to 90%. Thus the increase in college entrance rates was greater among affluent than among low-income children, suggesting that the growth in inequality may have had different effects on children from different family backgrounds.

## HYPOTHESES ABOUT THE EFFECT OF INEQUALITY

Income inequality can affect educational attainment in several ways. The first is through the incentives provided by higher returns to schooling. The second is through the declining utility of family income. Income inequality can also affect educational attainment through processes that are independent of a family's own income. Social scientists have identified at least three such processes. They involve changes in subjective feelings

[2] The percentage of 16- to 24-year-old high school graduates who had a GED increased from 15.8% in 1980 to 17.8% in 1990.

of relative deprivation or gratification, changes in the political processes that shape educational opportunities and costs, and changes in economic segregation.

## Change in Incentives

Part of the growth in inequality in the United States was due to increased returns to schooling (Murphy and Welch 1992; Juhn, Murphy, and Pierce 1993).[3] Because higher returns increase the incentive for children to stay in school, we would expect educational attainment to increase when economic inequality increases.[4]

## The Declining Utility of Family Income

If the relationship between educational attainment and parental income is linear, then when the rich gain a dollar and the poor lose a dollar, the educational attainment of the rich will increase by exactly as much as the educational attainment of the poor decreases, leaving the mean unchanged. However, suppose that a 1% increase in income generates the same absolute increment in educational attainment, regardless of whether income is initially high or low. If the relationship between parental income and children's schooling takes this semilogarithmic form, and all else is equal, a costless redistribution of income from richer to poorer households will increase children's mean educational attainment, because shifting a dollar from the rich to the poor increases the education of poor children by a larger percentage than it decreases the education of rich children.[5]

[3] Rising returns to schooling is not the main source of inequality growth. The within-education group variance of income rose almost as fast as the between-group variance of income (Juhn et al. 1993; Karoly 1993), and educational attainment accounts for only 15%–20% of the variance in income initially.

[4] Welch (1999) notes that the proportion of men working full-time, year around, with at least one year of college increased greatly after 1980 when the returns to schooling also increased. Welch takes this as evidence that men responded to the increase in returns to schooling by getting more schooling and that the increase in schooling is therefore a benefit of the rise in inequality. However, the test of the response to the rise in the return to schooling is not the increase in schooling among workers but rather the change in schooling for all members of young cohorts.

[5] Mean educational attainment might not increase when the rich get richer, and even if it does, the increase might not be efficient. If the rich "overinvest" in schooling when they get richer and the poor "underinvest," the mean level of educational attainment might stay the same, but the efficiency of the investment would decline. In this article, I assume that no one overinvests in schooling.

## Relative Deprivation and Gratification

Social comparison theory assumes that individuals evaluate themselves relative to others. Relative deprivation theory holds that people compare themselves to others who are more advantaged than themselves (Merton and Kitt 1950; Davis 1959; Runciman 1966; Williams 1975).[6] Imagine two families with the same income. Family A lives in a wealthy area, while family B lives in a poor area. Assuming their choice of where to live is entirely exogenous and that other families in the same area are their only reference group, relative deprivation theory predicts that members of family A will feel more deprived than members of family B. Feelings of relative deprivation can lead to isolation and alienation from the norms and values of the majority. If children feel relatively deprived, they may be less inclined to study or stay in school. Relative deprivation can also make parents feel stressed and alienated, lowering their expectations for their children or reducing the quality of their parenting (McLoyd 1990).

Relative deprivation theories assume that children or parents compare themselves to others who are better off, while largely ignoring those who are worse off. If parents all compare themselves to the richest people in society, for example, they will feel poorer whenever the rich get richer. Of course, people also compare themselves to others who are worse off. Sociologists refer to this as "relative gratification" (Davis 1959). If either children or their parents mostly compare themselves to the poorest people in society rather than to the richest, increases in inequality will make most people feel richer because the distance between them and the people at the bottom of the distribution will grow. If people mostly compare themselves to some real or imagined national average, increases in inequality will make the rich feel richer and the poor feel poorer. How this will affect either educational attainment or other outcomes is unpredictable.

Relative deprivation usually cannot be directly observed, so it is often inferred from its behavioral manifestations. A large social-psychological research literature uses experimental evidence to document the importance of interpersonal comparisons, in general, and relative deprivation,

[6] An important distinction is between individual relative deprivation, in which an individual compares his or her personal situation to the situation of other individuals, and group relative deprivation, in which a person compares his or her relevant group's situation with the situation of another group. Growing inequality can affect both sorts of relative deprivation, but I mainly emphasize individual comparisons, not group comparisons. Individual comparisons are more likely to lead to isolation and stress, while group comparisons are more likely to lead to collective action (Gurr 1970; Smith, Spears, and Hamstra 1999).

in particular.[7] Most of the sociological research on the importance of interpersonal comparisons to educational outcomes has been done in the context of neighborhood and school effects. In one of the earliest of such efforts, Davis (1966) argued that reference groups have both a comparison function and a normative function (as "sources and reinforcers of standards"). Although the latter could make living in an affluent area an advantage for low-income children, the former could make it a disadvantage because it fosters academic competition and relative deprivation. Davis showed that the more academically selective a college was, the lower any given student could expect his grades to be. As a result, students who chose selective colleges were less likely to choose careers that required graduate training. Other studies find that attending high school with high-achieving classmates reduces educational attainment, while attending school with high-SES classmates increases it. Because SES and achievement are correlated, attending a high-SES school has little net effect on educational attainment. (See Jencks and Mayer [1990] for a review of these studies.) These studies do not prove that children *feel* relatively deprived when they must compete with higher achieving students, but they demonstrate that more advantaged classmates or neighbors can be both an advantage and a disadvantage. When a child's own family income stays the same but inequality increases, the child will be exposed both to more advantaged and more disadvantaged children. This could have either positive or negative effects on the child's educational attainment.

### Changes in Political Behavior

Changes in inequality can affect political behavior. Some research suggests that increases in economic inequality may decrease voters' willingness to support redistributive policies at the national level (Perotti 1996; Alesina and Rodrik 1994). This could also happen at the state or local level. For example, high levels of inequality could encourage the rich to enroll their children in private schools, making them less interested in supporting public schools. But high levels of inequality could also increase voters' willingness to support redistributive policies if they fear political instability (Piven and Cloward 1993) or think that poverty contributes to crime.[8] Other research suggests that redistributive spending reduces economic inequality at the national level (Gustafsson and Johansson 1999).

[7] For compilations of recent research and summaries of older research see Ellemers, Spears, and Doosje (1997) and Suls (1991).

[8] Relative deprivation is an important explanation for the relationship between crime and economic inequality (Nettler 1984; Messner and Tardiff 1986; Rosenfeld 1986) and for collective action more generally (Gurr 1970).

Redistributive policies can thus be both a cause and an effect of economic inequality. Disentangling cause from effect using cross-national data (as these studies do) is difficult, because samples are generally very small, lag structures are uncertain, and exogenous shocks that constitute national experiments are rare. Still it is clear that changes in economic inequality can in principle affect political support for redistributive policies, which can thereby affect spending on schools.[9]

Nationwide, per pupil expenditures for elementary and secondary schooling have increased since 1970, and spending has become more equal across school districts in many states (Murray, Evans, and Schwab 1998; Card and Payne 1998). Research on the effect of per pupil school expenditures on children's school performance is equivocal (Elliott 1998; Hanushek 1996; Hedges, Laine, and Greenwald 1992), but most evidence suggests that higher expenditures improve children's test scores by at least a little, which could in turn increase their educational attainment.

Research also shows that higher college tuition reduces enrollment and graduation. (Kane [1999] summarizes this research.) Although real tuition rates at state four-year colleges and universities have increased since 1980, so has both state and federal financial aid for college students (U.S. Department of Education 1998). The number of two-year community colleges, which have low tuition, has also increased. However, the extent to which state differences in economic inequality affect the cost of attending a public college in the state is unknown.

