Intergenerational Sources of Socioeconomic Inequality in Children's Reading and Math Achievement[†]

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Abstract

We describe and analyze the level of inequality in children's reading and math achievement by family socioeconomic status. We examine the role of distinct components of socioeconomic status in shaping the inequality across three generations. Our focus is on parent and grandparent income, education, and cognitive skills; however, we also examine the effect of parents' wealth and neighborhood economic status. Data for this study come from the Panel Study of Income Dynamics (PSID) and the PSID Child Development Supplement (CDS). We use data from Wave II of CDS, which was fielded in 2002 and includes achievement test scores in math and reading for just under 2,000 children aged 5–18 years. The paper also illustrates the use of methods to analyze the sources of inequality in children's achievement (and other similar measures) that incorporate multilevel regression-based decomposition and summary measures such as Gini coefficients and concentration indices. Our results show that there are strong effects of parent-generation socioeconomic status on children's achievement; they also reveal limited direct effects of grandparent socioeconomic status on grandchild achievement after controlling for parent-generation socioeconomic status.

Keywords: Children's academic achievement; socioeconomic inequality; intergenerational effects; parents and grandparents

Introduction

Children's educational achievement—and their acquisition of math and reading skills in particular—are important for a successful transition into adult life. Previous research has shown, for example, that academic skills are associated with educational attainment, adult economic status, and health outcomes (Farkas, 2003; Murnane, Willett and Levy, 1995; Strenze, 2007), although noncognitive abilities also play a role (Heckman, Stixrud, and Urzua, 2006). *Inequality* in children's achievement by socioeconomic status is of particular research and policy significance because it is intrinsically undesirable and because of its potentially important role in the intergenerational transmission of disadvantage. In this paper, we investigate the dimensions of intergenerational socioeconomic status and family background that matter most for inequality in children's achievement.

There are two main goals of this paper. First, we describe and analyze the level of inequality in children's achievement according to different dimensions of family socioeconomic status. The analysis emphasizes the importance of understanding the role of distinct components of socioeconomic status in shaping the transmission of inequality across generations. Second, we answer the call made by Mare (2011) in his presidential address to the Population Association of America to examine multigenerational effects of family socioeconomic status on inequality in children's achievement by examining the effects of parents' and grandparents' status. In particular, we describe the relationship between grandparent-generation socioeconomic status and grandchild educational outcomes and investigate whether that relationship is robust to including controls for parent-generation measures of socioeconomic status. Our focus is on parent and grandparent income, education, and cognitive skills; however, we also examine the effect of parents' wealth and neighborhood economic status. Data for this study come from the

Panel Study of Income Dynamics (PSID) and the PSID Child Development Supplement (CDS). We use data from Wave II of CDS, which was fielded in 2002 and includes achievement test scores in math and reading for just under 2,000 children aged 5–18 years.

The paper also illustrates the use of methods to analyze the sources of inequality in children's achievement (and other similar measures) that incorporate multilevel regression-based decomposition and allow us to examine the effects of inequality in the socioeconomic status measures themselves. Measures such as Gini coefficients and Lorenz curves, concentration indices and concentration curves, and regression-based decomposition (Kakwani, Wagstaff, and van Doorslaer, 1997) have been widely used in examining socioeconomic inequality in health outcomes (Costa-Font and Herandez Quevedo, 2012). However, few studies to date have examined socioeconomic inequality in children's achievement using these measures, although a recent paper by Sastry and Pebley (2010) is an exception. Rather, many previous studies have examined between-group disparities by comparing categorically-defined groups of children based on race or by constructing categories from measures of socioeconomic status. These more rudimentary methods suffer from limitations. For example, comparisons of outcomes for a "high-status" group against a "low-status" group are based on arbitrarily defined groups, ignore the middle-range of the distribution of socioeconomic status, and are sensitive only to changes in inequality that move individuals into or out of the high and low status groups.

There is a small, but growing, body of research examining intergeneration effects on children's educational achievement and attainment, and much of this research in the United States uses data from PSID. Sharkey and Elwert (2011) used the PSID to examine grandparent neighborhood SES exposure on children's achievement, and uncovered clear multigenerational neighborhood effects. Their analysis did not, however, consider the more complex ways in which different sources of disadvantage (neighborhood poverty versus family poverty, for example) operated to affect children's achievement, and their results hence represent the gross effects of grandparent neighborhood environments. Roksa and Potter (2011) examined the effects of parent and grandparent social status on children's achievement, using comparisons across four categories (stable middle-class, new middle-class, new working-class, and stable working-class). These class variables were based entirely on the mother's and grandmother's educational attainment. Roksa and Potter found that children's test scores followed the social ordering of these four categories, thereby providing evidence that education of both prior generations mattered. Wightman and Danziger (2012) conduct a similarly-structured analysis that considered the effects of low socioeconomic status among parents and grandparents on children's educational attainment. They found that grandparent socioeconomic status was associated with children's educational outcomes even when controlling for parent's socioeconomic status.

