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# SCHOOL POVERTY CONCENTRATION AND KINDERGARTEN STUDENTS' NUMERICAL SKILLS

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# School Poverty Concentration and Kindergarten Students' Numerical Skills

## Introduction

Schools that enroll disproportionately high percentages of pupils from low-income families are widely believed to have negative consequences for student performance. Prior research has investigated the relationship of school poverty and outcomes in numerous ways, but the basic proposition is that school composition affects student learning, such that otherwise similar students realize different levels of achievement in schools with different proportions of low-income students (Coleman, et al. 1966; Jencks, et al., 1972; Gamoran, 1987; Hoffer, 1997).

This chapter updates and extends the research on compositional effects in several respects. First, past research using national samples has been largely confined to the middle and high school grades (Jencks and Brown, 1975; Hauser, Sewell, and Alwin,1976; Gamoran, 1987; Hoffer 1997), and we extend that research to the early elementary level of schooling. This is a useful extension in light of the large achievement differences normally found between economically-advantaged and –disadvantaged children at the beginning of secondary schooling. Shifting the focus to the beginning of formal schooling facilitates a more complete picture of when the learning gaps arise, and thus the factors most likely to contribute to them.

Second, previous research has not empirically examined how the specific organizational features of high-poverty schools directly affect learning outcomes. Researchers have emphasized the importance of school composition for student preparation and family support for education, extent of school resources, levels of teacher experience and background, and school and classroom normative climates. But the data needed to assess the relative importance of individual and school factors have not been available and the mechanisms that mediate the school-level effect independent of student background factors are thus not clear. In contrast, this chapter draws upon nationally representative data on kindergarten pupils and the schools they attend to estimate both the overall impact of school poverty on mathematics achievement and its impact on a variety of other school and schooling-experience variables that may in turn affect student learning.

Using multilevel statistical models, the analysis in this chapter proceeds by first estimating the effects of attending high-poverty versus low-poverty schools on student gains in mathematics from fall to spring during the kindergarten year. These analyses control for an array of individual background factors related to achievement gains, and also control for other school-level characteristics that might otherwise be confounded with effects of school poverty. Finally, we analyze the effects of high poverty schools on several schooling variables hypothesized to affect student achievement. These include classroom instructional variables as reported by the teachers, as well as program length, class enrollment size, teacher credentials, and teacher expectations, as well as social capital resources reported by the parents of the kindergartners.

## Policy Issues Related to High Poverty Schools

Education policy is often based on prior assumptions about the importance of specific educational outcomes, the factors that affect those outcomes, and the best means available to influence those causal factors. The concentration of poor children in public schools is significant to education policy both as a factor presumed to affect outcomes and as a marker for allocating differential financial resources such as Title I funding. As an independent causal factor, school composition is believed to influence school staffing and functioning, and student attitudes and orientations toward schools. In contrast, some policies may eschew any claim about the causal status of school composition, but may still direct special resources to schools based on their socioeconomic composition.

An example of a policy explicitly based on the assumption of the causal importance of school socioeconomic composition is the effort by some localities to desegregate schools in terms of SES factors (Kahlenberg, 2001; Plank, 1996). These policies are difficult to reconcile with widespread residential segregation along the lines of income, and generally have been met with strong resistance from some parents when tried or proposed.

Policies directed at reducing inequalities in outcomes between children from higher and lower income families may also target high-poverty schools, but without any assumption that the school composition is an important variable in its own right. The original premise of the largest Federal compensatory aid program, Title I, is that poor children performing below grade level need additional school-based resources in order to overcome the background disadvantages caused by household poverty. Currently, however, Title I funding is directed not to individual students, but instead to their schools. Prior to the 1994 reauthorization of the Elementary and Secondary Schools Act, schools mainly used Title

I (then called Chapter I) to fund special programs for low-income pupils. This requirement generated an often complex structure of “pull-out” programs with special staff and administrative procedures, and critics contended that these special services created an administrative burden for schools and stigmatized poor students, leading to lower expectations for their success among teachers and administrators. (See Borman, Stringfield, and Slavin, 2001, for background papers on Title I.)

In response to these problems, Title I was restructured in the 1994 reauthorization so that more of the funds would be directed to “school-wide” programs in schools with high concentrations of poverty students. The legislation gives broad latitude to acceptable school-wide programs, but does specify that they must be modeled on standards-based programs proven by research to be effective in raising student achievement. This new direction represents an important theoretical shift as well as an administrative change. The theoretical underpinning is that a concentration of low-income students presents special challenges to the school as an organizational totality, and that a school-wide strategy is more effective in producing higher student achievement.

This allocation strategy contrasts with the alternative policy advocated by some in the last round of debate over Title I, of providing resources directly to low-income families in the form of an educational tuition voucher. Voucher plans typically reflect a belief that poor children realize substandard educational outcomes primarily because the schools they attend are not competitive. Theoretically, vouchers would give parents an option of choice of schools for their children and would induce competition among schools to attract and retain poor students.

## Past Research on the Impact of High Poverty Schools

We identified three questions as central concerns for guiding our review of prior research: (a) To what extent is student achievement, particularly in the area of mathematics, associated with levels of school poverty status? (b) To what extent are those associations a reflection of distinctive organizational characteristics of the schools and their classrooms, as opposed to the family background of the individual students? And (c), which specific aspects of school and classroom organization are affected by school poverty?

## School Poverty and Student Achievement

While poverty status is well defined by Federal government rules for households and, by extension, the children in them, the poverty status of schools is subject to different measures and definitions. The Title I aid program, for example, typically serves “high poverty” schools in districts with 15 percent or more of the school-age children at or below the poverty threshold (NRC, 2000). The districts in turn typically allocate these Title I resources to schools on the basis of the numbers of students receiving free and reduced-price lunches. The percentages of poor students in schools receiving Title I funds thus tend to vary widely between and even within school districts.

In any case, Title I funding is typically tied to “either/or” measures of school poverty. In contrast, most of the analytic research related to the effects of school poverty has measured the construct as a continuum. Perhaps the most widely available measure is the percentage of students receiving free or reduced-price lunch (FRPL). But the index of household poverty status that underlies the FRPL eligibility is itself a somewhat arbitrary designation, for the underlying construct of household income is a continuous variable. Reflecting this, much research has used school averages of household income, parental education, or composite socioeconomic status, each measured either on interval or ordinal scales at the level of the individual student.

Continuous measures of school poverty or, conversely, school wealth are almost always found to be strongly associated with average levels of student achievement. The Equality of Educational Opportunity survey (Coleman, et al. 1966) was the first nation-wide study to document the relationships, and became the touchstone for dozens of national, state, and local surveys during the last 30 years. The Coleman analysis distinguished between the variance in student achievement that is found among students within schools versus variance found among schools’ average levels of achievement. From 80 to 90 percent of the variance in achievement test scores is typically found within schools, and thus cannot be accounted for by differences among schools. But of the 10 to 20 percent of the variance found between schools, measures of school socioeconomic status are usually found to account for about 50 to 70 percent. Other factors such as percent minority enrollment, school enrollment size, per pupil expenditures, teacher qualifications, and other aspects of enrollment, resources, and organization rarely account for more than about 10 percent more of the between-school variance.

Since government policy does not provide clear guidelines for defining high-poverty schools, researchers interested in categorical measures of school poverty have relied mainly on the distribution of schools to define broad categories of schools. Lippman, Burns, and McArthur (1996) define four categories of schools in terms of the percentages of students receiving free or reduced-price lunch: 0-5 percent, 6-20 percent, 21-40 percent, and 41 percent or more. Drawing on the grade 8 and grade 10 NELS:88 data, they show that a composite measure of academic achievement (combining reading comprehension and mathematics) is progressively and uniformly lower, the higher the rates of school poverty. The difference between the average score in schools with 0-5 percent and those with 41 percent or higher student poverty is 0.8 standard deviation units in both grades. Their results thus echo the strong correlations between continuous measures of school poverty and student achievement, and show that the relationship is fairly linear.

## Effects of School Poverty on Achievement

The second research question is whether there are effects of school composition on individual students. This kind of effect is widely referred to in the sociology literature as a “contextual effect” of the social mix on individuals. The Coleman et al. (1966) report on Equality of Educational Opportunity found that elementary and secondary school students attending schools with higher average levels of parental educational attainment had higher average reading achievement scores than otherwise similar students in schools with lower average parent education. The effect of school socioeconomic composition was much smaller than the effect of individual student socioeconomic background, but larger than any other measured aspect of either individual background or the school attended. Jencks et al (1972) corroborated this result in their reanalysis and extensions of the Coleman report. This basic finding is also supported by the Jencks and Brown (1975) analysis of the Project Talent data; and the Hauser, Sewell, and Alwin (1976) analysis of the Wisconsin data.

