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Achievement Gaps and Correlates of Early Mathematics Achievement: Evidence from the ECLS K–First Grade Sample[1]

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Abstract
In light of the NCLB Act of 2001, this study estimated mathematics achievement gaps in different subgroups of kindergartners and first graders, and identified child- and school-level correlates and moderators of early mathematics achievement. A subset of 2300 students nested in 182 schools from the Early Childhood Longitudinal Study K–First Grade data set was analyzed with hierarchical linear models. Relative to school mean estimates at the end of kindergarten, significant mathematics achievement gaps were found in Hispanics, African Americans and high poverty students. At the end of Grade 1, mathematics gaps were significant in African American, high poverty, and female subgroups, but not in Hispanics. School-level correlates of Grade 1 Mathematics achievement were class size (with a small negative main effect), at-home reading time by parents (with a large positive main effect) and school size (with a small positive main effect). Cross-level interactions in Grade 1 indicated that schools with larger class and school sizes had a negative effect on

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African American children's math scores; schools giving more instructional time to reading and math had a positive effect on high poverty students' scores, and schools with higher elementary teacher certification rates had a positive effect on boys' mathematics achievement.
Keywords: achievement gap; early childhood; primary grades; Early Childhood Longitudinal Study (ECLS); correlates and moderators of mathematics achievement.

Purpose

The passage of the No Child Left Behind (NCLB) Act of 2001 has drawn attention to achievement differentials in diverse U.S students, commonly referred to as the "achievement gap". By law, public schools are now held accountable for equitable achievement outcomes in subgroups of minority versus non-minority, normally-achieving versus exceptional, as well as socio-economically advantaged versus disadvantaged students (P.L 107–110, 115 Stat. 1425, 2002). As a consequence of such school reform legislation, disparities among children's mathematics achievement as well as factors that influence the observed differences, are now of central concern to researchers, practitioners, policy-makers and the public alike. Although much research now concludes that gender gaps in mathematics are declining in large scale examinations of adolescents and adults (see for example, Friedman, 1989), documentation is sparse on the mathematics gender gap in early school years. Questions surrounding the time at which mathematics achievement gaps first develop, groups in which they are consistently manifested, and circumstances under which they reduce or are sustained over time, is of particular relevance today. The isolation of school- versus child-level characteristics that potentially narrow observed differences in early mathematics achievement is a needed area of research.

This study estimates achievement gaps and correlates of early mathematics achievement with a particular focus on male versus female, poor versus well-to-do and various ethnic subgroups in the U.S. A main aim of the research was to estimate the size of mathematics achievement gaps manifested in early school years in the context of recently set reform agendas for schools to close gaps by 2014. As formal instruction in mathematics tends to be more consistently distributed in first grade rather than in kindergarten, the study focuses mainly on first grade achievement outcomes. At the same time, kindergarten gaps are estimated so that changes in achievement patterns can be meaningfully compared and interpreted.

A subset of data from the Longitudinal Kindergarten-First Grade Public Use file of the Early Childhood Longitudinal Study (ECLS) was analyzed. The ECLS, consisting of data collected between kindergarten entry (Fall 1998) and the end of first grade (Spring 2000), uses a nationally representative sample. Particular research objectives that guided the present study were to determine: (1) the extent to which variability in children's mathematics achievement in first grade is explained by child- versus school-level factors; (2) whether children's membership in a specific subgroup resulted in significant within-school achievement gaps in kindergarten and subsequently, in first grade, controlling for particular child background characteristics; (3) the degree to which selected, theoretically-supported or policy-relevant school factors significantly influenced first grade mathematics achievement, when some child background characteristics are controlled while others allowed to vary randomly by school; and (4) whether children's membership in particular ethnic, gender or poverty subgroups interacted with their school membership to affect mathematics scores, and school factors accounting for the variance in school slopes.

Kindergarten education varied based on length of day (half versus full day) in the ECLS sample (Walston & West, 2004). To assay the cumulative effects of K–1 years on end-of-first grade mathematics achievement in selected analytic models, child mathematics measures taken at kindergarten entry (K-entry) were used as indicators of prior achievement. In other models, end-of-kindergarten mathematics achievement measures (K-end) were used to control for differences in prior mathematics learning. The latter effects were interpreted as indicative mainly of children's first grade school experiences on end-of-first grade achievement, assuming all children entered with similar levels of prior preparation in mathematics. Results of both series of models are compared.

Theoretical Framework

Predictors with which to build explanatory models for early mathematics achievement were drawn from a review of a broad literature base that focused on four areas: the national push for reducing achievement gaps in mathematics; the documented demographic shifts in the U.S. and achievement trends in diverse students; early findings of the Kindergarten year ECLS sample; and existing evidence on child- and school-level correlates of achievement. That literature is now discussed, with specific attention devoted to research on early care, gender differences, and particular school practice variables, such as reduced class size, school size and teacher qualifications, and their expected influences on early mathematics achievement.

The NCLB Act's Emphasis on the Achievement Gap

The most recent legislative action on the standards-based reform movement in the U.S., the No Child Left Behind Act of 2001 (NCLB), uses challenging academic standards, coupled with *high-stakes standards-based testing* and accountability, as its main strategy for fostering school improvement (P.L 107–110, 115 Stat. 1425, 2002). For the first time in the history of national school reforms, the law places an emphasis on achievement by all groups of students, particularly those who are historically low-achieving, such as ethnic minorities, socio-economically disadvantaged or special needs students. To monitor the status of achievement gaps and ensure that historically low-achieving students receive much needed attention, NCLB mandates disaggregated reporting of state test scores. That is, schools must break down results on student performance by relevant subgroups in key subject areas such as reading and mathematics, and attempt to close achievement gaps evidenced in various sub-categories by 2014.

NCLB provides states with some flexibility in selecting appropriate standards-based assessments, as well as in defining the meaning of "Adequate Yearly Progress" (AYP) using performance standards (cut-scores) on state tests. However, the Act requires that schools monitor and reduce achievement lags in students belonging in high risk groups by the pre-set deadline. The lack of comparability in state standards and current practices for monitoring achievement gaps have raised concerns among researchers and policy-analysts (Linn, 2003; Linn, Baker & Betebenner, 2002).

The recruitment and retention of *qualified teachers* in schools is another NCLB strategy for enhancing school and student outcomes (see Section 1119, P.L 107–110, 115 Stat. 1425, 2002). Each local educational agency supported by NCLB funds must ensure that hired teachers are "highly qualified". Proof of teacher qualifications can be in the form of full state licensure or certification in the relevant area of specialization, a Bachelor's degree, professional development, classroom experience, and knowledge of a subject garnered over time. States are allowed freedom in devising ways by which teachers might demonstrate their competency and subject matter knowledge. Nevertheless, schools are expected to be in compliance by 2005–06. Schools in rural areas, where the same teacher might teach more than one subject, and secondary schools, where higher levels of subject area knowledge are needed, have been accorded some flexibility in meeting the NCLB requirements (http://www.ed.gov/nclb/methods/teachers/hqtflexibility.html).

Student Background Characteristics and Scholastic Achievement

Outside legislative mandates, what factors are likely to diminish or exacerbate the academic deficits in children in high risk subgroups at school? *Academic risk* factors that are frequently documented in the clinical and child development literature include ethnicity, age, gender, poverty and lack of parental education, family mobility, limited English proficiency, along with nutritional and health factors (for examples, see Garmezy, 1993; Garmezy & Masten, 1986; Werner, 1993). It is thus not unreasonable to think that children who are at academic risk due to multiple risk factors, such as membership in particular ethnic groups combined with high poverty levels, are likely to start school at a greater disadvantage.

However, the same body of literature also recognizes *protective* factors in children's personal, family, and school backgrounds that foster resilience despite observed child or family risk levels. For example, parenting and family socio-economic factors are viewed as major predictors of children's cognitive and social development because families play a central role in children's lives and both genetic and environmental influences are known to have a combined effect on their scholastic success (see Collins, Maccoby, Steinberg, Hetherington & Bornstein, 2000). Public initiatives, such as Head Start and Title 1 programs were founded to counter the well-documented negative relationship of children's poverty levels with their cognitive, social and physical development.

Influences of prior learning and poverty. A fairly recent meta-analysis of 60 studies determined that cognitive and social skills measured in late preschool years were predictive of performance in the same domains in the early school years (Laparo & Pianta, 2000). Effect sizes were positive (+0.49) for cognitive and academic predictors. The National Institute of Child Health and Human Development (NICHD Early Child Care Research Network, 2002) also reported results from studies on the positive influences of parenting and child-care centers on children's pre-academic skills. A recent longitudinal study of 1000 children showed that higher *quality of child care* and *experience in preschool* center-type activities were positive correlates of pre-academic skills and language (NICHD Early Child Care Research Network, 2002), with gender, ethnicity, family income, parenting and other background factors controlled. Higher quality of child care predicted better pre-academic and language outcomes, irrespective of the hours and type of care. Contrary to expectations, however, these researchers were not able to document that better quality child care would be advantageous to children from disadvantaged environments, such as low income households. That is, they did not find significant interaction effects between poverty and quality of care. They concluded that their findings were limited by their use of multiple regression models to test for interactions (p. 159).

