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EDUCATIONAL RESEARCHER 2014 43: 25 originally published online 12 November 2013
DOI: 10.3102/0013189X13512673

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An Investigation of the Relations Between School Concentrations of Student Risk Factors and Student Educational Well-Being

John W. Fantuzzo[1], Whitney A. LeBoeuf[1], and Heather L. Rouse[2]

This study investigated the unique relations between school concentrations of student risk factors and measures of reading, mathematics, and attendance. It used an integrated administrative data system to create a combined data set of risks (i.e., birth risks, teen mother, low maternal education, homelessness, maltreatment, and lead exposure) for an entire cohort of third-grade students in a large urban school district. At the school level, high concentrations of children with low maternal education, inadequate prenatal care, homelessness, and maltreatment were most significantly detrimental for student educational well-being. When concentrations of risks at the school level were considered simultaneously with race and poverty, the concentration of poverty was no longer significantly related to targeted educational well-being indicators. For reading achievement and attendance, concentrations of both poverty and race were not significant. Implications for school accountability and community collaborations are discussed.

Keywords: at-risk students; educational policy; hierarchical linear modeling; social context; urban education

The national need for school reform and school-level accountability has increased the importance of school effects research (Annie E. Casey Foundation, 2010). This body of research investigates how schools as whole systems affect their students' educational well-being (Coe & Taylor Fitz-Gibbon, 1998). School effects research has focused primarily on investigating how characteristics of schools' resources (e.g., type, class size, per pupil expenditures, and teacher qualifications) affect students' academic achievement (for review, see Teddlie & Reynolds, 2000). However this specific focus on school characteristics yielded mixed results. For example, some studies have shown that private schools have higher achievement levels and lower dropout rates than public schools (Morgan & Sorensen, 1999; Rumberger & Thomas, 2000); other research has found little or no significant private school advantage when resources and student characteristics are taken into account (Lee & Burkam, 2003; Raudenbush & Bryk, 1986; Rumberger & Palardy, 2005). Similar discrepancies have been found with respect to the impact of school size. Although some studies have shown that large schools have significantly worse outcomes than middle- or small-sized schools (Lee & Burkam, 2003; Lee & Smith, 1997), others have found no differences (McNeal, 1997; Phillips, 1997).

These equivocal findings revived concerns first raised in the Coleman Report (Coleman et al., 1966). This report stressed the importance of investigating the role of school composition of student characteristics in complex models investigating school effects. Research has demonstrated that schools with higher concentrations of minority students, students from low-income households, and students with disabilities are significantly more likely to demonstrate lower school averages in achievement (Caldas & Bankston, 1998; Rumberger & Palardy, 2005). Aikens and Barbarin (2008) found that these concentrations of characteristics at the school level contributed more to the achievement gap in reading than did individual-level characteristics. Lubienski and Lubienski (2006) showed that school demographics accounted for all of the observed variance in mathematics achievement previously attributed to public or private school status at both fourth- and eighth-grade levels. Similarly, Benson and Borman (2007) found that over half of the identified Black–White achievement gap in first grade reading could be attributed to the school composition of student economic characteristics.

The importance of accounting for concentrations of student characteristics at the school level is also documented by recent national studies. One key evaluation of over a decade of

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Educational Researcher, Vol. 43 No. 1, pp. 25–36
DOI: 10.3102/0013189X13512673
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accountability efforts across the United States revealed that the strongest predictor of adequate yearly progress had relatively little to do with school resources or school inputs, but rather the number of subgroups for which a school was held accountable under No Child Left Behind (Belfanz, Legters, West, & Weber, 2007). Similarly, a recent replication of the Coleman Report using more sophisticated statistical techniques found that student characteristics at both the individual and school levels left little remaining variation to explain in academic achievement across schools (Konstantopoulos & Borman, 2011). These studies emphasize the need to more carefully study how the concentrations of characteristics of the students who make up the school community relate to educational outcomes (Raudenbush & Willms, 1995).

Unfortunately, current approaches to investigating the concentrations of student characteristics have a substantial limitation for meeting this need. Much of this research has relied on the incomplete set of information collected by public school districts about the children they serve. Student enrollment records are often restricted to demographics such as gender, race, or ethnicity and whether a child qualifies for free or reduced lunch. This limitation has been noted in recent school effects research recognizing that most of the studies rely upon student characteristics that are conveniently accessible and do not portray students' actual risk experiences (Konstantopoulos & Borman, 2011). However, there are many other student and family factors that have been identified in the research literature as being of great importance to children's academic progress (e.g., low maternal education, maltreatment, birth risks). These factors need to be included to obtain a more comprehensive understanding of how concentrations of these student experiences in a school can affect the educational outcomes of all the students.