The analyses from the 1960s and 1970s, however, were mainly based on cross-sectional data, and thus shed little light on the effects of school composition on changes in achievement as students progress in their schooling careers. Gamoran’s (1987) analysis of the High School and Beyond data found that the average SES of high schools had a significant positive effect on vocabulary achievement gains between grade 10 and 12, when controlling for an extensive array of individual social and academic background variables and other aspects of school composition (race/ethnicity and grade 10 average achievement level). In contrast, the school-SES coefficients were positive but not significant for mathematics, reading comprehension, and civics, and were negative and not significant for science.

The absence of clear contextual effects on individual growth in the Gamoran (1987) HS&B analysis raise the possibility that associations between school-average SES composition and student achievement found in other studies simply reflect uncontrolled differences in starting levels of student achievement in poorer and wealthier schools rather than real effects. This is the main conclusion reached by Mayer and Jencks (1989) in their comprehensive review of the literature on neighborhood and school composition effects on student achievement. However, the time span for the HS&B longitudinal analyses was fairly short (two years in the high schools studies), and the picture may have changed if a longer time span had been examined. Evidence from the next U.S. Department of Education longitudinal study to follow the HS&B, the National Education Longitudinal Study of 1988 (NELS:88), is in fact consistent with that hypothesis. Hoffer (1997) analyzed the NELS:88 data from grade 8 to grade 12 and found significant positive effects of school-average SES on mathematics achievement gains.

## Factors Relating School Poverty with Student Achievement

Several types of general mechanisms have been hypothesized in the research literature as responsible for whatever independent effects of school poverty there may be on student achievement. The first is a resource hypothesis emphasizing the lower *levels of expenditures* on poorer students in schools with concentrated poverty. This perspective has been perhaps the most influential in public discourse and has been notably elaborated by Kozol (1991) in terms of basic aspects of school physical plants and educational materials such as books and computers. But it may also pertain to teacher quality if higher salaries are required to induce teaching less- advantaged children. If salaries are not responsive to the greater challenges, then schools with more poor children would get less qualified teachers.

A second set of hypotheses is tied more directly to student characteristics and related classroom processes. One is a *social psychological* theory emphasizing the beliefs and expectations of school personnel, particularly teachers, for the students (Gamoran, 1986; McPartland and McDill, 1982). The basic idea here is that teachers hold lower expectations for poorer students, based on stereotypical beliefs about the ability of these children. This in turn leads to lower expectations and demands for classrooms, depressing the achievement of all students.

A different kind of classroom-based mechanism refers to what Barr and Dreeben (1983) identify as the *technology* of teaching and classroom instruction. Teachers largely must work with their students as a group rather than as individuals, and dominant characteristics of the group are the main factors in teachers' decisions about what is covered and the pace of coverage. According to this perspective, teachers may hold different expectations for different groups of students, but these expectations are based on rational assessments of the group mastery levels rather than relatively disconnected stereotypes.

Other hypothesized mechanisms relate to processes outside the classrooms but which affect students' in-class behaviors and orientations. The concept of *social capital* developed by Coleman and Hoffer (1987), Coleman (1989), and Lareau (1989) suggests that social class segregation may reduce the information available to less-well educated parents about school operations and their children's progress. This may in turn lead to fewer educationally-helpful interactions between low-income parents and their children, and the parents and teachers, and lower probabilities of educational success than for similar families in contact with higher SES parents.

Evidence concerning how these various mechanisms operate is inconsistent and not conclusive. The social psychological and technological arguments are particularly difficult to untangle empirically, despite their conceptual difference. The central problem is the difficulty in determining whether the expectations that both models acknowledge are based on stereotypes or clearly perceived facts. In any case, the strongest evidence is that the social class composition of a school mainly affects achievement outcomes via its influence on the kinds and depth of instruction students receive. This is evident in the analyses of Barr and Dreeben (1983) of elementary schools, and in Gamoran's (1987) and Hoffer's (1997) analyses of high school data. The variables emphasized as most important by Barr and Dreeben are the pace of basal text coverage. Gamoran and Hoffer identify curriculum program placements and coursework completed in their high school analyses.

## Summary

In sum, past research using data from national samples shows that the overall correlation of school average student achievement and SES is consistently high, and cross-sectional analyses of individual achievement show positive effects of school average SES controlling for individual background. Evidence from longitudinal studies is mixed, with data from HS&B showing small or no effects, while data from the NELS:88 a decade later shows larger positive effects. One important shortcoming of the past research is that school socioeconomic composition has been treated as continuous rather than a categorical variable, and only linear and additive effects have been estimated. It may be the case, however, that the actual effects are neither. If, for example, school composition is particularly influential at the extremes, then a linear model would underestimate the actual effect. Similarly, if school SES composition interacts with other variables, an additive specification would misrepresent and misestimate the actual effect.

A second shortcoming is that few studies have sought to explain observed associations between school SES and student achievement outcomes. While a number of separate explanations have been advanced and some evidence gathered, the competing hypotheses have not been assessed in direct comparison with one another. Moreover, the measures of classroom instructional variables that have been used have been very limited, confined largely to the single dimension of content coverage.

## Hypothesis

Our analysis seeks to redress these shortcomings in previous research, while extending the scope of inquiry to the beginning of the elementary school years. The first hypothesis is that the basic association of school poverty and student achievement will be comparable to the patterns found in previous cross-sectional research on later grade levels. We expect that the association of social class with achievement within schools will be lower in the early elementary grades compared to later grades, but that the school-level associations will be similar. This hypothesis is based on the expectation that teachers in the early elementary grades are more concerned with bringing all children to common standards of numeracy and literacy than teachers in later grades who are more concerned with fostering high achievement. Nonetheless, this equalizing orientation within schools does not imply equalizing orientations across schools. To the contrary, we expect that teachers gear the challenges they make to where their students begin, and that these initial levels of student performance will parallel family advantages of parental education, income, and learning-enhancing resources.

The second hypothesis we address concerns the effect of the socioeconomic composition of the school on individual student achievement. While research has not found large independent effects of school composition controlling for the effects of individual background factors, the contextual effects may be larger in elementary as compared to secondary grades. This could occur because elementary classes match more closely the composition of their school as a whole than secondary level classes match their school. Secondary schools typically use homogeneous ability grouping in most academic subjects, and classes thus do not necessarily reflect the composition of the school as a whole.

Finally, we examine a set of hypotheses related to the factors that mediate the influence of school composition on student achievement outcomes. Past research suggests that the strongest factors are likely to be the extent to which mathematics concepts are covered and the pace at which the teacher moves the class through the curriculum. This will be assessed alongside the effects of the other main factors we identified, that is, school resources, teacher expectations, and social capital in the school and community of parents.

## Statistical Models

These hypotheses are tested with a series of regression analyses. The regressions are estimated with a mixed effects model, as implemented in the HLM software program (Bryk and Raudenbush, 1992). The primary dependent variable in the analyses is a measure of student gain from fall to spring. Before examining the fall-to-spring gains, it is useful to estimate the relationship of school poverty and the fall kindergarten math scores. This gives a picture of the magnitude of achievement differences at the onset of formal schooling, and provides a context for the analysis of school effects on gains over the kindergarten year. The first relationship we assess is the extent to which the kindergartners' fall mathematics scores vary between elementary schools. This is a simple partitioning of the variance in math scores into within-school and between-school components. In the two-level (school and students within schools) HLM framework, the components are developed as follows:

$$Fall\_Math_{ij} = B_{0j} + r_{ij} \tag{1}$$

$$B_{0j} = g_{00} + u_{0j}. \tag{2}$$

Equation (1) shows that the fall math score of kindergarten student $i$ in school $j$ can be divided into two components, the mean kindergarten fall math score for school $j$ ($B_{0j}$) and a child-specific difference from the mean, ($r_{ij}$). The within-school variance component is estimated as var($r_{ij}$). Equation (2) divides the school mean score into the grand mean and a school-specific difference from the grand mean, $u_{0j}$. The between-school variance component is estimated as var($u_{0j}$).

The next relationship we assess is the extent to which the variance in school-mean fall math scores is associated with school levels of poverty. Equation (2) is elaborated by adding a measure of poverty in school $j$:

$$B_{0j} = g_{00} + g_{01}(school\ poverty)_j + u_{0j}. \tag{3}$$

The proportion of the variance in school mean math achievement associated with the poverty level of the school is calculated then as {[var($u_{0j}$) - var($u_{0j}$)]/ var($u_{0j}$)}.