Influences of ethnic differences. A 1994 report published by the U.S. Department of Education (NCES, 1995a) concluded that African American children were less likely to be enrolled in pre-primary education relative to Whites, and were more likely to be below modal grade for their age in school. The same report showed that White-African American gaps in mathematics, reading, and science appeared as early as age 9, and did not narrow with age. Over the years, Hispanic children have also been found to start school with less preschool experience than White children and the achievement gap between these two groups was found to widen considerably by 1993 (17% to 38%) (NCES, 1995b). The Hispanic-White gap was also found to appear at age 9 and persisted through age 17, but there were areas in which the gap seemed to narrow.

Evidence from other longitudinal studies of adolescents suggests that certain subgroups among particular ethnic minorities tend to perform better than other students of the same ethnic origin.

Grissmer and colleagues (1994), for instance, found that Hispanic White youth demonstrate different achievement gains over time relative to their Hispanic Black counterparts. Systematic studies on Asian students in the U.S. are rare, possibly because they are perceived to perform well, or as well as the majority ethnic group in U.S. schools.

Are there any signs of the *ethnic achievement gaps* reducing? As the literature suggests, manifestation of achievement gaps in early school years is predicated on background differences in young children, which affect their school readiness levels as well as social and cognitive potential (Boethel, 2004). There is some evidence that early care programs such as the Head Start give a significant boost to children from low income environments, particularly African American children (see Lee, Brooks-Gunn, Schnur, 1988; Hubbs-Tait et al, 2002). Such evidence would suggest that with appropriate parenting and pre-school care, achievement gaps could narrow before children start kindergarten.

Lee (2002) observed an overall reduction in ethnic achievement gaps on the *National Assessment of Educational Progress* (NAEP) and the *Scholastic Aptitude Test* (SAT) through the 1980s, and concluded that schools had made "great progress toward equity". African American-White and Hispanic-White gaps narrowed in the early 1980s. In the late 1980s and 1990s, however, the performance gaps either stabilized or widened again, corresponding with the onset of standards-based reforms.

Using recent NAEP results in reading, mathematics and writing, some states are demonstrating that the achievement gap is reducing after the passage of NCLB, according to National Governors' Association (NGA) Clearinghouse (www.subnet.nga.org). Despite high mobility rates, Department of Defense schools show the smallest gaps between White and African American students, even in fourth grade. Multi-faceted approaches to building educational programs, use of "best" practices and improvement of teacher quality are identified by the NGA as key factors that alter and influence student achievement outcomes.

Gender differences. Gender differences in mathematics are now documented to be small and decreasing over time, but they exist in college entrance examinations (Friedman, 1989; 1995; Hyde, Fennema, & Lamon, 1990). Whether due to socialization differences, innate genetic differences, or different spatial aptitudes influenced by combined genetic-environmental factors, the gender gap in mathematics is one that seems to interest both researchers and policy-makers. Friedman's (1995) meta-analysis examining correlational studies of spatial and mathematics skills in males versus females led to the conclusion that the relationship was stronger in males than females in many studies, showing gender-specific relationship patterns that favored males. In select samples, however, the relationship between spatial concepts and mathematics ability was stronger in females—leading to the conclusion that motivation, career goals, and factors such as socialization in the environment moderate such relationships. The jury is thus still out as to *gender differences* and moderators of mathematics skills in younger school-going children from developed countries such as the U.S.

School-level Correlates of Student Achievement

Reviews of literature on standards-based school reforms (Chatterji, 2002; Darling-Hammond, 1998; Knapp, 1997) as well as empirical studies (see for examples, Ferguson, 1991; Ferguson & Ladd, 1996; Sirotnik & Kimball, 1999) conclude that high student achievement on standards-based tests is more likely when teachers are certified to teach and both teachers and school leaders are appropriately trained on the new content standards. In light of NCLB's emphasis on *teacher qualifications* and professional development, these factors merit continuing evaluation.

Efficient allocation of *resources* to support particular reforms, such as through the infusion of technology, reduced school and class sizes, alignment of classroom instructional practices with new content standards, longer blocks of time dedicated to subject-specific instruction, alignment of practices to meet needs of diverse student populations, higher levels of parent involvement in children's education, is also expected to influence achievement at all levels. School context factors, such as overall poverty levels in the student body, have also been shown to affect leadership behaviors, schooling practices, and organizational culture (Hannaway & Talbert, 1993; Hannaway & Kimball, 1998), and in turn, academic outcomes.

Discussions of *class size* as a reform initiative often center on cost effectiveness issues rather than on what schools and teachers actually do with the added resources that could moderate student outcomes when class sizes are small. The experimental Tennessee STAR project provided evidence that classes with under 20 pupils have positive effects on students' academic performance in early school years (Finn & Achilles, 1999). Molnar et al. (1999) also examined classroom processes in smaller classes in Wisconsin, documenting that smaller classes lead to more individualized instruction, with greater variety in instructional activities. A large scale study in the U.K, conducted by Blatchford and colleagues (2002) also supports to the latter contention—more individualized attention is evident in smaller-size classes, and potentially facilitates an environment in which students' early academic difficulties can be tackled.

Does *school size* matter at the elementary level? Based on existing research from the past decade, effective school sizes at the elementary level were determined to lie at 300–400 students (Williams, 1990), making schools of 500 or more students too large for educating younger learners. Some recent research syntheses concluded that small schools are better at raising student achievement, especially for minority and low income students. Small schools were also found to increase attendance, teacher satisfaction, and parent and community involvement (see Williams, 1990; Ayers, Bracey, & Smith, 2000).

Although seemingly dated, the "effective schools" literature identified a strong school leadership, a focus on academic outcomes (success orientation and academic press values), a positive and orderly school climate, and teachers' positive expectations for students as educationally effective factors for disadvantaged students (see, for example, Brookover, Beady, Flood, Schweitzer, & Wisenbaker, 1979; Clark, Lotto, & McCarthy, 1980; Edmonds, 1979; Rowan, Bossert, & Dwyer, 1983. While this work faced criticisms from methodological and substantive perspectives because studies often failed to arrive at common factors supported by solid statistical evidence (see for example, Purkey & Smith, 1983, Rosenholtz, 1985), some "effective schools" factors have surfaced in the recent literature on standards-based reforms, and merit further empirical testing at the elementary level.

Early Findings from the ECLS

The ECLS data, the focus of the present study, permits a unique look at subsets of a nationally representative sample of kindergartners on a range of cognitive, behavioral, and health indices. Zill and West (2001) reported descriptive statistics from the ECLS-K data from the 1998–99 kindergarten class. Their initial analyses show considerable variation in children's knowledge and skills as they enter school. Descriptive breakdowns of the first year sample suggest that the variations in achievement were partially related to age, gender, and family risk factors. Family risk was defined based on low maternal education, welfare dependency or poverty status, having one parent at home, and having parents whose native language is not English. Children's health and behaviors were, in turn, found to be dependent on family risk factors. Disturbingly, 33% of Hispanic students were found to have two or more family risk factors; 27% of African Americans fell in the same category; while 17% of Asians had the same profile. In contrast, 6% of White students were categorized in the same family risk category in the ECLS-K sample.

Consistent with literature in clinical and child development fields, Zill and West (2001) also reported that socio-demographic risk factors, such as single parent families, high levels of poverty, and transiency, were more common among kindergartners from ethnic minorities than among those from White families in the ECLS-K sample, and that the at-risk children started with lower scores on cognitive assessments in kindergarten.

Given the policy directions set by the standards-based reform movement and NCLB, the need is high for additional and replicated evidence on direct and moderating effects of particular school practices and policies in the early school years. New information has begun to emerge with data on the ECLS, but very little is available on school-level correlates and moderators of early mathematics achievement in high risk groups emphasized in the NCLB. Further, it is not clear as to whether stable achievement gaps in mathematics form as early as in first grade, how large they are, and whether gaps are comparable in magnitude in all high risk subgroups identified in the legislation. The present study addressed these unresolved issues.

Method

Procedures used for identification or construction of child- and school-level variable measures, for setting up a data set with complete information on chosen variables, and for testing particular analytic models, are described next.

School- and Child-level Factors Selected for Study

Separate sets of factors were selected at the child- versus school-level for analysis. At the child level, variables included child development factors (age of the child in months and gender), socio-demographic factors (ethnicity, family's socio-economic status), and cognitive measures taken prior to formal schooling (mathematics achievement scores in the beginning and at end of kindergarten—K-entry and K-end scores). The ethnic minority sub-samples of interest in this study consisted of children coded as African-American (non-Hispanic), Asian, Hispanic (race specified), and Hispanic (race unspecified) students in the ECLS database. The term "poverty" refers to students falling at or below the second quintile on the continuous measure of family socio-economic status used in the ECLS.

At the school level, variables included appropriately aggregated context factors (poverty rate, school size), school inputs (mean class size, teacher certification rates), organizational practice/policy factors (success orientation and academic press values, levels of teacher support for planning and professional development, student attendance rate, incidence of individualized educational plans (IEPs, an index of exceptional education services), and several parent involvement factors–such as, on average, how long parents read to children at home every week; overall education support at home, parent satisfaction with school activities, and parental involvement in school functions. School means on the child poverty index and prior achievement were built into the models as controls in some HLMs. Initially, all theoretically relevant variables were incorporated in the models; in the final models, variables with negligible and/or statistically non-significant effects or excessive missing data were dropped from the analyses.