There is a separate research literature that has estimated intergenerational correlations in IQ or educational achievement, and which has supplemented the sizeable number of studies that have examined intergenerational correlations in economic status (for reviews of the latter, see Black and Devereux, 2011; Bjorklund and Jantti, 2009; and Solon, 1999). In a study using IQ data from Swedish military enlistment tests, Bjorklund, Eriksson, and Jantti (2010) found a correlation of 0.35 for the IQ scores of fathers and sons and of 0.47 for brothers. Black, Devereux, and Salvanes (2009) used similar data from Norway and found an intergenerational correlation of 0.38 for the IQ scores of fathers and sons. Anger and Heineck (2010) used data from the German Socio-Economic Panel to study parent-child correlations in abbreviated measures of cognitive ability. Restrictions based on the participation of parent-child pairs in the survey and missing data resulted in a small and potentially select sample. They found intergenerational correlations of 0.45 and 0.50 for two separate measures of cognitive ability (coding speed and verbal fluency). Brown, McIntosh, and Taylor (2011), in a study based on the British National Child Development Study that followed a cohort of children born in 1958 and used math and reading test scores at age 7 years for both parents and children, found an intergenerational correlation of 0.16 for reading skills and roughly half that value for math skills. More broadly, the canonical result from behavioral genetics studies is that the parent-child correlation in IQ is 0.5 (Bouchard and McGue, 1982; Devlin, Daniels, and Roeder, 1994; Sacerdote, 2011). Despite the established literature examining parent-child and sibling correlations in achievement, none of these prior studies have examined intergenerational correlations in achievement among grandparents and grandchildren. However, a simple application of the stylized finding suggests that the observed grandparent-grandchild correlation in achievement should be 0.25.

The conceptual framework that guides our analysis is based on grandparent-generation measures of socioeconomic status having indirect effects on the academic achievement of their grandchildren—which operate instead by shaping the parent-generation socioeconomic status indicators. Thus, grandparent-generation income and wealth have the potential to affect grandchild reading and math test scores largely by improving economic status, educational attainment, and academic achievement of the parent generation. We consider educational outcomes, such as years of schooling and vocabulary or reading test scores, as indicators of status although the latter are clearly also measures of achievement. Hence, there may be pathways through which grandparent-generation characteristics—such as reading-related achievement—may directly affect children, particularly if the grandparents have an active role in raising their grandchildren. One goal of our analysis is to examine these direct links, after controlling for parent-generation characteristics. However, we cannot easily identify the pathways through which these grandparent-grandchild links may operate, and instead view these potential links as capturing the intergenerational transmission of ability as well as investments in education-related activities inside and outside the home (see Solon, 2004).

One contribution of our conceptual and methodological approach is to view the influence of grandparent- and parent-generation socioeconomic status measures on children's achievement inequality as having two distinct components. The first is the degree of inequality in the grandparent- or parent-generation measure of socioeconomic status, while the second is the strength of the association with the children's achievement measure. Thus, socioeconomic inequality in children's achievement can arise from factors that have a high degree of inequality (such as household wealth) but perhaps a modest association with achievement or it can arise from socioeconomic variables (such as years of schooling) that are less inequitably distributed but have perhaps a stronger association with children's achievement. Distinguishing between these different types of effects has potentially important research and policy implications, particularly for intergenerational transmission of inequality. This is because there are distinct challenges and opportunities associated with bringing about changes in the *distribution* of social and economic characteristics from changes in the *effects* of characteristics.

Our analysis is descriptive in nature. The potentially endogenous effects of the socioeconomic characteristics we examine is mitigated—but not eliminated—by the use of integrated measures (such as wealth and family income averaged over five-year periods), and characteristics that are determined in the distant past rather than potentially shaped by reciprocal effects. Nevertheless, there may be unmeasured factors that operate over time and across generations to affect both socioeconomic status and children's academic achievement.

We begin, in the next section, by describing the methods we use to summarize and analyze socioeconomic inequality in children's achievement. Next, we describe the data that we use for the analysis. We then present our results, and end the paper with discussion of the main findings.

Methods

To summarize and analyze socioeconomic inequality in children's achievement, we used Lorenz and concentration curves together with their summary measures, the Gini coefficient and the concentration index. To decompose overall and socioeconomic inequality in children's achievement, we used a regression-based decomposition approach.

Lorenz curves and Gini coefficients are used to describe overall levels of inequality, for both children's achievement and the socioeconomic status measures. Concentration curves and indices are used to describe inequality in children's achievement by socioeconomic status. These measures were originally developed to study inequality in income, wealth, and the incidence of taxes (Kakwani, 1977), and have a number of strengths compared to alternative approaches to describing and analyzing inequality (Wagstaff et al., 1991).

The Gini coefficient is derived from the Lorenz curve, which graphs the cumulative proportion of children ranked in ascending order by their achievement test score (on the *x*-axis) against the cumulative proportion of test scores (on the *y*-axis). If there was perfect equality in test scores, the Lorenz curve would lie along the diagonal. The farther below the diagonal the Lorenz curve lies, the higher the degree of inequality. The Gini coefficient summarizes the overall level of inequality. It is defined as twice the area between the diagonal and the Lorenz curve. The Gini coefficient provides a scale-free measure of the overall level of inequality and is a standardized measure of variance in children's test scores.

A concentration curve graphs the cumulative proportion of children ranked in ascending order by a measure of socioeconomic status (on the *x*-axis) against the cumulative proportion of test scores (on the *y*-axis). While the Lorenz curve portrays the concentration of test scores according to distribution of the test scores themselves, the concentration curve plots the concentration of children's test scores according to the distribution of children by socioeconomic status. If there was no association between socioeconomic status and test scores, then the concentration curve would be a straight line along the diagonal. Because test scores tend to be positively associated with socioeconomic status, inequality favoring higher socioeconomic status individuals places the concentration curve below the diagonal. The farther the concentration curve lies below the diagonal, the more inequalities in test scores favor those of higher socioeconomic status. The concentration index is the bivariate analog of the Gini coefficient and is defined as twice the area between the concentration curve and the diagonal. Concentration indices are directly comparable with Gini coefficients, because they are based on the same principles.