After estimating these descriptive regressions of the fall math scores, the analysis moves to a focus on the fall-to-spring gains in math achievement. Since the elapsed time between the fall and spring test administrations differed across the sampled schools and students, we standardized the fall-to-spring gains by dividing the difference by the number of days between each student's two tests. Paralleling equations (1)-(3), we first estimate the unconditional proportions of variance in the gain scores found within and between elementary schools. These estimates also indicate whether fall-to-spring gains in mathematics achievement have substantial and statistically significant variation between elementary schools.

$$Math\_Gain_{ij} = B_{0j} + r_{ij} \tag{4}$$

$$B_{0j} = g_{00} + u_{0j}. \tag{5}$$

Equation (4) represents the math gain of student $i$ in school $j$ as the sum of the mean kindergarten math gain score for school $j$ ($B_{0j}$) and a child-specific difference from that mean, ($r_{ij}$). The next relationship we assess is the extent to which the variance in school-mean fall-to-spring math gain scores is associated with school levels of poverty. Equation (5) is elaborated by adding a measure of poverty in school $j$:

$$B_{0j} = g_{00} + g_{01}(school\ poverty)_j + u_{0j}. \tag{6}$$

It should be noted that the coefficient $g_{01}$ does not give an estimate of the "contextual effect" of school poverty on math gains. The contextual effect is defined as the difference in a student's score attributable to school poverty, after adjusting for the student-level effects of poverty and other background variables. The background variables include prior math and reading achievement scores along with demographic variables, including student socioeconomic status. To estimate the contextual effect, we use the following equations:

$$Math\_Gain_{ij} = B_{0j} + B_{kj}(student\ background)_{ij} + r_{ij} \tag{7}$$

$$B_{0j} = g_{00} + g_{01}(school\ poverty)_j + u_{0j}. \tag{8}$$

The next set of questions we address is one of how the effect of school poverty compares with other school-level variables of general interest. These include school sector (public, Catholic, other religious, and other private), school enrollment size, and minority student proportional enrollment. Adding these additional factors to equation (8), the coefficients of other school factors are obtained as a new set of $g_{0k}$:

$$B_{0j} = g_{00} + g_{01}(school\ poverty)_j + g_{0k}(other\ school\ factors)_j + u_{0j}. \tag{9}$$

The last set of questions we address concern the influence of school poverty levels on various aspects of school functioning ostensibly related to student achievement. These explanatory variables or mechanisms are mainly conceptualized at the levels of teachers and classrooms. They include class time (half day versus full day), emphasis on mathematics, teacher expectations, and family social capital.[1] While these could be modeled as an additional hierarchical level, the ECLS data are fairly sparse at the class or teacher level. We thus model them at the student level:

$$Math\_Gain_{ij} = B_{0j} + B_{kj}(student\ background)_{ij} + B_{lj}(class\ variables)_{ij} +$$

$$B_{mj}(family\ social\ capital)_{ij} + r_{ij} \tag{10}$$

## Sample

The data drawn on for this analysis are from the base year of the Early Childhood Longitudinal Study of Kindergartners (ECLS-K). The ECLS-K is sponsored by the U.S. department of Education's National Center for Education Statistics. The study began in the fall of 1998 with a sample of 21,260 kindergarten students from about 1,000 schools. Schools were selected from a national frame of all institutions that included a kindergarten class. The frame was stratified by geographic region, school control (public, Catholic, other religious private, other private), location (urban, suburban, rural), and minority enrollment. Schools were selected within strata with probability proportional to enrollment size. Target samples of 24 kindergarten students per school were randomly selected and minority students were oversampled within schools.

The data used in the analyses presented here are from students who participated in both the fall and spring kindergarten data collections, and who have complete data on mathematics achievement at both time points, social background (collected from the parents), school data (collected from the principals), and classroom data (collected from the teachers). This produced a subset of 11,708 students from 751 schools. Most of this sample attrition was attributable to school-level non-cooperation in the spring,

[1] The effects of class enrollment size and teacher qualification (years of teaching experience and highest degree earned) were estimated in preliminary models but the variables dropped from the final models because the effects were not significant.

particularly on the side of the student assessment, and high rates of nonresponse to the spring teacher and parent surveys.

The large attrition of cases from the original sample raises the question of whether the analytic subsample differs in important respects from the population of kindergartners and their schools. Appendix Table 1 compares the descriptive statistics using all available data for each variable ("the original sample") to that of the listwise-deletion analytic sample. These data indicate that the analytic sample is slightly more advantaged in terms of SES variables, more white, slightly higher achieving, and more concentrated in the public sector. The largest differences evident in Appendix 1b are that the proportions of Hispanic students and non-Catholic private school students are much smaller in the analysis sample. Explanations of these differences are not included in the ECLS project documentation. Speculatively, the loss of Hispanic-background kindergartners may reflect exclusion of these students from one or both achievement testing sessions because of a lack of English proficiency. The private school attrition may be a function of lower school-level participation in the non-Catholic private sector, a pattern consistent with past national studies (NELS:88 and High School and Beyond).

## Measures and Descriptive Statistics

### School Poverty

School poverty is the primary independent variable in our analyses. The measure used here is based on the ECLS-sampled parents' reports of their household income. We coupled the household income data with information on the number of household members reported by the parents to create measures of eligibility for free or reduced-price lunch (FRPL) under the USDA school lunch program guidelines. Dichotomizing this into eligible for either free or reduced-price lunch versus ineligible, we then calculated the percent of sampled kindergarten students eligible in each school.

We used this measure of school poverty instead of the principals' reports of the percent of kindergarten students receiving free or reduced price lunch because the principal report was missing for many schools. (This was also true of the principal's report of whether the school was receiving Title 1 funds.) For the 602 schools with both a principal report and our aggregated measure, we found a school-level correlation of 0.68 between the principal's report of school poverty and the aggregated student measure of poverty. The principals tended to report lower proportions of kindergartners at the poverty level than those estimated with the ECLS sample (36 percent versus 40 percent), but no systematic patterns of differences between the two measures were evident in our analyses. The correlation between school-average spring math scores and the principal report of poverty was –0.29, while the correlation between the math scores and the aggregated measure of poverty was –0.36.

In order to assess whether nonlinear relationships are present between school poverty and student outcomes, we divided the continuous school poverty variable into four ordered categories. These were defined to approximate quartiles of the kindergarten student enrollment distribution. The lowest poverty group ranges from 0 percent to 17 percent of the kindergartners eligible for FRPL, while the highest poverty group ranges from 66 percent to 100 percent of the kindergartners eligible for FRPL[2].

## Student-Level Measures

*Student mathematics achievement* is the primary dependent variable in our analyses. The ECLS measured achievement both directly with individual child assessments and indirectly with instruments completed by the kindergarten teachers of each sampled child. This analysis is confined to the direct child assessment data. The general domains of reading, mathematics, and “general knowledge” (a mix of geography, other social studies, and science) achievement were assessed, but only the mathematics components are included in this analysis.

The achievement tests were adapted to each child’s ability, meaning that the questions asked of each child varied depending on the child’s pattern of right and wrong answers to previous questions. The results of the tests were equated by means of Item Response Theory methodology. Two main types of mathematics achievement scores are available in the ECLS-K database: IRT scores and proficiency scores. The IRT scores are expressed in a metric defined as the “estimated number of correct answers.” The proficiency scores are tied to particular competencies or skill areas, and are expressed as the child’s probability of being proficient in that subdomain of mathematics. The skill areas are defined hierarchically, and include (from lowest to highest) (a) number and shape recognition, and counting; (b) identification of relative size of objects; (c) recognition and manipulation of ordinality and sequencing; (d) addition and subtraction; and (e) multiplication and division.

[2] School districts enrolling more than 15 percent of FRPL students are eligible for Title 1 funds. However, actual allocations to schools vary widely between and even within school districts, and there is not a uniform Title 1 definition of “high poverty” school. Based on the 15 percent district-level allocation threshold, one could argue that our measure should reflect that policy guideline rather than the simple quartiles. It turns out, though, that our measure is close enough to that guideline that no significant differences in any of the analyses presented here result from using our quartile-based definition versus a definition reflecting the Title 1 threshold. For the later, we used categories defined as 0-17%, 18-40%, 41-65%, and 66-100% of kindergartners eligible for FRPL.

As shown in Table 1, the fall-to-spring average gain in composite mathematics achievement was 8.3 points, which was equal to 0.97 spring-term standard deviation units. This is quite large compared to what is typically found in later grade levels. The rightmost columns of Table 1 indicate that students attending lower poverty schools registered higher composite mathematics scores in both the fall and spring assessments. The gains on the composite measure are lowest in the highest poverty schools, but are greatest for students in the medium-low poverty schools. In the fall, there was a 6.8-point difference between the low and high poverty groups, and this difference was slightly larger (7.4 points) in the spring.

The probability-of-proficiency subscales indicate that, overall, 94 percent of kindergartners began school proficient in the “counting, number, and shape” domain. By spring, 99 percent of kindergartners were proficient. Since the starting level of proficiency was so high in this domain, the fall-to-spring growth was inevitably small. Ceiling effects of that sort are not likely to be much of a factor limiting gains on the other proficiency subscales.

Differences in gains made by students attending low poverty schools vs. high poverty schools were relatively large for the math subtest scores. Because the students in high poverty schools started kindergarten at relatively low levels of proficiency, they gained more on the basic math proficiency task of “counting, number, and shape recognition” and “relative size.” In contrast, students in lower-poverty schools gained more on higher proficiency tasks such as “Ordinality and Sequence” and “Addition and Subtraction.”

*Student background* includes family socioeconomic status, poverty status, race/ethnicity, gender, child’s age in months, whether both parents are present in the household, the number of siblings living in the household, whether the primary language of the child’s household is English, and whether the child has a disability. All of these measures are based on reports from the parents of the sampled children, and the ECLS data collection contractor constructed all composite indicators and imputations for missing values.