Variables/Measures: Operational Definitions

Table 1 provides descriptive statistics on all variables used in the analyses at the child and school levels. The operational definitions of different constructs, their theoretical and psychometric bases, and coding methods are described briefly next, and detailed in Appendix A.

Table 1
Descriptive Statistics on Level 1 and Level 2 Variables

Variable name	N	Mean	SD	Minimum	Maximum
Level 1: Child Characteristics					
Age in months	2300	79.89	4.10	70.13	94.77
Math score at K-entry, C1RMSCAL	2300	20.75	7.18	7.18	56.91
Math score at K-end, C2RMSCAL	2300	29.26	8.51	9.14	57.25
Math score at Grade 1, C4RMSCAL	2300	45.06	8.37	12.20	60.50
African American (%)	2300	0.12	0.33	0	1
Hispanic-1 (%)	2300	0.06	0.25	0	1
Hispanic-2 (%)	2300	0.05	0.22	0	1
Asian (%)	2300	0.03	0.18	0	1
Poverty (%)	2300	0.29	0.46	0	1
Gender (Male=1; %)	2300	0.49	0.50	0	1
Level 2: School Characteristics					
Number of children nested in schools	182	16.74	4.76	10	33
Teacher support	182	14.30	2.90	4	20
School success orientation	182	12.84	1.64	8	15
Student attendance rate	182	97.46	1.14	93.02	99.73
Education support at home	182	10.85	0.94	7.92	13.90
Parent satisfaction	182	6.23	0.77	4.84	10
Class size	182	21.50	4.74	11.84	52
Class time to reading and math	182	3.82	1.06	2	8
School size	182	0.85	0.36	0	1
Public versus private sector	182	0.89	0.31	0	1
Individualized Educational Plans	182	5.45	9.65	0	67.94
At home reading time	182	0.58	0.17	0.20	1
Parent involvement	182	6.65	0.80	5.10	9
Teacher certification rate-Elementary	182	0.79	0.28	0	1
School-level controls					
K-end Math	182	33.26	5.55	19.80	48.02
K-entry Math	182	22.83	4.55	12.81	38.26
Poverty rate	182	38.57	29.16	0	100
Minority rate	182	0.33	0.34	0	1

The ECLS mathematics assessment. The ECLS mathematics assessment is a multi-level, interview-based assessment that was administered in two stages, using an adaptive design. First, children received a 12–20 item routing test. Their performance on the routing test determined the second stage form that would be at the appropriate difficulty level for different children. For individual children, scores on the full set of test items were estimated using Item Response Theory (IRT) procedures. IRT equating methodology was used to place all items on a common scale, making scale scores comparable across children at different levels, regardless of the items to which they responded.

The item content of the ECLS mathematics assessment is as follows: *number and shape* (identifying one-digit numerals, recognizing geometric shapes, and one-to-one counting of up to 10 objects); *relative size (*reading single-digit numbers, counting beyond 10, recognizing a sequence of patterns, and using non-standard units of length to compare objects); *ordinality and sequence* (reading 2-digit numerals, recognizing the next number in a sequence, identifying ordinal position in a sequence, and solving a simple word problem); *addition and subtraction* (solving simple addition and subtraction problems); and *multiplication and division* (solving simple multiplication and division problems and recognizing more complex number patterns). Reliability of scores from the ECLS mathematics assessments are reported to be in the following ranges: .88–.95, for ability estimates on IRT scale scores; and .78–.88, for the routing tests (NCES et al., 1999).

First grade mathematics outcome measure (C4RMSCAL). IRT-scaled scores from the ECLS mathematics assessment, taken at the end of first grade, were used a dependent variables in HLM equations after their distribution properties were examined in the larger ECLS sample.

Prior achievement in mathematics (C1RMSCAL, C2RMSCAL). IRT-scaled scores from the ECLS mathematics assessment, taken either at the beginning (K-entry) or end of kindergarten (K-end), were used as child-level predictors or as dependent variables after their distribution properties were examined in the overall ECLS sample with all available cases. Both the kindergarten measures were preferred over prior mathematics measures taken at the beginning of first grade (C3RMSCAL), as about 2/3 of the original sample had missing data on this measure. A possible summer lag between the end of kindergarten and first grade was anticipated to have been made up by the end of the Grade 1 year.

Survey constructs. Composite measures were created with selected item sets from different ECLS questionnaires to serve as predictors. Indices created with child-level data were aggregated by school, and treated as school-level factors. The descriptions of each survey construct, data sources from which they were extracted, and results of various psychometric analyses on variables, are detailed in Appendix A.

Exploratory factor analytic work (principal components analysis followed by varimax rotation) was done to extract relatively independent but theoretically meaningful factors. Internal consistency reliability estimates of factor-supported composites were obtained using Cronbach's alpha prior to incorporating the index scores into HLM equations as child- or school-level factors. Item-factor loadings of .40 and above, and Cronbach's alpha estimates of .70 were used as criteria for psychometric defensibility of indices. All available cases in the ECLS database were used for various psychometric analyses—the range of cases varied from 4,637 to 11,379 for these examinations.

Unique variable definitions. In this study, the "special education" service variable refers to the *incidence or percent of* IEPs, aggregated by school. That is, the percents of children in the study sample were those identified by their schools as having IEPs on file. Appendix B, Table B3 provides the frequency breakdown on the ECLS survey item that served as the data source (U4IEP) for this variable. The unique variable definition yields lower percents than national estimates of students with disabilities (typical range from 10–15%). Elsewhere, Walston and West (2004) reported the percent representation of students with disabilities in the larger ECLS sample was 12% (2568 out of 21260), close to the national estimate.

Likewise, the "poverty" variable is not based on student enrollment in free or reduced lunch programs at schools (as found in many policy studies), but rather the ECLS composite for socio-economic status computed for individual children based on parent education, occupation and income (see Appendix A). The lower two quintile ranges in this continuous SES measure were selected as a cut to identify "high poverty" students. The percents in the original ECLS sample and initially screened study sample were thus at or around 40%; the final 2300 cases had a lower poverty rate (29%) by this definition (see Table B1 in Appendix B). However, when school-level aggregates were computed, the mean poverty rate across schools was about 39% (see Table 1, lower panel).

Finally, "Reading Time" given by parents at home was based on an individual item that was *separate* from the items used to construct remaining parent involvement composites from the Parent Questionnaire. This item asked how long parents read to their child at home (more than 30 minutes per week versus less, a (1/0) binary variable). The data were incorporated in the models as a school-level aggregate–a proxy for family care/parenting variable shown to influence future academic performance of children.

Prior to running the HLMs, the relationship of this variable with other school-level aggregates, such as a school's aggregated poverty rate across sampled children, was examined to identify possible suppressor effects (see Appendix B, Table B2, for a correlation table). The magnitude of these overlaps was judged to be too small to cloud subsequent interpretations of results with multiple predictors. As is evident, Reading Time, averaged by school, correlated -.087 (n.s.) with the Poverty rate, and .18 ($p < .05$) with the Educational Support variable. The latter correlation suggested that schools with higher levels of parental support for education also had higher at-home reading time values. Several of the correlations in Table B2 were similarly meaningful and were formally tested with HLMs.

Sample Size and Composition

Utilization of multiple data elements and composite variables necessitated a careful examination of missing data in the data set prepared for analysis. Some decisions were made on how best to retain an optimal sample size with as much complete data as possible on variables that were relevant to the research objectives. Normalized sample design weights using the C124PW0 variable were applied, as recommended by ECLS staff, to retain original degrees of freedom.

To start, all grade-retained children were screened out by including only those who were first-time kindergartners (P1FIRKDG=1) and first-time first graders in traditional classrooms and schools (T4GLVL=4) with data available on the weighting variable. Next, new variable measures were constructed as described previously and a child-level file was created using all cases with complete data on gender, poverty, race, and prior achievement and outcome indicators. Lastly, a school-level file was created, aggregating all school factors to be tested in HLMs, including at least 10 students within each school. Missing values on 6 constructs were imputed with the mean substitution procedure in SPSS (detailed at the end of Appendix A). The final data set for the present analysis yielded 182 schools with 2300 cases. The composition of the screened study sample with weighted and unweighted cases, compared to the original ECLS sample and the final data set, is described in Appendix B, Table B1 on key demographic variables.

Descriptive Statistics on Child and School-level Variables

The top panel in Table 1 shows descriptive statistics on child-level (Level 1) variables in the dataset (N=2300). As is evident, 12% of the sample were Blacks, 6% belonged to the Hispanic-1 group (race specified), 5% were Hispanic-2 (race unspecified), and 3% were Asian children. The children had a mean age of 79.89 months at the beginning of first grade; 29% were from high poverty households; and about half (49%) were male. At the school level, the number of children nested in schools varied from 10–33, with a mean of 17. This number is different from the "class size" variable and reflects children sampled by school per the ECLS sample design, where on average, 5 children and 3 classrooms were sampled from each school.

Analytic Models

A series of two-level models, with children's achievement modeled at the child-level, nested under schools at the second level, were run with the HLM Version 5.02 program (Raudenbush, Bryk, Cheong & Congdon, 2001). The research rationale for each HLM was as follows.

