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Abstract

We examined family and neighborhood sources of socioeconomic inequality in children's reading and mathematics achievement using data from the 2000–2001 Los Angeles Family and Neighborhood Study. To describe inequality in achievement scores, we used Gini coefficients and concentration indices and multilevel regression models. There was no inequality in children's achievement by family income once other variables in the model were held constant. Mothers' reading scores and average neighborhood levels of income accounted for the largest proportion of inequality in children's achievement. Neighborhood economic status appears to be strongly associated with children's skills acquisition.

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Introduction

Acquisition of basic skills during childhood in reading and mathematics is important to success in adult life (Kerckhoff et al. 2001; Hauser et al. 2000; Farkas et al. 1997). Farkas et al. (1997: 918) found that "cognitive skills are powerful determinants of access to cognitively demanding jobs and higher wages, even when the effects of schooling, work experience, and social class background are controlled for." *Inequalities* in children's skills achievement—especially inequalities tied to socioeconomic status (SES)—are particularly important because of their potential role in the intergenerational transmission of disadvantage. Analyses of inequalities in children's skills are useful for identifying the dimensions of SES that matter most for children's learning and identifying the pathways through which key dimensions of SES operate. These studies can help to develop effective policies and interventions for improving children's learning—particularly among disadvantaged children—and thus to break the cycle of low achievement across generations.

In this paper, we examine socioeconomic inequality in children's reading and mathematics achievement in Los Angeles, California. We use Gini coefficients and concentration indices—developed to study income inequality—to examine overall inequality and socioeconomic inequality in reading and mathematics scores before and after controlling for child, family, and neighborhood variables using multilevel statistical models. Our main objective is two-fold: first, to estimate the inequality in children's test scores by neighborhood economic status, before and after controlling for child, family, and other neighborhood characteristics, and, second, to assess the relative importance of inequality in children's achievement by neighborhood economic status compared to inequality based on parental characteristics, such as mothers' schooling and test scores and family income and assets. This approach also puts our multilevel model-based estimates of neighborhood effects on children's achievement into a broader context and provides a useful means to interpret our results.

Family SES and the home environment appear to have an important effect on cognitive development (e.g., Guo and Harris 2000; Yeung et al. 2002; Todd and Wolpin 2006). There are also strong theoretical reasons to believe that neighborhoods are important. For example, poorer neighborhoods are likely to have lower quality institutions such as schools—a key factor in cognitive achievement (Rivkin et al. 2005). However, data and methodological problems have often limited the ability of previous research to assess neighborhood effects on child development. Our analysis is based on data from the Los Angeles Family and Neighborhood Survey (L.A.FANS) that were designed specifically for studying neighborhood effects. The data include a large number of Latinos and other race/ethnic groups, in contrast to previous research on this topic which has been based on samples comprised almost exclusively of whites and African Americans. Including Latinos is important because the skills gap between Latinos and whites is roughly equal in size to the gap between African Americans and whites (Perie and Moran 2005) and because Latinos are a rapidly increasing proportion of the U.S. population. Our analysis incorporates controls for family immigration status and residence in a predominantly immigrant neighborhood, and other dimensions of family background, that provide clearer findings about the net effects of neighborhood economic status on children's achievement.

Our findings indicate that a substantial fraction of overall observed inequality in children's achievement is systematically associated with family and neighborhood SES, accounting for about one-third of the variation in mathematics achievement and a somewhat smaller fraction for reading achievement. Our adjusted inequality measures—which use the multilevel model estimates to control for child, family, and neighborhood characteristics, including other measures of SES—reveal that mothers' reading skills and years of schooling and tract median income are the SES measures most strongly associated with children's test score inequality. The large effect of average neighborhood income on children's achievement is a particularly important result that has implications for policy and for future research.

Previous Research

Increasing income inequality and residential segregation by SES and race/ethnicity between the 1960s and the 1990s (Neckerman and Torche 2007; Jargowsky 1997; Logan et al. 2004) generated concern about the consequences of concentrated disadvantage for children's development. Studies in the 1990s by Brooks-Gunn, Duncan and colleagues (Leventhal and Brooks-Gunn 2000) tested the hypothesis that poor neighborhoods reduce children's cognitive skills over and above the effects of family socioeconomic disadvantage. Although they showed that neighborhood economic status was associated with children's cognitive skills, they found that the important factor was neighborhood affluence, not poverty. The effects were also strongest for whites, rather than race/ethnic minority children as had been hypothesized. A serious problem in these (and other) studies is that unmeasured family characteristics may lead some families to choose good neighborhoods and to invest in other ways in their children (Duncan and Raudenbush 1998), jeopardizing the unbiasedness and consistency of estimated neighborhood effects. Other studies that included a more complete set of family characteristics or used statistical methods to control for unobserved family characteristics found that poorer neighborhoods have negative effects on children's educational attainment (Ginther et al. 2000; Aaronson 1997, 1998; Solon, Page, and Duncan 2000).

Results from two new sets of studies have recently been published. The first group is the Moving to Opportunity (MTO) housing experiment, in which predominantly African American female-headed families living in housing projects were assigned vouchers by lottery for housing in low-poverty neighborhoods (Kling et al. 2007). The results showed no significant effect of the treatment on reading and mathematics scores for children after 4–6 years (Sanbonmatsu et al. 2006). The reason, the authors suggest, is that school quality in the treatment and control groups was more similar than neighborhood quality. They conclude that benefits from improved neighborhood environments alone may be small (Sanbonmatsu et al. 2006: 1).

Sampson and colleagues (2008) have criticized the MTO study for focusing exclusively on children exposed to serious disadvantage and the short evaluation period. They conclude that "...residential mobility programs for those who grow up in poverty do not necessarily provide the appropriate test of the causal effects of neighborhood social contexts" (Sampson et al. 2008: 852). Using data from a representative sample of African American children observed longitudinally, they show that living in poor neighborhoods decreases children's subsequent verbal ability by the equivalent of one year of school. The effects of neighborhood poverty persist for many years even after children move out of poor neighborhoods. The MTO results have also been criticized for selection bias: the low uptake rate for families offered housing vouchers makes it likely that those who moved to middle-class neighborhoods were not representative of the group assigned to treatment (Turley 2003).

A second group of studies is based on newer observational data. Several of these studies focus on educational attainment or school grades (e.g., Crowder and South 2003; Fischer and Kmec 2004; Pong and Hao 2007), but we limit our discussion to studies of cognitive skills. The results have been mixed. Turley (2003) and Kohen et al. (2002) examined the effects of neighborhood characteristics on test scores for preschoolers—using the Panel Study of Income Dynamics Child Development Supplement (PSID-CDS) and the Canadian National Longitudinal

Survey of Children and Youth (NLSCY), respectively. Turley (2003) found that higher neighborhood income was associated with better test scores, but only for whites. For blacks, the effect occurs only when there is a high proportion of African Americans in the neighborhood. The effects of neighborhood disadvantage were stronger for children who had lived in their neighborhood for a longer duration. Kohen et al. (2002) found that both neighborhood affluence and poverty were significantly related to verbal ability even when family SES was held constant. These effects were mediated by neighborhood disorder and social cohesion. A third study by Caughy and O'Campo (2006) of African American preschoolers in Baltimore found that family characteristics did not explain a significant relationship between neighborhood poverty and poorer problem-solving skills. However, when they assessed the role of neighborhood social processes as mediating variables, they found no significant effects, perhaps because of the small sample size (N=200).

Ainsworth (2002) used the National Educational Longitudinal Survey to examine the effect of neighborhood social structure on high school students' test scores. Like studies by Brooks-Gunn et al., Ainsworth concludes that high-status neighbors, not neighborhood deprivation, have a significant effect on students' test scores. However, restriction of his sample to youth who lived in the same neighborhood from 1988 to 1992 limits the study's generalizability and may also strengthen the effect of neighborhood characteristics, as Turley's (2003) results suggest.

These studies have several limitations. First, with the exception of Sampson et al. (2008) and Caughy and O'Campo (2006), none use multilevel statistical models—i.e., models which reflect the hierarchical structure of the data, allow identification of observed and unobserved family and neighborhood effects, and provide corrected standard errors. Second, they typically include a limited set of family characteristics, thus increasing chances that observed neighborhood effects are in fact due to unobserved family attributes. Third, these studies focus either exclusively on African American children or primarily on whites and African Americans, despite the increasing numeric, social, and economic importance of the Latino population and its significant disadvantage in cognitive skills relative to whites. Finally, none of these studies have examined inequality or the SES dimension of inequality in children's achievement. This omission has made difficult both the substantive interpretation of these studies' findings about neighborhood effects and the quantification of the relative contribution of neighborhood characteristics to inequality in children's achievement.