The SES composite variable used in the analysis was constructed from data on household income, parents’ education, and parents’ occupation. All data were collected in the parent interviews. Missing data on each component were imputed using a hot-deck methodology. Each component was standardized to a z-score metric of mean equal to 0 and standard deviation equal to 1, and the z-scores then averaged. The resulting composite ranges from -4.75 to +2.75.

The household income variable (after the hot-deck imputations) was used in conjunction with information on household size to construct a dichotomous indicator of household poverty status. Poverty status was defined in terms of income and household size. The dollar-amount thresholds for each household size were taken from the 1998 U.S. Census Bureau Current Population Survey. The proportion of the kindergartners living in poverty-level households was estimated by the ECLS at 17 percent (Table 2).

Parents and school records provided information on the student's gender, race-ethnicity, age, number of siblings in the household, and language spoken at home. The sample included approximately equal numbers of male and female students. The average age of the respondents was 68.6 months. Most students in this sample reported living with two parents (77 percent) and on average had 1.4 siblings living in the household (Table 2).

Parents were allowed to indicate more than one race for their child and the ECLS thus contains a mixed race category. The ECLS documentation indicates, however, that almost all parents identified the child in just one category. The figures in Table 2 show the analysis sample of children was 14 percent black, 12 percent Hispanic, 2 percent Asian, 1 percent Pacific Islander, 1 percent American Indian, and 2 percent mixed race.

The rightmost columns in Table 2 show that the median family income of students in low poverty schools is almost four times higher than that of students who attend high poverty schools ($75k versus $20k). Similarly, parents of students in low-poverty schools were nine times more likely than parents of students in high-poverty schools to have a college degree (63 versus 8 percent). Children in high-poverty schools are markedly different on whether English is the child's home language and whether the child lives with both parents in the household. Race and ethnicity differences between the school poverty categories are generally quite large. Black (5 percent) and Hispanic (7 percent) children are least represented in low-poverty schools and most represented in high-poverty schools (Black=38 percent, Hispanic=20 percent).

## School-Level Measures

In addition to the school poverty measure described above, the other school-level variables used in the analysis include school sector and percent minority enrollment. These are described in Table 2. The average school enrolls about 31 percent of its students from racial/ethnic minority groups. About 68 percent of the schools are public, 9 percent are Catholic schools, 13 percent other religious, and 10 percent are other private schools.

## Teacher and Classroom Measures

Teacher and classroom explanatory variables include a dichotomous indicator of whether the class meets for a full day or a half day,[3] the teacher's level of education degree attainment, teacher's years of experience, a Likert-scale measure of teacher expectations for student success, several indicators of instructional emphases, and three measures of social capital (see Table 3). About 56 percent of the students in the study attended full-day kindergarten programs, and the average kindergartner attended a class with about 20 students enrolled. Only 1 percent of the kindergartners were taught by teachers with less than a BA degree, while 29 percent were taught by teachers with just a BA degree, 33 percent by teachers with a BA plus some graduate study, and 37 percent by teachers with a Masters or higher. Average teacher experience in the study schools was 9.1 years with a standard deviation of 7.4 years.

*Teacher expectations* are measured using the teacher's agreement with the statement "Many of the children I teach are not capable of learning the material that I am supposed to teach them." Responses were recorded on a five point Likert-scale that ranged from 1='Strongly Disagree' to 5='Strongly Agree.' Response on this variable was reverse-coded to indicate the impact of more positive expectations on student's math achievement.

The amount of *time devoted to teaching math* was measured in both the number of days per week and the number of minutes per day that teachers devote to teaching mathematics. There appears to have been some confusion among teachers on whether they reported the minutes in terms of the time on the days they teach math versus total minutes per week divided by five days. Because of this confusion, we used the teachers' reports of the number of days per week they devoted to teaching mathematics. Responses on this variable ranged from 1='Never' to 5='Daily'.

The ECLS also included extensive batteries asking the teachers how often they use various instructional activities to teach mathematics. Exploratory factor analyses of these batteries identified four scales that emphasize the use of basic skill exercises, use of individualizing and creative methods, and use

[3] We conducted preliminary analyses (not presented here) with various measures of class size and adult-child ratios. Hypothesizing that the effects of class size on student outcomes may depend on the adult-child ratio, we constructed a typology of classes by cross-classifying the three-level categorical enrollment variable with a dichotomous indicator of whether the teacher had one or more paid aides in her class. For the exploratory regression analysis, this six-cell typology was converted to a set of 0-

of open-ended activities. *Basic skill emphasis* was measured by teacher reports on the frequency of using of worksheets, textbooks, and chalkboard-type exercises. Responses ranged from 1='Never', 3='Two or three times a month', 6='Daily' (Cronbach Alpha=.59). *Individualizing methods* include teacher reports on 5 items that measure use of explanations to solve problems, real life experiences, peer tutoring, mixed-ability group methods, and hands on problem-solving activities with partners. Responses ranged from 1='Never' to 6='Daily' (Cronbach Alpha=.75). *Open-ended activities* include use of counting and geometric manipulatives (Cronbach Alpha= .72), and use of games, music, and dance (Cronbach Alpha=.76). In constructing each of the teacher instructional measures, each component of the scale was standardized to a z-score metric with the mean equal to 0 and standard deviation equal to 1, and the z scores then averaged.

*Social capital* concepts are measured with three different indicators. One measure refers to the average number of times parents attend various school events during the kindergarten year. The events include fund raising, parent advisory meetings, volunteered, open house, school events, and PTA meetings. This measure was also constructed by standardizing each component of the scale to a z-score metric with mean equal to 0 and standard deviation equal to 1, and averaging the z scores.

Parent's attendance of the parent-teacher conferences was excluded from the summary scale as conferences do not reflect a common factor. Conferences instead appear often to result from problems the child is having in school, and this was used as a separate indicator. Responses on this item ranged from 0 to 50 and had a high positive skew. To normalize the distribution and avoid misleading estimates from extreme outliers, we recoded the responses to range from 1 to 3 or more conferences.

The third measure of social capital captures the number of parents of the child's classmates that the child's parents talk to regularly. This is closest to the Coleman concept of "intergenerational closure," which Coleman viewed as particularly important to social capital in school settings. Responses on this item ranged from 0 to 38 and, again, were positively skewed. Responses were recoded to range from 0 to 6 or higher to normalize the distribution.

Descriptive statistics of kindergarten program characteristics by level of school poverty are shown in the rightmost columns of Table 3. Students in medium-high and high-poverty schools are much more likely to be in full-day classes. Class sizes across the four groups of poverty seem to be similar. Teachers

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1 dummy variables. None of these proved to have significant effects on gains and we thus omitted them from the analyses described in the tables.

in high-poverty schools tend to have fewer years of experience teaching kindergarten classes and also have lower expectations of their students. Teacher expectations of students are highest among teachers in low-poverty schools.

## Effects of School Poverty on Math Achievement

The effect of school poverty on mathematics achievement in kindergarten was estimated using the HLM methodology of Bryk and Raudenbush (1992). A series of two-level models were assessed and the results of this analysis for composite math scores are listed in Tables 4 and 5.

Model 1 in Table 4 is a “fully unconditional” specification corresponding to equations (1) and (2). It is included simply to partition the total variance in the kindergartners’ fall math achievement into within and between-school components. The results at the bottom of the table show that the total variance in fall math achievement is equal to 52.50 (=9.53+42.97), and that 18 percent (=9.53/52.50) of it is between-school variance. The between-school variance is lower than that found in other national studies at higher grade levels. The grade 8 NELS:88 data showed 27 percent between-school variance in mathematics achievement (Ho & Willms, 1996). Hotchkiss (1984, p. 49) found 22 percent of the variance in the High School and Beyond grade 12 math scores was between schools.

The second model in Table 4 adds only the indicators of school poverty status to the fall math achievement equation. The (omitted) reference category for these three dichotomous indicators is the set of schools with less than 18 percent of their students below the poverty line. The coefficients show substantively large, negative,and statistically significant associations of each poverty level with fall math scores. The effects are fairly linear, with differences of 1.95 to 2.32 math score points (0.24 to 0.32 SD units) between each level. The difference between the average fall math scores in the schools with the lowest levels of poverty and those with the highest (=-6.69) is very large by any reckoning, equal to .93 SD units. Compared to the standard of model 1, the addition of school poverty indicators accounts for 56 percent [=(9.53-4.17)/9.53] of the between-school variance in fall math scores.

Models 3 and 4 in Table 4 shift from the cross-sectional focus of models 1 and 2 to a focus on fall-to-spring changes in the students’ math scores. We use a difference (“gain”) score for the dependent variable in these analyses, and standardize the fall-to-spring difference score by dividing it by the number of calendar days for each student between the two tests (the metric is multiplied by 100 in order to facilitate the tabular presentation). The results for model 3 show that about 9 percent of the overall variance in fall-to-spring kindergarten math gain scores is among schools.