A developmental-ecological model is a useful conceptual framework to understand the variation in risks experiences associated with poverty. As Huston and Bentley (2010) have indicated, poverty is not a singular experience but instead is one associated with a complex web of specific social disadvantages. The developmental component of this model recognizes that children's competencies are compromised by the effects of varied risk experiences over time, thus rendering children less able to negotiate future challenges and capitalize on opportunities to develop increasingly complex sets of skills (Ayoub et al., 2006; Neuman & Celano, 2006). The ecological aspect of this model stresses that school-related competencies are associated not only with direct experiences of risks but also with exposure to others in their proximal systems who may have experienced these risks themselves, such as siblings at home or peers at school and in the neighborhood (Bronfenbrenner, 2005; Huston & Bentley, 2010).

The complexities of this developmental-ecological model require substantial information about risk factors, children's competencies, and the proximal contexts in which they develop in order to examine the influence of multiple known risks to development. Municipal public agencies, like health and child welfare, are required to collect information documenting known biological and social risks in the child development literature. For example, psychological and medical researchers have suggested that biological birth risks such as preterm birth and low birth weight directly affect cognitive development through organic deficits in brain development (Nosarti et al., 2002; Peterson, 2003). Family risk factors have also been linked to children's delayed educational progress. Having a mother without a high school education has been consistently shown to be a negative predictor of children's achievement outcomes and behavioral adjustment problems (Ricciuti, 2004). Children who experience homelessness evidence lower cognitive and achievement abilities than their peers who are not homeless (Better Homes Fund, 1999; Myers & Popp, 2003). Research also demonstrates the negative relations between child abuse and delayed language and general cognitive abilities (Cicchetti, 2004; Cicchetti & Toth, 2005).

Although this collection of research documents the individual impact of these developmental risks on child outcomes, there has not been an examination of how the concentrations of students experiencing risks factors within a school affect academic achievement. The use of scientifically prepared integrated data from multiple public surveillance systems serving school-age children is an innovation that holds promise to meet this need (Duran, Wilson, & Carroll, 2005). Data that meet scientific quality standards can be integrated across systems and used for research and evaluation purposes. For example, children who have been maltreated, who experience homelessness, or who have been exposed to high levels of lead are monitored by these publicly funded systems because of the documented risk of these experiences to their individual educational and psychological well-being (U.S. Congress, 2003). In partnership with such systems, education researchers can capitalize on the existing information contained in these databases to examine how school concentrations of these risks influence student outcomes.

Study Purpose

The purpose of the present study was to examine the unique relations between school concentrations of student risk factors and measures of reading, mathematics, and attendance for an entire cohort of students in third grade in the School District of Philadelphia, the eighth largest school district providing public education to students living in the poorest of the 10 largest cities in the United States (U.S. Census Bureau, 2010). This study addressed limitations of previous research by using integrated longitudinal records from multiple public service systems to identify biological and familial risk factors and aggregating them at the school level. The primary research question of this study was how much of the variation in reading, mathematics, and attendance is associated with the concentrations of students experiencing early risk factors within each school? The comprehensive model investigating these relations controlled for (1) school percentages of student demographics, (2) individual demographics, and (3) individual student risk experiences.

Method

Sample and Measures

Researchers obtained a fully integrated, de-identified dataset for this study through the Kids Integrated Data System (KIDS), a capacity in the City of Philadelphia designed to provide integrated administrative datasets for research to inform policy and practice. Administrative data from relevant municipal agencies

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Table 1
Student Demographics and Risk Factors for the Study and Analytic Samples