## Economic Segregation

The effect of economic inequality depends to some extent on the geographical proximity of the rich to the poor. This assumption is built into conventional measures of inequality, which describe the dispersion of income among all households in some geographic area, such as a nation, state, or neighborhood. Durlauf (1996) argues that as inequality increases, the rich and poor have less in common and therefore segregate more geographically. According to this argument, the degree of economic in-

[9] Given a progressive tax rate, anything that makes the rich richer would increase the revenue available to pay for schools. Over the long run, voters can decide to change the progressivity of taxes. On average, state and local taxes are slightly progressive. For example, in 30 large cities in 30 different states in 1995, a family of four with an income of $25,000 paid an average of 8.2% of their income in state and local taxes, while a family of the same size with an income of $75,000 paid on average 9.6% of their income in taxes (U.S. Bureau of the Census 1998). Some economists assume that less redistributive tax policies lead to more economic growth and hence that inequality (within broad limits) is associated with economic growth. Greater economic growth could lead to greater tax revenues, even if the tax rate declines.

equality at, say, the city level may affect the degree of economic segregation within the city. This will in turn affect the degree of economic inequality within neighborhoods. Wilson (1987) argues that economic segregation causes economic inequality, rather than the other way around. This happens because economic and racial segregation reduce the quality of inner-city schools and other institutions and leads to a spatial mismatch between jobs and low-skilled workers. Both Durlauf and Wilson argue that economic segregation hurts children's life chances.

A pernicious potential consequence of economic inequality is to recreate economic inequality in the next generation. This could happen if inequality benefits advantaged children and hurts disadvantaged children. For example, if economic inequality is associated with increased economic segregation, this could hurt low-income children's educational attainment while increasing high-income children's educational attainment. Because educational attainment is associated with future earnings, this could exacerbate inequality in the next generation.

The remainder of this article assesses these possibilities empirically. I first estimate the effect of economic inequality on children's educational attainment. Second, I test the hypothesis that the effect of inequality is different for rich and poor children. Third, I assess how much of the effect of inequality is due to the increase in returns to schooling. Fourth, I assess how much of the effect of inequality is due to the nonlinear relationship between parental income and children's educational attainment. Finally, I test the hypotheses that the effects of inequality are the result of changes in (1) the level of economic segregation in states, (2) state per pupil expenditures on primary and secondary schooling, and (3) the cost of attending college at state institutions. Both economic segregation and the political behavior that affects school resources can be behavioral manifestations of either relative deprivation or relative gratification. Because it is impossible in my data to measure feelings of relative deprivation or gratification directly, it is impossible to completely isolate their effects.

## DATA AND METHODS

Most research on the social consequences of economic inequality estimates a model in which inequality in a geographic area, such as a nation or state, predicts an aggregate-level outcome, such as the mortality rate or the crime rate for the geographic area. Most research on educational attainment, in contrast, uses individual-level data to predict years of schooling from measures of family background and characteristics of the labor market. Some research combines individual-level data with aggregate data to predict, say, the effect of neighborhood social composition

on children's educational attainment, holding constant their family background. These models of "neighborhood effects" or "school effects" have many well-known estimation problems (Tienda 1991; Manski 1993; Jencks and Mayer 1990). Nonetheless, such models do solve some of the problems associated with using exclusively aggregate data. In this article, I estimate models similar to those used to estimate neighborhood effects. I estimate the effect of state-level inequality on individual children's educational attainment, often holding the children's family characteristics constant.

## Level of Aggregation

Economic inequality may have different effects at different levels of aggregation. Theory provides little guidance as to which geographic unit is most relevant for the relationship between inequality and educational attainment. If school financing plays a crucial role in educational attainment, the relevant units of aggregation are the political jurisdictions that fund public schools and universities. Nationwide, states and local school districts typically provide roughly equal amounts of money for elementary and secondary schooling, with relatively little money coming from the federal government. State funds tend to equalize district funding, so the state pays a greater share for poor districts and a smaller share for rich districts (Murray et al. 1998). It follows that decisions about the degree of inequality in school district funding are primarily made at the state level. If household income inequality affects educational outcomes primarily by affecting taxpayers' inclination to fund public education, the state may be the right level of aggregation.

On the other hand, school districts also share in funding decisions and make significant decisions about policies that affect educational outcomes. Income inequality *within* school districts might affect both voters' inclination to pay taxes for schools and other school policies. However, parents often choose their school district partly on the basis of who lives there. If the same parental characteristics that cause parents to choose one district over another also affect their children's educational outcomes, and if these parental characteristics are not measured accurately, the estimated effect of school district inequality on educational attainment could be biased. This form of selection bias should be less important for estimating the effect of state-level characteristics on educational attainment because parents are less likely to move to a different state than to move to a different school district in order to improve their children's educational prospects.

Theories about the effect of income inequality that involve interpersonal comparisons are ambiguous about what is the most relevant geographic unit because it is not clear how individuals select the people to whom

they compare themselves. If children compare themselves to the people they see on television, the nation as a whole is probably the relevant comparison group. If the nation is the relevant comparison group, the only way to study the impact of inequality would be to make cross-national comparisons or comparisons across time. If children compare themselves mainly to their neighbors and classmates, inequality in a relatively small geographic area, such as a neighborhood or school attendance area, may be more relevant than inequality in a larger unit. But, as I have noted, selection problems are likely to be more serious at the level of the neighborhood or school district. In this article, I use states as aggregation units. States may not be the only or even most salient unit of aggregation, but there are sound theoretical reasons to expect states to be important. As we will see, they are empirically important.

## Data

The educational attainment of a state's residents affects inequality, and vice versa. This is not likely to be a problem in the short run for high school graduation because while economic inequality in a state can affect the probability that a teenager will graduate from high school, it takes some time for the high school graduation rate to affect the dispersion of household incomes in the state. Using economic inequality in a state to predict the educational attainment of the adults in the state would pose a more serious problem because the direction of causality is unclear. This problem is exacerbated by the fact that many adults no longer live in the state where they were raised, and the distribution of income in a state may affect the kinds of migrants who settle there.

To solve these problems, I use data from the Panel Study of Income Dynamics (PSID) to estimate the effect of state economic inequality measured during adolescence on children's eventual educational attainment. I estimate separate models for a child's chances of completing high school, entering college, completing four years of college, and for years of completed schooling, because income inequality is likely to have different effects on enrollment choices at different ages and at different levels of schooling. My PSID sample includes all respondents who were in the data set when they were 12–14 years old and when the educational outcome of interest was measured. I count respondents as having graduated high school if they reported that they had completed 12 or more years of schooling when they were 20 years old. The analysis of high school graduation therefore includes all respondents who were in the sample at ages 12–14 and at age 20 ($N = 3{,}504$). I count respondents as having attended college if they reported completing one or more years of college by the time they were 23 years old. I count them as having graduated college if

they report having completed at least 16 years of schooling by the time they were 23 years old. For these outcomes, therefore, respondents had to be in the PSID sample when they were ages 12–14 and at age 23 ($N = 3{,}240$).[10]

Most of my measures of state characteristics come from the 1970 1% Public Use Microdata Sample (PUMS) of census data and from the 1980 and 1990 5% PUMS. Values for a few other state characteristics come from published sources, as described in the appendix. The appendix also provides more detail on the sample and the variables used in this article.

## The Measure of Inequality

I use the Gini coefficient as a measure of inequality mainly because of its familiarity.[11] The correlation between a state's Gini coefficient and two other commonly used measures of economic inequality (the standard deviation of log income and the ratio of the ninetieth to the tenth percentile) are very high (0.925 and 0.963). The correlation between inequality in the top half of a state's income distribution (the 90 to 50 ratio) and inequality in the bottom half of its distribution (its 50 to 10 ratio) is also high (0.721). The correlation between each of these alternative measures of state income inequality with individual's educational attainment is negative but small (none differs from zero by more than 0.061). Thus it is not clear that any one measure of economic inequality is likely to be better than another at predicting educational attainment.

I use census data to calculate the Gini coefficient for each state in 1970, 1980, and 1990. I then use linear interpolation to create a Gini coefficient

[10] I measure high school graduation two years after students' normal date of graduation and college enrollment up to five years after the normal enrollment age. However, I measure college graduation only about a year after the normal college graduation date. If inequality affects the timing of school transitions, these different "grace" periods could be a problem. For example, if rising inequality delays but does not reduce college graduation, my estimates would be upwardly biased estimates of the effect of inequality on college completion. Because I require children to be in the sample from adolescence on, increasing the age at which I measure educational outcomes reduces the sample size considerably. However, I did experiment with measuring college completion and educational attainment at age 25 (three years after the normal age of college graduation), and the point estimates were similar to those in the models reported here.

