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Concentrated Affluence:
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Social Environments and
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DRU-2400/10-LAFANS

May 2003

***RAND Labor & Population
Working Paper Series 03–24***

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Concentrated Poverty vs. Concentrated Affluence: Effects on Neighborhood Social Environments and Children's Outcomes

May 1, 2003

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The authors are grateful to the Russell Sage Foundation's Social Inequality Program and the National Institute of Child Health and Human Development (R01HD41486) for support of this research.

Introduction

American cities have long been characterized by a highly uneven spatial distribution of physical and human capital, e.g., income, educational attainment, housing stock. In the decades prior to 1900, deindustrialization of cities, structural changes in labor demand, racial discrimination, outmigration of the middle class, and public policies regarding residential segregation, public housing, and highways systems led to increasing concentration of poverty in poor minority urban neighborhoods (Wilson, 1987 and 1996; Massey and Eggers, 1990; Massey and Denton, 1993; Jargowsky, 1997). Despite substantial economic and social changes during the past decade, results from the 2000 census show only small overall declines in residential segregation by race and income during the 1990s (Logan et al., 2001; Mare and Cort, 2003).

Residential segregation facilitates the intergenerational transmission of poverty if growing up in a poor neighborhood negatively affects children's social and behavioral development and opportunities for success. Numerous studies have shown that social problems, such as health status, school performance, behavior problems, substance abuse, early sex and parenthood, delinquency, and violence are geographically clustered in concentrated poverty neighborhoods.¹ Moreover, there is a solid basis in social theory for the idea that social environments, including home, school, peers, and neighborhoods, strongly influence children's development (e.g., Bronfenbrenner, 1986; Coleman, 1988, Wilson, 1987, 1996). However, prior to Jencks and Mayer's influential review in 1990, there was little persuasive evidence that neighborhood conditions were causally related to child outcomes, and, if so, exactly how and why (Jencks and Mayer, 1990).

Since 1990, many new studies of neighborhood effects studies have appeared. These studies have generally been motivated by concern about the role of concentrated poverty neighborhoods—specifically, very poor, predominantly African American inner city neighborhoods—in hampering children's development (see, for example, Brooks-Gunn et al., 1997). However, the results of several studies have shown that the presence of *affluent* neighbors has a great impact on children's outcomes than neighborhood poverty levels (Brooks-Gunn et al., 1997; Duncan and Raudenbush, 1999, Sampson et al., 1999). For example, Brooks-Gunn and her colleagues (1997) conclude that:

Living in areas with greater concentrations of middle-class neighborhoods was associated with greater achievement for adolescents, as it was with enhanced cognitive development and early achievement among young children. Our theories point to a number of possible causes, ranging from the resources and neighborhood services that affluent neighbors bring with them, to the kinds of role models and direct labor-market connections they may provide. (Brooks-Gunn et al., 1997: 282)

Another major finding from recent studies is that a substantial part of the variation in children's outcomes by neighborhood income can be accounted for by differences in family

¹ See reviews by Jencks and Mayer (1990), Gephart (1997), Aneshensel and Sucoff (1996), Robert (1999), Sampson et al. (2002), Leventhal and Brooks-Gunn (2000), and Ginter et al. (2000). The geographic clustering of disadvantage and negative outcomes in American cities and its importance for public policy is, of course, not a new observation; for example, see Burgess (1930).

income and other family characteristics. In other words, when family characteristics such as income, family structure, and parents' educational attainment are held constant, the relationship between children's outcomes and neighborhood income levels is substantially reduced. Moreover, Ginter et al. (2000) show that the more complete the set of family characteristics that is held constant, the greater the decline in the size and significance of coefficients on neighborhood variables. They conclude that the results of many neighborhood effects studies are likely due, at least in part, to omitted variables at the family level. Nonetheless, their analysis and others find that some neighborhood characteristics retain significant effects even after extensive controls for family and individual characteristics are introduced.²

In this paper, we examine the effects of neighborhood poverty and affluence, other neighborhood characteristics, and family characteristics on two indicators of children's development: reading-related and math-related achievement. Our analysis makes several important contributions to research in this area. First, we examine the degree of socioeconomic inequality in children's achievement scores using a novel approach based on summary measures analogous to the Gini coefficient of income inequality. By calculating inequality in children's achievement scores according to levels of neighborhood income, we can estimate the proportion of total inequality in children's achievement test scores that are accounted for by neighborhood differences in income, before and after controlling for other child, family, and neighborhood characteristics. Furthermore, we can compare the inequality in children's achievement test scores by neighborhood income to inequality in test scores according to family factors such as family earnings and mother's education. Second, the analysis includes stronger controls for family-level effects, both by employing a richer set of family characteristics and by including a family-level random effect. Better controls for family-level effects allow us to draw clearer conclusions about the net effects of neighborhood conditions on children's outcomes. Third, we investigate the role of neighborhood-level median income compared to indices of concentrated poverty and concentrated affluence. In other words, we examine whether the density of poor or affluent families is more or less important than the overall level of income in the neighborhood. Finally, the analysis investigates neighborhood effects in Los Angeles, based on data from the new Los Angeles Family and Neighborhood Survey (L.A.FANS-1). Los Angeles differs considerably, physically and socially, from urban areas such as Chicago, which have figured centrally in previous research on concentrated poverty neighborhoods. Our objective is to determine whether the same types of relationship observed elsewhere are also seen in a newer urban area such as Los Angeles.

In the next two sections of the paper, we describe the data and provide background information on Los Angeles County. The subsequent section presents an analysis of the degree to inequality in children's achievement scores by income and a decomposition of the inequality measure. We then describe the methods used in the multivariate analysis. The final section of the paper is a conclusion and discussion.

² Ginter et al. (2000) suggest that neighborhood characteristics which are most closely associated with the outcome investigated (e.g., local school dropout rates with and an individual's level of educational attainment) are most likely to remain significant.

Data

This study is based on data from the first wave of the Los Angeles Family and Neighborhood Survey (L.A.FANS) which was fielded in a sample of 65 census tracts throughout Los Angeles County. The L.A.FANS is a longitudinal survey, designed to answer research questions about the effects of neighborhood social environments on outcomes for adults and children in Los Angeles. Wave 1 of the L.A.FANS survey began in April 2000 and was completed at the end of 2001.