Unconditional (null) model. The first analysis involved the use of a one-way random effects ANOVA, also called the unconditional or null model. This analysis was motivated by the need to partition the total variance in achievement into within- and between-school components. The variance estimates were obtained by fitting an HLM where each child's end-of-first grade achievement score, y_{ij}, is explained by the estimated school mean, β_{j0} and unique error associated with that child, r_{ij}. School means were explained by the grand mean, G_{00} and unique error for each school, $u_{j.}$

$$y_{ij} = \beta_{j0} + r_{ij}.$$
$$\beta_{j0} = G_{00} + u_{j.}$$

The analysis with the null model yielded answers to three questions: How much do individual students vary around their school means ? How much of total variance in mathematics achievement is attributable to schools? and How precise an estimate of the population mean is the school mean, β_{j0}? These questions were answered by examining the variance estimates within schools (σ^2) and between schools (τ), and the size of the intraclass correlation (proportion of total variance that is between schools). ICC values greater than .10 indicate that there are sufficient within-school dependencies to justify multi-level analysis. A reliability estimate for school mean estimates (intercepts, β_{j0}), is reported in the HLM output. A criterion of .60 was set for the reliability of the intercepts. Subsequent models incorporating predictors at both levels were evaluated against these initial variance estimates.

Random intercepts model with only child-level predictors. The next series of HLMs was specified to answer two main questions: Given the estimated within- school variance, what proportion of that variance in achievement can be accounted for by child background characteristics, such as their age, prior achievement in math , gender, poverty, and ethnicity ? Compared to school mean estimates and controlling for other child background characteristics, how large are the achievement gaps in selected ethnic, poverty, and gender groups? The school-level model remained as in the null model; predictors were all entered in the child level equation.

All predictors were centered around their school means; thus, the estimated coefficients for each risk group showed the within-school achievement differential, controlling for the other child background characteristics serving as predictors in the models but allowing variability between schools—a primary research objective for the study.

$y_{ij} = \beta_{j0} + \beta_{j1}$ (African American) $+ \beta_{j2}$ (Hispanic-Race specified)
$+ \beta_{j3}$ (Hispanic-Race unspecified) $+ \beta_{j4}$(Asian) $+ \beta_{j5}$(Prior Achievement)
$+ \beta_{j6}$(Poverty) $+ \beta_{j7}$(Male) $+ \beta_{j8}$(Age) $+ r_{ij}$.

$\beta_{j0} = G_{00} + u_{j.}$.
$\beta_{j1} = G_{10}$
β_{j2} through β_{j8} (all slopes fixed as in β_{j1}).

Gaps were estimated at the end of kindergarten and in Grade 1, using both the K-entry and K-end mathematics measures as prior achievement indicators in separate models. Findings were compared. The models were evaluated against the null model by examining the proportion of unexplained within-school variance that was accounted for, after all the child-level predictors were included in the model.

Random intercepts model with child level covariates and school-level predictors. In the third series of HLMs, theoretically-supported school variables were modeled to explain between-school variability in achievement, with child-level predictors also entered. Effects of child-level predictors that were main focus of the study, ethnicity, gender, and poverty were again allowed to vary randomly between schools—that is, they were group (school) mean-centered. School aggregates on poverty and prior achievement were reentered in second level equations as context controls to study effects of other school factors, adjusted for these average effects. Remaining child-level factors, such as age, were now centered around the grand mean, and served as a constant across schools. Again both the K-entry and K-end mathematics measures were used as covariates at the child-level in different runs to compare findings.

$y_{ij} = \beta_{j0} + \beta_{j1}$ (African American) $+ \beta_{j2}$ (Hispanic-Race specified) $+ \beta_{j3}$ (Hispanic-Race unspecified) $+ \beta_{j4}$(Asian) $+ \beta_{j5}$(Prior Achievement) $+ \beta_{j6}$(Poverty) $+ \beta_{j7}$(Male) $+ \beta_{j8}$(Age) $+ r_{ij}$.

$\beta_{j0} = G_{00} + G_{01}$(Mean Poverty) $+ G_{02}$(Mean Prior Achievement) $+ G_{03}$ (School Size)
$+ G_{04}$ (Mean Class Size) $+ * G_{05}$(Mean Teacher Variables)
$+ * G_{06}$ (Mean Organizational Variables) $+ G_{07}$ (Mean Reading Time)
$+ *G_{08}$ (Mean Parent Involvement Variables) $+ u_j$,

where

$\beta_{j1} = G_{10}$
β_{j2} through β_{j8} (all slopes fixed as in β_{j1}).

(* indicates that there is more than one coefficient in this predictor category.)

This series of HLMs revealed the degree to which the selected school factors significantly and positively influenced first grade mathematics achievement in schools, as main, additive effects. The reduction in the variance estimate of u_j enabled a calculation of the proportion of originally estimated between-school variance (from the Null Model) that could be explained by the school factors chosen, and an evaluation of the usefulness of models. A comparison of models examining K-entry to Grade 1 versus K-end to Grade 1 effects was also made. Slope parameters for predictors at the child level were again fixed; that is, the influence of individual child-level characteristics was not set to vary by school.

Random intercepts and slopes models, with explanatory variables to examine cross-level interactions. Finally, to answer questions as to whether mathematics achievement varied due to interaction of a child's risk group membership modeled in the child-level equation and schools in which they belonged, modeled at the second-level, slopes for these predictors were next allowed to vary randomly. Here, only the K-end mathematics measure was used as a covariate. When statistically significant slope variance was found, the equation for that slope parameter was modeled with school-level predictors to identify significant explanatory variables. For example, with the poverty variable, the questions were: Does mathematics achievement vary significantly in poor versus well-to do children who belong in different schools? If so, what school variables significantly explain the achievement variance in the slopes? The equations were:

$$\beta_{j6}(\text{ Poverty}) = G_{60} + u_6,$$

to examine if the poverty slope, β_{j6}, had significant variance when modeled as a random variable. To identify significant explanatory variables, the subsequent equation was built as follows:

$$\beta_{j6} = G_{60} + +G_{61} \text{ (Mean Minority)} + {}_{G62}\text{(Mean Poverty)} + G_{63} \text{ (Mean Prior Achievement)}$$
$$+G_{64}\text{(School Size)} + G_{65}\text{(Mean Class Size)} + {}^*G_{66} \text{ (Mean Teacher Variables)}$$
$$+ {}^*G_{67} \text{ (Mean Organizational Variables)} {}^*G_{68} \text{ (Mean Parent Involvement Variables)} + u_6.$$

These analyses were pursued with one slope modeled at a time. The number of schools with necessary data at the school level dropped in the cross-level models and are reported in tables with results. The reliability of the slopes and intercepts was checked at each stage of the analysis and are also reported.

Results

The results of the final models are presented in Tables 2–10. A few predictors that did not significantly contribute to the variance of achievement (such as early childhood certification rate) were dropped from reduced models.

Child versus School Variance Components in First Grade Mathematics

How much variability in first grade mathematics achievement could be attributed to children versus schools? The results with the unconditional model for mathematics are presented in Table 2. Children were found to vary significantly around their school means, as evidenced in the statistically significant *t* value. The within-schools variability in achievement was estimated at 66.06; the between-schools variability was estimated at 16.37. This yielded an intraclass coefficient (ICC) of .198, showing that about 20% of the total variability in mathematics achievement could be attributed to schools (i.e., between-school variance). The estimated school mean was 44.28 (*SE*=0.34). The reliability of this estimate was .76.

Table 2
First Grade Mathematics Variance Partitioned to Students versus Schools: Results from Null Model

Variable	Parameter estimates			d.f.	p
Fixed Effect	Coefficient	SE	t		
School mean[a], G_{00}	44.28	0.34	129.30	181	< .01
Random Effect	Variance Component		X^2		
School level effect, u_{oj}	16.37		831.95	181	< .01
Child level effect, r_{ij}	66.06				

[a] Reliability of intercept (school mathematics mean estimates at end of Grade 1) = .76
Variance Attributable to Schools (ICC) = [16.37/(16.37+66.06)]= .20

Mathematics Achievement Gaps in Kindergarten and First Grade

What were the within-school achievement differentials in kindergarten and first grade of different ethnic, gender and poverty groups, adjusting for K-entry versus K-end variability in children's mathematics achievement? How much of the within-school variance in first grade achievement was accounted for by the chosen predictors? Tables 3–5 provide the estimates on the size and significance of mathematics achievement gaps and child-level predictors. Figures 1-3 present a pictorial view of the achievement gaps.

Table 3
Kindergarten Achievement Gaps: Results from Random Intercepts Model with Level 1 Predictors and K-Entry Measures of Prior Achievement

Variable	Parameter estimates			d.f.	p
Fixed effects	Coefficient	SE	t		
School mean[a], G_{00}	28.20	0.35	80.58	181	< .01
Within-school effects					
Age in months	0.02	0.03	0.66	2291	.51
Poverty Status Gap	-0.56	0.25	-2.23	2291	.03
African American Gap	-1.55	0.45	-3.40	2291	< .01
Hispanic-1 (Race sp.) Gap	0.14	0.49	0.28	2291	.78
Hispanic-2 (Race Not sp.) Gap	-0.90	0.46	-1.95	2291	.05
Asian Gap	0.01	0.54	0.02	2291	.99
Gender Gap (Male vs. Female)	0.08	0.24	0.36	2291	.72
Achievement at K-entry	0.92	0.02	42.00	2291	< .01
Random effects	Variance Component		X^2		
School level effect, u_{oj}	20.43		2276.48	181	< .01
Child level effect, r_{ij}	24.61				

[a] Reliability estimate of intercept = .91
Within-school variance accounted for by Level 1 predictors: [(66.08-24.61/66.08)]= .64.