Model 4 adds the school poverty measures to the level-2 equation. The coefficients of these and other independent variables are interpreted as effects on gains from fall to spring. The large negative effects of medium and moderate levels of school poverty seen in model 2 disappear at this point, meaning that school poverty at those levels is not related to math gains during the kindergarten year. However, there is a significant negative effect of attending a high-poverty school on fall-to-spring gains. The estimated effect (b=-0.35) translates into 0.70 points on the math test per 200-day school year. This is equal to 0.08 SD units on the spring math score (SD=8.6 points, from Table 1), and is substantively noteworthy. Accumulated across the 9 years of k-8 elementary schooling, this would amount to about .72 SD units additional disadvantage for children in high poverty schools compared to their low-poverty school counterparts, on top of a .93 SD unit gap at the beginning of kindergarten.

The three HLM models in Table 5 add an array of additional independent variables to the basic fall math achievement and fall-to-spring change models. The student-level equation in both models 1 and 2 is expanded to include measures of student background. One purpose of models 1 and 2 in Table 5 is to assess the extent to which these additional aspects of student background, many of which are correlated with school poverty level, account for the effect of attending school with high poverty on fall math scores and fall to spring math gains shown in models 2 and 4,able 4.

For fall math achievement scores (model 1, Table 5), the school poverty coefficients are smaller than those in Table 4 model 2, but still show negative and statistically significant associations of each poverty level with fall math scores. The effects are again fairly linear, with differences of .49 to 1.22 math score points (0.07 to 0.17 SD units) between each level. The difference between the adjusted-average fall math scores in the schools with the lowest levels of poverty and those with the highest (=-2.88) is substantial and equal to .40 SD units.

Comparing the school poverty coefficients between model 4, Table 4 and model 2 Table 5 it is clear that these aspects of student background as a whole do account for all of the negative effect of school poverty.A second purpose of model 2 in Table 5 is to identify other important background factors related to fall-to-spring gains in math achievement. The coefficients for the student level variables show several significant effects on both fall math achievement and fall-to-spring gains in math achievement. The positive effect of child age on fall math and math gains represents at face value an effect of maturity, but may also be associated with unmeasured aspects of child-rearing. Female children gain significantly less than males, but the effect (b=-0.17, t=-2.73) is not large in substantive terms. Perhaps the most striking result in models 1 and 2 is the evidence that black children gain much less than white children on both fall math achievement (b=-1.74, t=-6.64) and math gains (b=-0.84, t=-6.65). This effect is estimated with controls for variables associated with race and achievement, particularly family SES, poverty status, and whether both parents are present in the home.[4] Children from higher SES families also show greater gains over the kindergarten year (b=0.30, t=5.19), thus increasing the fall SES differentials among the children.

The number of siblings in the households has a significant negative effect on fall math achievement (b=-0.29, t=-3.67), while two parent households has positive effects on fall math achievement (b=.55, t=3.02). Finally models 1 and 2 in Table 5 also shows that children with disabilities gain significantly less on fall math achievement and on average in mathematics between fall and spring. While the nature of the child's disabilities is not specified here, the ECLS did collect this information along with information on the kinds of school services the child received.

Model 3 in Table 5 adds a number of additional school-level variables to the level-2 equation. While we have already found that school poverty does not have significantly negative effects on fall-to-spring math gains once controls for individual student background are added, this model provides some comparative information on other school variables of interest. These include school minority enrollment, enrollment size, and sector. The results in Table 5 do not point any statistically significant or substantively important effects among these indicators.[5]

## Effects of Teacher and Classroom Variables on Composite Math Achievement Gains

[4] We also assessed whether the effect of race on math gain differed by level of school poverty. The results (not tabulated here) suggest blacks may be at less of a disadvantage in low poverty schools than in high poverty schools, but the cross-level interaction terms were not statistically significant.

[5] We also estimated, but do not present here, the effects of school poverty on each of the individual math subtests included in Table 1. The results are similar to that found for the composite math gains. The effects of school poverty on each of the subtests are neither consistent nor strong. Medium poverty has significant positive effects on "Relative Size" and "Ordinality and Sequence" subtests. Why children in medium-poverty schools gain more on these subscales is not clear. A significant negative relationship between high poverty and the math subtest "Add & Subtract" is also evident, but, again it is not clear why the negative effects are not found for the other subscales. While some significant effects of school poverty on the math subscales are thus found, the inconsistency and small magnitude of the effects do not revise the conclusions from Table 6, that the independent effects of school poverty on math gains in kindergarten are negligible.

The final phase of our analysis is an effort to identify aspects of school organization and classroom functioning related to student mathematics achievement, and which may also be influenced by school poverty enrollments. These include the variables discussed in reference to the larger constructs of school resources, expectations, teaching technology, and social capital. Our strategy here is first estimate the relationships of our indicators of these constructs with fall-to-spring math gains, and then to assess – for those variables which have significant effects – the extent to which the variables are related to school poverty. Results of an HLM analysis assessing the effects of teacher-classroom variables on student mathematics achievement after controlling for individual background, prior math and reading achievement, school poverty, and school demography are reported in Table 6.

Results in Table 6 show significant effects of the length of kindergarten school day and teacher expectations of student learning on math achievement. Students who attend full-day kindergarten programs as compared to those who attend half-day kindergarten programs tend to have higher gains in mathematics (b=.39, t=4.76). Students whose teachers had high expectation of student learning had significantly higher math gains than students whose teachers had low expectation of student learning (b=.10, t=2.00). The effects of other classroom resource variables, including class enrollment size and adult-student ratio, teacher education credentials, and teacher years of experience, were all found to be insignificant and excluded from the final models.

Teaching technology refers broadly to what teachers do in their classes. Teachers who use student centered and problem based activities (b=.16, t=2.66) and worksheet, texts, and chalkboards (b=.22, t=4.03) to teach mathematics have students who score higher on math achievement. Teaching math using music and movement, and using math-related manipulable objects and games have no significant effects on math gains.

Social capital generally refers to relations among parents and among parents and school personnel that support academic success. The frequency of attending parent-teacher conferences has significant negative relationship with math gains (b=-.14, t=-3.60). This is consistent with the hypothesis that parent-teacher conferences focus on problems that children are experiencing, and that the greater the problems, the more frequent the conferences. The estimated negative effect would in that case be spurious, simply reflecting problems rather than actually causing them. In contrast, the frequency of attending other school events has a positive relationship with math gains (b=.14, t=2.50). The number of other parents that the child's parent talks with on a regular basis has a small and marginally significant positive effect on math gains (b=.04, t=1.93).

## Effects of School Poverty on Teacher and Classroom Variables

Our final step is to estimate effects on school poverty concentration on the teacher and classroom variables that have significant effects on achievement growth. These include the length of kindergarten program; teacher expectation; use of student centered and problem based activities; use of worksheets, text books, and chalkboard; frequency of parents attending school events and parent-teacher conferences; and parents knowing other parents. To estimate the effects of school poverty on them, we ran separate models where the effects of school poverty were assessed after controlling for the effects of student background. Results of these analyses can be found in Table 7. These results show that schools with higher concentrations of poverty (compared to schools with low poverty) are more likely to have full-day programs and use worksheet, text, and chalkboards as their method of teaching, but are less likely to have high expectations of their students' ability to learn and talk to other parents in the school. The effects of these mediating variables thus work at cross purposes, with the first two increasing achievement while the third and fourth ones diminish it.

## Summary and Conclusions

Children from low-income and particularly poverty-level families begin elementary school at levels of mathematics mastery that are substantially lower than those of their more affluent counterparts. While children generally make large strides in their numeracy skills over the kindergarten year, the initial disadvantages associated with lower socioeconomic status are larger at the end of kindergarten. This is particularly true for black children, and the results we presented portend large racial gaps in math achievement across elementary and into secondary schooling.

Poor children are more concentrated in some elementary schools more than others, reflecting familiar patterns of socioeconomic and racial/ethnic segregation in housing. Schools with high concentrations of low-income children show much lower average levels of math achievement at the beginning of kindergarten, and we have found evidence that kindergartners in those schools learn significantly less about mathematics from fall to spring than other children. This apparent contextual effect of high poverty concentration disappears, however, when we take into account the student-level effects of social background, particularly SES and race/ethnicity. The main message then, is that individual initial disadvantages are important predictors of lower learning gains in any school context, and that resources and efforts focused on disadvantaged children and their families are especially needed to reduce the achievement gaps.

Our efforts to identify promising avenues for improvement are only preliminary at this point, and the ECLS data base includes many more measures that deserve careful analysis. The single factor that stands out most clearly thus far, however, is the length of the kindergarten day. Children in full day kindergartens gained substantially more on the test of math knowledge and skills than otherwise comparable children in half-day classes. Low-income children are actually slightly more likely to attend full day classes than higher-income children, and this thus serves to reduce the SES-related achievement gap. But many more low-income children are not receiving full day kindergarten, and expanding this important resource would benefit all students. An additional factor predicting achievement and related to school poverty concentration is the teacher's expectation of student performance. Teacher expectations appear to be lower in higher poverty schools, and this functions to reduce the kindergartners' gains in mathematics from fall to spring.