Conceptual Issues

Family Determinants of Cognitive Skills Acquisition

Children's cognitive skills are strongly associated with family SES--in particular, parents' income and education. Guo and Harris (2000) find that lower-SES children are exposed to: (1) a poorer home physical environment (i.e., housing quality and safety), (2) less cognitive stimulation, (3) poorer health, (4) poorer child care, and (5) a less consistent and warm parenting style. They also show that mothers' and children's cognitive skills are strongly associated, independently of mothers' education or family income. Mothers' skills may be important because mothers with better cognitive skills provide greater cognitive stimulation to children and because cognitive ability is inherited. Yet a measure of mothers' skills is rarely included in studies of children's achievement. The omission is particularly problematic in studies of neighborhood effects on children's achievement because parents' cognitive skills may also affect their ability to move to high-quality neighborhoods, holding constant income and educational attainment.

A second family characteristic not typically included in studies of children's cognitive skills is family wealth or assets. Holding income constant, African American and Latinos have substantially less wealth compared to whites (Smith 1999; Oliver and Shapiro 1997). Latino immigrants have even fewer assets than native-born Latinos (Kochnar 2004). Assets have an effect—independent of income—on families' investments in children's home environment, child care, and health. But assets also determine families' neighborhood "choice set" and ability to buy a house. The omission of information on assets from previous studies increases the risk that their estimates of neighborhood effects were biased due to endogeneity caused by omitted parental characteristics that are associated with neighborhood choice and children's achievement.

Neighborhood Determinants of Cognitive Skills Acquisition

Based on ideas developed by Jencks and Mayer (1990), Wilson (1987), Coleman (1988), and Sampson et al. (1999), we hypothesize that neighborhoods can affect children's cognitive development in four ways. First, disadvantaged neighborhoods frequently have poorer institutions, such as schools, child care, and recreational programs. Local funding of public schools means that school quality is typically associated with neighborhood economic status (Sampson et al. 2008). The situation may be exacerbated in neighborhoods with high residential turnover and concentrated poverty, because parents in these neighborhoods may be less involved in schools and improving school quality.

Although schools are clearly important, children spend most of childhood outside of school (Downey et al. 2004). Studies of school-age children suggest that most of cognitive skills inequality comes from neighborhood and family sources *outside* of schools because schools themselves tend to reduce inequality (Entwisle and Alexander 1992, 1994; Downey et al. 2004).

Second, very poor neighborhoods are often stressful and hazardous places in which to live (Kling et al. 2007). Parents are more likely to use harsh parenting styles, to withdraw emotionally from their children, and to focus on children's safety rather than cognitive development (McLoyd 1990; Klebanov et al. 1994, Leventhal and Brooks-Gunn 2000). Children may, therefore, be more isolated from others and from cognitively stimulating environments and experiences.

Third, neighborhoods can be a locus of collective socialization, social control, and support for children which may all affect cognitive development indirectly. Children in poor neighborhoods are less likely to be exposed to well-educated, successful adult role models who provide examples of the value in reading and problem-solving skills (Wilson 1987). Neighbors who know and trust each other can also collaborate to support neighborhood children's development, to exercise social control through enforcement of appropriate behavior, and to improve local institutions for children. Sampson et al. (1999) suggest that this collaboration is more difficult to achieve in disadvantaged neighborhoods, particularly those with high residential turnover, substantial race/ethnic heterogeneity, and large numbers of immigrants. However, Pong and Hao (2007) suggest that immigrant neighborhoods may be more effective at monitoring and controlling children's behavior because shared cultural values act as a form of social capital among residents.

Fourth, children's cognitive skills may be affected by the language environment in their neighborhood (Sampson et al. 2008; Pong and Hao 2007). Children learn language by hearing and using it. In concentrated poverty neighborhoods, children may be less exposed to adults and peers who speak standard English and also less exposed to hearing language, in general, because parents' safety concerns reduce social interactions. Pong and Hao (2007) suggest that neighborhood language environments are particularly important for children of immigrants, because English is often not spoken at home. In neighborhoods where standard English is spoken, children learn to speak fluent English from friends and other adults. But in immigrant ethnic neighborhoods, children of immigrants are much less likely to become fluent in standard English than children of native-born parents.

Developmental Stages and Variation in the Effects of Neighborhoods by Age

Children's cognitive abilities are developed throughout childhood, with changes at each period building upon those of previous periods (Aber et al. 1997; Kail 2006; Shonkoff and Phillips 2000). Consistent with observational studies on developmental stages, recent studies of brain development indicate a clear age pattern to neurological development (Gogtay et al. 2004; Waber et al. 2007). Although genetic factors are important, neurological development is highly sensitive to environmental factors such as cognitive and non-cognitive stimulation, social and physical interaction, and the warmth and support that children receive (Shonkoff and Phillips 2000). The results of recent brain research have led many observers to emphasize early childhood as the key period for cognitive development (Heckman 2006). Other studies have shown that cognitive performance increases dramatically during middle childhood (Weber et al. 2007) and that brain maturation associated with cognitive skills continues through adolescence (Gogtay et al. 2004).

Aber et al. (1997) and McCulloch and Joshi (2001) hypothesize that neighborhood effects on children's outcomes are likely to increase as children grow older and interact more independently with neighbors and peers. In early childhood, children's environments are more circumscribed and controlled by parents. Neighborhoods influence young children indirectly by affecting parents, home environments, and child care and early school settings. For example, parents in stressful neighborhoods may use less supportive parenting styles and emphasize safety over cognitive stimulation. Young children in disadvantaged neighborhoods may also be detrimentally affected by lower-quality child care centers, kindergartens, and playgrounds. Children spend more time during middle childhood in school and with peers and less time at home, leading to increased importance of school quality, peer norms, and a child's self-perception and perception of the environment (Klebanov et al. 1997). During this period there are likely to be larger effects of local institutions, the neighborhood social environment, and the local language environment. In adolescents, these factors become even more influential as teen life centers increasingly on peers, informal social groups, and local institutions.

A major limitation of previous studies of neighborhood effects on children's well-being is that they generally focus exclusively on either early childhood or on late adolescence (Leventhal and Brooks-Gunn 2000). Because of non-comparable study designs and limitation to a single age group, the evidence on the age patterns of neighborhood effects on children's achievement is limited. Two exceptions are studies by Brooks-Gunn et al. (1993) and McCulloch and Joshi (2001) both of which compare children by developmental period and find effects of neighborhood disadvantage, particularly at the ages when children first enter school. Other studies have shown that neighborhood effects are more consistent for school-age children than for preschoolers (Duncan and Raudenbush 1999) and that there are significant neighborhood effects on adolescent achievement (Leventhal and Brooks-Gunn 2000). Our study makes an important contribution to the literature by comparing the effects of neighborhoods across three developmental stages using the same data and methods.

Research Questions

Our primary goal is to determine the magnitude and significance of inequality in children's cognitive skills by neighborhood and family-level SES. How much of children's skills inequality is associated with SES? Is there significant inequality in children's skills by neighborhood SES after controlling for the effects of family SES? And are there significant differences in children's skills inequality by developmental stage?

A secondary goal is to assess the effects of other neighborhood and family characteristics on children's test scores. At the neighborhood level, we examine whether high residential turnover, race/ethnic diversity, and high immigrant concentration are associated with children's reading and mathematics scores as the hypotheses outlined above suggest. At the family level, we investigate differences by race/ethnicity and immigrant status in reading and mathematics scores and assess whether mothers' reading scores and family assets are associated with children's cognitive skills as hypothesized.

Methods

To examine inequality in children's skills development, we use several measures developed to study income inequality: Lorenz and concentration curves and their summary measures, the Gini coefficient and concentration index. Lorenz curves and Gini coefficients describe the degree of inequality in child achievement itself. Concentration curves and indices—bivariate extensions of Lorenz curves and Gini coefficients—describe inequality in children's test scores by SES.