It should be noted that "achievement gap" in Tables 3–5 are the multilevel regression coefficients. They are interpreted as the achievement difference of a selected subgroup (e.g., African American vs. others) as compared to the estimated school mean (the intercept), controlling for prior achievement and other demographic characteristics.

Table 3 show that achievement gaps at the end of kindergarten, controlling for K-entry mathematics achievement, are significant in high poverty, African American, and Hispanic-2 (race not specified) subgroups. The school mean is estimated at 28.20. A high poverty child is estimated to score lower than the school mean by -0.56 units ($p < .05$); an African American child by -1.55 units ($p < .001$), and Hispanic-2 children by -0.90 ($p = .05$). There is *no* gender gap evident. Children who have higher mathematics scores at the start are predicted to do significantly better at the end of kindergarten with a coefficient of +.92 ($p < .01$), controlling for other factors within schools. About 64% of the variability in children's mathematics achievement at the end of kindergarten is explained by the predictors modeled.

Table 4 coefficients show that significant mathematics gaps are manifested again in first grade in African American children versus other ethnic groups (-2.01 points, $p < .01$) and in high poverty versus well-to-do children (-1.72, $p < .01$), but not for the Hispanic subgroups. There is now a small but significant gender gap, with males showing an advantage over females (+0.53, $p < .10$). K-entry mathematics scores are modeled with other predictors as covariates. The within-school mean estimate is close to the estimate in Table 1, 44.96 (SE=0.36). About 43% of the variability in children's mathematics achievement in Grade 1 is explained by the predictors modeled, a lower proportion than that in Table 3 possibly because schooling and other background factors begin to influence mathematics outcomes more heavily in Grade 1 than at K-end.

Table 4
First Grade Mathematics Achievement Gaps: Results from Random Intercepts Model with Level 1 Predictors and Kindergarten Entry Measures of Prior Achievement

Variable	Parameter estimates			d.f.	p
Fixed effect	Coefficient	SE	t		
School mean[a], G_{00}	44.96	0.36	122.15	181	< .01
Within-school effects					
Age in months	-0.05	0.03	-1.33	2291	.18
Poverty Status Gap	-1.72	0.38	-4.49	2291	< .01
African American Gap	-2.01	0.54	-3.70	2291	< .01
Hispanic-1 gap (Race specified)	0.64	0.49	1.30	2291	.19
Hispanic-2 gap (Race not specified	-1.00	0.69	-1.43	2291	.15
Asian Gap	-0.48	0.65	-0.74	2291	.45
Gender Gap (Male vs. Female)	0.53	0.27	1.89	2291	.05
Achievement at K-entry	0.75	0.03	23.05	2291	< .01
Random Effect	Variance Component		X^2		
School level effect, u_{oj}	14.63		1178.73	181	< .01
Child level effect, r_{ij}	37.77				

[a] Reliability estimate of intercept = .83
Within-school variance accounted for by Level 1 predictors: [(66.06-37.77)/66.06] = .43.

With K-end mathematics scores used as prior achievement measures in Table 5, the gaps reduce marginally in size but remain statistically significant at the .05 alpha level in the *same groups* of children. The observed change in gap estimates is small, but the effects of the kindergarten year's experiences on Grade 1 mathematics achievement are evidenced in the 10% difference in achievement variance explained. In all, 53% of the within-school variance in achievement is accounted for by the child-level predictors in the second model. The school-level mean in first grade mathematics achievement is again close at 44.71 (*SE*=0.36). The reliability of the school mean estimates in both first grade models is high at .83 and .87, respectively.

Table 5
First Grade Mathematics Achievement Gaps: Results from Random Intercepts Model with Level 1 Predictors and K-end Measures of Prior Achievement

Variable	Parameter values			d.f.	p
Fixed effect	Coefficient	SE	t		
School mean[a], G_{00}	44.71	0.36	121.92	181	< .01
Within-school effects					
Age in months	-0.03	0.03	-0.90	2291	.37
Poverty Status gap	-1.40	0.33	-4.19	2291	< .01
African American gap	-1.24	0.50	-2.48	2291	.01
Hispanic-1 gap (race specified)	0.39	0.52	0.76	2291	.44
Hispanic-2 gap (race not specified	-0.53	0.66	-0.79	2291	.42
Asian gap	-0.53	0.54	-0.99	2291	.32
Gender gap (Male =1)	0.49	0.25	1.95	2291	.05
Achievement at K-end	0.70	0.01	36.36	2291	< .01
Random Effect	Variance Component		X^2		
School level effect, u_{oj}	16.19		1524.32	181	< .01
Child level effect, r_{ij}	30.84				

[a] Reliability estimate of intercept = .87
Within-school variance accounted for by Level 1 predictors: [(66.06-30.84)/66.06] = .53.

As expected, gaps are slightly smaller in magnitude in Table 5 than those presented in Table 4. This is because children's initial mathematics variability is now statistically controlled using mathematics measures taken at K-end, just prior to their entry into first grade. The within-school Grade 1 results indicate the following (Table 5): an increase in children's age by one month marginally drops the school mathematics mean by 0.03 units (p=.37), children's membership in the high poverty group (poverty status=1, versus others) significantly decreases the mean by -1.40 units (p< .01). A male child, versus females, scores 0.49 units above the estimated school mean (p=.05) in mathematics. An African American child, versus others, is estimated at scoring -1.24 units below the estimated school mean (p< .01). Hispanic-1 children (race specified) score 0.39 units above; Hispanic-2 (race unspecified) children score -0.53 units below; while an Asian child is estimated to score -0.53 units below the school mean—but none of the achievement differentials for the last three ethnic groups are statistically significant at the 10% error level once K-end mathematics variability is controlled. Finally, for every unit increase in the mathematics achievement score at the end of kindergarten, a first grader scored 0.70 units higher on the first grade measure of mathematics (p< .01).

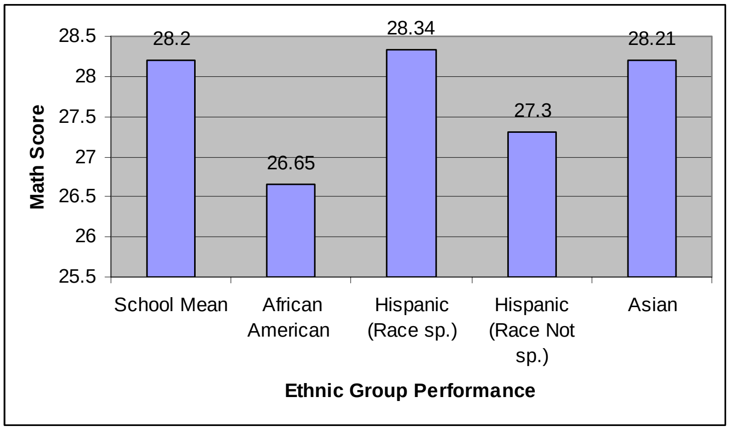

Figure 1. End of Kindergarten Math Achievement Gaps Controlling for K-Entry Achievement.

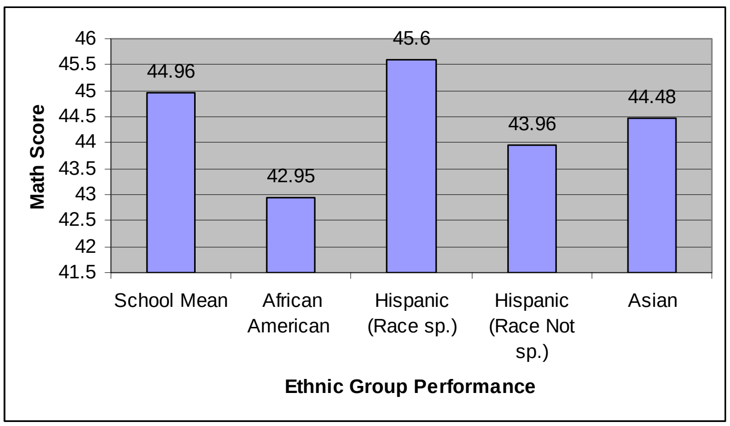

Figure 2. First Grade Math Achievement Gaps Controlling for K-Entry Achievement.

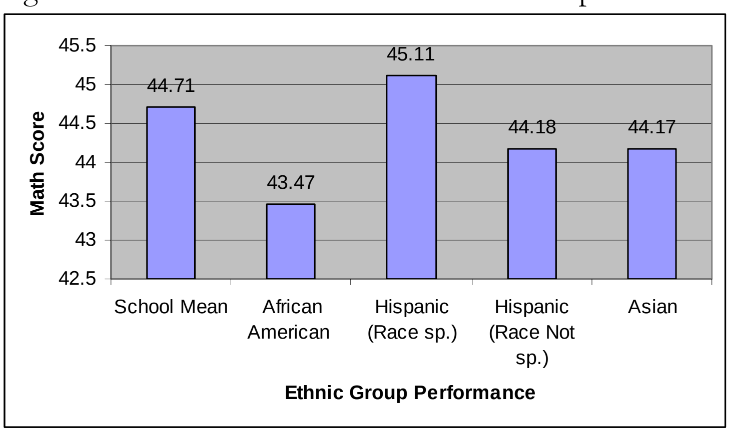

Figure 3. First Grade Math Achievement Gaps Controlling for K-End Achievement.