While much more work is needed to identify useful ways of reducing the learning gaps between poverty and middle-class students in the early elementary grades, these preliminary findings suggest that the concentration of poverty-level students in particular schools is not a critical factor in and of itself. How resources are allocated within schools to poor children appears to be of greater importance, and further research should pursue that line of inquiry.

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Table 1. Weighted Means and Standard Deviations of Mathematics Achievement by School Poverty: 1998-1999 Kindergartners.

| | | Sample Total | School Poverty Levels | | | |
|---|---|---|---|---|---|---|
| | | Mean (Std. Dev.) | Low (0 - 17%) | Medium-Low (18-40%) | Medium-High (41-65%) | High (66-100%) |
| **Mathematics Achievement Scales** | | | | | | |
| Composite Math IRT scale | | | | | | |
| | Fall | 20.1 (7.2) | 23.2 (7.7) | 20.8 (6.8) | 18.4 (6.6) | 16.4 (5.5) |
| | Spring | 28.4 (8.6) | 31.4 (8.5) | 29.6 (8.1) | 26.8 (8.3) | 24.0 (7.6) |
| | Gain | 8.3 | 8.2 | 8.8 | 8.4 | 7.6 |
| **Probability Proficiency Scales** | | | | | | |
| Count, Number, Shape | | | | | | |
| | Fall | 0.94 (.16) | 0.98 (.08) | 0.96 (.12) | 0.92 (.18) | 0.88 (.22) |
| | Spring | 0.99 (.05) | 1.00 (.02) | 1.00 (.03) | 0.99 (.06) | 0.98 (.09) |
| | Gain | 0.05 | 0.02 | 0.04 | 0.07 | 0.10 |
| Relative Size | | | | | | |
| | Fall | 0.59 (.36) | 0.74 (.31) | 0.64 (.34) | 0.50 (.37) | 0.40 (.35) |
| | Spring | 0.88 (.22) | 0.94 (.15) | 0.92 (.17) | 0.84 (.24) | 0.77 (.30) |
| | Gain | 0.29 | 0.20 | 0.27 | 0.34 | 0.37 |
| Ordinality & Sequence | | | | | | |
| | Fall | 0.22 (.32) | 0.35 (.37) | 0.24 (.32) | 0.16 (.28) | 0.09 (.20) |
| | Spring | 0.59 (.38) | 0.72 (.34) | 0.65 (.36) | 0.52 (.39) | 0.39 (.38) |
| | Gain | 0.37 | 0.37 | 0.41 | 0.36 | 0.30 |
| Add & Subtract | | | | | | |
| | Fall | 0.04 (.13) | .08 (.18) | 0.04 (.13) | 0.02 (.09) | 0.01 (.06) |
| | Spring | 0.19 (.28) | .27 (.31) | 0.21 (.28) | 0.15 (.24) | 0.09 (.18) |
| | Gain | 0.15 | 0.19 | 0.17 | 0.13 | 0.08 |
| Multiply & Divide | | | | | | |
| | Fall | 0.00 (.05) | 0.01 (.07) | 0.00 (.04) | .00 (.04) | 0.00 (.00) |
| | Spring | 0.03 (.11) | 0.04 (.15) | 0.02 (.11) | .02 (.09) | 0.01 (.05) |
| | Gain | 0.02 | 0.03 | 0.02 | 0.02 | 0.01 |
| **Sample Size** | | 11,708 | 3,617 | 3,485 | 2,596 | 2,010 |

Table 2. Weighted Means and Standard Deviations of Student Background and School Background by School Poverty: 1998-1999 Kindergartners.

| | **Sample Total** | **School Poverty Levels** | | | |
|---|---|---|---|---|---|
| | **Mean (Std. Dev.)** | **Low (0 - 17%)** | **Medium-Low (18-40%)** | **Medium-High (41-65%)** | **High (66-100%)** |
| **Student Background Variable** | | | | | |
| Median Family Income | $45,000 | $75,000 | $50,000 | $32,000 | $20,000 |
| % Poverty | 17% | 2% | 9% | 21% | 45% |
| % Parent College Grad | 33% | 63% | 34% | 17% | 8% |
| Composite SES | 0.08 (.76) | .61 (.69) | .14 (.67) | -0.18 (0.60) | -.47 (.65) |
| % Primary Language non-English | 6% | 4% | 4% | 6% | 10% |
| % Disability | 15% | 12% | 16% | 17% | 15% |
| % Both Parents in Home | 77% | 89% | 83% | 71% | 55% |
| % Child is Female | 49% | 51% | 48% | 47% | 51% |
| % Child is Black | 14% | 5% | 8% | 15% | 38% |
| %Child is Hispanic | 12% | 7% | 9% | 14% | 20% |
| % Child is Asian | 2% | 3% | 2% | 2% | 2% |
| % Child is Pacific Islander | 1% | 0% | 0% | 1% | 1% |
| % Child is American Indian | 1% | 1% | 1% | 1% | 4% |
| % Child is Mixed Race | 2% | 2% | 2% | 2% | 3% |
| % N of Siblings | 1.4 (.99) | 1.3 (.87) | 1.4 (.98) | 1.3 (1.01) | 1.6 (1.1) |
| Child Age in Months | 68.6 (4.4) | 68.4 (4.4) | 68.7 (4.3) | 68.8 (4.3) | 68.6 (4.4) |
| **Sample Size** | 11,708 | 3,617 | 3,485 | 2,596 | 2,010 |
| **School Background Variables** | | | | | |
| Average % Minority Students | 30.5 (32.5) | 20.1 (27.0) | 22.4 (26.3) | 31.7 (28.0) | 58.7 (36.8) |
| % Catholic Schools | 9% | 15% | 12% | 2% | 7% |
| % Other Religious Schools | 13% | 31% | 9% | 1% | 2% |
| % Other Private Schools | 10% | 23% | 5% | 4% | 0% |
| **Sample Size** | 751 | 218 | 208 | 165 | 160 |

Table 3. Kindergarten Students' Program Characteristics by School Poverty: 1998-99 Kindergartners.

| **Program Characteristics** | **U.S. Total** | **School Poverty Levels** | | | |
|---|---|---|---|---|---|
| | **Mean (Std. Dev.)** | **Low (0 - 17%)** | **Medium-Low (18-40%)** | **Medium-High (41-65%)** | **High (66-100%)** |
| Percent in full-day kindergarten | 56% | 44% | 52% | 66% | 63% |
| Average class enrollment | 20.0 (3.8)<br>n=11,654 | 19.8 (4.0)<br>n=3,350 | 19.8 (3.6)<br>n=3,325 | 20.3 (3.7)<br>n=2,503 | 20.3 (3.6)<br>n=1,876 |
| | | | | | |
| ***Teacher Education*** | | | | | |
| | n=11,060 | n=3,318 | n=3,341 | n=2,474 | n=1,927 |
| Associate or Less than Associate Degree | 1% | 3% | 1% | 0 | 0 |
| Bachelor's Degree | 29% | 29% | 26% | 29% | 33% |
| Bachelor + 1 year Post Graduation | 33% | 32% | 32% | 32% | 37% |
| Post Graduate Degree | 37% | 36% | 40% | 39% | 30% |
| Teachers experience in teaching kindergarten (years) | 9.1 (7.4) | 9.1 (7.3) | 9.3 (7.3) | 9.6 (7.5) | 8.0 (7.2) |
| Teacher expectation of student learning | 4.1 (.83) | 4.4 (.70) | 4.2 (.73) | 4.0 (.85) | 3.8 (.97) |
| | | | | | |
| ***Teaching Technology*** | | | | | |
| Frequency of teaching math per week | 4.8 (.47) | 4.7 (.52) | 4.8 (.49) | 4.9 (.40) | 4.8 (.42) |
| Teach math using individualized and problem based activities | -.02 (.71) | -.15 (.69) | -.07 (.71) | .08 (.70) | .11 (.72) |
| Teach math using worksheet, text, chalkboard | -.03 (.74) | -.07 (.77) | -.14 (.70) | .02 (.70) | .13 (.78) |
| Teach math using music and movement | -.03 (.86) | -.20 (.81) | -.06 (.84) | .11 (.88) | .07 (.89) |
| Teach math using manipulatives and games | -.02 (.81) | -.16 (.88) | -.06 (.82) | .09 (.74) | .08 (.75) |
| | | | | | |
| ***Social Capital*** | | | | | |
| Avg. number of times parents attend school events | .02 (.56) | .15 (.60) | .03 (.56) | -.04 (.51) | -.11 (.48) |
| Number of other parents that child's parent talk with regularly | 1.9 (2.00) | 2.8 (2.1) | 1.9 (1.9) | 1.4 (1.7) | 1.3 (1.7) |
| Number of parent-teacher conferences attended this year | 1.51 (.90) | 1.5 (.76) | 1.6 (.85) | 1.5 (.93) | 1.4 (1.1) |
| **Sample Size** | 11,708 | 3,617 | 3,485 | 2,596 | 2,010 |