These measures have several strengths compared to other indicators of inequality (Wagstaff et al. 1991; Kakwani 1977). They are based on *all* individuals, regardless of where on the distribution they fall. The Lorenz curve and Gini coefficient reflect the entire distribution of test scores; the concentration curve and index reflect the socioeconomic dimension to the overall distribution of test scores. The concentration curve and index are sensitive to *any* change in the population distribution by SES (holding each person's test score fixed). A commonly used alternative is the ratio of achievement of a high-status group compared to a low-status group (e.g., mean test scores in the top income quintile compared to mean scores in the bottom quintile). This ratio ignores the entire middle-range of the SES distribution and is sensitive only to movements of individuals into or out of the high- and low-status groups, which are often defined arbitrarily.

Although the Gini coefficient is commonly used to characterize inequality in income and wealth, it can be applied to other outcomes such as children's test scores. The Gini coefficient is derived from the Lorenz curve, which plots the cumulative proportion of children ranked in ascending order by their test score (on the *x*-axis) against the cumulative proportion of the children's test scores (on the *y*-axis). If there was perfect equality in children's scores, the Lorenz curve would lie along the diagonal; in this case, children who scored below the 50th percentile on the test together would account for half of all correct answers (summed over all children). The farther that the Lorenz curve lies below the diagonal, the higher the degree of inequality. The Gini coefficient summarizes the overall level of inequality. It is defined as two times the area between the diagonal and the Lorenz curve, $L(x): \; G = 1 - 2\int_0^1 L(x)\,dx$. The Gini coefficient ranges between zero (perfect equality) and one (perfect inequality), and provides a scale-free measure of overall inequality and, in our application, a standardized measure of variance in test scores. Moreover, Gini coefficients are directly comparable with concentration indices, because they are both based on the same principles.

To describe inequality in children's achievement by SES we plot concentration curves. A concentration curve shows the cumulative proportion of children ranked in ascending order by a measure of SES (on the *x*-axis) against the cumulative proportion of the children's test scores (on the *y*-axis). While the Lorenz curve portrays the concentration of test scores according to distribution of the scores themselves, the concentration curve shows the concentration of test scores according to the children's distribution by SES. If there was no association between SES and children's test scores, the concentration curve would be a straight line along the diagonal. In this case, children who were below the fiftieth percentile on the SES measure (e.g., were in the lower half of the income distribution) together would account for half of all the test scores (summed over all children). For SES indicators that are positively associated with test scores, inequality favoring higher SES children would place the concentration curve below the diagonal. The farther the concentration curve lies below the diagonal, the more that inequalities in test scores favor children from families of higher SES.

Our goal is to compare inequality in children's achievement by SES across different SES measures. We perform this comparison using concentration curves. When two concentration curves do not cross, the one farther from the diagonal represents unambiguously greater inequality based on any derived index of inequality that respects the principle of transfers (Atkinson 1970). When concentration curves do cross, unambiguous comparisons are impossible through visual inspection of the curves. In this situation, it useful to construct the corresponding concentration index for each curve and compare these values.

A limitation of the standard Gini coefficient and concentration index is that they incorporate a weighting scheme that reflects a particular characterization of aversion to inequality, one that is sensitive to changes in the middle of the SES distribution. Hence these measures do not definitively resolve the underlying ambiguity that exists when the Lorenz or concentration curves intersect. Extended versions of the Gini coefficient and concentration index are available that incorporate alternative weighting schemes reflecting different patterns of inequality aversion (Wagstaff 2002; Yitzhaki 1983). However, we use the standard versions because they are well-known and alternative weighting schemes are unlikely to affect the results significantly.

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. The formula for the Gini coefficient is $G = (2/n\bar{x})\,\mathrm{cov}(x_i, R_i')$ and for the concentration index is $C = (2/n\bar{x})\,\mathrm{cov}(x_i, R_i)$, where x_i is the *i*th child's test score, $\bar{x}$ is the mean test score, R_i is the *i*th child's relative rank when children are ordered by SES, and R_i' is the relative rank when children are ordered by test scores. This formula for the Gini Coefficient is numerically-equivalent to the expression based on the Lorenz curve presented above. Using the expressions for *G* and *C*, the relationship between the Gini coefficient and the concentration index can be written as follows (Kakwani 1980):

$$G = \frac{\rho(x, R_i')}{\rho(x, R_i)} C\,. \tag{1}$$

The ratio of the correlation coefficients is known as the "rank correlation ratio" (Pyatt et al. 1980) and reflects the divergence in children's ordering when they are ranked by test scores compared to when ranked by SES. The upper bound of the rank correlation ratio is one, which is reached when children's ranking by test scores is identical to their ranking by an ascendant measure of SES and when the concentration and Lorenz curves overlap completely. Equation (1) and the upper bound of unity for the rank correlation ratio imply that the concentration index for test scores can never exceed the Gini coefficient and reflects the fact that the concentration curve based on an ascendant measure of SES must always lie between the Lorenz curve and the diagonal. When there is no socioeconomic inequality in test scores, the concentration curve coincides with the diagonal and the concentration index has a value of zero.

With individual-level data, the concentration index is calculated numerically as follows (Kakwani et al. 1997):

$$C = \frac{2}{n\bar{x}} \sum_{i=1}^{n} x_i R_i - 1,$$

where the relative rank for the *i*th child is $R_i = (2i-1)/2n$. To calculate the standard error for the concentration index, we use a convenience regression with individual-level data (Kakwani et al. 1997). We use the Newey and West's (1987) procedure to control for serial correlation in the relative ranks and heteroscedasticity. We extend this approach to account for the L.A.FANS stratified multilevel and multistage sample design by bootstrapping the entire procedure.

Adjusted Socioeconomic Inequality in Children's Achievement. For each SES measure we calculate adjusted concentration indices which reflect inequalities in achievement scores net of other factors. The adjusted and standard (or unadjusted) concentration indices together allow us to separate socioeconomic inequalities in test scores into two components. The first is the net level of socioeconomic inequality in achievement scores according to the single SES measure under consideration. This independent component indicates the extent to which a change in inequality in a single socioeconomic factor (e.g., family income) is likely to affect inequalities in child achievement when all other factors (e.g., mother's schooling) are unchanged. The second component reflects inequality in child achievement associated with all other factors that are held constant in the adjusted concentration index, as well as the model error term and the random effects. For example, part of family income's effect on children's achievement scores is likely due to the fact that higher education levels for mothers and other related factors are associated with both higher children's test scores and higher family earnings.

We calculate adjusted values of the concentration indices using predicted values for test scores from multilevel linear regression models. These predicted values hold all other variables constant at their sample-wide means while allowing each single SES measure, in turn, to retain its actual values. This approach is conservative: it assumes that variable effects are additive and that none affects test scores through any other variables—i.e., that there are no joint or indirect effects. Advantages of this approach include the comparability of model results with findings from previous research, its relative parsimony, and the straightforward incorporation of multilevel effects. A limitation is that it is based on a model of the conditional mean, and the estimated relationships at the conditional mean are assumed to hold at all other points of the conditional distribution. An alternative approach is to use conditional quantile regression, which allows distinct covariate effects at different points of the test score distribution and derivation of the conditional distribution (Koenker 2005; Hao and Naiman 2007).

The multilevel regression models for children's test scores also allow us to investigate the effects of family and neighborhood characteristics on achievement levels. These models include family- and neighborhood-level random effects to control, respectively, for the correlation among siblings and among children living in the same neighborhood. Multilevel models provide corrected standard errors that adjust for clustering of observations. These models also provide measures of the magnitude and significance of unobserved but shared characteristics at each hierarchical level.

As discussed above, a general problem faced by previous studies is that unmeasured family characteristics, such as the parents' motivation for children's success, may affect both children's development and parents' neighborhood choice. Less commonly considered is the fact that unmeasured family characteristics may also affect neighborhood characteristics directly. For example, parents who value children's achievement may interact in different ways with neighbors and may be more likely to participate in neighborhood improvement efforts and in local schools. These potential and complex associations caused by unmeasured family factors may produce biased estimates of neighborhood effects on children's achievement.