When comparing socioeconomic inequality in test scores across different measures of socioeconomic status, unambiguous comparisons are only possible when concentration curves do not cross. In such a situation, the curve farther from the diagonal represents unambiguously greater inequality based on any derived index that respects the principle of transfers (Atkinson 1970). When concentration curves do cross, unambiguous comparisons are not possible; in this situation, an ordering based on the concentration index provides one approach to comparing inequality in test scores according to different measures of socioeconomic status. However, inspection of the concentration curves themselves can provide useful insights regarding the comparative nature of inequality in an outcome according to two (or more) different socioeconomic indicators.

Our goal is to decompose the overall inequality in children's tests scores according to contributions from different socioeconomic status measures using a regression-based approach. This method also allows us to examine inequality in test scores by socioeconomic status, based on the concentration index, before and after controlling for other covariates.

The starting point is the calculation of the Gini coefficient, *G*, for an achievement test score measure, y_i, which is given by the following expression:

$$G_y = (2/\bar{y})\operatorname{cov}(y_i, R_i^y), \qquad (1)$$

where R_i^y is the relative rank of the *i*th child when ordered by his or her test score: $R_i^y = (2i-1)/2n$. The concentration index for test score, y_i, and the k^{th} socioeconomic status indicator, x_i^k, is:

$$C_{yx^k} = (2/\bar{y})\operatorname{cov}(y_i, R_i^{x^k}), \qquad (2)$$

where $R_i^{x^k}$, is the relative rank of the *i*th child when ordered by his or her k^{th} socioeconomic status indicator.

We decompose the "explained" (by the regression model) component of the Gini coefficient, *G*, for children's predicted test scores, $\hat{y}_i$, using the following regression-based formula (Sastry, 2013):

$$G_{\hat{y}} = \sum_k \frac{\hat{\beta}^k \bar{x}^k}{\bar{y}} G_{x^k} K_{x^k y} = \sum_k C^*_{yx^k} K_{x^k y}. \qquad (3)$$

The first term on the right hand side of this equation, $\hat{\beta}^k \bar{x}^k / \bar{y}$, is the estimated elasticity in children's achievement with respect to the k^{th} socioeconomic status measure, x^k, evaluated at the sample means ($\bar{x}^k$ and $\bar{y}$). The term $K_{x^k y}$ is known as the rank correlation ratio (Pyatt et al. 1980) and reflects the divergence in ordering of individuals when they are ranked by test scores compared to when they are ranked by socioeconomic status. The upper bound of the rank correlation ratio is one, which is reached when individuals' ranking by test scores is identical to their ranking by an ascendant measure of socioeconomic status—which occurs when the concentration and Lorenz curves overlap completely. Finally, G_{x^k} is the Gini coefficient for the k^{th} socioeconomic status measure. The product of the first two terms (the elasticity of *y* with respect to *x* and the Gini coefficient for *x*) provides an "adjusted" measure of the concentration index, $C^*_{yx^k}$, which is known as the partial concentration index (Gravelle, 2003). This is equivalent to the concentration index based on the predicted value of *y* that holds all other socioeconomic status variables constant at their sample-wide means except for x^k , which is allowed to vary with *y*.

The decomposition in Equation (3) is based on a linear regression model, and the use of predicted values means that only the explained variation in well-being can be decomposed. Note, however, that we can decompose the sources of unexplained variance among individual, family, and neighborhood components using a multilevel model.

To calculate standard error for the concentration index with individual-level data, we use a convenience regression (Kakwani et al. 1997) together with Newey and West's (1987) procedure to control for serial correlation in the relative ranks and heteroscedasticity. To account for the hierarchical-clustering of the survey data, we bootstrapped the procedure for calculating standard errors (Efron and Tibshirani, 1993).

Data

Our analysis is based on data from the Child Development Supplement to the Panel Study of Income Dynamics (PSID/CDS). The Panel Study of Income Dynamics (PSID) is a nationally-representative longitudinal survey that has been conducted since 1968 (McGonagle et al., 2012). The baseline survey included a representative sample of 3,000 families and an additional sample of 2,000 low-income families. All of these families, including splitoffs, were followed in subsequent waves. By 1996 the number of families in the study had grown to nearly 8,500 because of splitoffs. The original low-income sample was reduced by approximately two-thirds in 1997. All of the children in our sample came from this resulting PSID "core" sample which in 1997 comprised of 6,168 families.

The PSID Child Development Supplement (CDS) was launched in 1997. Families were selected from PSID for the CDS if they had at least one child under 13 years of age. There were 2,705 households eligible for the CDS and interviews were completed in 2,394 households (a response rate of 88 percent). Up to two children were randomly sampled in eligible families. In CDS-I, information was collected from a total of 3,563 children. In 2002–2003, a second wave of CDS was completed on these same children who were then 5–18 years of age. A total of 2,907 children were included in the CDS-II sample, out of a total of 3,191 who were eligible for the study (a response rate of 93 percent). A total of 2,633 children (91 percent of the total) completed the cognitive assessments in CDS-II. Children who were missing information on covariates resulted in a total of 740 cases being dropped from our analysis sample. The main missing variables that led to cases being dropped were primary caregivers' test scores (476 cases dropped) and information on the grandparent generation (234 cases dropped). An additional 30 cases were dropped due to missing information on the other variables. Differences in reading and mathematics test scores between children in the analysis and those excluded from the sample due to missing covariates were substantively small and statistically insignificant (results not shown). The final CDS-II analysis sample comprised of 1,893 children.

The 1,893 children in PSID/CDS-II belong to 1,322 families; half of these families contribute one child to the sample and the other half contributes two children, for an average of 1.5 children per family. These families are, in turn, distributed across 1,156 neighborhoods—which, for the purpose of this study, are defined as tracts based on 2000 U.S. Census boundaries. There are a mean of 1.1 families and 1.6 children per neighborhood, with a range of 1 to 7 families per neighborhood and 1 to 11 children per neighborhood.