L.A.FANS is based on a multistage clustered sampling design. First, census tracts in Los Angeles County were divided into three strata based on the percent of the tract's population in poverty in 1997. The three strata are: very poor (those in the top 10 percent of the poverty distribution), poor (tracts in the next 30 percent of the poverty distribution), and non-poor (tracts in the bottom 60 percent of the distribution). To achieve an oversample of poor and very poor tracts, 20 tracts were sampled in the poor and very poor strata. An additional 25 tracts were sampled in the non-poor stratum, for a total of 65 tracts (see Sastry et al., 2000 for more detail). In the second stage, census blocks were sampled within each tract and all dwelling units were listed in sampled blocks. In the third stage, households were sampled within each block and screened. Approximately 40-50 households were interviewed in each census tract, for a total sample size of 3,100 households.

In households with children, one child was chosen at random (designated the Randomly-Selected Child or RSC) from all household members age 17 and younger. If the child had one or more siblings, one of these was chosen at random as a second sampled child (designated the Sibling or SIB). Interviews were conducted with sampled children's Primary Caregiver (or PCG, usually the child's mother) and with sampled children over age 9. L.A.FANS collected extensive information on the household socioeconomic status, family life, neighborhood life, residential mobility, program participation, health status, and many other topics. To permit comparisons with national-level survey data, the L.A.FANS employed standard, well-tested batteries of questions from the Panel Study of Income Dynamics, the National Longitudinal Survey, the National Survey of Families and Households, and other national surveys.

The analysis in this paper is based on the L.A.FANS child and sibling samples (RSCs plus SIBs). There are a total of 3,140 children in these two samples, which together provide a representative sample of children age 17 and younger in the County. For all sampled children, mothers provided extensive information on family life, socioeconomic status, and the child's history and current status. Children age 9 and older were also interviewed about school, behavior, and family relations.

Children age 3 and older completed the subtests of Woodcock-Johnson Revised (WJ-R) 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 Johnson, 1989; Woodcock and Mather, 1989). The following three tests were administered in L.A.FANS:

- (1) Letter-Word Identification;
- (2) Passage Comprehension; and
- (3) Applied Problems.

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. The Letter-Word Identification and Passage Comprehension tests can be combined to provide a broad measure of reading achievement.

In L.A.FANS, children ages 3 to 5 completed the Letter-Identification and Applied Problems assessments. Children ages 6 to 17 also completed the Passage Comprehension assessment. Primary caregivers completed only the Passage Comprehension assessment. Tests were administered in English or Spanish depending on language ability and preference of the respondent.

Raw scores were converted to standardized scores and percentile ranks based on the subject's age and a set of national norms (McGrew, Werder, and Woodcock, 1991). In cases where birth dates were missing (those missing birth dates were mostly PCGs), they were imputed based on the respondent's age. The standard scores have a mean of 100 and a standard deviation of 15. Percentile ranks indicate the percentage of subjects in the selected age segment of the norming sample who had the same or lower scores. Both standard scores and percentile ranks can be used for summaries and comparisons.

Table 1 presents the standardized scores and percentile rankings for each test for children and mothers. The fact that the means and standard deviations of children's scores are very close to the mean and standard deviation for the national norms (i.e., 100 and 15, respectively) shows that scores for children in the L.A.FANS sample differ very little, on average, from the national norms. By contrast, the mean for L.A.FANS' PCGs' scores is considerably below the national norm mean of 100, indicating that these mothers read more poorly than the average adult population, in part because of the high proportion of immigrant mothers interviewed in the L.A.FANS sample. The remaining analysis in this paper is based on the standardized scores rather than the percentile rankings.

Los Angeles County

The setting for this study is Los Angeles County, California. The total 2000 county population of about 9.5 million was 45% Latino, 31% white, 13% Asian-Pacific Islander, and 10% African American. Los Angeles is a major destination for immigrants: in 2000, about 30% of the population was foreign born. These figures, however, underestimate the size of migration streams since Los Angeles is an initial point of entry into California for both immigrants and for migrants from other states who subsequently move on to other counties (Frey, 1995). Recent immigration has dramatically changed many neighborhoods, as immigrants replace African

Americans and native-born Latinos in inner city areas, and the displaced former inner-city dwellers move into increasingly multi-ethnic communities elsewhere in the County (Frey and Farley, 1996; Clark, 1996). Residential segregation by ethnicity is not as extreme as in many mid-west and northeastern cities, but is, nonetheless, a major force in the social and political life of Los Angeles. Residential segregation by race and ethnicity declined only slightly in Los Angeles between 1990 and 2000 (Logan, 2002; Mare and Cort, 2003).

As described above, the L.A.FANS is based on a probability sample of *all* neighborhoods throughout Los Angeles County, with an oversample in poorer neighborhoods. The sample therefore includes an extremely diverse set of neighborhoods, varying from densely-populated central city areas to rural mountain and desert areas to the more suburban neighborhoods of the San Fernando Valley and along the ocean. Even “inner city” areas in Los Angeles reflect a more “suburban” style of development with lower density housing and no single central urban core. However, in some neighborhoods high-rise apartments are the norm.

Inequality and Socioeconomic Inequality in Children’s Achievement

What is the degree of socioeconomic inequality in children’s achievement scores in Los Angeles? And how much of the total variation in children’s achievement scores is accounted for by inequalities in achievement scores according to socioeconomic status? To answer these questions, we draw on two inequality measures: (1) Gini coefficients, to describe the overall degree of inequality in child achievement outcomes, and (2) concentration indices, to describe the degree of inequality in children’s scores associated with their families’ socioeconomic status. We also examine the graphical complements of these two measures, namely Lorenz curves and concentration curves.

Inequality in Test Scores

Our first step is to quantify inequality in children’s development using the Gini coefficient. Although this measure is more 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), as shown in Figure 1. If there were perfect equality in children’s test scores, then the Lorenz curve would lie along the diagonal. This would indicate, for example, that children who scored below the 50th percentile on the test together accounted for half of all correct answers (summed over all children, and assuming all questions were of uniform difficulty). The farther the Lorenz curve falls below the diagonal, the higher the degree of inequality. Often, however, a summary of the overall level of inequality is most useful, and the Gini coefficient provides this measure. The Gini coefficient is defined as two times the area between the diagonal and the Lorenz curve. It ranges between zero, which implies perfect equality, and one, which implies perfect inequality. For our purposes, the Gini coefficient is useful in that it provides a scale-free measure of the overall level of inequality in the population and, in particular, a standardized measure of the variance in test scores. Moreover, Gini coefficients are directly comparable with concentration indices, because they are both based on the same basic principles.

The Gini coefficients for standardized achievement scores are shown in the last column of Table 1. The Gini coefficients are very similar across the four standardized test scores for children. This is not surprising because the magnitude of the Gini coefficients is determined by the variance of the standardized achievement test scores. Because the variance of the standardized test scores is set to be 15, the Gini coefficient will be approximately the same for each test.