The multilevel models that we use in this analysis allow us to control for unobserved family effects, but assume that these effects are uncorrelated with the included covariates. The data demands for modeling such correlations are high, and exceed what is currently available from L.A.FANS and most other data sets. However, we are able to incorporate controls for a number of family background characteristics, such as mothers' test scores and height, family assets, and children's birthweight, that are beyond what have been used in previous research. These additional variables may affect both neighborhood choice and children's achievement, and thus including them should lead to better estimates of neighborhood effects. But there are aspects of family background and parental behavior that remain unmeasured in our analysis and hence the problem of unobserved heterogeneity is mitigated, but not solved, by our comprehensive controls for family characteristics.

Data

The data are from the Los Angeles Family and Neighborhood Survey (L.A.FANS), a stratified, multistage, clustered random-sample survey of 3,100 households conducted between April 2000 and December 2001 in 65 census tracts in Los Angeles, California (Sastry et al., 2006). In households with children (70% of the sample) one child was chosen at random from all household members 17 years of age and younger. If the child had siblings, one was chosen at random as a second sampled child. Interviews were conducted with children's primary caregiver—nearly always the children's mother. Sampled children three years of age and older and their mothers completed subtests of the Woodcock-Johnson Revised assessments (Woodcock and Mather 1989) to assess reading and mathematics skills. Our analysis is based on

2,350 children aged 3–17 years who completed the reading and mathematics assessments. These children are a representative sample of children in this age range in Los Angeles.

Child Outcomes. The Woodcock Johnson-Revised Test of Achievement is designed to assess individual scholastic achievement (Woodcock and Mather 1989). We use two subtests of the Woodcock-Johnson Revised assessments: Letter-Word Identification and Applied Problems. The Letter-Word Identification test assesses symbolic learning and reading identification skills. The Applied Problems test assesses mathematics reasoning. Tests were administered in English or Spanish depending on respondents' language ability and preference. Although different versions of the test were administered in Spanish and English, the two tests were designed to produce comparable scores. Raw scores were converted to standardized scores based on the subject's age and national norms (McGrew et al. 1991). Norming by age allowed us to compare test scores across children of different ages. The standard scores have a population mean of 100 and standard deviation of 15.

The mean standardized scores on the reading and mathematics achievement tests for children in L.A.FANS were 102.6 and 102.0, respectively, slightly higher than the national norms of 100 for each test. The sample standard deviations of 18.3 for reading and 17.4 for mathematics were slightly above the standard deviation of 15 based on national norms and directly determine the Gini coefficient values of 0.0969 for reading and 0.0944 for mathematics. Because the Gini coefficient is a measure of variance, its magnitude is determined by our use of normed test scores. Normed scores facilitate comparisons by age, across groups, over time, and with other achievement tests. However, Gini coefficients based on normed scores cannot be compared directly with those for the unstandardized SES measures or interpreted as large or small, except when compared to results for similar outcomes from equivalently normed samples.

We would expect a close correspondence between Gini coefficients for test scores in the L.A.FANS sample and those for a normed national sample because the standard deviations are similar.

Explanatory Variables. The multilevel models incorporate explanatory variables at the child, family, and neighborhood levels. Child characteristics include age, sex, race/ethnicity, test language, and birthweight. The average age of test-takers was 9.7 years (SD=4.2). The sample included equal numbers of males and females. The majority of children (63%) were Latinos, reflecting the demographic composition of Los Angeles. Whites were the second largest group at 19%. Blacks were just under 10% and Asians comprised 7%. The average birthweight was 3.4 kilograms (SD=0.6). Four out of five children took the assessments in English and the remainder in Spanish.

Family characteristics include the mother's immigration status, the standardized test score from the WJ-R Passage Comprehension test of reading skills, years of schooling, and height. We also include the log of total family income and of total family non-housing assets. The majority of mothers (63%) were immigrants, with two-thirds having immigrated to the U.S. prior to 1990. Children of native-born mothers comprised 37% of the sample. Mothers had a mean score of 85 on the reading assessment, which is one standard deviation below the population mean, and had completed 11.5 years of education on average. Mothers' mean height was 161 cm, close to the national mean of 162 cm for women 20 years of age and older (Ogden et al. 2004).

At the neighborhood level, our multilevel models include tract median family income from the 2000 U.S. Census to measure economic status. Initial analyses also included adult educational attainment, but it was highly correlated with other characteristics and not statistically significant and, therefore, was dropped from the models reported here. We include median income rather than composite indicators such as concentrated poverty or affluence that were used in previous studies based on a preliminary analysis in which we replicated Brooks-Gunn et al.'s (1997) concentrated poverty and affluence indices and compared their effects on test scores with that of neighborhood median income in a multilevel model. Results (not shown) indicate that neighborhood median income is more closely associated with children's test scores than the composite indices. The tract median income had a mean of $44,000. This variable was not log-transformed (unlike family income and assets) because the log transformation reduced model fit compared with the untransformed variable. Controlling for tract income also accounts for the oversampling of poor neighborhood in L.A.FANS (Sastry et al., 2006), while maximizing the efficiency of the parameter estimates.

We also include three other neighborhood variables which previous theoretical work—described above—suggests may affect children's development: race/ethnic diversity, residential stability, and immigrant concentration. These measures are also based on tract-level 2000 U.S. Census data. The tract race/ethnic diversity score reflects the probability that any two people chosen at random from the tract were of different race/ethnic groups, defined as Latino, white, African American, Asian, and Native American. The residential stability and immigrant concentration measures are based on factor analysis scores of tract measures that are highly correlated. The residential stability index included the percent of households that did not move between 1995 and 2000, owner-occupied households, dwellings in multiple-unit structures, and non-family households. On average, 50% of the residents in these neighborhoods had moved into their current dwelling since 1995. The immigrant concentration index includes the percent of the population that was non-citizens, foreign born (total, post-1990 arrivals, and post-1995 arrivals), Spanish-speakers, and Latino. On average, L.A.FANS tracts included 40% foreign-born neighborhood residents.

Table 1 shows summary statistics for the five measures of SES. We also show the Gini coefficient for each of these measures. Inequality in family income for the L.A.FANS sample corresponds closely to the equivalent measure for the United States as a whole (DeNavas-Walt and Cleveland 2002).

Results

One-third of the total variation in mathematics achievement and one-fifth of the variation in reading achievement among children in Los Angeles are associated with SES differences, according to our results. This finding is largely independent of which SES measure is examined. However, after adjusting for the other SES measures and background characteristics, the net contributions to inequality in children's test scores vary considerably across the specific SES variables. In particular, mothers' own reading scores and tract median income account for the largest proportion of total inequality in children's achievement. In contrast, there is essentially no inequality in children's reading and mathematics scores by family income once other variables in the model are held constant.

Figure 1 provides a graphical illustration of inequality in mathematics achievement by tract median income. In Figure 1, Panel A shows the Lorenz curve for children's mathematics scores, the unadjusted concentration curve for these scores by tract median income, and the same concentration curve adjusted for all other variables in the model. The area between each of the curves and the diagonal represents the level of inequality; our objective is to compare the areas associated with the three curves. The relative sizes of the three areas are shown more clearly in Panel B of Figure 1, which plots the deviations of each curve from the diagonal. This figure shows that the area between the concentration curve and the diagonal is about one-third of the area between the Lorenz curve and the diagonal. Thus, one-third of the total inequality in mathematics scores is associated with systematic differences in these scores by tract median income. The remaining inequality in mathematics scores—which represents two-thirds of the total inequality in scores and corresponds to the area between the Lorenz curve and the concentration curve—is due to child, family, and neighborhood characteristics unrelated to neighborhood income. Similarly, the area between the adjusted concentration curve and the diagonal covers about fifty percent of the area between the unadjusted concentration curve and the diagonal. This result indicates that half of the systematic difference in mathematics scores by tract median income is due to differences in average neighborhood income itself. The other half is due to factors correlated with tract median income, such as family income and assets, which are held constant in the regression model used to calculate the adjusted concentration curve. Finally, comparing the area between the adjusted concentration curve and the diagonal with the area between the Lorenz curve and the diagonal, shows that about one-sixth of the total inequality in children's mathematics scores is due to the independent effect of systematic differences in these scores by tract median income.

The results for the Gini coefficients and concentration indices—covering both reading and mathematics scores and all five SES measures—are presented in Table 2. We focus on these numerical results, rather than the full set of graphs, because they provide a convenient summary, support straightforward significance tests, and offer a well-established means to resolve ambiguity in the graphical results when curves intersect. However, we also present graphs showing the adjusted concentration curves for the two achievement tests in Figure 2.