School–Level Correlates of Mathematics Achievement

Which school practice or policy variables influence mathematics achievement of first graders? The results are presented separately in Tables 6–7 for models that used K-entry versus K-end measures of mathematics as covariates in the Level 1 models, and show consistent results, with one exception. In all, 75–79% of the estimated between-school variance reported in Table 2 (16.37), was explained by the modeled school level predictors, showing the utility of the models (see table notes).

Table 6
Main Effects of School Variables in Level 2: Results of HLM with Level 1 Covariates and K-Entry Measures as Controls

Variable	Parameter estimates			d.f.	p
Fixed school effect	Coefficient	SE	t		
School mean[a], G_{00}	44.47	0.28	154.62	166	< .01
Fixed school effects					
Class size	-0.05	0.03	-1.64	166	.09
Frequency of Individualized educational plans	-0.02	0.02	-0.95	166	.34
Student attendance rate	0.00	0.23	0.01	166	.99
Parental support for education	-0.28	0.23	-1.23	166	.21
Parental satisfaction with school	-0.05	0.25	-0.23	166	.81
School size	0.95	0.55	1.71	166	.08
Public school	0.36	0.64	0.57	166	.56
Time parents read to children at home	1.73	1.04	1.65	166	.09
Parent Involvement levels	-0.25	0.37	0.69	166	.48
Teacher support	-0.08	0.07	-1.24	166	.21
School success orientation	-0.16	0.10	-1.57	166	.11
% Teachers with Elementary Certification	0.51	0.61	0.84	166	.40
Class time dedicated to reading and math	0.24	0.18	1.28	166	.19
Context Controls at School-level					
% Low SES students	-0.002	0.01	-0.19		.84
K-Entry Achievement	0.68	0.07	9.48	166	< .01

[a] Reliability estimate for intercept = .55
Between-school variance in achievement accounted for by school predictors: [(16.37-3.41)/16.37)]=.79.

In Table 6, effects are estimated following children's exposure to kindergarten and first grade experiences cumulatively, equalized across schools on K-entry mathematics scores but varying on ethnicity, poverty and gender. Consistent with prior research, class size has a small negative and significant effect at the 10% error level (-0.053, $p< .10$), showing that with average increases in teacher-reported numbers of children in classrooms, there is a small drop in school mathematics means. Because the effects are estimated on school aggregates, the influences are smaller in magnitude than may be obtained for individual children's scores. A large positive correlate is the school's average on parent-reported at-home reading time. Here, a unit change (30 minutes or more versus less) in the predictor results in gains of 1.73 units on school mathematics achievement means ($p< .10$). School size is the third statistically significant correlate at the 10% level, but in an unexpected direction. Operationalized as 500+ versus less than 500 students (a binary variable), a value of 1 resulted in 0.95 point increase in school mathematics means, indicating that larger school sizes yielded higher mathematics scores in schools.

Table 7
Effects of School Variables: Results of HLM with Level 1 Covariates and K-end Measures of Prior Achievement

Variable	Coefficient	SE	t	d.f.	p
Fixed effect					
School mean[a], G_{00}	44.30	0.26	165.97	166	< .01
School effects					
Class size	-0.05	0.03	-1.65	166	.09
Frequency of Individualized educational plans	-0.01	0.02	-0.92	166	.35
Student attendance rate	0.00	0.23	0.03	166	.97
Parental support for education	-0.30	0.23	-1.31	166	.19
Parental satisfaction with school	-0.05	0.25	-0.20	166	.84
School size	0.89	0.54	1.64	166	.09
Public school	0.45	0.63	0.72	166	.47
Time parents read to children at home	1.71	1.06	1.61	166	.10
Parent Involvement levels	-0.34	0.37	-0.90	166	.36
Teacher support systems	-0.09	0.07	-1.27	166	.20
School success orientation	-0.17	0.10	-1.66	166	.09
% Teachers with Elementary Certification	0.57	0.60	0.95	166	.34
Class time dedicated to reading and math	0.24	0.18	1.28	166	.19
Context Controls in school-level equations:					
% Low SES students (school aggregate)	-0.00	0.01	-0.40		.68
K-end Achievement	0.69	0.07	9.33	166	< .01

[a] Reliability estimate for intercept = .63
Between-school variance in achievement accounted for by Level 2 predictors: [(16.67-4.00)/16.67)]=.76.

In Table 7, children vary in terms of gender, ethnicity, and poverty, and are now equalized on prior mathematics preparation at K-end. Thus, pupils can be expected to be less variable at the end of Grade 1 than the model in Table 6 and only Grade 1 effects are estimated. Again, class size, reading time at home and school size variables have similar and significant effects, in the same directions. In addition, a counter-intuitive result is obtained with the school success variable, where unit increases on the composite resulted in small drops in school means by -0.18 points ($p < .10$). The other school predictors do not have significant main effects.

Interaction of Child's African American Status with Schools

Because African American children were found to have statistically significant gaps, a further question dealt with whether their performance varied by school when K-end measures were controlled. Other ethnic group interaction analyses were prohibited by a reduction in the number of schools available for analysis that included children from Asian and Hispanic subgroups.

Table 8
Cross-level Interaction Effects of African American Group Membership and School on First Grade Mathematics

Variable [a]	Parameter values			d.f.	p
Random effects	Variance Component		X^2		
School level intercepts, u_{oj}	3.51		138.50	57	< .01
African American slopes, u_{3j}	4.36		82.62	72	.18
Child level effect, r_{ij}	37.44				
Fixed effects	Coefficient	SE	t		
Intercept for Af. Am. slope	-0.59	0.43	-1.38	166	.16
Class size	-0.18	0.11	1.62	166	.10
% Low SES students	0.06	0.02	2.85	166	< .01
School size	-2.13	1.10	-1.93	166	.05
Parent involvement	- 1.81	0.80	-2.25	166	.05

[a] Reliability estimate of intercept = .46; Reliability estimatee of slope = .19
Variance explained in slopes = [(4.36-1.29)/4.36] = .70.

Table 8 shows that there was no significant cross-level interaction between a child's membership in African American versus other ethnic group and their school, as evidenced in the results on the slope parameter. The intercept for the African American slope was -0.599 (p=.16), a statistically non-significant and somewhat lower value than the initial gap estimates in Tables 3-5. The initial variance estimate for school slopes was 4.36 (p =.18). The lack of a significant interaction in this model was based on 73 schools only (see d.f. and chi squared value), and suggested that while African American children's mathematics achievement varied, it was not significantly different based on school membership.

Because initial deficit estimates were significant in this subgroup, an explanatory model was built to isolate school factors that accounted for whatever school slope variance was manifested in the data with 73 schools. These results showed that with increased class sizes, African American children scored significantly lower by -0.18 units, over and above the initial deficit estimate of -0.599 units (p=.10.); with increased school sizes, likewise, they scored significantly lower by -2.13 units (p=.05); in high versus low poverty schools their performance remained much the same (.06, p< .01); in schools with higher parent involvement levels, their performance was significantly lower (-1.81, p=.06)—a counter-intuitive finding. These variables dropped the initial variance estimate to 1.29, accounting for 70% of the variability evidenced in school slopes.

Interaction of Child's Poverty Status with Schools

Table 9 presents the results on the second interaction question showing that mathematics performance of high and low poverty children varied significantly by school (variance estimate of slope, u_{7j} =5.51, p=.000). The intercept indicated that across all schools, high poverty children were scoring -1.01 units lower compared to low poverty children (compare with gap estimates in Tables 3-5). Significant explanatory variables for slope variability were school averages on total time teachers gave per day to reading and mathematics instruction (30–60 minutes per day versus less) with a positive coefficient of +0.54 (p=.08); IEPs in school, with a small negative coefficient of -0.06 (p< .10); and public versus private sector with a larger negative effect of -2.60 (p=.03). The last result showed that public schools fare worse than private/other schools in affecting mathematics performance of high poverty students. In this analysis, schools with higher poverty rates scored as well as those with lower poverty rates (+0.03, *p*=.03). The intercept reliability was found to be .47, and initial slope reliability was 0.31, with 10% of variance in slopes accounted for by the school factors modeled (final variance estimate=4.97).

Table 9
Cross-level Interaction Effects of Poverty Group Membership and School on First Grade Mathematics

Variable[a]	Parameter estimates			d.f.	p
Random Effect	Variance component		X^2		
School level intercepts, u_{oj}	3.54		258.56	137	< .01
School poverty slopes, u_{8j}	5.51		222.14	152	< .01
Child level effect, r_{ij}	29.88				
Fixed Effect	Coefficient	SE	t		
Intercept for Poverty Slope	-1.01	0.34	-2.94	166	< .01
Class time to Reading and Math	0.54	0.31	1.72	166	.08
Individualized Educational Plans	-0.06	0.03	-1.69	166	.08
Public school	-2.60	1.23	-2.14	166	.03
% Low SES Students	0.03	0.02	1.75	166	.07

[a] Reliability estimate of intercept = .47; Reliability estimate of slope = .31
Variance explained in slopes= (5.51-4.97)/5.51= .10.