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**Table 4: Effects of School Poverty on Fall Math Scores and Fall-to-Spring Math Achievement Gains: 1998-1999 Kindergartners.**

| | Fall Math Score | | | | | | Fall-to-Spring Math Gain Score | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | | | Model 2 | | | Model 3 | | | Model 4 | | |
| | *Effect* | *SE* | *t-value* | *Effect* | *SE* | *t-value* | *Effect* | *SE* | *t-value* | *Effect* | *SE* | *t-value* |
| ***Student-Background Effects*** | | | | | | | | | | | | |
| Intercept (Mean Achievement) | 20.14 | 0.14 | 147.88 | 23.19 | 0.25 | 94.64 | 4.48 | 0.04 | 107.89 | 4.51 | 0.08 | 54.41 |
| ***School-Level Effects*** | | | | | | | | | | | | |
| Med-Low Poverty (18 to 40%) | | | | -2.42 | 0.30 | -8.03 | | | | 0.18 | 0.11 | 1.57 |
| Med-High Poverty (41 to 65%) | | | | -4.74 | 0.31 | -15.52 | | | | -0.08 | 0.12 | -0.65 |
| High Poverty (66 to 100%) | | | | -6.69 | 0.30 | -22.29 | | | | -0.35 | 0.12 | -2.89 |
| ***Variance Components*** | *Est.* | *Chi Sq* | *df* | *Est.* | *Chi Sq* | *df* | *Est.* | *Chi Sq* | *df* | *Est.* | *Chi Sq* | *df* |
| Between School Variance | 9.53 (18%) | 3393.25 | 750 | 4.17 | 1763.54 | 747 | 0.66 (10%) | 1816.22 | 750 | 0.63 | 1755.41 | 747 |
| Within School Variance | 42.97 (82%) | | | 42.78 | | | 7.02 (90%) | | | 7.02 | | |
| ***Model Statistics*** | | | | | | | | | | | | |
| Reliability Intercept | 0.68 | | | 0.52 | | | 0.51 | | | 0.50 | | |
| % variance explained at School Level | 0 | | | 0.56 | | | 0 | | | 0.05 | | |
| % variance explained at Child Level | 0 | | | 0 | | | 0 | | | 0 | | |

**Note:**
Models are weighted at both school and individual levels; Level 1 generalizability is used in all models. Level 1 Prior achievement is grand mean centered and fixed. Level 2 varibles are grand mean centered. List-wise deletion is used.

Table 5: Effects of Student-level and School-level Control Variables and School Poverty on Fall Math Score and Math Achievement Gains: 1998-1999 Kindergartners.

| Independent Variables | Model 1 Dep. Var: Fall Math Score | | | Model 2 Dep. Var.: Fall-to-Spring Math Gain | | | Model 3 Dep. Var.: Fall-to-Spring Math Gain | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Effect* | *SE* | *t-value* | *Effect* | *SE* | *t-value* | *Effect* | *SE* | *t-value* |
| ***Student-Background Effects*** | | | | | | | | | |
| Intercept (predicted level of dep. var.) | 22.10 | 0.26 | 83.98 | 4.59 | 0.13 | 35.43 | 4.55 | 0.16 | 29.33 |
| Fall Math Achievement | | | | -0.10 | 0.01 | -12.57 | -0.10 | 0.01 | -12.57 |
| Fall Reading Achievement | | | | 0.06 | 0.01 | 9.20 | 0.06 | 0.01 | 9.17 |
| Child is Female | 0.05 | 0.13 | 0.38 | -0.17 | 0.06 | -2.73 | -0.17 | 0.06 | -2.69 |
| Child Age in Months | 0.41 | 0.02 | 20.42 | 0.02 | 0.01 | 2.81 | 0.02 | 0.01 | 2.80 |
| Race/ethnicity (compared to White) | | | | | | | | | |
| Black | -1.74 | 0.26 | -6.64 | -0.84 | 0.13 | -6.65 | -0.87 | 0.13 | -6.47 |
| Hispanic | -1.56 | 0.28 | -5.48 | -0.19 | 0.11 | -1.64 | -0.21 | 0.12 | -1.78 |
| Asian | 0.58 | 0.46 | 1.26 | 0.28 | 0.24 | 1.16 | 0.29 | 0.25 | 1.17 |
| Pacific Islander | -0.94 | 0.99 | -0.95 | -0.25 | 0.44 | -0.57 | -0.28 | 0.44 | -0.63 |
| American Indian | -2.08 | 0.50 | -4.15 | -0.29 | 0.34 | -0.85 | -0.30 | 0.35 | -0.86 |
| Mixed Race | -1.20 | 0.48 | -2.50 | 0.14 | 0.39 | 0.35 | 0.13 | 0.39 | 0.34 |
| Household at or below Poverty Level | -0.22 | 0.20 | -1.10 | -0.16 | 0.10 | -1.66 | -0.16 | 0.10 | -1.64 |
| Composite SES | 2.55 | 0.15 | 17.21 | 0.30 | 0.06 | 5.19 | 0.30 | 0.06 | 5.12 |
| Two Parent Household | 0.55 | 0.18 | 3.02 | 0.07 | 0.10 | 0.70 | 0.07 | 0.09 | 0.71 |
| Number of Siblings in the Household | -0.29 | 0.08 | -3.67 | 0.06 | 0.04 | 1.43 | 0.06 | 0.04 | 1.42 |
| Primary Lang not English | -0.44 | 0.32 | -1.37 | -0.07 | 0.14 | -0.52 | -0.09 | 0.14 | -0.63 |
| Child has Disability | -2.25 | 0.21 | -10.97 | -0.46 | 0.11 | -4.17 | -0.46 | 0.11 | -4.15 |
| ***School-Level Effects*** | | | | | | | | | |
| % Minority Students in School | | | | | | | 0.00 | 0.00 | 0.65 |
| Total School Enrollment | | | | | | | 0.05 | 0.04 | 1.28 |
| School Sector (compared to Public) | | | | | | | | | |
| Catholic | | | | | | | 0.11 | 0.14 | 0.76 |
| Other Religious | | | | | | | 0.31 | 0.18 | 1.73 |
| Other Private | | | | | | | -0.10 | 0.26 | -0.36 |
| School Poverty (compared to Low Poverty 0 to 17%) | | | | | | | | | |
| Med-Low Poverty (18 to 40%) | -1.17 | 0.25 | -4.65 | 0.30 | 0.11 | 2.82 | 0.34 | 0.11 | 3.01 |
| Med-High Poverty (41 to 65%) | -2.39 | 0.28 | -8.70 | 0.17 | 0.12 | 1.39 | 0.21 | 0.14 | 1.47 |
| High Poverty (66 to 100%) | -2.88 | 0.28 | -10.46 | 0.13 | 0.14 | 0.95 | 0.14 | 0.17 | 0.82 |
| ***Variance Components*** | *Est.* | *Chi Sq* | *Df* | *Est.* | *Chi Sq* | *Df* | *Est.* | *Chi Sq* | *Df* |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Between School Variance | 2.50 | 1385.19 | 747 | 0.60 | 1745.65 | 747 | 0.60 | 1730.61 | 742 |
| Within School Variance | 36.37 | | | 6.72 | | | 6.72 | | |
| ***Model Statistics*** | | | | | | | | | |
| Reliability Intercept | .44 | | | 0.50 | | | 0.50 | | |
| % variance explained at School Level | 74% | | | 9% | | | 9% | | |
| % variance explained at Child Level | 15% | | | 4% | | | 4% | | |

**Note:** Models are weighted at both school and individual levels. List-wise deletion is used. Level 1 generalizability is used in all models. Level 1 fall achievement, child age In months, and number of siblings are grand-mean centered. Other level-1 variables are not centered; level-2 variables are grand mean centered. Level-1 variables are all fixed.