The specific family relationship between CDS children and the two prior generations is based on the survey design as well as survey outcomes. In CDS, each child's primary caregiver was selected as the main informant regarding the child. For almost 90 percent of children, the primary caregiver was the child's mother. However, in five percent of cases, the primary caregiver was the child's father; in three percent of cases it was a grandmother; and in the remaining three percent of cases it was someone else. For convenience, we refer to all primary caregivers as "mothers." In essentially all cases, the 1972 PSID respondent was a grandparent of the child. Interestingly, for 60 percent of CDS children, the grandparent was one of the mother's parents (for the remaining 40 percent, the grandparent was one of the father's parents). The larger representation of matrilineal links between children and grandparents in the PSID sample likely reflects the prevalence of single parenthood in which children are far more likely to reside with their mothers, and fathers may be absent, estranged, or even unknown.

Using the restricted PSID geocode file, we matched children in the sample to the median family income from the 2000 U.S. Census for the tract in which they resided. Although a geocode file is also available for the early years of PSID, which can, in principle, be linked to the 1970 U.S. Census, missing data are a major problem because many households resided in locations that had not yet been assigned a census tract (Sharkey and Elwert, 2011).

Child Achievement Outcomes

Children in PSID/CDS-II completed subtests of the Woodcock-Johnson Revised standardized assessments (Woodcock and Johnson, 1989). The Woodcock Johnson-Revised Test of Achievement (WJ-R ACH) includes a battery of tests designed to assess individual scholastic achievement (Woodcock and Mather, 1989). In CDS-II, children were administered the Letter-Word Identification and the Applied Problems tests. Mothers of CDS children were administered the Passage Comprehension test in the first round of the CDS in 1997.

The Letter-Word Identification test assesses symbolic learning (matching a picture with a word) and reading identification skills (identifying letters and words). The Passage Comprehension test includes multiple-choice items that require the subject to point to the picture represented by a phrase and items in which the subject reads a short passage and identifies a missing key word. The Applied Problems test measures the subject's skill in analyzing and solving practical mathematics problems, and provides an assessment of mathematics reasoning.

Tests were administered in English or Spanish depending on language ability and preference of the respondent. Different versions of the test were administered in Spanish and English; however, the Spanish and English versions of each test were designed to produce comparable scores for the same skill level, regardless of the test language. We used the Applied Problems test to assess children's math skills, the Letter-Word Identification test to assess children's reading skills, and the Passage Comprehension test to assess mothers' reading skills.

We analyzed standardized scores that were calculated based on the subject's raw score and age and a set of national norms (McGrew, Werder, and Woodcock, 1989). Norming by age allowed us to compare achievement test scores across children of different ages. The standard scores have a population mean of 100 and standard deviation of 15.

Summary statistics for the children's achievement tests are presented in the top panel of Table 1. The mean standardized scores on the reading and mathematics achievement tests were slightly higher than the national norms of 100 for each test: the mean test scores were 103.5 for reading and 102.2 for mathematics. The standard deviations for both tests also exceeded slightly the national norms of 15: the sample standard deviations were 18.7 for reading and 16.7 for mathematics. The values of the Gini coefficients were 0.0982 and 0.0910 for reading and mathematics, respectively.

These Gini coefficient values were determined by the variance of the test scores, which were based on normed scores that have an underlying standard deviation of 15. The use of normed scores is a customary practice that facilitates comparisons by age, across groups, over time, and with other achievement or IQ tests. However, the use of normed scores means that the corresponding Gini coefficients cannot be interpreted independently as being large or small and cannot be compared to non-normed measures of inequality in achievement.

We can use the multilevel structure of the PSID/CDS-II children to examine the variance in children's test scores accounted by family and neighborhood membership. The results, presented in Table 2, show that the reading and mathematics test scores are both highly clustered by family and by neighborhood. When examining family and neighborhood on their own—i.e., without accounting for the fact that families are nested within neighborhoods, just under half of the total variance in both reading and math scores is associated with family factors (48 percent for reading, 45 percent for math) and a slight lower percentage with neighborhood factors (44 percent for reading, 39 percent for math). However, when we estimate a variance components model that accounts for both levels of clustering simultaneously, neighborhood membership accounts for twice as much of the variance compared to family membership for both reading test scores (32 percent vs. 16 percent) and math test scores (29 percent vs. 15 percent). Estimates of family-level clustering of children's test scores provide a measure of sibling correlation in test scores that can be compared to estimates from the literature described above.

Measures of Socioeconomic Status

Socioeconomic status indicators for the parent (G2) and grandparent (G1) generations are listed in the bottom two panels of Table 1, along with their descriptive statistics. Characteristics of the G2 generation comprised the mother's reading test score and years of schooling, the average family income in constant dollars over the previous five calendar years (1997–2001), family wealth, and the neighborhood median family income in 1999. Characteristics of the G1 generation comprised of the 1972 household head's vocabulary test score and years of schooling and the five-year average family income from 1968 to 1972 in constant dollars.

In Table 1, for each of the status indicators we present the mean, standard deviation, observation count, and the Gini coefficient and its standard error. There was substantially more inequality in G2 family wealth, with a Gini coefficient of 0.906, than in G2 average family income, which had a Gini coefficient of 0.426. Comparing G1 and G2 average real family income reveals the well-documented increase in income inequality, with the Gini coefficient rising from 0.335 to 0.426. These results parallel estimates from the Census Bureau (2000), which show the Gini coefficient for household income increasing from 0.394 in 1970 to 0.456 in 1998. Across generations in the study period, there was also a substantial increase in average schooling: mean schooling increased from 9.5 years for G1 individuals in 1972 to 13.0 years for G2 individuals in 2002. Inequality in years of schooling declined substantially, with the Gini dropping from 0.263 for G1 individuals in 1972 to 0.087 for G2 individuals in 2002. The mother's reading was standardized, and reveals that the mean score for this group was about half a standard deviation below the mean of the normed national sample.