Interaction Effects of Child's Gender with Schools

Finally, Table 10 shows that the effect of a child's gender on mathematics achievement varied by school (variance estimate of slope=2.11, *p*=.005). Overall, the intercept, reflecting the mean achievement of boys, was 0.30 units higher than for girls in first grade (the earlier gap estimates were around 0.49, about 0.19 units higher). One school-level factor, teacher certification rates in elementary education, yielded a statistically significant and large positive effect for boys versus girls (+2.49, *p*=.009). Statistically significant explanatory variables that had negative effects for boys versus girls were the following: schools' teacher support levels (-0.17, *p*=.05) and school averages on parent involvement (-0.87, *p*< .05). To interpret these negative findings for teacher support, as an example, boys scored 0.17 units lower in mathematics than girls in schools where teacher support was reportedly a unit higher. The reliability of intercepts in the full analytic model was .54, and the reliability of the slope was .19. A total of 24% of the variance in slopes was explained by the modeled school variables (final variance estimate for slopes=1.61).

Table 10
Cross-level Interaction Effects of Gender Group Membership and School on First Grade Mathematics

Variable[a]	Parameter estimates			d.f.	p
Random effects	Variance Component		X^2		
School level intercepts, u_{oj}	5.32		375.99	162	< .01
School level slopes, u_{8j}	2.11		229.98	177	< .01
Child level effect, r_{ij}	30.24				
Fixed effects	Coefficient	SE	t		
Intercept for Male Slope	0.30	0.25	1.20	167	0.22
Elementary Teacher Certification	2.49	0.95	2.61	167	< .01
Teacher Support	-0.17	0.09	-1.95	167	0.05
Parent Involvement	-0.87	0.52	-1.66	167	0.09

[a] Reliability estimate of intercept = .54; Reliability estimate of slope = .19
Variance explained in slopes= [(2.11-1.61)/2.11] =.24.

Discussion

The ECLS data allowed a deeper examination of achievement gaps and school factors that directly affect or moderate children's mathematics achievement levels in isolated subgroups—thus addressing a void in the literature. The merit of particular school practices and policies, such as class size reduction and higher teacher qualifications, could also be evaluated in the context of mandatory school reforms ensuing from legislation such as the NCLB Act. Several findings in the present study support current educational policy directions; others contradict conventional or theoretical expectations. In conclusion, these findings are discussed along with limitations and areas for further research.

Representativeness of the ECLS Data Set

Table B1 (in Appendix B) and Table 1 show that the present sample was generally representative of the national ECLS sample in terms of gender and ethnicity, but somewhat underrepresented on the poverty status variable. The smaller number of cases (*N*=2300 in 182 schools) resulted from a search for an optimal data set with complete data on all school and child-level variables of interest in the present investigation. In the final data set, enough cases were present in each of the subgroups of interest and on variables selected for study to enable examination of main effects at each level and cross-level interactions on school practice/policy issues discussed in the review of literature.

Mathematics Achievement Gaps

In interpreting the achievement gaps in the present study, it should again be borne in mind that gap estimates are regression coefficients that represent differences of a defined group on the outcome measure, as compared to the school means and controlling for other modeled child background factors. This definition is different from the NCLB approach, which uses mean differences computed with a specified reference group in mind (e.g., African American versus White).

The results show that the pattern of ethnic and gender gaps in mathematics changes from kindergarten to first grade. However the influence of higher poverty levels is consistently negative on achievement, even when prior knowledge, gender and ethnicity are controlled. Likewise, prior mathematics preparation has a strong positive and significant effect on subsequent achievement measures, with other factors held constant. In kindergarten, African Americans and one Hispanic group show signs of emerging gaps, but the gap in Hispanics declines to a non-significant level in Grade 1. Also, there is no gender gap evident until formal mathematics instruction begins in Grade 1.

The statistically significant advantages estimated for children who start with higher initial mathematics measures (measures taken either at K-entry or K-end) are consistent with prior research discussed in this paper. Institution of statistical controls on pre-Grade 1 mathematics achievement in the analytic models wipes out potential differences in quality of early childhood care, parenting, and known differences in full and half-day kindergarten exposure in different children in the ECLS sample. All these variables have been shown in the literature to be factors that influence school readiness of entering first graders, particularly those who start with academic challenges. The quality of educational experiences before and during the kindergarten year may be critical in influencing subsequent mathematics achievement patterns in diverse children.

From a school practice and policy perspective it is clear that children of different minority groups exhibit slightly different patterns of mathematics achievement in Grade 1. Contrary to expectations set by prior research on ethnic achievement gaps in both older and younger pupils (Lee, 2002; NCES, 1995a, 1995b; Zill & West, 2001), Hispanic children *did not* show statistically significant mathematics achievement gaps in first grade, irrespective of whether K-entry or K-end mathematics variability was controlled. Asians were estimated to score slightly lower, although this last coefficient was again not better than chance. That significant ethnic achievement gaps are manifested in African American, but not in other ethnic subgroups, when K-end or K-entry mathematics achievement variability is controlled in first grade children should be noted.

Likewise, that mathematics gender differences are small but significant as early as in first grade should be also noted by educators and policy-makers. The finding on mathematics gaps in children from economically disadvantaged families is consistent with results on national tests at all levels of schooling. It is imperative that such gaps are followed through elementary school and as children start their middle and high school years. Shifts in the size of the mathematics gaps should be closely monitored. More importantly, schools should find ways to address domain-specific needs of learners as they arise at the classroom level. Timely detection and diagnosis of curriculum-specific needs in learners would give schools and teachers the opportunity to prevent mathematics gaps from developing in later years.

School Level Correlates of Mathematics Achievement

When partitioned, about 20% of the total variability in children's mathematics achievement was between-schools variance. The main effects models explained about 75–79% *of that between-schools variance* estimate, showing class size, reading time at home, school size, and school success (academic press) orientation as significant school level correlates at the 10% error level—consistent outcomes on three counts controlling for K-entry or K-end variability (Tables 6–7). Alimitation is that these correlates were significant at the 10% error level.

However, the finding that class size negatively affected school achievement means is also consistent with results from other research efforts, such as the Tennessee STAR investigations (Finn & Achilles, 1999), which showed positive effects of reduced class size in early grades. The effects reported here are of unit increases in mean teacher-reported class size on school mathematics score averages; hence they are small in size. Each unit in the class size variable stands for an additional child. The descriptive data (Table 1) suggest that class sizes in ECLS schools went up to as many as 52 pupils in a class (Mean= 21.50, *SD*=4.74). The literature shows that with smaller classes, teachers are able to individualize their instruction more and employ a range of instructional practices (Molnar et al, 1999) that may be more developmentally appropriate.

More reading time given by parents, on average, had a large positive effect on school mathematics achievement means, controlling for children's background characteristics. Although the study did not establish causal links, the association of mathematics achievement with increased reading activities at home is encouraging. In early years, cognitive development in children may not be subject-specific, hence increased at-home reading activities could potentially result in gains in both mathematics and reading.

A comment on some of the counter-intuitive findings. The positive rather than negative effects of larger school size on early mathematics achievement may have to do with larger schools having more resources. Another explanation may be the lack of representativeness of the sample on this variable. The breakdown on school size in the initially screened 12,710 ECLS cases had shown that 31% of the children were in schools with 300–499 students, with 19% in even smaller schools. This indicated that the remaining 50% belonged in schools that exceeded 500 students—a less than desirable school size for elementary schools. A 500 cut was thus used to define the school size variable. However, Table 1 shows that following selection of the study sample, just 15% of the 182 schools were "large" (with more than 500 students), while the remaining 85% were "small" schools. This distribution might have tilted results.

On the success orientation variable, schools dealing with challenging student populations often tend to have organizational cultures with high academic press values. Yet, they may show relatively poor academic outcomes because they serve struggling students. That administrator reports of school success orientation had a negative but statistically significant influence on mathematics achievement in schools might have resulted from this last reality. The low correlations in Table B2 (Appendix B) suggest that results were likely not affected by suppressor effects of other school-level variables in the models.

Cross-level Interaction Effects

The more interesting results of this study were on moderators of Grade 1 mathematics achievement gaps. Several cross-level interaction results were in expected directions and may point to some school policy/practice actions, keeping in mind that the evidence is correlational. With the achievement variability that was found in African American children by school, increased class and school sizes affected mathematics achievement negatively, and at-home reading time was positively associated with mathematics achievement. For poor versus well-to-do children, more instructional time per day to mathematics and reading had a positive and significant effect on school achievement means—another affirming finding. Further, higher teacher certification rates in elementary education affected boys' mathematics achievement in a clearly positive direction. As much as a 2-point gain in achievement was estimated to result for boys in schools with unit increases in schools' teacher certification rates. This last finding, although showing differential effects by gender on mathematics achievement, is consistent with the results of the companion ECLS study by this author, where the school certification rate showed a large positive main effect on first grade reading achievement. The need for improving qualified teacher recruitment and retention is currently emphasized in the NCLB legislation; however, policy implementation varies in some regions when certified teachers are in short supply.

Finally, increased IEPs in schools had a significant but small negative effect on mathematics school means of high poverty students. NCLB requires that schools set common benchmarks for achievement of special versus normally-achieving student populations; this may not be a reasonable expectation. It should be noted again in evaluating the implications of these findings that the IEP indicator in this study did not correspond to the percent of students with disabilities in the ECLS sample, and does not reflect national estimates of special education enrollments (Table B3).