[11] The Gini coefficient is the proportion of the total area below the 45 degree line that lies above the Lorenz curve, which plots the cumulative percentage of households against the cumulative percentage of income received by them. See Firebaugh (1999) for a comparison of inequality measures across countries. See Atkinson (1970, 1983) for a discussion of statistical differences among inequality measures.

for each state in each intercensus year for which I have PSID data.[12] I assign children the level of inequality in their state when they were 14 years old. The national Gini coefficient increased from 0.361 in 1970 to 0.368 in 1980 then to 0.381 in 1990. The Gini coefficient also varies across states. In 1970, the lowest state Gini coefficient was 0.320, and the highest was 0.427. In 1990, the lowest was 0.337, and the highest was 0.438. The standard deviation of the Gini coefficient across states was 0.027 in 1970, 0.018 in 1980, and 0.022 in 1990.

## RESULTS

### The Effect of Inequality on Mean Educational Attainment

If the degree of economic inequality in a state were a random accident, we could compare educational attainment in states with high and low levels of inequality, assume that all else was more or less equal across states, and treat observed differences in educational outcomes as a by-product of economic inequality. The effect of inequality (*Gini*) in state $s$ and year $t$ on the educational attainment ($E$) of individual $i$ would then be given by the value of $\beta_g$ in the following model:

$$E_{ist} = \beta_0 + \beta_g Gini_{st14} + \epsilon_{ist}, \tag{1}$$

where $\epsilon_{ist}$ is the usual random error term and $t14$ indicates that it is measured at age 14.

Model 1 of table 1 shows the results of equation (1) for all four outcomes. In all models in table 1, the $t$-statistics are corrected for the fact that individuals are clustered in states and years. For high school graduation, enrolling in college, and graduating college, the results are from a probit model. The cell entries are partial derivatives evaluated at the mean of the distribution. The results for years of schooling are estimated with an OLS model. Cell entries are unstandardized regression coefficients. Using model 1 for the entire sample, the effect of the Gini coefficient is negative for all outcomes, but it is not statistically significant at the 0.05 level for any outcome.

States vary in many ways besides their level of economic inequality. Some of these differences are associated with both economic inequality and with educational attainment. In this article, I try to estimate what would happen to educational attainment as a result of an exogenous

[12] Nationwide inequality increased somewhat more rapidly in the later part of the 1970s than in the earlier part of the decade. During the early 1980s, the increase in inequality was nearly linear. Any deviation from the linear trend is a source of measurement error in the inequality measure, and thus it probably biases the coefficient of the Gini coefficient toward zero.

TABLE 1
EFFECT OF GINI COEFFICIENT ON EDUCATION OUTCOMES

| Model and Outcome | Full Sample | High Income | Low Income |
|---|---|---|---|
| Model 1, no controls: | | | |
| High school graduate (probit partial derivative) ..... | −.619 | .118 | .680 |
| | (−1.480) | (.220) | (.970) |
| Enrolled in college (probit partial derivative) ..... | −.347 | 2.252 | −.226 |
| | (−.560) | (2.560) | (−.330) |
| Graduated college (probit partial derivative) ..... | −.559 | .881 | −.424 |
| | (−1.130) | (1.180) | (−1.060) |
| Years of schooling (OLS unstandardized coefficient) ... | −4.579 | 6.128 | −2.994 |
| | (−1.668) | (1.579) | (−.974) |
| Model 2, controls region and year dummies, %black, %Hispanic, mean income, and unemployment rate: | | | |
| High school graduate (probit partial derivative) ..... | .222 | .908 | −1.417 |
| | (.270) | (.940) | (−.990) |
| Enrolled in college (probit partial derivative) ..... | 3.404 | 4.763 | −.190 |
| | (2.900) | (2.930) | (−.150) |
| Graduated college (probit partial derivative) ..... | 1.024 | 2.715 | −1.639 |
| | (1.150) | (2.010) | (−2.320) |
| Years of schooling (OLS unstandardized coefficient) ... | 10.565 | 19.769 | −8.750 |
| | (2.160) | (2.978) | (−1.386) |
| Model 3, adds returns to schooling: | | | |
| High school graduate (probit partial derivative) ..... | .070 | .885 | −1.564 |
| | (.090) | (.910) | (−1.100) |
| Enrolled in college (probit partial derivative) ..... | 2.892 | 4.090 | −.213 |
| | (2.440) | (2.460) | (−.160) |
| Graduated college (probit partial derivative) ..... | .711 | 2.346 | −1.734 |
| | (.770) | (1.660) | (−2.330) |
| Years of schooling (OLS unstandardized coefficient) ... | 8.637 | 18.604 | −9.586 |
| | (1.760) | (2.739) | (−1.518) |

NOTE.—*t*-statistics are in parentheses and are corrected for clustering in states and years.

change in economic inequality. An exogenous increase in inequality might result from polarization of the job distribution due to industrial restructuring or from a technological innovation that changed the skill needs of employers and therefore changed the wage premium for some skills. In response to such changes, states might differ in how much inequality increased depending on the skill distribution in the state, the available mechanisms for increasing high-premium skills, the generosity of the state's social programs, the "culture" of the state, and many other factors. To estimate the effect of an exogenous change in inequality, one must control all the exogenous determinants of inequality that also affect educational attainment.

To control potentially relevant omitted variables, I first include dummy

variables for the Northeast, South, and Midwest to control characteristics of the region that remain unchanged over the period of observation. An alternative strategy would be to control state fixed effects. Such a model would be equivalent to estimating the within-state effect of a change in inequality. 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 inequality, 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 inequality. Third, including state fixed effects greatly reduces the degrees of freedom available to estimate the model, which in turn increases the standard errors of the estimates. Nonetheless, I test the sensitivity of my model to inclusion of state rather than region fixed effects and report those results below.

I control year fixed effects to account for the secular national trend in educational attainment. With both region and year fixed effects, all 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 can change over time. Past and present racial and ethnic discrimination means that racial and ethnic diversity can affect economic inequality and educational attainment. I control the percentage of state residents who were African-American and the percentage who were Hispanic in the year a child was 14 years old.[13]

A state's average household income is negatively correlated with economic inequality, and mean household income could obviously affect children's educational attainment. The correlation between mean household income and the state Gini coefficient was $-0.724$ in 1970, $-0.425$ in 1980, and $-0.559$ in 1990.[14]

[13] In principle, inequality could affect the racial composition of the state, and vice versa. But in practice, inequality cannot have much effect on a state's racial composition, because the interyear correlation for both percentage black and percentage Hispanic are about 0.98.

[14] The negative correlation could reflect a negative effect of inequality on mean income rather than the other way around. However, empirical research on the relationship between economic inequality and economic growth at the national level is inconclusive. (See Forbes [2000] for a recent review of this evidence.) In addition, it is not clear that the (unknown) factors that generate a correlation between inequality and subsequent economic growth at the national level would also apply to the economies of U.S. states. Because inequality and mean income are highly correlated, and because it seems likely that state income levels affect inequality more than vice versa in the United States, I control state mean income.

I also control the state unemployment rate measured at the same time as inequality is measured. 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. The correlation between the state unemployment rate and the Gini coefficient is only −0.047. 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. Research is inconclusive about the effect of local unemployment rates on educational attainment (Betts and McFarland 1995; Kane 1994; Manski and Wise 1983; Grubb 1988).

With fixed effects and control variables, the model becomes

$$E_{ist} = \beta_0 + \beta_g Gini_{st14} + \beta_x X'_{st14} + \gamma_r + \gamma_t + \epsilon_{ist},$$

where $\gamma_r$ is a set of dummies for the regions and $\gamma_t$ is a set of dummies for the year in which inequality is measured. In this model, $X'$ represents exogenous state characteristics that may have changed over time, including racial composition, the unemployment rate, and mean income.

The results from this model are shown in model 2 in the first column of table 1. With these controls, the effect of the Gini coefficient is positive for all outcomes and statistically significant at the 0.05 level for enrolling in college and years of schooling.