Results

We first present the multilevel regression results for children's achievement test scores, followed by a summary of sources of inequality in children's achievement, and then a decomposition of the sources of inequality.

<u>Multilevel Regression Model Results</u>

We estimated three model specifications for the reading and math achievement test scores. Model 1 included the G2 variables alone, Model 2 the G1 variables alone, and Model 3 both the G1 and G2 variables. These three model specification provide insights into the relative importance of the G1 and G2 variables for the achievement levels of the G3 children.

The results from Model 1, presented in Table 3, indicate that mother's education and test score along with tract median family income are all strongly positively related to both reading and math test scores for children. In addition, family average income is positively related to children's math test scores. Family wealth is not associated with either test score outcome. The results from Model 2 indicate that average family income and the vocabulary test score for the grandparent-generation are both associated with children's reading and math test scores. However, the grandparent-generation education variable is not associated with either of these test scores.

The Model 3 results reveal that the effects of the parent-generation variables are robust to adding the grandparent-generation variables, but that the effects of the grandparent-generation variables decline substantially. For children's reading and math test scores, there are modest declines in the estimated coefficients for mother's education and test score and for tract median income; all of these variables remain statistically significant. The effects of the grandparent-generation average family income and vocabulary test score are reduced substantially in models for both child test score outcomes, with the former variable rendered statistically insignificant (and close to zero) in the model for reading test scores. There are very different changes across the models in the effects of parent's and grandparent's test scores on children's reading scores: the effects of the parent's test score declines from 1.22 to 1.03 after controlling for grandparent characteristics, but the effect of the grandparent's test score declines by more than half, from 1.22 to 0.55. There are qualitatively similar results for the math test score models. Likewise, the effects of parents' average family income on children's math test scores declines marginally, from 0.16 to 0.15, after controlling for grandparent characteristics, while the effects of grandparents' average family income declines substantially, from 0.62 to 0.16. A parallel finding occurs in the model for children's reading test scores, although the effect of grandparent average family income is no longer statistically significant and is very close to zero after controlling for parent-generation characteristics. These results suggest that a substantial fraction of the effects on children's test scores of grandparent-generation characteristics operate through their effects on the parent-generation characteristics.

Finally, the Model 3 results reveal that the effects of unobserved family factors, which are captured by the random effects, decline modestly for children's reading scores (from 16 percent of total variance to 14 percent) but substantially for children's math scores (from 15 percent to 6 percent). Unobserved neighborhood factors also decline by about half—from 32 percent to 16 percent for reading and from 29 percent to 13 percent for math.

Inequality in Children's Achievement

Our analysis of inequality begins by examining the degree of systematic inequality in children's reading and math test scores by each of the parent and grandparent variables. The results are presented in Table 4, and show the observed or total concentration index values (which do not control for any of the other variables) as well as the partial or net concentration index values (which control for all other variables). We also present standard errors of the estimates and indicate the level of statistical significance. For example, the bottom row of the top panel in Table 4 shows inequality in children's reading test scores by the grandparent-generation vocabulary test score. The point estimate of the observed concentration index is 0.0296, which is statistically significant at the .01 level; the partial concentration index is 0.0008, which is not statistically significant. We also present these two estimates as percentages of the Gini coefficient for the reading test score. These results show that the grandparent-generation vocabulary test score accounts for 30 percent of the overall variation in math test scores before controlling for any other variables and less than one percent after controlling for all other variables.

For all of the independent variables that we examined, there are high levels of observed inequality in children's reading and math test scores. For reading achievement, the variables account for between 23 percent and 37 percent of the overall inequality in test scores, and all of these observed concentration index estimates are statistically significant at the .01 level. For math, all of the variables are also statistically significant at the .01 level and account for between 25 and 43 percent of the observed inequality. There does not appear to be a clear pattern across variables in the value of the observed concentration index for either reading or math test scores, although for both test scores the highest values for the concentration index are for parent-generation average family income and the lowest values are for grandparent-generation years of education.

When we control for all of the independent variables simultaneously and examine the partial concentration index, the results change substantially. For both reading and math test scores, the three variables most strongly associated with inequality in children's achievement are mother's reading test score, mother's years of education, and neighborhood median family income. The partial concentration index is highest by mother's reading test scores for children's reading test scores and math test scores (although the latter is tied with the concentration index value for tract median family income). Grandparent-generation average family income has a small, but statistically significant (at the .05 level), partial concentration index for both of the children's test scores. On the other hand, parent-generation average family income has a substantively small and statistically insignificant partial concentration index value for both reading and math test scores, which is also the case for parent-generation wealth and grandparent-generation years of education. The grandparent-generation vocabulary test score has a statistically significant partial concentration index value for math but not for reading.

The partial concentration index values allow us to rank-order inequality in children's reading or math achievement according to the different variables we examined. However, the ordering between any pair of variables is only unambiguous in cases where the two corresponding adjusted concentration curves do not intersect. In Figure 1, we plot for children's math test scores a transformation of the adjusted concentration curves—which are depicted as deviations of each curve from the diagonal (the results are not altered, but are easier to see). The figure shows that several of the curves cross and hence cannot be ranked unambiguously. For example, the adjusted concentration curves for tract average income and for mother's reading scores intersect (which is not surprising, given that they have identical estimated values for the partial concentration index). However, both cures are further from the diagonal than the curve for any of the other variables—indicating that there was unambiguously more inequality in children's math scores by neighborhood income and mother's reading scores than by mother's schooling, average family income for the parent- or grandparent-generation, or any of the other variables.