Limitations and Future Research

Because secondary analysis of large scale national surveys does not permit causal interpretations of various school effects—the evidence presented here is correlational. The controls instituted were statistical rather than experimental. The composition of the data set, variable definitions, missing data on surveys, and particular variables selected for modeling, all affected findings obtained. Some of the significant negative coefficients obtained with parent, administrator, and teacher survey indices need further confirmation. Some ethnic group interactions could not be examined due to reduction in available cases. Future studies should thus attempt to further validate and replicate the findings reported here with multiple ECLS data sets. Direct and moderating effects of other variables, such as methods of mathematics instruction and children's cognitive development on mathematics achievement, should also be examined to better inform future school policies and practices.

Despite the limitations noted, several results were replicated across analytic models tested. Monitoring of achievement gaps and a search for significant correlates and moderators of achievement should thus continue in other similar populations, and especially with longitudinal data from the ECLS sample in Grades 3 and 5.

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Madhabi Chatterji, Associate Professor of Measurement, Evaluation, and Education at Teachers College, Columbia University, has research interests in designing classroom- and school-based assessment systems; development and validation of construct measures with classical and Rasch measurement methods; and in evaluating standards-based educational reforms and small- and large-scale interventions with systemic models. Her most recently-initiated research, supported by the National Science Foundation in 2004, deals with addressing K-12 achievement gaps in mathematics using a teacher-mediated model of "proximal" assessment and data use. Another line of inquiry deals with gathering research-based evidence on field interventions using mixed-method research designs.

Appendix A
Description and Psychometric Properties of ECLS/Survey Indices

Child Variables

Child's socioeconomic status-poverty: This index was based on a categorical measure of socio-economic status (W1SESQ5) provided by NCES that broke down a continuous measure of socio-economic status built on parent education, occupation, and income, into five categories by quintile. The first and second quintile categories were coded as 1 (low SES, High Poverty), and quintiles 3-5 were coded as 0 (high SES, Low Poverty). This measure yielded much the same results as the continuous SES composite and was used because of its interpretability. In different models, this measure was used as a Level 1 (based on child quintile category) as well as a Level 2 predictor (based on school means).

Teacher Variables

Teacher certification variables-ECERT, ECCERT (Source: Teacher Questionnaire B-B4ELEMCT, B4ERLYCT). These variables were dummy coded, with a 1 to indicate if the teacher had elementary certification (B4ELEMCT) versus not, 0; or early childhood certification (B4ERLYCT) versus not. Only the former was used in the final models based on preliminary findings. School aggregates on certification rates were entered in HLMs.

Teacher support composite-TSUP_1 (Source: Administrator Questionnaire). This index was composed of four self-report items giving administrator reports on whether the school had an active professional development program and gave teachers planning time, time for professional growth and incentives for improvement (S2PRODEV, S2ACTSTF, S2ADEQTE, S2INCENT). The index was supported by results of a principal components analysis with a pre-rotation eigenvalue of 2.01, with component loadings following varimax rotation of .63 to .83. The Cronbach's alpha reliability estimate of composite scores was .71. This index is interpreted as the extent to which a child was exposed to a school with high levels of teacher supports. A school-level aggregate of TSUP was entered into HLMs at Level 2.

School/Organizational Indices

School success orientation- S_SUC1 (Source: School Administrator Questionnaire). The S_SUC1 composite was based on five self-report items indicating leader reports of the degree of success schools have in emphasizing childrens' academic learning, namely, raising test performance, providing challenges to high achievers, added help for low achievers, and being open to new ideas (S2SUCC6-7, 10-11). The factor yielded a pre-rotation eigenvalue of 1.19 using principal components analysis, and factor loadings of .53 to .77 following varimax rotation. The alpha reliability estimate of the composite was .73. Means at the school level were utilized for HLMs.

Class size, CSIZE: (Source: Teacher Questionnaire, Part A). This was a numeric index computed as follows with responses to two items on the teacher questionnaire asking separately for the # of boys versus # of girls in their classroom. CSIZE=A1BOYS+A1GIRLS. Again, means at the school level were used for HLMs.

Class time to reading and math, TIM_1: (Source: Teacher Questionnaire Part A). This was a numeric index computed as follows with responses to two items on the teacher questionnaire, dealing with how much time in minutes, teachers dedicated to reading and math activities in their classrooms per day: TIM=A2MINRD +A2MINMTH. These two items loaded on a principal component with an eigenvalue of 1.57 before rotation, and had varimax rotated factor loadings of .88 and .83. The alpha reliability was .87. School-level means on the composite were used in HLMs.

Parent Involvement Indices

Educational support-EDSUP (Source: Parent Questionnaire). This index was based on parent/guardian reports of whether or not they did math, writing, and mathematics with their child at home. This 3-item set had a pre-rotation eigenvalue of 2.5, and factors loadings from .31 to.78 following varimax rotation. The Cronbach's alpha estimate was .65.

Parent satisfaction with school activities, PAR_S (Source: Parent Questionnaire). This 4-item index was dealt with whether the school provides opportunities for parent and community involvement, and for tracking how their child is doing. PARSCHL=HOWCHD+P2CHILDR+P2CHANCV+P2COMMUN. PAR_S was the school mean. Following satisfactory factor extraction, the obtained alpha reliability of the composite was .75.

Parent involvement, PARINV (Source: Parent Questionnaire). COMPUTE PARINV=P2ATTENB+ P2PARGRP +P2ATTENS +P2VOLUNT+ P2FUNDRS. This index showed the degree to which parents reported involvement in school based on attending events and functions, volunteering, fundraising etc. As in the others, principal components analysis helped identify this subset of items; however, it yielded a lower alpha reliability of .56. P_INV was the school mean.

Other Child-level Demographic/Background Variables

At the child level, several background variables were dummy-coded for analysis. These were gender (Male=1, Female=0), ethnicity in groups of interest (Asian=1, Others=0; African American=1, Others=0; Hispanic (race specified)=1, Others=0; and Hispanic (race unspecified)=1, Others=0). In addition, age of the child in months in grade 1, a continuous measure, was included in the preliminary analysis.

Other School-Level Variables

At the school level, urbanicity (urban=1, other (rural/ suburban)=0), school size(greater than or equal to 500=1, less than 500=0), and school sector (public=1, other=0) were dummy coded. Each school's total IEPs, an index of exceptional education services (SPCED) provided by the school, was computed. Likewise, student attendance was computed as a percent of total days attended in the school year. This last index was based on the number of absences reported for each child in the ECLS database. All school level indices were aggregated across children within each school.

Imputed Values:

The number of values imputed with the mean substitution procedure of SPSS was as follows: EDSUP_1, 1 case; TSUP_1, 23 cases; S_SUCC, 33 cases; S_ATT, 38 cases; CSIZ_1, 15 cases; TIM_1, 55 cases.

Appendix B
Supplementary Tables

Table B1
Representiveness of Final Data Set as compared with ECLS Sample

Variable	ECLS-K Sample	Initially Screened Study Sample (weighted)	Final Data Set
Number of cases	17212	14742	2300
Poverty Status (Low SES,)	6958 (40.4%)	5885 (39.9%)	667(29%)
Gender (Males)	7429 (50.4%)	8867 (49%)	1127 (51.6%)
Ethnicity-Black	2441 (14.2%)	2374 (16%)	276 (12%)
Ethnicity-Hispanic 1	1388 (8.1%)	1346 (9%)	138 (6%)
Ethnicity-Hispanic 2	1560 (6.4%)	1430 (9.7%)	115 (5%)
Ethnicity-Asian	1093 (6.4%)	448 (3%)	69 (3%)

Table B2
Correlations of School-level Variables

Variable	Teacher Support	School Succes	School-Attend.	Educ. Suppt.	Parent Satis.	Class size	Class time to reading/math	Poverty	School size	IEPs	At home reading time
Teacher Support	—										
School Success	.165**	—									
School Attendance	-.042	-.057	—								
Educational support	-.010	.028	.002	—							
Parent Satisfaction	.001	-.125*	-.064	-.083	—						
Class size	-.004	-.041	.184**	-.009	-.012	—					
Class time to reading/math	.132*	-.144*	-.152*	-.028	-.112	.128*	—				
Poverty	.097*	-.200**	.035	-.033	-.013	.117*	.278**	—			
School size	.126**	.031	.061	-.023	-.095*	.150**	-.073	.078	—		
IEPs	.097*	-.002	.003	-.006	.025	-.068	.036	.083	.025	—	
At home reading time	.121*	.008	-.037	.180**	.014	-.114*	.117	-.087	.012	.067	—
Parent Involvement	.114*	-.169**	.022	-.003	.206**	.103*	.186**	.484**	.228**	.071	.004

*p < .05; **p < .01

Table B3

Frequency distributions on Selected Variables in Initially Screened Sample

Category	ECLS sample within category
Total school enrollment (used in study)	
0-149	445
150-299	1915
300-499	3996
500-749	3620
800+	2734
Individualized Education Plans (Variable: U4IEP, used in study)	
Does not have IEP	9012
Has IEP	775
Diagnosed Learning Program (Variable: P3 HEQ020; not used in study due to missing data)	
No	213
Yes	270
Missing	12436

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