I next try to separate the effect of the incentive provided by greater returns to schooling from other effects of inequality. Imagine two states where inequality grows by the same amount and mean income does not change. In state A, inequality within education groups increases, perhaps because employers increase the pay of workers with noncognitive skills not usually learned in school. In state B, inequality grows because the returns to schooling increase. In both states, the rich, on average, get richer and the poor, on average, get poorer. If the effect of inequality on educational attainment were entirely due to the incentive effect of increased returns to schooling, educational attainment would increase in state B but not in state A.

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 ages 18–65. I estimate the effect of state returns to schooling ($R_{st}$) when a child was 14 years old on his or her eventual educational attainment. I use returns when a child was age 14 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, in turn, make college attendance very difficult. Second, I assume that the rate of return to schooling 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. Thus the model becomes

$$E_{ist} = \beta_0 + \beta_g Gini_{st14} + \beta_r R_{st14} + \beta_x X'_{st14} + \gamma_r + \gamma_t + \epsilon_{ist}.$$

The results for this model are shown in model 3 in the first column of table 1. States with high returns to schooling also have higher levels of inequality, so the effect of the Gini coefficient in these models is smaller than in models that omit returns to schooling. These results suggest that a one standard deviation increase in a state's Gini coefficient (i.e., a change of 0.02) increases children's chances of enrolling in college by 0.058 (13.4% of the mean) and increases their overall educational attainment by 0.173 years. These results suggest that the positive effect of inequality on educational outcomes is only partly due to the incentive provided by the rising returns to schooling. If the return to schooling were an entirely exogenous cause of the increase in inequality, this model would provide the best estimate of the effect of inequality on educational attainment.[15]

### The Effect of Inequality on Rich and Poor Children

The last two columns in table 1 show the results of these three models separately 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 midpoint 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 divisions of the sample, such as quartiles, provide qualitatively similar results but with larger standard errors. A model that interacts household income with the Gini coefficient and all other 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.

Columns 2 and 3 for model 3 in table 1 show that living in a high-inequality state improves all educational outcomes for high-income children and hurts all educational outcomes for low-income children. The

[15] It is possible that schooling opportunities in a state affect the returns to schooling. Absent migration, states with less postsecondary schooling opportunities will have a lower supply of highly educated workers, raising the wage premium and creating more inequality. This would also presumably increase the incentive to go to college. Over time, states would then reach an equilibrium in which they provided the "right" supply of college graduates to meet the state's demand for college graduates. If this happens, there would be little variation across states in returns to schooling.

positive effects of the Gini coefficient on college enrollment and years of schooling are statistically significant at the 0.05 level for high-income children. Only the negative effect of inequality on graduating college is statistically significant at this level for low-income children. Thus the overall positive effect of the Gini coefficient on enrolling in college and on years of schooling in column 1 is entirely due to the positive effect for high-income children. Inequality has no overall effect on college entrance because the positive effect of inequality for high-income children is offset by the negative effect for low-income children.

## The Processes through which Inequality Affects Educational Attainment

I first separate the effect of inequality on educational attainment that is due to the nonlinearity of families' own income from the other effects of inequality. These estimates answer the question, How would children's educational attainment differ if their families had the same income (averaged over several years) and they lived in states with the same mean income and returns to schooling, but different levels of economic inequality?

To estimate the importance of the declining utility of family income, we first must determine the approximate functional form of the relationship between parental income and children's educational attainment. Table 2 shows that any of three nonlinear functions of household income averaged over three years is a better predictor of educational outcomes than a linear model in which an extra dollar always has the same effect, regardless of a family's initial income. But the differences among the three nonlinear forms are relatively small. Thus while the effect of family income is probably nonlinear, these data do not allow one to choose among the nonlinear specifications. I use log income as a measure of nonlinearity because of its theoretical appeal and ease of interpretation. To determine how much of the effect of inequality on educational attainment is due to the nonlinear relationship between family income and children's educational attainment, I estimate the following equation:

$$E_{ist} = \beta_0 + \beta_Y lnY_{ist12-14} + \beta_g Gini_{st14} + \beta_x X'_{st14} + \gamma_r + \gamma_t + \epsilon_{ist}.$$

In this equation, $\beta_Y$ captures the effect of family income when children were 12–14 years old, while $\beta_g$ captures the effects of inequality that operate independently of a household's own income.

Comparing model 4 in table 3 with model 3 in table 1 for all children shows that controlling log household income decreases the positive effect of the Gini coefficient on all outcomes. But the reductions are modest, and the remaining effects of the Gini coefficient are still positive. Con-

TABLE 2
EFFECT OF SELECTED FUNCTIONAL FORMS OF HOUSEHOLD INCOME ON MEASURES OF EDUCATIONAL ATTAINMENT

| Dependent Variable | Linear | Logarithm | Cube Root | Logarithm Plus Extreme Deciles |
|---|---|---|---|---|
| High school graduate ($\chi^2$) ... | 174.52 | 214.69 | 218.26 | 219.28 |
| Entered college ($\chi^2$) ..... | 386.94 | 401.35 | 417.50 | 425.81 |
| College graduate ($\chi^2$) ..... | 252.06 | 273.21 | 278.61 | 290.99 |
| Years of schooling ($R^2$) ..... | .127 | .129 | .136 | .137 |

SOURCE.—PSID data described in the appendix.
NOTE.—The model with "logarithm plus extreme deciles" predicts educational attainment from log household income, a variable equal to one if the child was in the richest income decile and another variable equal to one if the child was in the poorest income decile.

trolling parental income reduces the effect of the Gini coefficient on the educational outcomes of both high- and low-income children. But most of the positive effect of inequality on high-income children and most of the negative effect of inequality on low-income children does not operate through the effect of families' own income.

Most models of neighborhood or school effects begin with an individual-level model of an outcome such as high school graduation then add an aggregate-level variable for the neighborhood or school social composition. For example, such a model might predict high school graduation from family background characteristics such as parental education and income and a school or neighborhood-level variable such as mean family income (Crane 1991; Evans, Oates, and Schwab 1992; Mayer 1991). In such models, family background variables are intended to control for the fact that parents select the schools their children attend and the neighborhoods in which they live. To see if parental selection across states with different levels of inequality is a problem, I control two other measures of family background, namely, whether the child is black and parental education. Model 5 in table 3 shows that for the whole sample controlling these variables somewhat reduces the effect of the Gini coefficient on the measures of educational attainment. With these background measures controlled, omitted family background variables are less likely to be a source of bias, since other family background characteristics that affect state of residence are likely to be correlated with parents' race and education.

The results in model 5 in table 3 suggest that increasing the Gini coefficient by 0.02 would increase college enrollment by 0.047 or about 10% of the mean through processes unrelated to children's own income. This increase accrues entirely to high-income children. A 0.02 increase in the Gini coefficient would increase schooling by 0.322 years for high-income

TABLE 3
THE EFFECT OF THE GINI COEFFICIENT IN MODELS SEPARATING THE EFFECT OF PARENTS' INCOME FROM OTHER EFFECTS OF INEQUALITY

| Model and Controls | Full Sample | High Income | Low Income |
|---|---|---|---|
| Model 4, controls variables in model 3 plus log household income: | | | |
| High school graduate (probit partial derivative) ..... | .051 | .600 | −1.372 |
| | (.060) | (.640) | (−.940) |
| Enrolled in college (probit partial derivative) ..... | 2.636 | 3.560 | −.028 |
| | (2.170) | (2.170) | (−.020) |
| Graduated college (probit partial derivative) ..... | .213 | 1.998 | −1.513 |
| | (.240) | (1.420) | (−2.190) |
| Years of schooling (OLS unstandardized coefficient) ... | 7.157 | 17.057 | −7.970 |
| | (1.572) | (2.712) | (−1.275) |
| Model 5, adds child's race, parents' education: | | | |
| High school graduate (probit partial derivative) ..... | −.281 | .292 | −1.816 |
| | (−.350) | (.320) | (−1.200) |
| Enrolled in college (probit partial derivative) ..... | 2.344 | 3.150 | −.243 |
| | (1.850) | (1.890) | (−.180) |
| Graduated college (probit partial derivative) ..... | .077 | 1.957 | −1.586 |
| | (.080) | (1.340) | (−2.170) |
| Years of schooling (OLS unstandardized coefficient) ... | 5.435 | 16.124 | −10.161 |
| | (1.184) | (2.499) | (−1.617) |

NOTE.—*t*-statistics are in parentheses and are corrected for clustering in states and years.

children and decrease schooling by 0.203 years for low-income children through processes unrelated to family income.