Socioeconomic Inequality in Test Scores

Next, we describe the degree of inequality in children's achievement by their family's socioeconomic status. To do so, we plot concentration curves, which are the bivariate extension of the Lorenz curve. A concentration curve plots the cumulative proportion of children ranked in ascending order by their measure of socioeconomic status (on the x -axis) against the cumulative proportion of the children's test scores (on the y -axis). In other words, instead of looking at the concentration of test scores according to distribution of test scores themselves (as for the Lorenz curve), the concentration curve shows the concentration of test scores according to the distribution of children by socioeconomic status. The farther the concentration curve lies below the diagonal, the more that inequalities in children's test scores favor children from families or neighborhoods of higher socioeconomic status. A close examination of the concentration curve also provides insights into the nature of inequality across the distribution of the socioeconomic status measure being examined. For instance, the point on the x -axis at which the concentration curve is furthest below the diagonal indicates the boundary between two groups in the population: one that has a smaller share of the outcome than their representation in the population and the other that has a larger share.

Panel A in Figure 2 shows both the Lorenz curve and the concentration curve by family earnings³ for children's standardized scores on the Passage Comprehension test. The shape of the two curves can be more easily seen in Panel B of Figure 2, where we plot the deviation of each curve from the diagonal (bottom two curves shown on the graph). Of primary interest in Figure 2 is the relationship between the area between the Lorenz curve and the diagonal, on one hand, the area between the concentration curve and the diagonal on the other hand. From Figure 2, it can be seen that the area associated with the concentration curve is approximately one-quarter of the area associated with the Lorenz curve. This indicates that about one-fourth of the total variation in children's standardized scores on the Passage Comprehension test is accounted for by systematic differences in these scores according to family income. The remaining inequality in test scores—which represents three-quarters of total inequality in scores and corresponds to the area between the Lorenz curve and the concentration curve—is accounted for by child and family characteristics unrelated to family income.

We are interested in examining the relationship between children's standardized test scores and two other measures of socioeconomic status: the PCG's (mother's) educational attainment in years and the median family income in the neighborhood (tract). We are also interested in examining inequality in children's scores by the PCGs' Passage Comprehension

³ Total family income from all sources (including, for example, government transfers and earnings on assets) is a better measure of overall economic status. We are in the process of creating family income variables from L.A.FANS-1 and we will use them in subsequent versions of this analysis.

score, which provides a measure of family background and hence insights into the intergenerational transmission of inequality in scholastic achievement. To undertake a more systematic analysis that includes, for example, the calculation of standard errors, we shift to using the concentration index, which is the bivariate analog of the Gini coefficient. The concentration index is defined as twice the area between the concentration curve and the diagonal. The concentration index is calculated as follows (see Kakwani, Wagstaff, and van Doorslaer, 1997):

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

where x_i is the standardized test score for the i th child, $R_i = (2i-1)/2n$ is the relative rank for the i th child, and \bar{x} is the mean of the standardized test score. The variance for the concentration index (which takes into account serial correlation in the data) is calculated as

$$\hat{V}ar(C) = \frac{1}{n} \left[\frac{1}{n} \sum_{t=1}^n a_t^2 - (1+C)^2 \right],$$

where

$$a_t = \frac{x_t}{\bar{x}} (2R_t - 1 - C) + 2 - q_t - q_{t-1}$$

and

$$q_t = \sum_{j=1}^t x_j / \sum_{j=1}^n x_j .$$

Table 3 shows the mean and standard deviation for family earning, maternal education, maternal reading scores, and neighborhood-level household income for the L.A.FANS sample. We also include the Gini coefficient for family earnings in the L.A.FANS sample, which corresponds closely to the equivalent measure for the entire country published by the U.S. Census Bureau.

In Table 3, we present the concentration index for each type of achievement test and each of the four independent variables. We also present a more intuitive set of measure of socioeconomic inequality in test scores to help readers interpret the magnitudes of the concentration index. In particular, we show mean standardized test scores by quintile of each of the independent variables: family earnings, mother's years of schooling, mother's Passage Comprehension score, and neighborhood median income. We also show the ratio of the mean for the top quintile to the bottom quintile. For example, the first row of the table shows that children from the top one-fifth of the income distribution have Passage comprehension test scores that are on average 1.11 times higher than children from the bottom one-fifth of the income distribution. Note that the concentration index provides a better measure of

socioeconomic inequality in test scores because, in contrast to the ratio of scores for the top to bottom quintiles, scores across the full range of the distribution are used in the calculation of the concentration index. Nevertheless, when comparing the independent variables, the ranking of socioeconomic inequality in test scores based on the ratio of average test scores for the top to bottom quintiles provides the same ordering as that based on the concentration index. For instance, based on both the top-quintile to bottom-quintile ratio and the concentration index, socioeconomic inequalities in Passage Comprehension test scores are highest based on the mother's test score, followed by mother's years of schooling, tract median family income, and, lastly, family earnings. For the two reading tests (Passage Comprehension and Letter Word Identification) and for the Broad reading score, both the ratios and the concentration indices are highest for maternal reading scores, indicating that children's reading ability is most strongly associated with maternal reading ability. In the case of Applied Problems, the greatest inequality in children's test scores is associated with mother's educational attainment.

For both Applied Problems and Letter Word Identification, the inequality in scores associated with neighborhood level median income is higher than the inequality associated with family earnings, suggesting that living in a low income neighborhood has a greater effect on inequality in test scores than coming from a low income family.

Decomposing Socioeconomic Inequality in Children's Achievement

Our analysis has shown that achievement scores are unequally distributed by family earning, maternal education, maternal reading scores, and neighborhood income. However, these variables are interrelated and are also associated with other child, family, and neighborhood characteristics. To estimate inequalities in achievement scores for each socioeconomic status measure that are net of other factors, we undertake a decomposition analysis. This analysis decomposes socioeconomic inequalities in test scores into two components. One component is due to other characteristics of the child that are related to the socioeconomic measure in question but are more strongly associated with the particular achievement score. For example, part of the effect of family earnings on achievement scores is likely due to the fact that higher levels of education for mothers is associated with both higher test scores for children and higher family earnings. The second component is the net level of socioeconomic inequality in achievement scores, which is of considerable interest from both a research and policy perspective. This measure indicates the extent to which a change in inequality in a single factor—such as family earnings—is likely to affect inequalities in child development when all other factors (e.g., mother's years of schooling) are unchanged.