The results in Table 2 show the unadjusted concentration index standardized by the Gini coefficient and the adjusted concentration index standardized by the Gini coefficient and by the corresponding unadjusted concentration index. The actual index values (see Appendix A), are straightforward to interpret when compared across SES measures and to assess in terms of their statistical significance. However, the standardized inequality coefficients—which are interpreted as the percentage of overall or socioeconomic inequality accounted for by each concentration index—provide more intuitively appealing and substantively meaningful results.

The top panel in Table 2 shows the ratio of the concentration index to the Gini coefficient, which indicates the proportion of total inequality in reading or mathematics skills that is attributable to inequality in each SES variable. Between 19% and 26% of the total inequality in children's reading scores is associated with systematic differences by SES. Mothers' reading scores and schooling account for the largest variation in children's reading scores while tract median income accounts for the smallest. In contrast, all five SES measures account for very similar percentages (33%–35%) of the overall variation in mathematics scores. These results reflect the high correlation among SES measures and the effects of other child, family, and neighborhood characteristics.

The adjusted concentration index values control for the effects of the other SES measures and the additional child, family, and neighborhood characteristics described above. The center panel of Table 2 presents the ratio of the adjusted concentration index to the Gini coefficient for each SES indicator. This measure shows the proportion of children's skills inequality that is associated with the net effect of each SES indicator.

For children's reading achievement, mother's reading scores have by far the largest net effect among the five SES measures. Figure 2 reveals that there is unambiguously greater net SES inequality in children's reading achievement by mother's reading score than by any of the other SES measure. Almost one-quarter of total inequality in children's reading scores is due to the net effects of mother's reading scores. The next largest net association is for tract median income, which accounts for 11% of the total inequality in children's reading scores. For children's mathematics scores, mother's reading score and tract median income have the largest net effects; each is associated with 16% of total inequality. The overlapping adjusted concentration curves for mother's reading score and tract median income in the bottom panel of Figure 2 highlight the ambiguity of this finding—in particular, when children are ranked by the specific SES measure in question, mother's reading score makes a greater contribution to inequality in children's mathematics achievement below the median while tract median income makes a greater contribution to inequality above the median. The other three SES measures have lower net levels of association with inequality in reading and mathematics achievement. Mother's schooling is associated with 9% of total inequality in children's reading achievement and 8% in mathematics achievement. Family assets independently account for 4% and 7% of total inequality in reading and mathematics, respectively. Figure 2 shows that for both of these cases, similar percentages of adjusted socioeconomic inequality in achievement scores are associated with intersecting adjusted concentration curves. Finally, after controlling for other factors, there is no net association between family income and children's achievement in either reading or mathematics.

The adjusted levels of inequality in children's test scores are generally substantially smaller than the observed levels. These results are summarized in the bottom panel of Table 2 as the ratio of the adjusted to the unadjusted values of the concentration index. The ratios show the proportion of observed inequality in achievement scores for each SES measure that remains after taking other factors into account. The net effect of mothers' reading scores on children's reading scores is 89% of the observed effect. For mathematics, the comparable ratio was 49%. The ratio of the net association to the observed association for tract median income is 58% for reading and 49% for mathematics. It is substantially smaller for mothers' schooling (31% for reading and 23% for mathematics) and for family assets (20% for both reading and mathematics). Finally, for family income this ratio is only 9% for reading and 1% for mathematics, indicating that the observed association between family income and children's reading and mathematics achievement is due almost entirely to the other SES measures and child, family, and neighborhood characteristics.

A key finding is the high level of inequality in children's reading and mathematics achievement by tract median income. Neighborhood income is more strongly associated with inequality in children's reading and mathematics achievement than family income or assets or mother's schooling. Previous research has not generally considered the effects of median neighborhood income but has focused instead on the effects of the extremes of the income distribution—i.e., concentrated poverty and affluence (Brooks-Gunn et al. 1997; Sampson et al. 1997). Our results for tract median income may also reflect the effects of concentrated poverty and affluence. However, all these measures are highly correlated and median tract income represents the simplest and clearest indicator, and provides a more direct explanation of the relationship between neighborhood SES and children's outcomes.

Results by Children's Age

To examine whether our results varied by children's developmental stage, we repeated the preceding analysis for three separate age groups corresponding to specific developmental stages: early childhood (3–7 years of age; a total of 798 children), middle childhood (8–12 years; 848 children), and adolescence (13–17 years; 704 children). The results are presented in Table 3.

The top panel shows the percent of total inequality in test scores explained by observed socioeconomic inequality in test scores, for each achievement score, age group, and SES measure; the bottom panel shows the percent of total inequality in test scores explained by each of the adjusted measures of socioeconomic inequality in test scores. The actual values of the indices and their standard errors are presented in Appendix A.

Our results by children's developmental stage are complex but are generally consistent with the results for the entire sample. For reading, the proportion of total inequality attributable to observed inequality by SES is generally highest for the youngest children, declines in middle childhood, and increases again for adolescents. For instance, mothers' reading scores account for 20% of inequality in reading achievement for the youngest children, 19% for children in middle childhood, and 30% for adolescents. For the youngest age group alone the five SES measures account for very similar percentages of the overall variation in reading scores (28%–31%). For the older two age groups, mother's reading score and schooling account for the largest percentages of inequality in children's reading scores while family income and assets and tract median income account for similar but smaller percentages; this pattern is similar to that for the sample as a whole. For mathematics, observed inequality by SES generally accounts for an increasing percentage of the overall variation in test scores across age groups. For example, observed inequality by tract median income accounts for 30% of the overall variation in mathematics scores in early childhood, 36% in middle childhood, and 40% in adolescence. This age-pattern of results conforms to our expectations, in contrast to the findings for reading. For each age group—as for the sample as a whole—all five SES measures account for very similar percentages of the overall inequality in mathematics achievement: 30%–33% for the youngest children, 30%–36% in middle childhood, and 37%–43% for adolescents.

The second panel in Table 3 is based on adjusted values of the concentration index which control for the effects of the other SES measures and child, family, and neighborhood characteristics. The findings are broadly consistent with those for the entire sample but reveal a number of interesting differences by age group. For the youngest children, mothers' reading scores have by far the largest adjusted effect among the five SES indicators, accounting for 20% of the overall inequality in reading achievement and 16% of the overall inequality in mathematics. The adjusted effects of the four remaining SES indicators are of only minor importance for children in the 3–7 year old age group, accounting for 6% or less of overall inequality in reading and mathematics achievement. Mother's reading score continues to have the largest adjusted effect among the SES indicators for inequality in reading for children in middle childhood and, especially, in adolescence. For these two oldest age groups, tract median income emerges as the second most important SES measure, followed by the mother's schooling. For adjusted inequality in mathematics scores by SES, mother's reading score is the most important factor for the youngest children and for adolescents, but tract median income accounts for the largest adjusted percentage of overall inequality in test scores in middle childhood and a close second in adolescence. Family assets and mother's schooling are also associated with inequality in mathematics achievement in adolescence and, to a much lesser extent, in middle childhood.

The age-specific results for adjusted inequality in children's achievement by mother's reading score serve to reinforce our conclusion from the entire sample about the importance of this variable. Net inequality in children's reading and mathematics achievement by mother's reading score generally increases with age and is highest for adolescents. There is also significant adjusted inequality in children's reading and mathematics achievement by tract median income for the two older age groups—but not for the youngest age group. These findings are consistent with the notion that the environment outside the home is more important for older children while the home environment is most important in early childhood.

Multilevel Model Results

The detailed multilevel linear regression model results for children's reading and mathematics achievement are presented in Table 4. These results provide the basis for the preceding adjusted inequality analysis and are of interest in their own right. We also report standardized coefficients from the multilevel regression analysis, which, despite some well-known limitations, provide a bridge between these results and those from the inequality analysis.

The results for the multilevel model of children's reading achievement indicate that a child's sex, race/ethnicity, and test language are significantly related to reading scores. Girls score significantly better than boys. Latinos and African Americans receive substantially lower reading scores than whites; Asians score substantially better than whites. Birthweight is unrelated to reading scores. The test language is also significantly related to reading scores: children who took the test in Spanish scored higher than those who took it in English. We suspect that this difference may be an artifact of different tests in the two languages.