Next I test the hypothesis that economic segregation between school districts accounts for the effect of economic inequality. If we divide a state into mutually exclusive geographic areas such as school districts, we can decompose the total variance of household income for the state ($\sigma^2_{ts}$) into two additive components: a between-area component ($\sigma^2_{bs}$) and a within-area component ($\sigma^2_{ws}$). This yields the identity

$$\sigma^2_{ts} = \sigma^2_{bs} + \sigma^2_{ws}.$$

The ratio of the between-area variance to the total variance ($\sigma^2_{bs}/\sigma^2_{ts}$) is a measure of economic segregation (Jargowsky 1996). In the absence of economic segregation, all areas have the same mean income and $\sigma^2_{bs}/\sigma^2_{ts} = 0$. With complete economic segregation, there is no income var-

iation within geographic areas and $\sigma^2_{bs}/\sigma^2_{ts} = 1$.[16] Thus my measure of economic segregation is the percentage of a state's total income variance that is between school districts in the state.[17]

Comparing model 6 in table 4 to model 5 in table 3 shows that controlling economic segregation hardly changes the effect of the Gini coefficient on any measure of schooling. This is because, contrary to what one might have expected, economic segregation between school districts has a small and statistically insignificant (at 0.05) effect on all these measures of educational attainment, so controlling it does not appreciably alter the effect of the Gini coefficient. (See tables A2–A4 in the appendix.)

To see if the effect of inequality operates through state support for schooling, I estimate a model that controls state per pupil expenditures on primary and secondary schooling, college tuition at the state's flagship institution, and the amount of grant money available for college tuition per state resident ages 15–24 years old.

Model 7 in table 4 shows that, for the whole sample, controlling these variables reduces the positive effect of inequality on enrolling in college to close to zero. It leaves a negative, statistically significant residual effect of inequality on graduating college and a negative but statistically insignificant effect on years of schooling. Controlling these variables reduces the positive effect of inequality on high-income children's educational attainment and increases its negative effect on low-income children's educational attainment. Greater state spending on schooling is associated with higher college enrollment and graduation, and states with more inequality spend more on schooling, thus reducing potential negative effects of inequality.

The full regression results from this model are shown in tables A2–A4 in the appendix. High tuition reduces a child's chances of enrolling in and graduating from college. Thus it also reduces years of schooling. This

[16] There are many other possible measures of economic segregation (White 1987; James 1986). 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 percentage of residents with a particular characteristic who would have to move for the group to be equally represented in all neighborhoods. These measures were developed to estimate racial segregation, so they require classifying people into discrete categories. Some research has measured economic segregation with such measures (Massey and Eggers 1990), but because income is continuous, by breaking income into discrete categories, this approach throws away potentially valuable information (Jargowsky 1996).

[17] I have replicated these results using the variance of state income between census tracts as the measure of segregation, and the results are very similar to the results using school districts. I show the results using school districts because they are relevant political jurisdictions for schooling outcomes.

TABLE 4
THE EFFECT OF THE GINI COEFFICIENT IN MODELS CONTROLLING STATE EDUCATION VARIABLES

| Model and Controls | Full Sample | High Income | Low Income |
|---|---|---|---|
| Model 6, controls variables in model 5 plus economic segregation: | | | |
| High school graduate (probit partial derivative) ..... | −.450 | −.104 | −1.394 |
| | (−.500) | (−.110) | (−.820) |
| Enrolled in college (probit partial derivative) ..... | 2.504 | 3.323 | −.327 |
| | (1.810) | (1.820) | (−.210) |
| Graduated college (probit partial derivative) ..... | .063 | 1.852 | −1.474 |
| | (.060) | (1.190) | (−1.730) |
| Years of schooling (OLS unstandardized coefficient) ... | 5.465 | 12.378 | −8.216 |
| | (1.114) | (1.847) | (−1.185) |
| Model 7, adds college tuition, grants for college tuition, and per pupil expenditure for elementary and secondary schooling: | | | |
| High school graduate (probit partial derivative) ..... | −.375 | −.247 | −1.145 |
| | (−.430) | (−.260) | (−.750) |
| Enrolled in college (probit partial derivative) ..... | .193 | .908 | −1.876 |
| | (.130) | (.420) | (−1.260) |
| Graduated college (probit partial derivative) ..... | −2.404 | −1.049 | −2.156 |
| | (−1.920) | (−.540) | (−3.150) |
| Years of schooling (OLS unstandardized coefficient) ... | −2.709 | 3.545 | −14.395 |
| | (−.483) | (.420) | (−2.110) |

NOTE.—*t*-statistics are in parentheses and are corrected for clustering in states and years.

is the case whether the child comes from a high- or low-income family. On the other hand, more state grant money for college increases college graduation but has a small and statistically insignificant effect on enrolling in college and on years of schooling. This is because grants for tuition increase college attendance for high- but not low-income students. This is consistent with other evidence on the effect of the costs of attending college (Kane 1999). Per pupil spending on elementary and secondary schooling increases college completion. It also increases college attendance for low-income but not high-income children.

## Sensitivity Analysis

To see if these results are robust to alternative models, I first substituted state dummy variables for region dummy variables. Second, I estimated a two-stage least-squares model that instruments the Gini coefficient. This model is intended to control unobserved heterogeneity in state charac-

teristics that could bias the estimated effect of the Gini coefficient. In the interest of brevity, I report only the estimates for years of schooling.

When I substitute state fixed effects in model 3 for the whole sample, the Gini coefficient on years of schooling is 12.646, which is similar to the 8.637 shown in table 1, but the $t$-statistic for the state fixed-effects model is only 0.761. Similarly, for children above the median income, the coefficient for the Gini coefficient is 23.809 ($t = 1.099$), and for children below the median income, it is $-4.074$ ($t = -0.066$). Again, the point estimates are similar to the estimates from models with region dummy variables, but the $t$-statistics are very small. In all cases, estimates from the region fixed-effects model were within the 95% confidence interval of the state fixed-effects estimates.

Economic inequality has increased partly because rising returns to skill have increased wages more in some industries than in others. I use this fact to create an instrument for predicting changes in economic inequality that are arguably determined by national economic forces and thus exogenous with respect to other changes at the state level. The reasoning for the instrument is that if a technological "shock" raised wages in some industries and not others, and if the state's industrial mix could not respond quickly, the industrial mix when the shock occurred should produce a state-level change in inequality over the short to medium run when all else is equal. The industrial mix at the time of the shock would presumably affect educational attainment at that time, but it would affect subsequent changes in educational attainment only through its effect on inequality, including its effect on returns to schooling. The appendix describes my measure of industrial mix.

When I re-estimate model 3 for the whole sample as a two-sided least squares model with this instrument, the effect of the Gini coefficient on years of schooling is 3.769, which is about half the OLS estimate. However, the sampling error of this estimate is very large (11.28), so this test is inconclusive.

## CONCLUSIONS

My results suggest five conclusions. First, the growth in inequality since 1970 probably did not have much affect on high school graduation.

Second, the growth in inequality since 1970 increased overall years of schooling mainly by increasing college entrance rates. Model 3 in table 3 suggests that a one standard deviation increase in the Gini coefficient results in a 0.058 increase in a student's probability of going to college (13.4% of the mean) and an additional 0.173 years of schooling.

Third, the growth in income inequality contributed to an increase in

inequality in educational attainment between rich and poor children. A 0.02 increase in the Gini coefficient is associated with a reduction of 0.192 years in low-income children's schooling and an increase of 0.372 years in high-income children's schooling. This is not primarily because the growth in inequality increased the income of rich but not poor children's families. The differential effect of inequality on high- and low-income children persists even when their families' incomes are controlled.

Fourth, the effect of inequality is only partly due to the nonlinear relationship between parental income and children's outcomes and the incentive provided by increasing returns to schooling. Fifth, an increase in per pupil expenditures at the elementary and secondary level and lower college costs are positively associated with state inequality, and both raise educational attainment. Greater inequality is also associated with greater economic segregation, but this does not appear to affect children's educational attainment.