To determine the effect of each variable, we estimate multilevel models for each of the children's test scores. These models incorporate a family-level random effect to control for the correlation in test scores among the siblings in the sample. The random effects model also provides a measure of unobserved family factors in addition to corrected standard error estimates. Next, we obtain predicted values for test scores based on these models. These predicted values hold other socioeconomic and demographic factors constant at their sample-wide means while allowing the socioeconomic status measure of interest to retain its actual values. We use these predicted values to calculate the *net* concentration index for each socioeconomic status measure. We then compare the net index to the gross index (from Table

3). This comparison of the gross and net concentration index values provides an indication of the extent to which, for each socioeconomic status indicator, inequalities in child development are independent of other factors.

Panel B of Figure 2 shows the overall results for the Passage Comprehension test; the curve labeled “adjusted concentration curve” indicates the shape and size of the curve adjusted for all the variables in the model.⁴ As is apparent from the graph, holding constant all variables in the model substantially reduces the area above the adjusted concentration curve compared with the unadjusted curve. This indicates that there is little net inequality in children’s Passage Comprehension scores according to family earnings.

The full set of results for all achievement tests are shown in Table 4. The top line of the table shows the Gini coefficient for each achievement score while the panel below this shows the values of the concentration index. The ratio of the concentration index to the Gini coefficient provides a measure of the percent of total variation in the particular achievement score that is explained through socioeconomic inequalities. The results show, for example, that inequality in family earnings accounts for 20-30% percent of the total variation in achievement scores: inequality in family earnings accounts for 24 percent of the total variation in the Passage Comprehension score, 20 percent of the Letter-Word Identification score, 25 percent of the Broad Reading score, and 30 percent of the Applied Problems score. The mother’s Passage Comprehension score accounts for the highest proportion of the total variation in achievement scores: approximately one-third of the inequality in broad reading and mathematics reasoning is accounted for by the mother’s reading skills.

The subsequent panel in Table 4 shows the adjusted concentration index values, which represent the net levels of socioeconomic inequality in achievement scores after controlling for all other factors (child, family, and neighborhood background characteristics, including the other measures of socioeconomic status). Below this we present the net percent of total variation in achievement scores explained by each measure of socioeconomic status, which is obtained by dividing the Gini coefficient by the net or “adjusted” concentration index. A comparison of the gross and net concentration indices is presented in the last panel of the table, which shows the proportion of the gross inequality in achievement scores according to each socioeconomic status measure that are not accounted for by other factors.

The results show that effects of family earnings and mother’s years of schooling are reduced substantially when other variables are held constant. For example, for the Passage Comprehension test, variation in family earnings explains 24 percent of the total variation in test scores; after controlling for all other variables, only three percent of the total variation is explained by family earnings. The bottom panel shows that family earnings retain only 14 percent of their gross explanatory power after we adjust for other factors. On the other hand, the effects of the mother’s Passage Comprehension score and, to a lesser extent, tract median family income continue to explain a sizeable portion of the total variation in achievement scores even after controlling for other variables. Maternal reading scores account for 23-27 percent of the variation in child reading achievement, though they account for a lower percentage (16 percent) of the child’s Applied Problems score. Interestingly, neighborhood median family income

⁴ The full list of variables held constant in the model is shown in Tables 6 and 7.

accounts for a larger portion of the variation in each test than family earnings does, both before and after controlling for other factors. For Applied Problems, the maternal reading score and tract median income account for 16-17% of the variation. In all cases, the maternal reading score also accounts for more of the net variation than maternal educational attainment.

Thus, a substantial portion of the socioeconomic inequality in children's achievement is related to maternal reading ability. These results suggest that programs seeking to improve children's academic performance are likely to have a greater effect if they focus on improvements in parents' literacy (and perhaps numeracy, which we do not measure) in poor families and neighborhoods. They also point to the presence of strong intergenerational effects, to the extent that mother's reading scores are likely to have been shaped during her childhood (and her own mother's scores).

Child, Family and Neighborhood-level Determinants of Children's Achievement

The final part of our analysis examines the consequences of living in concentrated poverty vs. concentrated affluence neighborhoods on children's achievement scores. We employ the results of the statistical models used to carry out the decomposition described above to examine the relative importance of neighborhood poverty and affluence, other neighborhood characteristics, and family and child characteristics on children's achievement.

The distributions of independent variables included in the models are shown in Table 5. Child characteristics included in the model are the child's age, sex, language the test was taken in, race/ethnicity, and birthweight. On average, children in our analysis sample are 9.7 years old and about equally male and female. Four out of five children took the test in English and the remainder in Spanish. The majority of children were Latino, in part because of the L.A.FANS oversample of very poor and poor neighborhoods.⁵ The average birthweight was 3.4 kilograms.

Family-level characteristics include the mother's immigration status, household composition, the mother's Passage Comprehension test score, number of years of schooling of the mother, the log of family earnings, and the number of children in the household. The majority of children's mothers are immigrants, with most having immigrated to the United States before 1990. Almost three-quarters of L.A.FANS children were living with two parents at the time of interview. Mothers had an average score of 85 on the Passage Comprehension test (one standard deviation below the population mean) and completed 11.5 years of education. On average, there were 2.2 children per household.

We include three neighborhood-level characteristics reflecting neighborhood compositional characteristics shown by previous research to be related to children's development: tract level median family income, immigrant concentration, and residential stability. The latter two measures are indices, constructed based on factor analyses of a set of tract measures that were highly correlated with each other. The immigrant concentration index included measures from the 2000 census on the percent of the population that was foreign born, non-citizens, Spanish-speakers, and of Latino ethnicity. The residential stability index incorporated the following measures: percent of dwellings in multiple-unit structures, percent of

⁵ These results are unweighted. Future versions of this paper will use weights to correct for the oversamples.

households that were owner-occupied, percent of households that were non-family, and the percent of households that did not move in between 1995 and 2000. The average median tract income was \$44,000. On average, L.A.FANS tracts included approximately 10% immigrants (i.e., non-native born neighborhood residents). Approximately 10% of the residents in these neighborhoods, on average, had moved into their current dwelling within the past five years.

Table 7 shows the results of separate multilevel models estimated for each test score. Each model includes a family level random effect.⁶ The random effect provides an indication of the proportion of variation in children's test scores which is due to unobserved family level characteristics shared between the siblings included in the analysis. Therefore, it allows us to investigate the effects of neighborhood-level variables net of measured and unmeasured family characteristics. The random effect also produces corrected standard errors. At the bottom of the Table 7, we present the estimated variance of the family random effect and show the proportion of total variance due to unobserved family effects (i.e., family effects other than those included in the model). The estimates indicate that between 21 and 32 percent of the variance in children's test scores is due to unobserved family effects.