Among family characteristics, immigration status is strongly related to reading scores. Holding other variables constant, children of immigrant mothers have substantially higher reading achievement than children of native-born mothers. Moreover, children of recent immigrants have the highest scores on this test. The coefficient on mother's reading score is large and highly statistically significantly. For each point increase in the mother's score, the child's score increased by one quarter of a point. Mothers' educational attainment is also strongly positively related to reading scores. An additional year of education increases the child's score by about one-third of a point. Neither family income nor family assets have a statistically significant association with reading scores.

The only neighborhood characteristic that has a statistically significant effect on reading scores is tract median income, which is positively and strongly associated with reading scores. A $10,000 increase in tract median income increases reading scores by 0.87 points. Contrary to expectation, neighborhood immigrant concentration, residential stability, and race/ethnic diversity are unrelated to reading scores.

Results for mathematics achievement are similar to those for reading, with a few exceptions. First, mathematics scores do not differ significantly by child sex. Second, child age has a statistically significant and negative effect on mathematics achievement: older children score more poorly relative to their age-group peers in mathematics than do younger children. Third, children tested in Spanish have statistically significantly lower mathematics scores than children tested in English. Fourth, although birthweight makes no difference for reading scores, it is significantly and positively associated with mathematics scores. Fifth, immigration status confers less advantage for mathematics achievement than for reading. Sixth, mother's height is associated with mathematics achievement (at the .10 significance level) but not reading. Finally, neighborhood residential stability has a statistically significant negative association only with mathematics achievement, despite expectations that residential stability would be positively associated with achievement. However, previous research suggests that low rates of mobility may be indicative of neighborhood problems (Duncan and Aber 1997; Korbin and Coulton 1997).

The bottom of Table 4 shows the estimated fraction of the error variance in achievement scores due to unobserved family and neighborhood factors. After controlling for the variables in the model, about one-quarter of the total variation in reading and mathematics scores is accounted for by unobserved family factors and 1–2% by unobserved neighborhood factors.

Finally, in order to relate the results from our multilevel regression models to the preceding inequality analysis we examine standardized coefficients for the five measures of SES. Standardized coefficients—obtained by multiplying each regression coefficient by the ratio of the standard deviation for that variable and the standard deviation for the children's test score—are interpreted as the effect of a one-standard deviation change in the SES measures on the standard deviation of children's scores. Because standardized coefficients reflect both the variance of the SES measure and the magnitude of its effects on variance in scores, they provide similar information to the adjusted measures of socioeconomic inequality in children's achievement. The ordering of the standardized coefficients matches almost exactly that of the adjusted inequality measures, with the standardized coefficients for the children's reading highest for mother's reading score (0.230), followed by tract median income (0.131), mother's schooling (0.079), family assets (0.034), and family income (0.020); for children's mathematics, the standardized coefficient is highest for tract median income (0.192) followed by mother's reading score (0.168), mother's schooling (0.078), family assets (0.072) and family income (0.003). However, the standardized coefficients have a number of shortcomings—widely discussed in the literature (e.g., Achen 1982; Greenland et al. 1986; Kim and Ferree 1981; King 1986)—which make them less suitable for answering questions about socioeconomic inequality in children's achievement. Foremost among these limitations—given the goals of our analysis—is that the standardized coefficients are not embedded within a framework for studying inequality, as the concentration measures are. Thus, the standardized coefficients are difficult to interpret and compare across samples. In contrast, the adjusted concentration indices that measure net socioeconomic inequality in children's test scores can be assessed and interpreted in the context of overall inequality in test scores, using the Gini coefficient, and the observed socioeconomic inequality in children's achievement, based on the unadjusted concentration index. A large and growing literature has established the theoretical, methodological, and applied foundations for this type of analysis.

Discussion

We examined socioeconomic inequalities in children's reading and mathematics achievement in Los Angeles. We used data from the Los Angeles Family and Neighborhood Survey, which were designed to study neighborhood effects and offered better controls for family background characteristics, and multilevel statistical models. There is a long-standing concern in the neighborhood effects literature about the consequences of unobserved heterogeneity related to both neighborhood choice and children's achievement, and our analysis extended previous research on this topic. In particular, the data and methods allowed us to adjust for certain measured and unmeasured aspects of family background that reduced—but did not eliminate—the problem of unobserved heterogeneity, which remains a potential concern.

Our unadjusted results show that there are sizable socioeconomic inequalities in children's skills associated with neighborhood median income and family SES, including mother's reading achievement and schooling and family income and assets. Differences in family and neighborhood SES are associated with at least one-fifth of the total inequality in children's reading scores and about one-third of the total inequality in children's mathematics scores.

Children in higher SES families score better on the assessments primarily because their mothers have better reading skills and more schooling and because they live in higher-income neighborhoods. After adjusting for all of the independent variables in the model, family income was essentially unrelated to children's reading scores. With robust controls for family background—such as mothers' reading scores and education—the effects of family income and, to a lesser extent, family assets *per se* do not appear to explain observed socioeconomic inequalities in children's reading and mathematics achievement. This result is similar to findings of other researchers (Jencks and Phillips 1988; Mayer 1997).

Mothers' reading score has the strongest association with inequality in children's achievement among the five SES measures once all other factors are held constant, except for 8–12 year olds who have a stronger association between tract median income and inequality in mathematics achievement. The strong net association between mothers' and children's reading skills is likely due to the intergenerational transmission of ability and effects of the home learning environment. In other analyses (not shown), we found that mothers with higher reading scores were more likely to read to children regularly, to have children's books in the house, and to enjoy reading themselves—all behaviors that can contribute to children's reading skills. For children's mathematics scores, net inequality is highest for mother's reading score (along with tract median income). These results suggest that programs aimed at reducing socioeconomic inequality in children's skills acquisition should focus specifically on children whose parents have poor reading skills (and perhaps numeracy skills, which we do not measure)—for example, by targeting higher quality early childhood and school-based programs to these children or by providing adult literacy education to parents.

We find large effects of average neighborhood income on children's reading and mathematics achievement. Living in a low-income neighborhood appears to have a greater effect on inequality in test scores than coming from a low-income family. Moreover, low neighborhood income was more strongly associated with socioeconomic inequality in test scores than seemingly more direct factors, such as mother's education, after controlling for other variables. The effects of average neighborhood income were particularly strong for 8–12 and 13–17 year olds. Our results suggest that reducing the variation across neighborhoods in average levels of income would help to equalize reading and mathematics achievement among children. A key policy prescription would be to reduce residential segregation by family income and to create more economically-integrated neighborhoods. At the same time, improvements in neighborhood income, at any given level, should lead to higher levels of academic achievement for children—at least over the long run, as Sampson and et al. (2008) suggest.

We also examined the association of other neighborhood structural characteristics with children's skills acquisition. Contrary to hypotheses about the local language environment, neighborhood immigrant concentration was not significantly related to reading or mathematics scores. Our results also showed that neighborhood race/ethnic diversity is unrelated to children's skills and that residential stability has no effect on reading skills, but a significant and negative association with mathematics skills. The latter finding is consistent with the argument—cited earlier—that low residential mobility may be indicative of neighborhood problems.

The results for family characteristics show that, relative to whites, Latinos and African Americans have significantly lower reading and mathematics scores. The African American-white gap is considerably larger than the Latino-white gap for mathematics scores. This is true even when all other family and neighborhood characteristics are held constant, indicating that African American and Latino children face forms of disadvantage in skills acquisition not captured by socioeconomic and other factors in the model. Asians, by contrast, have significantly higher scores on both tests compared to whites. Children of immigrants perform significantly better on skills tests, with the best scores obtained by the most recent immigrants. When given equal opportunity, children of immigrants appear to learn reading and mathematics more effectively than children of native-born parents. The results also demonstrate the importance of considering parents' own cognitive skills and family assets in studies of children's skills acquisition. Mother's reading skills are strongly associated with children's reading and mathematics achievement and family assets are a significant predictor of children's mathematics scores—in contrast to the statistically insignificant effects of family income. Nevertheless, our results show that even when these and other family variables are included in the model, neighborhood median income has a strong and statistically significant effect on children's skills acquisition.