**Table 6: Effects of School Poverty and Teacher/Classroom Variables on Math Achievement Gains: 1998-99 Kindergartners.**

| | Math | | |
|---|---|---|---|
| | ***Effect*** | ***SE*** | ***t-value*** |
| ***Student-background Effects*** | | | |
| Intercept (Mean Achievement) | 4.46 | 0.15 | 28.99 |
| Prior Math Achievement | -0.10 | 0.01 | -13.08 |
| Prior Reading Achievement | 0.06 | 0.01 | 9.12 |
| Child is Female | -0.19 | 0.06 | -3.03 |
| Child Age in Months | 0.02 | 0.01 | 2.88 |
| Race/ethnicity (Compared to White) | | | |
| Black | -0.89 | 0.14 | -6.55 |
| Hispanic | -0.17 | 0.12 | -1.52 |
| Asian | 0.33 | 0.25 | 1.34 |
| Pacific Islander | -0.21 | 0.43 | -0.50 |
| American Indian | -0.31 | 0.34 | -0.91 |
| Mixed Race | 0.13 | 0.39 | 0.33 |
| Household Poverty Level (0=At or Above Poverty) (1=Below poverty) | -0.17 | 0.09 | -1.66 |
| Composite SES | 0.29 | 0.06 | 5.00 |
| Two Parent Household | 0.03 | 0.09 | 0.35 |
| Number of Siblings in the Household | 0.07 | 0.04 | 1.63 |
| Primary Lang not English | -0.05 | 0.14 | -0.32 |
| Child has Disability | -0.45 | 0.11 | -4.15 |
| ***Teacher-classroom Effects*** | | | |
| Student attends Half-day or Full-day Kindergarten program (0=Half day, 1=Full day) | 0.39 | 0.08 | 4.76 |
| Teacher Expectations of Student Learning | 0.10 | 0.05 | 2.00 |
| *Teaching Technology* | | | |
| Frequency of teaching math per week | 0.09 | 0.08 | 1.18 |
| Teach Math using individualized and problem based activities | 0.16 | 0.06 | 2.66 |
| Teach Math using worksheet, text, chalkboard | 0.22 | 0.05 | 4.03 |
| Teach Math thru music + movement | 0.01 | 0.06 | 0.20 |
| Teach Math thru manipulatives, games | -0.09 | 0.06 | -1.50 |
| *Social Capital* | | | |
| Avg. Number of times Parent attend school events | 0.14 | 0.06 | 2.50 |
| Number of other parents that child's parent talk with regularly | 0.04 | 0.02 | 1.93 |
| Number of parent-teacher conferences attended this year | -0.14 | 0.04 | -3.60 |
| ***School-Level Effects*** | | | |
| % Minority Students in School | -0.00 | 0.00 | -0.74 |
| Total School Enrollment | 0.05 | 0.04 | 1.27 |
| School Sector (Compared to Public) | | | |
| Catholic | -0.21 | 0.15 | -1.40 |
| Other Religious | 0.14 | 0.17 | 0.78 |
| Other Private | -0.35 | 0.25 | -1.41 |
| School Poverty (Compared to Low Poverty 0 to 17%) | | | |
| Med-Low Poverty (18 to 40%) | 0.32 | 0.11 | 2.96 |
| Med-High Poverty (41 to 65%) | 0.11 | 0.13 | 0.85 |
| High Poverty (66 to 100%) | 0.08 | 0.16 | 0.52 |

| ***Variance Components*** | ***Estimate*** | ***Chi-sq*** | ***df*** |
|---|---|---|---|
| Between School Variance | 0.50 | 1546.24 | 742 |
| Within School Variance | 6.69 | | |
| ***Model Statistics*** | | | |
| Reliability Intercept | 0.46 | | |
| % variance explained at School Level | 29% | | |
| % variance explained at Child Level | 4% | | |

**Notes:**
Models are weighted at both school and individual levels. Level 1 generalizability is used in all models. Level 1 fall achievement, child age in months, number of siblings, teacher expectations, social capital, and teaching technology variables are grand-mean centered; all other level-1 variables are not centered. All level-1 effects are fixed except the intercept. Level 2 variables are grand-mean centered. List-wise deletion is used.

**Table 7: Effects of Student Background and School Variables on Teacher/Classroom Variables: 1998-99 Kindergartners.**

| Teacher/Classroom Variables (Dependent Variables) | | Effects of School Poverty (Compared to low-poverty schools): Medium-Low Poverty (18-40%) | Medium-High Poverty (41-65%) | High Poverty (66-100%) |
|---|---|---|---|---|
| **Full-day Program** | *Effect* | 0.11 | 0.22 | 0.12 |
| | *SE* | 0.05 | 0.06 | 0.07 |
| | *t-value* | 2.34 | 4.06 | 1.85 |
| **Teacher Expectations of Student Learning** | *Effect* | -0.07 | -0.22 | -0.39 |
| | *SE* | 0.06 | 0.07 | 0.08 |
| | *t-value* | -1.23 | -3.18 | -4.83 |
| **Teach math using individualized and problem based activities** | *Effect* | 0.03 | 0.12 | 0.07 |
| | *SE* | 0.06 | 0.06 | 0.07 |
| | *t-value* | 0.53 | 1.82 | 0.91 |
| **Teach math using worksheet, text, chalkboard** | *Effect* | 0.04 | 0.20 | 0.26 |
| | *SE* | 0.07 | 0.08 | 0.09 |
| | *t-value* | 0.61 | 2.58 | 2.79 |
| **Average number of times parents attend school events** | *Effect* | -0.02 | -0.01 | -0.05 |
| | *SE* | 0.02 | 0.03 | 0.03 |
| | *t-value* | -0.89 | -0.30 | -1.46 |
| **Number of parent-teacher conferences attended this year** | *Effect* | -0.03 | -0.04 | -0.11 |
| | *SE* | 0.05 | 0.06 | 0.08 |
| | *t-value* | -0.50 | -0.63 | -1.42 |
| **Number of other parents that the child parents talk with regularly** | *Effect* | -0.54 | -0.81 | -0.72 |
| | *SE* | 0.10 | 0.12 | 0.13 |
| | *t-value* | -5.48 | -7.03 | -5.55 |

Note: Effect's, SE, and t-values are obtained from HLM analyses. Student-level and school-level controls are the same as in Table 5. Model specification, level of generalizability, and variable centering are the same as in Table 5.

Appendix 1a. Weighted Means and Standard Deviations of Student Mathematics Achievement, Student Background Variables, and School Program Characteristics: 1998-1999 Kindergartners.

| | | U.S. Total | | Study Sample (n=11,708) |
|---|---|---|---|---|
| | | Number of Students | Mean (Std. Dev.) | Mean (Std. Dev.) |
| **Test Scores** | | | | |
| Composite Math IRT Scale: | Fall | 17,233 | 19.4 (7.3) | 20.1 (7.3) |
| | Spring | 17,451 | 27.4 (8.8) | 28.4 (8.6) |
| **Background Variable** | | | | |
| Median Family Income | | 17,005 | $40,000 | $45,000 |
| % Poverty | | 17,005 | 19% | 17% |
| % Parent College Grad | | 17,005 | 30% | 33% |
| Composite SES | | 17,005 | -0.01 (.79) | .08 (.76) |
| % Primary Language non-English | | 16,367 | 11% | 6% |
| % Disability | | 16,406 | 14% | 15% |
| % Both Parents in Home | | 16,431 | 76% | 77% |
| % Child is Female | | 17,679 | 49% | 49% |
| % Child is Black | | 17,629 | 16% | 14% |
| %Child is Hispanic | | 17,629 | 19% | 12% |
| % Child is Asian | | 17,629 | 3% | 2% |
| % Child is Pacific Islander | | 17,629 | 0.5% | 1% |
| % Child is American Indian | | 17,629 | 1.4% | 1% |
| % Child is Mixed Race | | 17,629 | 2% | 2% |
| % N of Siblings | | 16,431 | 1.4 (1.02) | 1.4 (.99) |
| Child Age in Months | | 17,671 | 68.5 (4.4) | 68.6 (4.4) |
| **Program Characteristics** | | | | |
| % in full-day kindergarten | | 17,677 | 55% | 56% |
| Average Class Enrollment | | 15,984 | 20.0 (3.8) | 20.1 (3.8) |
| Teacher experience in teaching kindergarten (years) | | 17,102 | 8.95 (7.26) | 9.1 (7.4) |
| Teacher expectations of student learning | | 17,026 | 4.13 (.84) | 4.2 (.83) |
| *Teaching Technology* | | | | |
| Frequency of teaching math using different methods per week | | 16,722 | 4.78 (.47) | 4.8 (.47) |
| Teach math using creative and group tutoring | | 16,863 | .00 (.71) | -.02 (.71) |
| Teach math using worksheet, text, chalkboard | | 16,874 | .00 (.75) | -.03 (.74) |
| Teach math using music and movement | | 16,855 | .00 (.89) | -.03 (.86) |
| Teach math using manipulatives and games | | 16,866 | .00 (.81) | -.02 (.81) |
| *Social Capital* | | | | |
| Avg. number of times parents attend school events | | 16,305 | .00 (.57) | .02 (.56) |
| Parents talk to other parents | | 16,273 | 1.9 (1.97) | 1.9 (2.00) |
| Parents attend parent-teacher conference | | 16,273 | 1.5 (.92) | 1.5 (.90) |

Appendix 1b. Weighted Means and Standard Deviations of School Characteristics: 1998-1999 Kindergartners.

| | U.S. Total | | Analytic Sample (n=751 schools) |
|---|---|---|---|
| **School Demographics** | **Number of schools** | **Mean (Std. Dev.)** | **Mean (Std. Dev.)** |
| Average % Minority Students | 850 | 30.2 | 30.5 (32.5) |
| % Public Schools | 866 | 65% | 68% |
| % Catholic Schools | 866 | 10% | 9% |
| % Other Religious Schools | 866 | 14% | 13% |
| % Other Private Schools | 866 | 11% | 10% |
| % Low Poverty Schools | 939 | 34% | 33% |
| % Medium-Low Poverty Schools | 939 | 27% | 27% |
| % Medium-High Poverty Schools | 939 | 20% | 21% |
| % High Poverty Schools | 939 | 19% | 19% |