Decomposing Inequality in Children's Achievement

We next use the regression model results together with the decomposition methods described above to examine the contributions of parent and grandparent characteristics to the overall inequality in children's test scores. The results, presented in Table 5, show how we can identify contributions of each variable in the regression models to the inequality in children's test scores. To illustrate the results, consider the effects of the grandparent-generation vocabulary test score variable on children's reading test score. Column 1 shows the elasticity of these two variables, indicating that a one-unit increase in the grandparent's test score is associated with a 0.48 point increase in children's reading test scores. The Gini coefficient for grandparent's test score of 0.1475 is moderate in magnitude, and the correlation ratio of 0.64 is just modestly lower than the average value for all of the variables. The product of these three variables shows the overall contribution of neighborhood income to children's test scores, which is that 10.6 percent of the explained variation (or 4.6 percent of the total variation) in children's test scores is associated with this variable. In contrast to the results in Table 4, the contributions of each variable to the total explained variation in test scores are additive.

Looking across the variables reveals an interesting set of findings. First, the variables that account for the largest percentages of the explained inequality in children's reading scores are the mother's test score (which accounts for 35 percent of the explained variation), the mother's years of education (28 percent), the parent-generation tract median family income (21 percent), and the grandparent-generation vocabulary test score (11 percent). Together, these four variables account for 94 percent of the explained variation and 41 percent of the total variation in children's reading test scores. For children's math test scores, all of the variables except for the parent-generation wealth and grandparent-generation years of education make meaningful contributions to explained inequality levels. The contributions to inequality in children's math test scores, in order, are tract median family income (which accounts for 28 percent of the explained variation), mother's test score (28 percent), mother's years of education (17 percent), grandparent-generation average family income (9 percent) and vocabulary test score (7 percent), and parent-generation average family income (7 percent). Together, these six variables account for 98 percent of the explained variation and 44 percent of the total variation in children's reading test scores.

Second, there is considerable variation in how each of these variables contributes to inequality in children's test scores. Mother's reading test scores and years of education have the lowest inequality (as measured by their Gini coefficients of 0.0871 and 0.0986, respectively), but the elasticity of their effects are large—indicating that a unit increase in each of these variables has a large effect on children's test scores. In contrast, the elasticities of the remaining variables are generally modest, while their Gini coefficients are moderate-to-large. For instance, the children's reading test score elasticity is 4.8 percent for parent-generation tract median family income and 4.8 percent for grandparent-generation vocabulary test score, while the Gini coefficients for these two variables are 0.2348 and 0.1475, respectively. Finally, for family average income, the elasticity has a low value of 1 percent, but the Gini has a large value of 0.4346, leading to a large contribution to explained variation in children's math test scores. Among the variables that have a statistically-significant association with children's test scores there was generally little variation in the rank-correlation ratio, indicating that there was a relatively consistent ordering of children according to the different independent variables.

Discussion

We examined socioeconomic inequality in children's reading and math achievement using national-representative data from PSID/CDS, focusing on the effects of parent and grandparent characteristics including years of schooling, reading/vocabulary test scores, and average family income. For the parent-generation, we also examined the effects of family wealth and neighborhood median family income; we were not able to examine these two variables for the grandparent generation because family wealth was not measured in the early years of PSID and only a fraction of PSID households were in census tracts in 1970.

We found high levels of inequality in children's test scores by mother's reading achievement and years of schooling, grandparent vocabulary achievement level, parent- and grandparent generation average family income, parent-generation family wealth, and parent-generation neighborhood median income. Observed differences in these various factors were systematically associated with between 23 and 43 percent of inequality in children's reading and math test scores.

Children in families of higher parental and grandparental socioeconomic status scored better on the assessments primary because their mothers had better reading skills and more schooling and because they lived in more affluent neighborhoods. The remaining socioeconomic status indicators were indirectly associated with family background. In particular, the association between grandparent-generation characteristics and child achievement was strong on its own, but declined substantially after controlling for parent-generation characteristics. Similar results for parent-generation wealth and average family income.

The strong association between a mothers' reading score and her child's achievement was likely the result of the intergenerational transmission of ability as well as the effects of the home learning environment. Specifically, mothers of higher socioeconomic status—including mothers with higher test scores—are likely to have better access to higher-quality resources (such as books, computers, and schools), and to be more efficient at converting these resources into cognitive development for their children (Guo and Harris, 2000).

There was a substantively important effect of average neighborhood income on children's achievement. This dimension of socioeconomic status was far more consequential for children's reading and math skills than measures such as family income and wealth and was comparable in magnitude to the effects of mother's years of schooling. Neighborhood socioeconomic status may affect children's achievement through a variety of factors, and there is a considerable literature examining the various pathways through which the effect may operate (see Sastry, 2012). For example, neighborhoods with higher incomes may have better schools, day-care facilities, libraries, after-school care, and extra-curricular activities that may, in turn, contribute to better child outcomes but may also attract other families who value such services and are able to pay for these services and can afford the cost of housing in the area. In other words, the findings may also reflect the effects of sorting of families by neighborhood. Finally, poor neighborhoods may be less supportive of parents and children and may have stressful environments that make it more difficult for families to promote learning and academic achievement. For instance, results from the Moving to Opportunity Study show that there was a causal effect of moving to a low-poverty neighborhood on improvements in adult mental health and subjective well-being (Ludwig et al., 2012).