The results for the reading tests indicate that a child's age, sex, race/ethnicity, and the language the test was taken in are significantly related to reading test scores. It is important to keep in mind that the standardized scores are normed by age to permit comparisons of scores across age groups. Moreover the Spanish and English versions of each test are designed to produce comparable scores for the same skills level, regardless of the language the test is taken in; however, different versions of the test were administered in Spanish and English. Nonetheless, age is significantly and negatively related to Passage Comprehension scores, although not to the Letter Word Identification scores. This result suggests that older children score more poorly on some aspects of reading than younger children. Girls score significantly better than boys on both reading tests. Latinos and African Americans received lower scores than whites on both reading tests, although the coefficient for blacks on the Letter Word Identification test was not significant. Asians scored better than whites on both tests, although only the Passage Comprehension coefficient is statistically significant. The language that the test was taken in was also significantly related to reading scores. Surprisingly, children taking the test in Spanish scores significantly lower on the Passage Comprehension test and significantly better on the Letter Word Identification test. Birthweight was unrelated to reading test scores.

Among family characteristics, immigration status is not significantly related to passage comprehension but is significantly and positively related to Letter Word Identification. *Ceteris paribus*, children of immigrant parents do substantially better on the Letter Word Identification tests than children of native-born parents. Moreover, children of recent immigrants have the highest scores on this test. Living with both parents positively affects reading score, although only the Passage Comprehension coefficient is significant. The PCG's reading test score is highly significantly and positively related to her children's reading scores. For each point increase in the mother's score, the child's score increases by one quarter of a point. Mother's educational attainment is also strongly and positively associated with reading scores. An additional year of education is associated with an increase in the child's score by about one-third of a point. Family earnings are positively related to reading scores, with the effect significant for

⁶ The next version of this paper will incorporate both family and neighborhood random effects.

all outcomes except the Passage Comprehension score. The number of children in the household has a marginal and negative effect on reading scores.

Two neighborhood characteristics have significant effects on reading scores. Median family income is strongly and positively associated with reading scores—the effect is considerably stronger than family earnings. Residential stability is negatively related to all achievement scores except Letter-Word Identification. Although researchers have hypothesized that residential stability should have beneficial effects on children’s outcomes by promoting a positive neighborhood social environment for children, empirical results have shown that low rates of mobility may be indicative of neighborhood problems (Duncan and Aber, 1997; Corbin and Coulton, 1997). Contrary to expectation, immigrant concentration is unrelated to reading scores.

Results for math scores (i.e., the Applied Problems test) are largely the same, with a few important differences which are outlined here. First, there is no significant difference in math scores by sex. Second, parental immigrant status appears to confer no advantage compared to children of native-born parents in terms of math scores. Third, while birthweight makes no difference for reading scores, it is significantly and positively associated with math scores. The log of family earnings is significantly and positively associated with math scores, but the number of children in the household is not significantly related.

In summary, these results show that child and family socioeconomic and demographic characteristics are strongly associated with children’s achievement. We also show that, even controlling for observed and unobserved family effects, tests scores vary considerably by neighborhood characteristics. Higher tract-level median income is consistently significantly related to higher tests scores.

Concentrated Poverty, Concentrated Affluence, vs. Median Income

In this final section of the analysis, we return to the issue of whether concentrated poverty or concentrated affluence neighborhoods have an effect on children’s development beyond that of tract median family income. Both concentrated poverty and concentrated affluence can be defined in many ways. We have chosen two strategies. First, we examine the effects of the percent of families that have very low income (annual family income less than or equal to \$24,000) and the percent of families that have high incomes (annual family income of \$75,000 or more). We define these variables for each of the L.A.FANS census tracts using Census 2000 data. Second, we replicate analyses conducted by Duncan and Aber (1997) and Sampson et al. (1997) which involve factor analysis of a number of socioeconomic variables measured at the census tract level using the 2000 census data. The factor analysis yielded two factors which we label concentrated disadvantage and concentrated affluence. The concentrated disadvantage index included the proportion of families that were female-headed and that had incomes less than or equal to \$24,000, and the percent of the population: below the poverty line, that were non-white and non-Asian, that were under 18 years, and that were welfare recipients. The

concentrated affluence factor included the proportion of families with annual income of \$75,000 or above, and the percent of the population that were English speakers and that were white.⁷

In Table 7, we investigate the effects of these two sets of variables on each achievement test. Only the results for neighborhood-level variables are presented, although each model includes the child and family level characteristics shown in Table 6 and 7 and a family random effect. This is because including the additional neighborhood measures altered the basic results for these other variables very little. We also compare the effects of each set of neighborhood poverty and affluence variables to a model which includes only neighborhood-level median family income. As shown in Table 6, median family income is strongly and significantly related to test scores.

The first column in Table 7 replicates the neighborhood-level results shown in Table 6 for each test. In the second column, we add the percent low income (less than \$24,000) and percent high income (\$75,000 or more) to the model including median income. Neither coefficient is statistically significant, except for the high income coefficient for Broad Reading (which is a combination of the other two reading tests). Perhaps surprisingly, with median income in the model, children in neighborhoods with a higher proportion of high income families score *lower* on reading than other children. Model III, however, shows that if median income is omitted, we essentially reproduce the Brooks-Gunn et al. (1997) and Sampson et al. (1997) results that the percentage of affluent neighborhoods is significantly and positively associated with children's outcomes.

Models IV and V investigate the effects of the two factor analysis-based indices of neighborhood disadvantage and affluence. In Model IV in which median income is included, the coefficients on these two indices are not statistically significant, except for math scores where the affluence index is positively and significantly related. When we omit median income in model V, we again see that the coefficient on the affluence index becomes positive and statistically significant for each test.

Earlier analyses that examined the role of concentrated poverty and affluence generally do not report results on median income. In other words, they examine the effects only of the tails of the income distribution and not the average level. To determine whether the overall income level captures more or less of the variation in children's achievement than the concentration of poor or affluent neighbors, we can compare the joint Chi-squared tests shown for each panel in the table. A comparison of Models I and III and Models I and V shows that in the case of each test, the model with median income fits the data better than the models including only the tails of the distribution. These results suggest that the most important effect of neighborhood income levels on children's achievement may be overall income level rather than the frequency of very poor or affluent neighbors.

⁷ The next version of the paper will incorporate additional indicators of concentrated affluence that were unavailable in time for the present analysis, including the percent of the population with white collar jobs and with a college education.