The results in this article present a problem. Growing income inequality raised mean educational attainment but also exacerbated disparities in educational attainment between rich and poor children. This is likely to contribute to economic inequality in the next generation. These findings suggest that it is important to find ways to reduce the potentially harmful effects of inequality on low-income children. The results in this article suggest that higher spending on elementary and secondary schooling and lower college tuition increase the educational attainment of low-income children and by doing so reduce the gap in schooling between high- and low-income children. But these efforts were not enough to prevent inequality from hurting low-income children's educational attainment.

This article has at least three potential limitations that invite further research. First, it focuses on inequality at the level of the state. Inequality in smaller geographic areas could either be more or less important than inequality at the state level (though the absence of an effect of segregation makes this somewhat unlikely). Inequality at the national level may also be more important than inequality in a state. Research that assesses the importance of inequality at different levels of aggregation would be very useful. Second, I may not have controlled all state characteristics that contributed both to changes in inequality and in educational attainment. This leaves the possibility that the estimates suffer from omitted variable bias. Unfortunately, the number of state characteristics that can be included is severely limited by the number of states and the small number of PSID families. A third closely related problem is that these estimates probably do not include all the important processes through which economic inequality affects educational attainment. We need better theories about the social consequences of economic inequality in general and about its consequences for educational attainment in particular. Without strong

theories, identifying the process through which inequality operates from empirical data involves substantial risks of both type 1 and type 2 error. Nonetheless, this article has demonstrated the importance of understanding the consequences of economic inequality for both advantaged and disadvantaged children.

## APPENDIX

### Description of the Data and Variables

#### *PSID Data*

I use data from the 1993 wave of the PSID. The high school graduation sample includes respondents ages 20–37 years old in 1993 who were not missing data on any variable. The sample for college enrollment, college graduation, and years of schooling includes respondents who were ages 23–37 years old in 1993 who were not missing data. Observations are weighted 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 1968–93). Variables are assigned to respondents based on their age. For example, I average family income when children were ages 12–14 years. Thus it was averaged over 1985–87 for children born in 1973 and over 1990–92 for children born in 1978. Following is a description of variables created with PSID data. Their means, standard deviations, and correlation are in table A1.

*High school graduate* is a dummy variable equal to "1" if the individual had either earned a GED or had 12 years of schooling by age 20, "0" otherwise.

*Enrolled in college* is a dummy variable equal to "1" if the individual had completed at least 13 years of schooling by age 23, "0" otherwise.

*Completed college* is a dummy variable equal to "1" if the individual had completed at least 16 years of schooling by age 23, "0" otherwise.

*Log family income* is cash income averaged over the three years when the child was age 12–14. 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 age 14. If this was missing, I use the mother's education when the child was age 13 and so on until age 11. If all of these values were missing, then I assigned the father's education when the child was age 14.

*Black* is a dummy variable 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) of the U.S. Census. In 1980 and 1990, I used the 5% samples. In 1970, I used the 1% sample because that is what is available.

*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 total income. To reduce problems of comparability over time that arise from changes in the Census Bureau's top-codes for income components, I created uniform income components and top-codes for all years. Variables are top-coded by reassigning values above the lowest ninety-ninth percentile of positive values among the years to the median of all values across years that lie above that lowest ninety-ninth percentile. The same was done for negative values using the highest first percentile as the cutoff. I sum the resulting components to get household income. All measures of income are adjusted to 1998 dollars using the CPI-U-X1. I use this income measure to calculate state-level measures of income and income inequality. Persons in group quarters were excluded from all calculations.

*Percentage black and percentage Hispanic* are estimated using 1970, 1980, and 1990 PUMS data. I use linear interpolation to assign values for the state in the year when the child was 14 years old.

*Returns to schooling* for individual $i$ in state $s$ and year $y$ is estimated for workers ages 18–65 using the following model:

$$lnW_{isy} = \beta_0 + \beta_s S_{is} + \epsilon_{is},$$

where $W$ is the hourly wage and $S$ is years of schooling. In this model, $\beta_s$ is the percentage increase in wages due to an additional year of schooling. I experimented with 12 different measures of returns to schooling, using different age groups and different functional forms, and estimating separate models for men and women. I use the measure that increased $R^2$ the most when added to the model of the effect of inequality. This measure also corresponds best to economic theory about the functional form of returns to schooling and produces an estimated return to schooling that is consistent with previous research (Winship and Korenman 1999; Mayer and Knutson 1999; Ceci 1991).

*Economic segregation* is estimated by calculating the total variance of household income for each state using the income measure described above. I calculate mean income for each census tract in the state using the STF4 and STF5 census files. 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.

*Industrial mix* of states in 1970 is measured by assigning each worker between the ages of 25 and 64 in a state the national mean earnings of workers in the same three-digit industry. I then calculate the dispersion of these means separately for each state, weighting each industry by the percentage of the state's workers in the industry. Thus for each state, I calculate the national mean wage in 1970 of workers in individual i's industry. I then calculate a new variable that assigns each worker in 1970 the average 1980 wage for his or her industry. I repeat this using average wages for 1990. I calculate the standard deviations of the 1970, 1980, and 1990 measures in each state. This measure, which I call "industrial mix," is the amount of interindustry income inequality we would expect to find in the state if the industrial mix had not changed between 1970 and 1990. The $R^2$ when I regress the change in the Gini coefficient on the change in industry mix is 0.365.

*Other State-Level Variables*

*Elementary and secondary public school expenditures per capita* is the state's total expenditure for elementary and secondary public schools divided by the state population of children ages 5–17 calculated for the year when the individual was age 14. State population data for 5–17 year olds are from the U.S. Census Bureau's web page. Elementary and secondary public school expenditures are from U.S. Bureau of the Census, *Statistical Abstract of the United States* annual volumes for 1970–90 (91st to 110th eds.).

*College tuition* is the in-state tuition for the state's flagship university. The data are from the Higher Education General Information Survey (U.S. National Center for Education Statistics, various years.)

*Grants for college* is the total price-adjusted need-based grant expenditures for a state divided by the number of state residents ages 15–24. The data are from the Higher Education General Information Survey (U.S. National Center for Education Statistics, various years.)

TABLE A1

CORRELATIONS AMONG VARIABLES

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. High school graduate | 1.000 | | | | | | | | | | | | | | | |
| 2. Enrolled in college | .022 | 1.000 | | | | | | | | | | | | | | |
| 3. Graduated college | .031 | .547 | 1.000 | | | | | | | | | | | | | |
| 4. Years of schooling | .041 | .787 | .731 | 1.000 | | | | | | | | | | | | |
| 5. Mean household income/$1,000 | .055 | .101 | .068 | .106 | 1.000 | | | | | | | | | | | |
| 6. %black in state | −.044 | −.089 | −.056 | −.080 | −.320 | 1.000 | | | | | | | | | | |
| 7. %Hispanic in state | .085 | .075 | .042 | .055 | .342 | −.119 | 1.000 | | | | | | | | | |
| 8. Child's race is black | −.114 | −.116 | −.137 | −.144 | −.124 | .330 | −.005 | 1.000 | | | | | | | | |
| 9. State Gini coefficient | −.030 | −.013 | −.022 | −.039 | −.570 | .170 | .188 | .156 | 1.000 | | | | | | | |
| 10. State returns to schooling | .030 | .036 | .030 | .048 | −.003 | .502 | .334 | .137 | .447 | 1.000 | | | | | | |
| 11. Log household income | .256 | .333 | .269 | .358 | .286 | −.208 | .120 | −.374 | −.184 | −.023 | 1.000 | | | | | |
| 12. Parent's education | .271 | .347 | .276 | .364 | .240 | −.213 | .092 | −.229 | −.141 | .060 | .425 | 1.000 | | | | |
| 13. Expenditures on schools/$1,000 | .064 | .133 | .103 | .125 | .706 | −.263 | .217 | −.133 | −.118 | .058 | .182 | .251 | 1.000 | | | |
| 14. College tuition/$1,000 | .004 | −.032 | −.023 | −.010 | .351 | −.091 | −.302 | −.068 | −.433 | −.046 | .066 | .042 | .317 | 1.000 | | |
| 15. Grants for college | .024 | .083 | .112 | .103 | .255 | −.118 | .302 | −.048 | .044 | .241 | .118 | .049 | .410 | .207 | 1.000 | |
| 16. Segregation | .042 | .084 | .103 | .102 | .243 | −.018 | .312 | −.017 | −.206 | .186 | .187 | .114 | .401 | .363 | .213 | 1.000 |
| Mean | .832 | .427 | .182 | 12.906 | 36.728 | 11.460 | 4.971 | .155 | .402 | .062 | 10.759 | 11.431 | 2.934 | 1.914 | .075 | .070 |
| SD | .374 | .494 | .386 | 2.121 | 4.526 | 7.744 | 6.170 | .362 | .018 | .011 | .657 | 2.661 | .780 | .772 | .079 | .033 |

SOURCE.—See data description in the appendix.