We found strong multigenerational effects on inequality in children's academic achievement before controlling for other variables, but relatively minor multigenerational effects after controlling for other indicators of socioeconomic status (and, in particular, indicators associated with the parent-generation). However, there were modest persistent links between grandparent-generation vocabulary test scores and children's reading and math achievement, and between grandparent-generation average family income and children's math achievement. However, the overall contribution of these multigenerational factors was relatively small, and represented only a fraction of the effect of parent-generation factors. Grandparent achievement may affect grandchild achievement through the intergenerational transmission of ability, while grandparent economic status may help pay for learning activities for grandchildren.

Our results showed that certain variables had a large elasticity but low inequality—such as mother's reading skills and education—which suggested that further reducing the inequality in the number of years of schooling or reading test scores among mothers would likely do little to reduce inequality in academic outcomes for children. Rather, it would likely be more beneficial to develop policies that work by promoting behavior related to child development that was prevalent among more educated and skilled mothers. This may involve, for example, promoting resources (such as children's books) and activities (such as reading to children) that related to children's learning. There are also important effects of neighborhood socioeconomic status on child achievement are based on a modest elasticity in the relationship between this variable and children's test scores but a large inequality in neighborhood socioeconomic status. The high level of residential segregation by family income appears to contribute to higher levels of inequality in children's achievement, and policies to reduce residential stratification by family income may be an appropriate policy response.

This study has several limitations, beginning with the fact that the results represent descriptive findings rather than causal effects. There are several data shortcomings, such as the lack of assessments of math skills for either the parent- or grandparent-generation respondents; however, the strong correlation between G1 and G2 reading and vocabulary test scores and G3 math skills suggests that the G1 and G2 assessments may capture broader dimensions of cognitive skills. A related limitation is that these assessments are only available for one parent and one grandparent, and that, in general, limited information is available on the non-PSID grandparents. Finally several potentially relevant measures are omitted because they were not available in the data, including grandparent wealth and grandparent neighborhood economic status.

Our findings are broadly consistent with previous findings from studies that have examined the correlation between parent and child cognitive skills. For example, our results indicate that 37 percent of the observed inequality in children's reading skills is associated with parent-generation reading skills. This finding is very similar to results indicating an intergenerational correlation in IQ of 35 percent for Sweden (Bjorklund et al. 2010) and 38 percent for Norway (Black et al., 2009). Our observed and adjusted results for inequality in children's reading and math skills based on grandparent-generation achievement are a novel contribution and indicate that there are multigenerational effects on inequality in children's academic achievement. However, and perhaps not surprisingly, the results suggest limited direct effects of grandparent socioeconomic status on grandchild achievement after controlling for parent-generation socioeconomic status.

Finally, the recent paper by Mare (2011) focused on intergenerational transmission of *inequality*, although few studies of demographic, health, educational, and social outcomes adopt the rich set of tools and measures that are available for characterizing and analyzing inequality itself. Our analysis highlighted one set of techniques that use regression-based decomposition along with these measures to analyze intergenerational effects of inequality on inequality.

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Table 1. Summary Statistics for Children's Reading and Math Achievement and Socioeconomic Status Measures in PSID/CDS-II

Measure	Mean	Std. Dev.	Observations	Gini (S.E.)
G3 outcomes (2002)				
Reading test score	103.5	18.7	1,893	0.0982 (0.0020)
Math test score	102.2	16.7	1,886	0.0910 (0.0017)
G2 variables (2002)				
Family avg. income ($)	58,886	64,160	1,322	0.4256 (0.0137)
Family wealth ($)	109,110	1,188,010	1,322	0.9057 (0.0279)
Education (years)	13.0	2.1	1,322	0.0871 (0.0020)
Reading test score	93.1	16.88	1,322	0.0978 (0.0024)
Tract median income ($)	50,035	22,266	1,156	0.2352 (0.0045)
G1 variables (1972)				
Family avg. income ($)	9,452	6,131	1,322	0.3353 (0.0076)
Education (years)	9.5	4.6	1,322	0.2637 (0.0092)
Vocabulary test score	9.0	2.5	1,322	0.1493 (0.0046)

Table 2. Family and Neighborhood Sources of Variation in Children's Reading and Math Achievement in PSID/CDS-II

Measure	**Reading**	**Math**
Unadjusted sources of variation		
Family	0.48%	0.45%
Neighborhood	0.44%	0.39%
Adjusted sources of variation		
Family	0.16%	0.15%
Neighborhood	0.32%	0.29%

Table 3. Multilevel Regression Model Results for Children's Reading and Math Achievement in PSID/CDS-II

Variable	Model 1		Model 2		Model 3	
Reading achievement						
G2 Family avg. income ($)	0.07	(0.08)	.	.	0.07	(0.08)
G2 Family wealth ($)	-0.01	(0.00)	.	.	-0.01	(0.00)
G2 Education (years)	1.41***	(0.25)	.	.	1.32***	(0.25)
G2 Reading test score	0.22***	(0.03)	.	.	0.20***	(0.03)
G2 Tract median inc. ($10k)	1.22***	(0.26)	.	.	1.03***	(0.27)
G1 Family avg. income ($)	.	.	0.50***	(0.09)	0.03	(0.09)
G1 Education (years)	.	.	0.13	(0.11)	0.07	(0.11)
G1 Vocabulary test score	.	.	1.22***	(0.21)	0.55***	(0.20)
Constant	58.06***	(3.23)	86.61***	(1.83)	56.40***	(3.36)
Variance components						
Family	0.17%***		0.19%***		0.14%***	
Neighborhood	0.14%***		0.19%***		0.16%***	
Model chi-squared (df)	308.69***	(5)	139.64***	(3)	321.77***	(8)
Observations	1,893		1,893		1,893	
Math achievement						
G2 Family avg. income ($)	0.16**	(0.07)	.	.	0.15**	(0.07)
G2 Family wealth ($)	0.00	(0.00)	.	.	0.00	(0.00)
G2 Education (years)	0.97***	(0.21)	.	.	0.84***	(0.22)
G2 Reading test score	0.18***	(0.03)	.	.	0.16***	(0.03)
G2 Tract median inc. ($10k)	1.55***	(0.22)	.	.	1.26***	(0.23)
G1 Family avg. income ($)	.	.	0.62***	(0.08)	0.16**	(0.08)
G1 Education (years)	.	.	0.12	(0.10)	0.08	(0.09)
G1 Vocabulary test score	.	.	0.98***	(0.18)	0.38**	(0.18)
Constant	63.79***	(2.79)	86.09***	(1.59)	63.47***	(2.90
Variance components						
Family	0.06%***		0.10%***		0.06%***	
Neighborhood	0.13%***		0.16%***		0.13%***	
Model chi-squared (df)	389.59***	(5)	200.94***	(3)	412.38***	(8)
Observations	1,886		1,886		1,886	