Discussion and Conclusion

In this paper, we have examined the levels and covariates of inequality in one set of measures of children's development: scores on standardized reading and math tests. Our results show:

- Children's test scores in Los Angeles are comparable to those in national samples, although their mothers' scores are, on average, substantially lower than the norm;
- Higher children's test scores are concentrated among children in more affluent families; a substantial proportion of this concentration is due to higher maternal reading levels and educational attainment and to the fact that these children live in more affluent neighborhoods;
- There are substantial differences in children's test scores by age, sex (in the case of reading) and race/ethnicity, even when family income, language of the test, and immigrant status is held constant;
- Maternal education and test scores are strong predictors of children's performance even when other family characteristics are held constant;
- Neighborhood level median income is an important predictor of children's achievement, even when observable and unobservable family characteristics are held constant;
- Neighborhood level median income appears to account for more of the variation in children's achievement than the concentrated poverty and concentrated affluence measures that are the focus of earlier research.

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Table 1. Summary Statistics for Achievement Tests in L.A.FANS

Measure	Mean	Std. dev.	Observations	Gini coef. (SE)
Children				
Passage Comprehension				
Standard score	98.2	17.5	1,942	0.0967 (0.0019)
Percentile rank	45.8	29.9	1,942	
Letter Word Identification				
Standard score	102.4	18.4	2,449	0.0972 (0.0015)
Percentile rank	52.9	30.0	2,449	
Broad Reading				
Standard score	100.5	17.5	1,941	0.0955 (0.0020)
Percentile rank	52.5	30.0	1,941	
Applied Problems				
Standard score	101.8	17.5	2,435	0.0935 (0.0019)
Percentile rank	52.5	30.1	2,435	
Mothers				
Passage Comprehension				
Standard score	84.9	18.2	1,475	0.1160 (0.0024)
Percentile rank	24.4	26.8	1,475	

Table 2. Summary Statistics for Socioeconomic Status Measures in L.A.FANS

Measure	Mean	Std. Dev.	Observations	Gini Coefficient (SE)
Family earnings	\$41,086	\$76,036	1,487	0.5540 (0.0163)
Mother's years of schooling	11.5	4.5	1,516	
Tract median family Income	\$44,646	\$26,740	1,544	
Tract percent not in poverty	73%	17%	1,544	

Table 3. Mean Achievement Test Scores by Quintiles of Independent Variables and Concentration Indices of Test Scores and Independent Variables in L.A.FANS

Variable	Quintiles					Ratio 5:1	Concentration Index	Sample size
	1	2	3	4	5			
Children								
Passage Comprehension								
Family earnings	95.7	94.1	95.7	99.3	106.5	1.11	0.0235 (0.0025)	1,869
Tract median family inc.	92.9	94.7	95.0	99.4	109.1	1.17	0.0304 (0.0023)	1,942
Mother's PC score	89.9	96.6	96.9	99.6	109.4	1.22	0.0362 (0.0024)	1,868
Mother's years of school	90.7	95.9	100.5	99.1	109.8	1.21	0.0357 (0.0022)	1,904
Letter Word Identification								
Family earnings	100.9	100.9	101.7	102.8	108.9	1.11	0.0192 (0.0021)	2,360
Tract median family inc.	99.2	100.1	100.6	101.9	110.9	1.12	0.0193 (0.0021)	2,449
Mother's PC score	96.4	100.9	102.1	103.7	110.4	1.15	0.0248 (0.0021)	2,362
Mother's years of school	99.1	99.3	102.6	103.3	111.6	1.13	0.0229 (0.0021)	2,407
Broad Reading								
Family earnings	96.6	97.3	98.8	101.6	108.2	1.12	0.0234 (0.0023)	1,868
Tract median family inc.	95.8	97.3	97.9	100.6	110.8	1.16	0.0269 (0.0023)	1,941
Mother's PC score	92.7	98.4	99.4	101.8	111.1	1.20	0.0335 (0.0023)	1,867
Mother's years of school	94.9	97.4	101.4	101.3	111.7	1.18	0.0310 (0.0023)	1,903
Applied Problems								
Family earnings	97.3	97.4	99.4	102.8	112.0	1.15	0.0283 (0.0021)	2,346
Tract median family inc.	96.1	98.4	98.8	102.7	113.7	1.18	0.0314 (0.0020)	2,435
Mother's PC score	94.8	99.6	100.6	103.6	112.1	1.18	0.0313 (0.0020)	2,348
Mother's years of school	95.1	99.1	104.2	101.8	114.0	1.20	0.0322 (0.0020)	2,393
Mothers								
Passage Comprehension								
Family earnings	81.6	79.0	80.3	85.9	99.2	1.22	0.0412 (0.0035)	1,444
Tract median family inc.	77.1	78.3	80.9	89.2	100.9	1.31	0.0560 (0.0031)	1,475

Table 4. Decomposition of Inequality in Scholastic Achievement in L.A.FANS

	Passage Comprehension		Letter Word Identification		Broad Reading		Applied Problems	
Gini coefficient	0.0967	(0.0018)	0.0975	(0.0016)	0.0955	(0.0017)	0.0946	(0.0015)
Concentration Index								
Family earnings	0.0235	(0.0025)	0.0192	(0.0021)	0.0234	(0.0023)	0.0283	(0.0021)
Tract median family inc.	0.0304	(0.0023)	0.0193	(0.0021)	0.0269	(0.0023)	0.0314	(0.0020)
Mother's PC score	0.0362	(0.0024)	0.0248	(0.0021)	0.0335	(0.0023)	0.0313	(0.0020)
Mother's years of school	0.0357	(0.0022)	0.0229	(0.0021)	0.0310	(0.0023)	0.0322	(0.0020)
Gross pct. of total variation explained through CI by:								
Family earnings	24%		20%		25%		30%	
Tract median family inc.	31		20		28		33	
Mother's PC score	37		25		35		33	
Mother's years of school	37		23		32		34	
Adjusted Conc. Index								
Family earnings	0.0032 ^{NS1}	(0.0025)	0.0063	(0.0020)	0.0052	(0.0023)	0.0076	(0.0021)
Tract median family inc.	0.0102	(0.0023)	0.0125	(0.0021)	0.0135	(0.0022)	0.0162	(0.0019)
Mother's PC score	0.0230	(0.0023)	0.0220 ^{NS2}	(0.0021)	0.0256	(0.0023)	0.0148	(0.0020)
Mother's years of school	0.0098	(0.0022)	0.0082	(0.0021)	0.0095	(0.0023)	0.0074	(0.0019)
Net pct. of total variation explained through adjusted CI by:								
Family earnings	3%		6%		5%		8%	
Tract median family inc.	11		13		14		17	
Mother's PC score	24		23		27		16	
Mother's years of school	10		8		10		8	
(Adjusted CI) / CI								
Family earnings	14%		33%		22%		27%	
Tract median family inc.	34		65		50		52	
Mother's PC score	64		89		76		47	
Mother's years of school	27		36		31		23	

Notes: NS1 = not significantly different from zero.