NOTE.—Means and SDs 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.

TABLE A2

PREDICTORS OF SCHOOL OUTCOMES FOR THE FULL SAMPLE

| VARIABLE | PROBIT PARTIAL DERIVATIVE | | | OLS COEFFICIENT |
|---|---|---|---|---|
| | High School Graduate | Enrolled in College | Graduated College | Years of Schooling |
| Gini coefficient | −.375 | .193 | −2.404 | −2.709 |
| | (−.430) | (.130) | (−1.920) | (−.483) |
| State mean income/$1,000 | −.009 | −.012 | −.015 | −.045 |
| | (1.600) | (−1.360) | (−2.300) | (−1.473) |
| State %black | .003 | .004 | .002 | .021 |
| | (1.470) | (1.470) | (1.280) | (1.774) |
| State %Hispanic | −.002 | −.005 | −.001 | −.014 |
| | (−.830) | (−1.310) | (−.280) | (−1.023) |
| State unemployment rate | −.005 | .000 | −.003 | −.012 |
| | (−1.770) | (.060) | (−.720) | (−.614) |
| Returns to schooling | 1.553 | 2.998 | 1.954 | 9.973 |
| | (.940) | (1.040) | (1.010) | (.866) |
| Log parental income | .087 | .208 | .099 | .771 |
| | (6.230) | (8.390) | (5.920) | (10.392) |
| Child is black | −.011 | .066 | −.047 | .000 |
| | (−.490) | (1.640) | (−1.980) | (.003) |
| Parent's years of schooling | .025 | .056 | .034 | .202 |
| | (7.610) | (7.810) | (7.260) | (10.350) |
| Segregation between school districts | .267 | .484 | .572 | 1.841 |
| | (.680) | (.790) | (1.390) | (.733) |
| Per pupil expenditures on schools/$1,000 | .025 | .068 | .054 | .265 |
| | (.870) | (1.400) | (1.770) | (1.532) |
| College tuition/$1,000 | −.026 | −.134 | −.072 | −.392 |
| | (−1.140) | (−3.910) | (−3.300) | (−3.069) |
| Grants for college tuition | −.134 | .059 | .307 | .331 |
| | (−.890) | (.260) | (2.280) | (.433) |

NOTE.—All models also control region and year dummy variables, as described in the text.

TABLE A3

PREDICTORS OF SCHOOL OUTCOMES FOR HIGH-INCOME SAMPLE

| VARIABLE | PROBIT PARTIAL DERIVATIVE | | | OLS COEFFICIENT |
|---|---|---|---|---|
| | High School Graduate | Enrolled in College | Graduated College | Years of Schooling |
| Gini coefficient | −.247 | .908 | −1.049 | 3.545 |
| | (−.260) | (.420) | (−.540) | (.420) |
| State mean income/$1,000 | −.013 | −.005 | −.006 | −.016 |
| | (−2.470) | (−.410) | (−.550) | (−.354) |
| State %black | .002 | −.002 | −.002 | −.005 |
| | (1.100) | (−.570) | (−.670) | (−.312) |
| State %Hispanic | .001 | −.008 | −.003 | −.018 |
| | (.320) | (−1.820) | (−.760) | (−1.095) |
| State unemployment rate | −.001 | .003 | −.004 | .004 |
| | (−.320) | (.440) | (−.750) | (.163) |
| Returns to schooling | .430 | 5.064 | 3.028 | 7.167 |
| | (.250) | (1.330) | (1.000) | (.436) |
| Log parental income | .054 | .268 | .157 | 1.051 |
| | (2.010) | (5.510) | (4.950) | (6.379) |
| Child is black | .029 | −.061 | −.132 | −.456 |
| | (1.580) | (−.960) | (−2.640) | (−2.504) |
| Parent's years of schooling | .017 | .064 | .055 | .219 |
| | (5.280) | (6.760) | (7.750) | (8.790) |
| Segregation between school districts | .743 | .767 | .745 | 3.888 |
| | (1.920) | (.940) | (1.130) | (1.086) |
| Per pupil expenditures on schools/$1,000 | .049 | −.006 | .014 | .066 |
| | (1.820) | (−.100) | (.300) | (.289) |
| College tuition/$1,000 | −.024 | −.135 | −.066 | −.251 |
| | (−1.070) | (−3.020) | (−1.930) | (−1.445) |
| Grants for college tuition | −.003 | .646 | .859 | 2.532 |
| | (−.020) | (2.240) | (4.160) | (2.230) |

NOTE.—All models also control region and year dummy variables, as described in the text.

TABLE A4
PREDICTORS OF SCHOOL OUTCOMES FOR LOW-INCOME SAMPLE

| | PROBIT PARTIAL DERIVATIVE | | | OLS COEFFICIENT |
|---|---|---|---|---|
| VARIABLE | High School Graduate | Enrolled in College | Graduated College | Years of Schooling |
| Gini coefficient | −1.145 | −1.876 | −2.156 | −14.395 |
| | (−.750) | (−1.260) | (−3.150) | (−2.110) |
| State mean income/$1,000 | .007 | −.021 | −.014 | −.070 |
| | (.600) | (−2.210) | (−3.270) | (−1.710) |
| State %black | .002 | .008 | .002 | .033 |
| | (.650) | (2.220) | (1.430) | (2.088) |
| State %Hispanic | −.008 | .000 | −.002 | −.016 |
| | (−1.640) | (.100) | (−.960) | (−.848) |
| State unemployment rate | −.014 | −.004 | −.002 | −.036 |
| | (−2.050) | (−.710) | (−.850) | (−1.402) |
| Returns to schooling | 5.518 | −.740 | .710 | 18.820 |
| | (1.570) | (−.250) | (.490) | (1.336) |
| Log parental income | .053 | .016 | .007 | .093 |
| | (1.600) | (.490) | (.470) | (.660) |
| Child is black | −.032 | .093 | −.002 | .205 |
| | (−.810) | (2.500) | (−.140) | (1.463) |
| Parent's years of schooling | .041 | .039 | .009 | .181 |
| | (6.310) | (5.330) | (3.090) | (7.001) |
| Segregation between school districts | −.778 | .207 | .007 | −1.810 |
| | (−.880) | (.270) | (.020) | (−.610) |
| Per pupil expenditures on schools/$1,000 | −.061 | .173 | .067 | .445 |
| | (−1.140) | (2.780) | (2.530) | (1.564) |
| College tuition/$1,000 | −.000 | −.078 | −.053 | −.548 |
| | (−.610) | (−1.910) | (−2.720) | (−2.928) |
| Grants for college tuition | −.273 | −.606 | −.246 | −3.170 |
| | (−.820) | (−2.300) | (−1.840) | (−2.854) |

NOTE.—All models also control region and year dummy variables, as described in the text.

## REFERENCES

Alesina, Alberto, and Dani Rodrik. 1994. "Distributive Politics and Economic Growth." *Quarterly Journal of Economics* 109:465–90.

Atkinson, Anthony B. 1970. "On the Measurement of Inequality." *Journal of Economic Theory* 2:244–63.

———. 1983. *The Economics of Inequality.* Oxford: Oxford University Press.

Betts, Julian, and L. McFarland. 1995. "Safe Ports in a Storm: The Impact of Labor Market Conditions on Community College Enrollment." *Journal of Human Resources* 30 (4): 741–65.