Table 1. Summary Statistics for Socioeconomic Status Measures in L.A.FANS

Measure	Median	Mean	Std. Dev.	Observations	Gini (S.E.)
Family income ($)	28,400	55,115	102,575	1,576	0.5786 (0.0145)
Family assets ($)	6,066	142,551	578,904	1,576	0.8732 (0.0064)
Mother's schooling (years)	12.0	11.6	4.4	1,576	0.1975 (0.0052)
Mother's reading achievement (score)	84.0	85.0	18.3	1,576	0.1160 (0.0027)
Tract median family income ($)	35,683	44,859	27,563	65	0.3054 (0.0225)

Table 2. Observed and Adjusted Indicators of Socioeconomic Inequality in Children's Reading and Mathematics Achievement in L.A.FANS

Measure	**Reading**	**Mathematics**
Observed concentration index divided by the Gini Coefficient × 100		
Family income	20%	34%
Family non-housing assets	21	35
Tract median family income	19	33
Mother's reading score	26	33
Mother's years of school	23	33
Adjusted concentration index divided by the Gini Coefficient × 100		
Family income	2%	0%
Family non-housing assets	4	7
Tract median family income	11	16
Mother's reading score	23	16
Mother's years of school	9	8
Adjusted concentration index divided by the observed concentration index × 100		
Family income	9%	1%
Family non-housing assets	18	20
Tract median family income	58	49
Mother's reading score	89	48
Mother's years of school	37	23

Table 3. Observed and Adjusted Indicators of Socioeconomic Inequality in Children's Reading and Mathematics Achievement in L.A.FANS by Child Age

	Reading			Mathematics		
Measure	3–7 years	8–12 years	13–17 years	3–7 years	8–12 years	13–17 years
Observed concentration index divided by the Gini Coefficient × 100						
Family income	31%	11%	20%	32%	35%	37%
Family non-housing assets	30	12	22	33	34	43
Tract median family income	28	12	22	30	36	40
Mother's reading score	30	20	31	33	32	39
Mother's years of school	28	16	28	30	30	43
Adjusted concentration index divided by the Gini Coefficient × 100						
Family income	6%	-2%	1%	1%	-2%	0%
Family non-housing assets	5	4	6	5	5	14
Tract median family income	6	13	14	6	22	20
Mother's reading score	20	19	30	16	13	23
Mother's years of school	6	9	9	4	7	10

Table 4. Multilevel Linear Regression Model Results of Children's Reading and Mathematics Achievement Scores in L.A.FANS

Variable	**Reading**		**Mathematics**	
Child age (years)	-0.03	(0.09)	-0.24***	(0.08)
Child sex				
Male[a]	.	.	.	.
Female	2.71***	(0.68)	-0.02	(0.63)
Child Race				
Latino	-3.09**	(1.26)	-2.81**	(1.18)
Black	-2.66*	(1.57)	-4.13***	(1.51)
White[a]	.	.	.	.
Asian	4.04**	(1.76)	4.74***	(1.66)
Other	1.00	(2.87)	0.59	(2.66)
Birthweight (kg)	0.58	(0.58)	1.16**	(0.54)
Language of test				
English[a]	.	.	.	.
Spanish	7.89***	(1.10)	-5.65***	(1.02)
Mother's immigration status				
Native-born[a]	.	.	.	.
Pre-1990 immigrant	3.63***	(1.13)	1.38	(1.05)
Post-1990 immigrant	6.03***	(1.32)	2.62**	(1.22)
Mother's reading score	0.23***	(0.03)	0.16***	(0.02)
Mother's education (years)	0.33***	(0.11)	0.31***	(0.10)
Mother's height (cm)	0.01	(0.05)	0.09*	(0.05)
Log family income	0.17	(0.20)	0.03	(0.19)

Log family assets	0.15	(0.12)	0.30***	(0.11)
Tract median family income ($10,000)	0.87***	(0.29)	1.21***	(0.30)
Tract race/ethnic diversity score	-3.65	(3.17)	-1.07	(3.23)
Tract residential stability score	-0.74	(0.57)	-1.22**	(0.58)
Tract immigrant concentration score	0.31	(0.89)	0.55	(0.90)
Constant	67.43***	(9.43)	63.14***	(8.82)
Fraction of error variance due to				
Family	0.22***		0.25***	
Neighborhood	0.01*		0.02**	
Model Chi-squared (df)	499.23***	(21)	418.54***	(21)
Observations				
Children	2,350		2,293	
Families	1,581		1,576	
Neighborhoods	65		65	

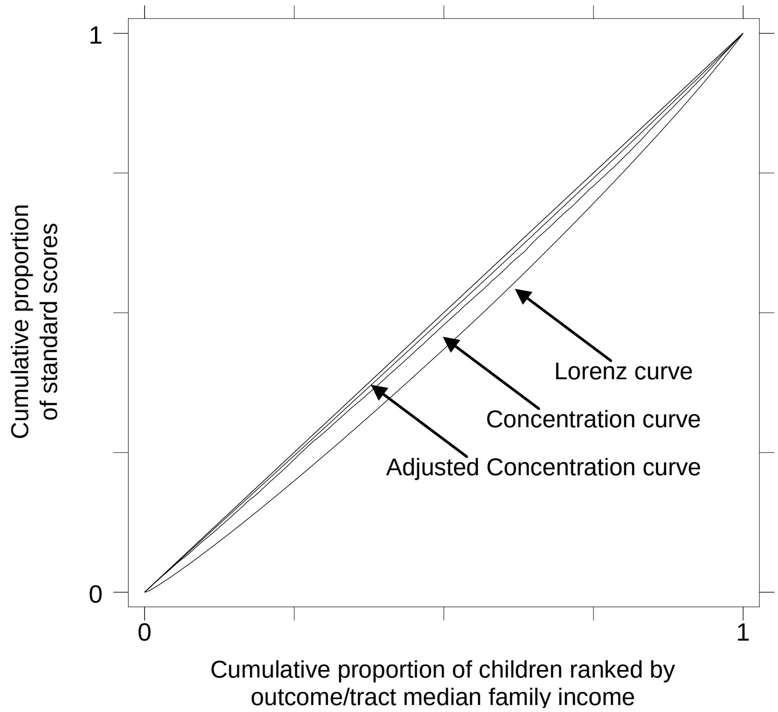
**p*<.10; ***p*<.05; ****p*<.01; standard errors in parentheses; models also include dummy variables to control for cases with missing birthweight (4%) and mother's height (4%).

Source: Authors' calculations using data from the 2000-01 L.A.FANS.

Notes: [a] Reference category.

Figure 1. Graphical Analysis of Socioeconomic Inequality in Children's Mathematics Achievement in L.A.FANS by Tract Median Family Income