NS2 = not significantly different from concentration index.

Table 5. Summary Statistics for Analysis Sample

Variable	Mean (std. dev) or percent
Child age (years)	9.69 (4.23)
Child sex	
Male	51%
Female	49
Race	
Latino	63%
Black	9
White	19
Asian	7
Other	2
Immigration status	
Native	37%
Pre-1990 immigrant	41
Post-1990 immigrant	22
Living arrangements	
One or neither parents	28%
Both parents	72
Language of test	
English	82%
Spanish	18
Birthweight (kilograms)	3.39 (0.62)
PCG's PC test std. score	84.55 (18.31)
Mother's education (years)	11.49 (4.36)
Log family earnings	8.48 (3.76)
Number of children in HH	2.22 (1.09)
Tract median family inc. (\$10,000)	4.40 (2.63)
Immigrant concentration	0.01 (0.97)
Residential stability	0.01 (0.97)
Observations	2,307

Table 6. Regression Results Based on Linear Model with Family-Level Random Effect

	Passage Comprehension		Letter Word Identification		Applied Problems		Broad Reading	
Child age (years)	-1.38***	(0.10)	-0.12	(0.09)	-0.21***	(0.08)	-1.03***	(0.10)
Child sex								
Male ^[a]								
Female	1.82***	(0.68)	2.65***	(0.69)	-0.07	(0.63)	2.18***	(0.69)
Child Race								
Latino	-3.60***	(1.25)	-3.18**	(1.24)	-3.24***	(1.18)	-4.04***	(1.24)
Black	-3.70**	(1.57)	-1.69	(1.59)	-3.61**	(1.50)	-3.55**	(1.56)
White ^[a]								
Asian	2.15	(1.70)	3.59**	(1.72)	4.13**	(1.63)	2.07	(1.68)
Other	-2.65	(2.79)	0.95	(2.86)	0.60	(2.71)	-0.55	(2.76)
Immigration status								
Native ^[a]								
Pre-1990 immigrant	0.65	(1.14)	3.62***	(1.13)	0.61	(1.06)	2.86**	(1.13)
Post-1990 immigrant	0.99	(1.35)	5.67***	(1.31)	1.36	(1.24)	3.98***	(1.34)
Living arrangements								
One or neither parents ^[a]								
Both parents	2.18***	(0.83)	1.14	(0.85)	2.17***	(0.78)	2.06**	(0.84)
Language of test								
English ^[a]								
Spanish	-4.53***	(1.21)	7.93***	(1.09)	-6.03***	(1.02)	5.74***	(1.21)
Birthweight (kilograms)	0.75	(0.57)	0.47	(0.58)	1.06**	(0.54)	0.54	(0.58)
PCG's PC test std. score	0.23***	(0.03)	0.23***	(0.03)	0.15***	(0.03)	0.26***	(0.03)
Mother's education (years)	0.39***	(0.11)	0.34***	(0.11)	0.31***	(0.10)	0.38***	(0.11)
Log family earnings	0.17	(0.11)	0.37***	(0.10)	0.42***	(0.10)	0.30***	(0.10)
Number of children in HH	-0.68*	(0.37)	-0.17	(0.36)	-0.29	(0.34)	-0.57	(0.36)
Tract median family inc.	0.74***	(0.25)	0.97***	(0.25)	1.24***	(0.24)	1.02***	(0.25)
Immigrant concentration	-0.37	(0.70)	0.66	(0.70)	0.55	(0.66)	0.18	(0.69)
Residential stability	-1.46***	(0.48)	-0.74	(0.47)	-1.44***	(0.45)	-1.18**	(0.48)
Constant	84.39***	(3.76)	66.46***	(3.69)	76.55***	(3.49)	75.26***	(3.76)
Family random effect var.	71.54***		59.99***		68.96***		57.26***	
Fraction of variance due to unobserved family effects	0.32		0.21		0.28		0.26	
Adjusted R-squared	0.29		0.16		0.22		0.26	
Model Chi-squared (df)	650.82*** (18)		384.21*** (18)		541.76*** (18)		576.41*** (18)	
Observations	1,826		2,307		2,293		1,825	

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

Source: Authors' calculations using data from the 2000-01 L.A.FANS Wave 1.

Notes: [a] Reference category.

Table 7. Results from Alternative Specifications of Tract-Level Variables

Outcome	Variable	Model I	Model II	Model III	Model IV	Model V
Passage Comprehension	Tract median family inc.	0.74*** (0.25)	1.78*** (0.69)	.	0.60 (0.47)	.
	Immigrant concentration	-0.37 (0.70)	-0.99 (0.84)	-0.48 (0.82)	0.46 (1.55)	1.64 (1.24)
	Residential stability	-1.46*** (0.48)	-1.65*** (0.52)	-1.28 (0.50)	-1.27** (0.58)	-0.87* (0.49)
	Pct. family inc. < \$24,000	.	0.16 (0.92)	0.10 (0.92)	.	.
	Pct. family inc. > \$75,000	.	-3.09 (2.02)	1.62* (0.86)	.	.
	Concentrated disadvantage	.	.	.	0.73 (0.86)	0.41 (0.83)
	Concentrated affluence	.	.	.	1.79 (2.25)	3.95*** (1.48)
	Joint Chi-squared test (df)	18.26*** (3)	20.86*** (5)	14.19*** (4)	19.45*** (5)	17.81*** (4)
Letter Word Identification	Tract median family inc.	0.97*** (0.25)	1.43** (0.68)	.	1.20** (0.47)	.
	Immigrant concentration	0.66 (0.70)	0.44 (0.84)	0.83 (0.82)	0.08 (1.54)	2.45** (1.23)
	Residential stability	-0.74 (0.47)	-0.85* (0.51)	-0.56 (0.49)	-0.89 (0.58)	-0.11 (0.49)
	Pct. family inc. < \$24,000	.	-0.09 (0.92)	-0.16 (0.92)	.	.
	Pct. family inc. > \$75,000	.	-1.45 (1.99)	2.31*** (0.86)	.	.
	Concentrated disadvantage	.	.	.	0.61 (0.86)	-0.02 (0.82)
	Concentrated affluence	.	.	.	-0.57 (2.26)	3.77** (1.48)
	Joint Chi-squared test (df)	17.47*** (3)	17.99*** (5)	13.58*** (4)	18.07*** (5)	11.61** (4)
Applied Problems	Tract median family inc.	1.24*** (0.24)	1.37** (0.65)	.	0.48 (0.45)	.
	Immigrant concentration	0.55 (0.66)	0.54 (0.80)	0.91 (0.78)	3.33** (1.46)	4.28*** (1.16)
	Residential stability	-1.44*** (0.45)	-1.49*** (0.48)	-1.22*** (0.46)	-0.78 (0.54)	-0.47 (0.46)
	Pct. family inc. < \$24,000	.	-0.19 (0.87)	-0.25 (0.87)	.	.
	Pct. family inc. > \$75,000	.	-0.51 (1.88)	3.09*** (0.81)	.	.
	Concentrated disadvantage	.	.	.	0.12 (0.81)	-0.14 (0.77)
	Concentrated affluence	.	.	.	4.63** (2.14)	6.37*** (1.39)
	Joint Chi-squared test (df)	35.83*** (3)	35.88*** (5)	31.33*** (4)	40.60*** (5)	39.43*** (4)
Broad Reading	Tract median family inc.	1.02*** (0.25)	2.17*** (0.69)	.	1.14** (0.47)	.
	Immigrant concentration	0.18 (0.69)	-0.40 (0.84)	0.23 (0.82)	0.04 (1.54)	2.29* (1.23)
	Residential stability	-1.18** (0.48)	-1.44*** (0.51)	-0.99** (0.49)	-1.22** (0.58)	-0.47 (0.49)
	Pct. family inc. < \$24,000	.	-0.16 (0.92)	-0.24 (0.92)	.	.
	Pct. family inc. > \$75,000	.	-3.62* (2.01)	2.14** (0.86)	.	.
	Concentrated disadvantage	.	.	.	0.71 (0.86)	0.10 (0.82)
	Concentrated affluence	.	.	.	0.19 (2.24)	4.32*** (1.47)
	Joint Chi-squared test (df)	23.70*** (3)	27.01*** (5)	16.87*** (4)	24.35*** (5)	18.32*** (4)