Note: Standard errors in parentheses; *p<.10; **p<.05; ***p<.01.

Table 4. Socioeconomic Inequality in Children's Reading and Math Achievement in PSID/CDS-II

	Observed concentration index			Partial concentration index		
Measure	**Estimate**	**Std. err.**	**Pct. of Gini**	**Estimate**	**Std. err.**	**Pct. of Gini**
Reading achievement						
G2 Family avg. income ($)	0.0360***	(0.0027)	36.7%	0.0018	(0.0027)	1.8%
G2 Family wealth ($)	0.0236***	(0.0026)	24.0%	-0.0006	(0.0009)	-0.6%
G2 Education (years)	0.0335***	(0.0024)	34.1%	0.0145***	(0.0028)	14.8%
G2 Reading test score	0.0365***	(0.0025)	37.2%	0.0178***	(0.0028)	18.1%
G2 Tract median inc. ($10k)	0.0322***	(0.0025)	32.8%	0.0116***	(0.0027)	11.8%
G1 Family avg. income ($)	0.0271***	(0.0027)	27.6%	0.0071**	(0.0032)	7.2%
G1 Education (years)	0.0225***	(0.0027)	22.9%	0.0018	(0.0025)	1.8%
G1 Vocabulary test score	0.0296***	(0.0022)	30.2%	0.0008	(0.0034)	0.8%
Math achievement						
G2 Family avg. income ($)	0.0395***	(0.0020)	43.4%	0.0039	(0.0027)	4.2%
G2 Family wealth ($)	0.0272***	(0.0023)	29.9%	0.0000	(0.0007)	0.0%
G2 Education (years)	0.0310***	(0.0024)	34.0%	0.0094***	(0.0030)	10.3%
G2 Reading test score	0.0345***	(0.0025)	37.9%	0.0144***	(0.0025)	15.8%
G2 Tract median inc. ($10k)	0.0357***	(0.0020)	39.2%	0.0144***	(0.0032)	15.8%
G1 Family avg. income ($)	0.0252***	(0.0023)	27.7%	0.0050**	(0.0022)	5.4%
G1 Education (years)	0.0231***	(0.0027)	25.3%	0.0019	(0.0022)	2.0%
G1 Vocabulary test score	0.0339***	(0.0021)	37.2%	0.0051*	(0.0026)	5.6%

Note: Standard errors with neighborhood- and household-level clustering in parentheses; *p<.10; **p<.05; ***p<.01; N=1,983.

Table 5. Decomposition of Overall Inequality in Children's Reading and Math Achievement in PSID/CDS-II

Measure	**Elasticity**	**Gini**	**Correlation Ratio**	**Contribution to Gini**	**Explained Percent**	**Total Percent**
	(1)	(2)	(3)	(4)=(1)×(2)×(3)	(5)	(6)
Reading achievement						
G2 Family avg. income ($)	0.4%	0.4352	0.76	0.0014	3.2%	1.4%
G2 Family wealth ($)	-0.1%	0.8986	0.23	-0.0001	-0.3%	-0.1%
G2 Education (years)	16.7%	0.0871	0.81	0.0118	27.8%	12.0%
G2 Reading test score	18.0%	0.0986	0.84	0.0149	35.1%	15.2%
G2 Tract median inc. ($10k)	4.9%	0.2348	0.75	0.0087	20.6%	8.9%
G1 Family avg. income ($)	0.2%	0.3348	0.67	0.0005	1.3%	0.5%
G1 Education (years)	0.7%	0.2565	0.44	0.0008	1.8%	0.8%
G1 Vocabulary test score	4.8%	0.1475	0.64	0.0045	10.6%	4.6%
Total				0.0425	100.0%	43.3%
Math achievement						
G2 Family avg. income ($)	0.9%	0.4346	0.81	0.0031	7.5%	3.4%
G2 Family wealth ($)	0.0%	0.8984	0.72	0.0000	0.1%	0.0%
G2 Education (years)	10.7%	0.0871	0.77	0.0072	17.3%	7.9%
G2 Reading test score	14.5%	0.0986	0.81	0.0116	28.0%	12.8%
G2 Tract median inc. ($10k)	6.1%	0.2348	0.82	0.0118	28.4%	12.9%
G1 Family avg. income ($)	1.5%	0.3349	0.75	0.0038	9.1%	4.1%
G1 Education (years)	0.7%	0.2560	0.47	0.0009	2.1%	1.0%
G1 Vocabulary test score	3.4%	0.1474	0.63	0.0031	7.5%	3.4%
Total				0.0414	100.0%	45.5%

Figure 1. Adjusted Concentration Curves for Socioeconomic Inequality in Children's Math Achievement in PSID/CDS-II