A. Lorenz Curve and Concentration Curves



B. Deviations of Lorenz Curve and Concentration Curves from Diagonal

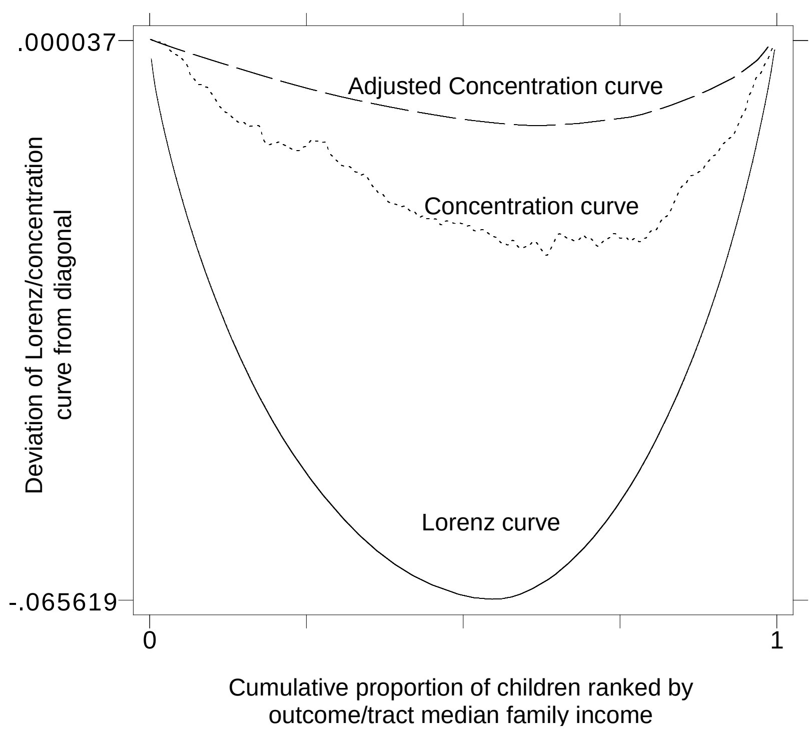
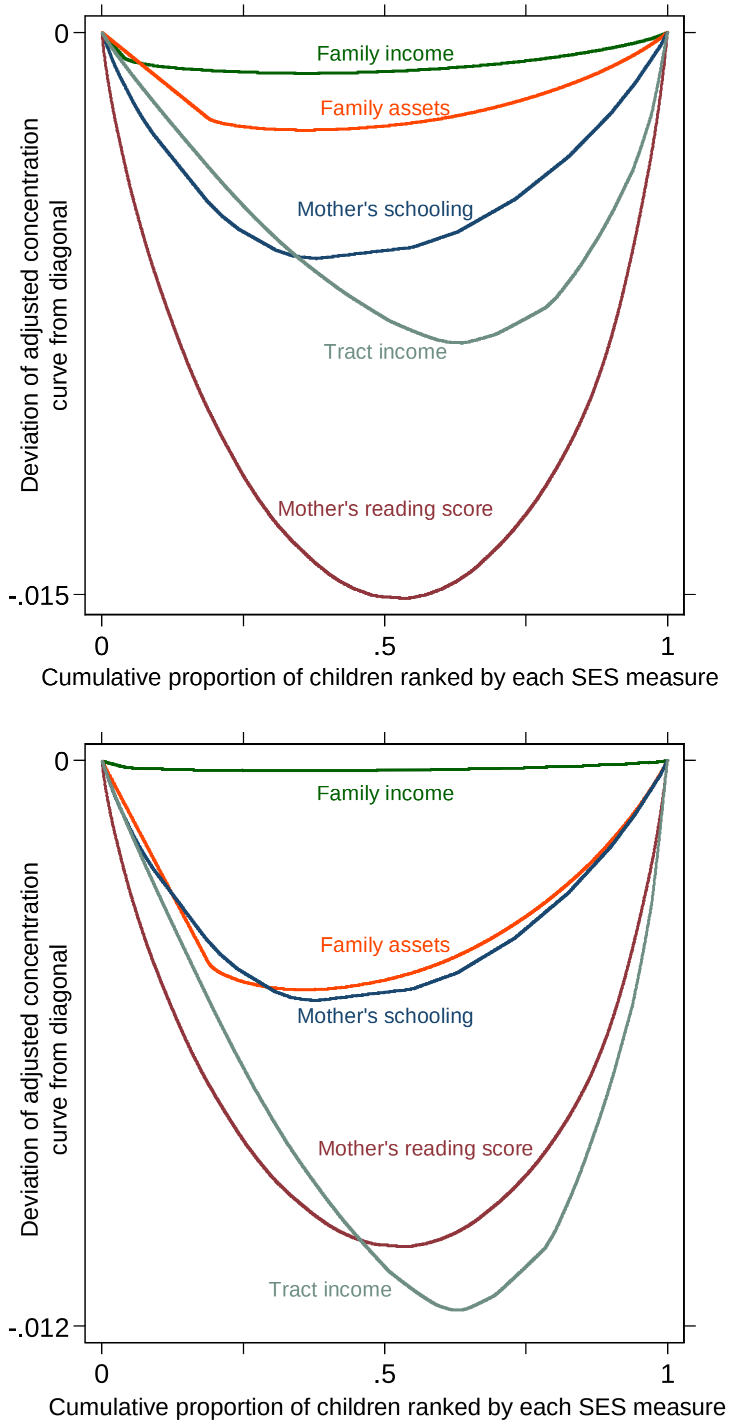


Figure 2. Adjusted Concentration Curves for Socioeconomic Inequality in Children's Reading (Top Panel) and Mathematics Achievement (Bottom Panel) in L.A.FANS, Shown as Deviations from Diagonal



Appendix A. Detailed Results for Gini Coefficients and Concentration Indices

The full set of results for the Gini coefficient and concentration index for both the reading and mathematics achievement tests is shown in Table A.1. The top line of the table shows the Gini coefficient. The middle panel shows the observed concentration index based on each of the five SES measures. Finally, the bottom panel shows the adjusted concentration index values based on predicted values from the multilevel regression models. The predicted values held all variables constant at their sample-wide means *except* the single independent variable of interest which retained its actual values. Table A.2 shows a parallel set of results for three separate age groups that correspond to specific developmental stages: early childhood (ages 3–7 years), middle childhood (ages 8–12 years), and adolescence (13–17 years).

Table A.1. Inequality in Children's Reading and Mathematics Achievement Scores in L.A.FANS

Measure	Reading		Mathematics	
Gini coefficient	0.0969***	(0.0019)	0.0944***	(0.0017)
Observed concentration index				
Family income	0.0192***	(0.0025)	0.0319***	(0.0022)
Family assets	0.0200***	(0.0024)	0.0334***	(0.0020)
Tract median family income	0.0187***	(0.0024)	0.0315***	(0.0023)
Mother's reading score	0.0248***	(0.0023)	0.0314***	(0.0022)
Mother's years of school	0.0226***	(0.0022)	0.0313***	(0.0023)
Adjusted concentration index				
Family income	0.0017	(0.0017)	0.0003	(0.0013)
Family assets	0.0036*	(0.0022)	0.0067***	(0.0020)
Tract median family income	0.0109***	(0.0027)	0.0153***	(0.0027)
Mother's reading score	0.0220***	(0.0022)	0.0150***	(0.0020)
Mother's years of school	0.0083***	(0.0021)	0.0071***	(0.0020)

*p<.10; **p<.05; ***p<.01; standard errors in parentheses.

Source: Authors' calculations using data from the 2000-01 L.A.FANS.

Table A.2. Inequality in Children's Reading and Mathematics Achievement Scores in L.A.FANS by Child Age

Measure	Reading						Mathematics					
	3–7 years		8–12 years		13–17 years		3–7 years		8–12 years		13–17 years	
Gini coefficient	0.0932***	(0.0027)	0.0974***	(0.0027)	0.0993***	(0.0037)	0.1018***	(0.0033)	0.0888***	(0.0022)	0.0900***	(0.0032)
Observed concentration index												
Family income	0.0288***	(0.0034)	0.0108***	(0.0041)	0.0197***	(0.0045)	0.0324***	(0.0036)	0.0314***	(0.0032)	0.0332***	(0.0036)
Family assets	0.0281***	(0.0035)	0.0116***	(0.0038)	0.0222***	(0.0043)	0.0339***	(0.0039)	0.0300***	(0.0031)	0.0385***	(0.0035)
Tract median family income	0.0261***	(0.0034)	0.0113***	(0.0037)	0.0216***	(0.0047)	0.0301***	(0.0038)	0.0318***	(0.0031)	0.0361***	(0.0038)
Mother's reading score	0.0279***	(0.0033)	0.0192***	(0.0036)	0.0310***	(0.0046)	0.0331***	(0.0036)	0.0287***	(0.0032)	0.0353***	(0.0040)
Mother's years of school	0.0265***	(0.0036)	0.0155***	(0.0037)	0.0276***	(0.0043)	0.0308***	(0.0038)	0.0266***	(0.0031)	0.0386***	(0.0037)
Adjusted concentration index												
Family income	0.0057***	(0.0020)	-0.0015	(0.0023)	0.0014	(0.0038)	0.0012	(0.0027)	-0.0014	(0.0018)	0.0002	(0.0021)
Family assets	0.0044*	(0.0034)	0.0036	(0.0034)	0.0064**	(0.0037)	0.0048*	(0.0038)	0.0045*	(0.0029)	0.0128***	(0.0027)
Tract median family income	0.0054*	(0.0040)	0.0122***	(0.0040)	0.0144***	(0.0050)	0.0061*	(0.0043)	0.0198***	(0.0035)	0.0179***	(0.0036)
Mother's reading score	0.0189***	(0.0032)	0.0181***	(0.0030)	0.0302***	(0.0046)	0.0165***	(0.0033)	0.0115***	(0.0032)	0.0203***	(0.0036)
Mother's years of school	0.0054*	(0.0032)	0.084***	(0.0032)	0.0090**	(0.0042)	0.0044	(0.0040)	0.0063**	(0.0028)	0.0089***	(0.0030)

*p<.10; **p<.05; ***p<.01; standard errors in parentheses.

Source:Authors' calculations using data from the 2000-01 L.A.FANS.

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