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

Source: Authors' calculations using data from the 2000-01 L.A.FANS Wave 1.

Figure 1. Illustration of a Lorenz Curve and Gini Coefficients

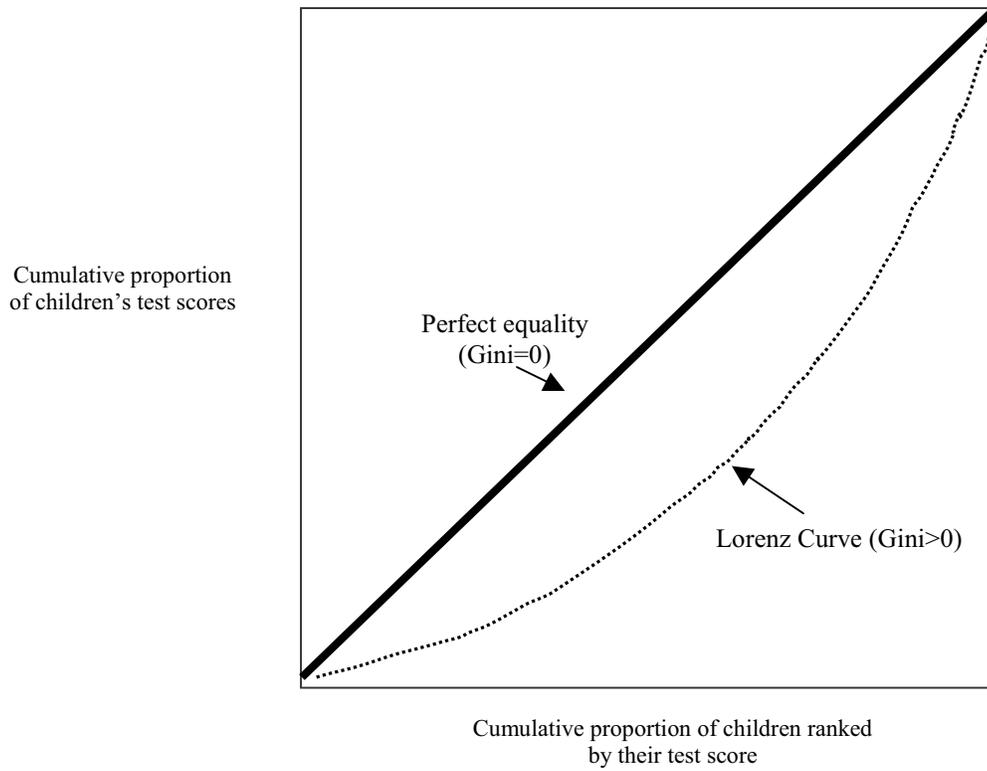
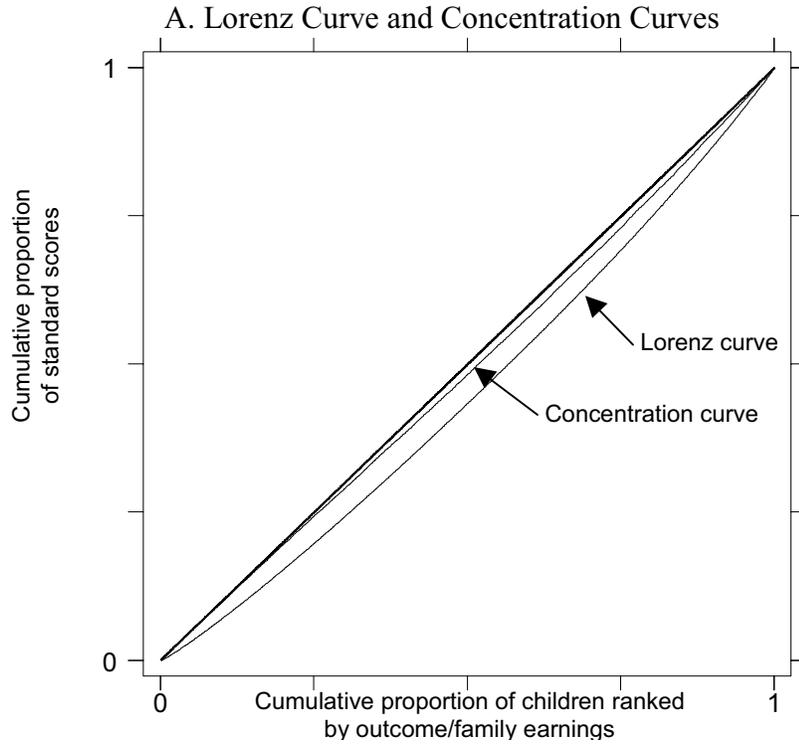


Figure 2. Graphical Decomposition of Inequality in Passage Comprehension Standard Score by Family Earnings



B. Deviations of Lorenz Curve and Concentration Curves from diagonal