Card, David, and Abigail Payne. 1998. "School Finance Reform, the Distribution of

School Spending, and the Distribution of SAT Scores." Working Paper no. 6766. National Bureau of Economic Research, Cambridge, Mass.
Ceci, Stephen J. 1991. "How Much Does Schooling Influence General Intelligence and Its Cognitive Components? A Reassessment of the Evidence." *Developmental Psychology* 27 (5): 703–22.
Crane, Jonathon. 1991. "The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing." *American Journal of Sociology* 96 (5): 1226–59.
Davis, James A. 1959. "A Formal Interpretation of the Theory of Relative Deprivation." *Sociometry* 22:280–96.
———. 1966. "The Campus as a Frog Pond: An Application of the Theory of Relative Deprivation to Career Decisions of Young Men." *American Sociological Review* 52: 511–18.
Durlauf, Steven. 1996. "A Theory of Persistent Income Inequality." *Journal of Economic Growth* 1:75–93.
Ellemers, Naomi, Russell Spears, and Bertjan Doosje, eds. 1997. *Social Identity Context, Commitment, Content.* New York: Blackwell.
Elliott, Marta. 1998. "School Finance and Opportunities to Learn: Does Money Well Spent Enhance Students' Achievement?" *Sociology of Education* 71 (3): 223–45.
Ellwood, David A., and Thomas J. Kane. 1999. "Who Is Getting A College Education? Family Background and the Growing Gaps in Enrollment." Unpublished manuscript. Harvard University, Kennedy School of Government.
Evans, William, William Oates, and R. M. Schwab. 1992. "Measuring Peer Group Effects: A Study of Teenage Behavior." *Journal of Political Economy* 100:966–91.
Firebaugh, Glenn. 1999. "Empirics of World Income Inequality." *American Journal of Sociology* 104 (6): 1597–1630.
Forbes, Kristin. 2000."A Reassessment of the Relationship between Inequality and Growth." *American Economic Review* 90 (4): 869–87.
Grubb, N. W. 1988. "Vocationalizing Higher Education: The Causes of Enrollment and Completion in Public Two-Year Colleges 1970–1980." *Economics of Education Review* 7 (3): 301–19.
Gurr, Ted R. 1970. *Why Men Rebel.* Princeton, N.J.: Princeton University Press.
Gustafsson, Bjorn, and Mats Johansson. 1999. "In Search of Smoking Guns: What Makes Income Inequality Vary over Time in Different Countries?" *American Sociological Review* 64 (4): 585–605.
Hanushek, Eric A. 1996. "School Resources and Student Performance." Pp. 585–605 in *Does Money Matter?* edited by Gary Burtless. Washington, D.C.: Brookings Institution Press.
Hedges, Larry V., Richard Laine, and Rob Greenwald. 1992. "Does Money Matter? Meta-Analysis of Studies of the Effects 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): 301–16.
Jargowsky, Paul A. 1996. "Take the Money and Run: Economic Segregation in U.S. Metropolitan Areas." *American Sociological Review* 61:984–98.
Jencks, Christopher, and Susan E. Mayer. 1990. "The Social Consequences of Growing Up in a Poor Neighborhood." Pp. 111–86 in *Inner-City Poverty in the United States*, edited by Laurence Lynn and Michael McGeary. Washington, D.C.: National Academy Press.
Juhn, Chinhui, Kevin Murphy, and Brooks Pierce. 1993. "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy* 101 (3): 410–42.
Kane, Thomas. 1994. "College Entry by Blacks since 1970: The Role of College Costs,

Family Background and the Returns to Education." *Journal of Political Economy* 102 (5): 878–911.

———. 1999. *The Price of Admission: Rethinking How Americans Pay for College.* Washington, D.C.: Brookings Institution Press.

Karoly, Lynn. 1993. "The Trend in Inequality among Families, Individuals, and Workers in the United States: A Twenty-Five Year Perspective." Pp. 19–97 in *Uneven Tides: Rising Inequality in America,* edited by Sheldon Danziger and Peter Gottschalk. New York: Russell Sage Foundation Press.

Lichter, Daniel, and David Eggebeen. 1993. "Rich Kids, Poor Kids: Changing Income Inequality among American Children." *Social Forces* 71 (3): 301–76.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies* 60 (3): 531–42.

Manski, Charles, and David Wise. 1983. *College Choice in America.* Cambridge, Mass.: 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 and Socioeconomic Mix Affect Graduation and Teen Fertility Rates?" Pp. 79–102 in *The Urban Underclass,* edited by Christopher Jencks and Paul Peterson, Washington, D.C.: Brookings Institution Press.

Mayer, Susan E., and David Knutson. 1999. "Does the Timing of Schooling Effect How Much Children Learn?" Pp. 79–102 in *Earning and Learning: How Schools Matter,* edited by Susan E. Mayer and Paul E. Peterson. Washington, D.C.: Brookings Institution Press.

McLoyd, Vonnie. 1990. "The Impact of Economic Hardship on Black Families and Children: Psychological Distress, Parenting and Socioemotional Development." *Child Development* 61:311–46.

Merton, Robert, and Alice Kitt. 1950. "Contributions to the Theory of Reference Group Behavior." Pp. 40–105 in *Studies in the Scope and Method of "The American Soldier,"* edited by Robert Merton and Paul Lazarsfeld. Glencoe, Ill.: Free Press.

Messner, Steven, and Kenneth Tardiff. 1986. "Economic Inequality and the Levels of Homicide: An Analysis of Urban Neighborhoods." *Criminology* 24:297–316.

Morris, Martina, Annette Bernhardt, and Mark Handcock. 1994. "Economic Inequality: New Methods for New Trends." *American Sociological Review* 59 (2): 205–19.

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

Murphy, Kevin, and Finish Welch. 1992. "The Structure of Wages." *Quarterly Journal of Economics* 107:215–36.

Murray, Shelia, William Evans, and Robert Schwab. 1998. "Education-Finance Reform and the Distribution of Education Resources." *American Economic Review* 88 (4): 789–812.

Nettler, Gwynn. 1994. *Explaining Crime,* 3d ed. New York: McGraw-Hill.

Perotti, Roberto. 1996. "Growth, Income Distribution, and Democracy: What the Data Say." *Journal of Economic Growth* 1:149–87.

Piven, Francis Fox, and Richard Cloward. 1993. *Regulating the Poor: The Functions of Public Welfare*. New York: Vintage Books.

Rosenfeld, Richard. 1986. "Urban Crime Rates: Effects of Inequality, Welfare Dependency, Region and Race." Pp. 116–30 in *The Social Ecology of Crime,* edited by James Byrne and Robert Sampson. New York: Springer-Verlag.

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.

Smith, Heather, Russell Spears, and Intse Hamstra. 1999. "Social Identity and the

Context of Relative Deprivation." Pp. 205–29 in *Social Identity: Context, Commitment and Content,* edited by Naomi Ellemers, Russell Spears, and Bertjan Doosje. Oxford: Blackwell Publishers.

Suls, Jerry, ed. 1991. *Social Comparison: Contemporary Theory and Research*. Hillsdale, N.J.: Lawrence Erlbaum.

Tienda, Marta. 1991. "Poor People and Poor Places: Deciphering Neighborhood Effects on Poverty Outcomes." Pp. 224–62 in *Macro-Micro Linkages in Sociology,* edited by J. Haber. Newberry, Calif.: Sage.

U. S. Bureau of the Census. 1998. *Statistical Abstract of the United States.* Washington, D.C.: Government Printing Office.

U.S. Department of Education, National Center for Educational Statistics. 1998. *Digest of Educational Statistics.* Washington, D.C.: Government Printing Office.

U.S. Department of Health and Human Services. 1998. *Trends in the Well-Being of America's Children and Youth*. Washington, D.C.: Government Printing Office.

Welch, Finis. 1999. "In Defense of Inequality." *American Economic Review* 89 (2): 1–17.

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

Williams, Robin Jr. 1975. "Relative Deprivation." Pp. 355–78 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 Julius. 1987. *The Truly Disadvantaged.* Chicago: University of Chicago Press.

Winship, Christopher, and Sanders Korenman. 1999. "Economic Success and the Evolution of Schooling." Pp. 49–78 in *Earning and Learning: How Schools Matter,* edited by Susan E. Mayer and Paul E. Peterson. Washington, D.C.: Brookings Institution Press.