	Study Sample (*n* = 10,639)	Smallest Analytic Sample (*n* = 10,117)
Student demographics		
Sex (male)	50.5	50.2
African American	66.5	67.0
White	14.4	14.4
Latino	14.4	13.9
Asian/Other	4.7	4.7
Economically disadvantaged	70.2	69.6
Risk factors		
Preterm or low birth weight	20.9	20.7
Inadequate prenatal care	34.4	34.4
Teen mother	24.7	24.6
High lead exposure	21.3	20.0
Child maltreatment	10.9	10.8
Mother without high school degree	26.2	26.1
Homeless shelter stay	9.2	9.9

were used for the present study and included the School District of Philadelphia, Department of Public Health (DPH), Department of Human Services (DHS), and Office of Supportive Housing (OSH). KIDS used state-of-the-art data management and data integration expertise to prepare scientifically credible integrative datasets for research projects. Data management included periodic reliability and validity auditing of data elements as well as quality standards for all data used in research and evaluation. Longitudinal archival administrative data were integrated for students who were born in Philadelphia and were enrolled in the School District of Philadelphia from kindergarten to third grade, resulting in a sample of 10,639 students. These selection criteria were established to ensure complete histories of early risk factors from City and School District records in accord with the framework of the developmental-ecological model. The average age of children at the end of third grade was 9.50 years (SD = 0.52) and half of the children in the sample were male (51%). Sixty-seven percent were African American, 14% White, 14% Hispanic, and 5% Asian/Other. The number of students in the 208 elementary schools who had complete data for each outcome ranged between 10,117 and 10,166. These students did not demonstrate different student demographics or risk factors as compared to the entire study cohort of 10,639 (see Table 1). The characteristics of the 208 elementary schools are listed in Table 2.

Preterm or low birth weight. The DPH provided the birth certificate records. Children were classified as preterm if they were born at less than 36 weeks gestation and/or low birth weight if they weighed less than 2,500 grams.

Inadequate prenatal care. The DPH birth records provided data regarding the mother's prenatal care experience. On U.S. birth certificates, inadequate prenatal care is defined as receiving no prenatal care, prenatal care only in the third trimester, or fewer than four prenatal visits overall.

Teen mother. The age of the mother at the time of the child's birth was obtained from the DPH birth records. The child was considered to have a teen mother if the mother was less than 20 years of age at the child's birth.

Mother without a high school degree. The number of years of education completed by the child's mother at the time of birth was obtained from the DPH birth records. Mother without a high school degree was indicated for children whose mothers were at least 18 years old and had completed less than 12 years of formal schooling.

High lead exposure. The DPH conducts lead exposure testing of the children residing in the city limits. The U.S. Centers for Disease Control and Prevention (CDC) defines a blood lead level of 10 micrograms (µg) per deciliter of blood (dL) as a level of concern (CDC, 2008); therefore, this study indicated children as having high lead exposure if they tested at 10 µg/dL or higher at any point before the end of third grade.

Homeless shelter stay. Information regarding children's homeless experiences was collected from the OSH and DHS in the municipality. Homeless shelter stay was determined by identifying (a) a mother within the OSH database who registered in a public shelter with children at any time between the child's birth and the end of third grade and/or (b) a child who had been placed in a DHS-funded homeless emergency shelter. If neither the parent nor the child were identified within these two systems, the child was classified as not having a homeless shelter stay.

Child maltreatment. Substantiated maltreatment was identified using data provided by the DHS. This system documents substantiated allegations of physical abuse that result in severe pain or dysfunction, medical neglect, sexual abuse, lack of supervision resulting in specific physical conditions or impairments, repeated injuries that have no explanation, or psychological

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Table 2
Student Demographics and Risk Factors Aggregated at the School Level (n = 208)

	Percentage	*SD*	Minimum	Maximum
Number of children (mean)	52.2	23.7	15	153
Race/ethnicity				
African American	68.4	32.7	0.0	100.0
White	14.1	23.6	0.0	96.7
Latino	12.5	20.4	0.0	87.8
Asian/Other	5.0	9.4	0.0	57.1
Economically disadvantaged	69.7	16.3	10.3	96.1
Preterm or low birth weight	20.8	7.2	4.9	48.0
Inadequate prenatal care	34.3	12.0	3.3	61.7
Teen mother	24.5	9.6	0.0	49.1
High lead exposure	21.3	11.8	0.0	51.1
Child maltreatment	10.9	6.0	0.0	29.4
Mother without high school degree	26.0	12.7	1.5	65.3
Homeless shelter stay	9.2	7.4	0.0	30.2

abuse substantiated by a physician. Children with a history of at least one substantiated allegation by the end of third grade were considered to have experienced the risk factor of substantiated maltreatment.

Student demographics. Student demographics were collected from school district enrollment records and included gender, race/ethnicity, and economic disadvantage (free or reduced lunch eligibility).

School aggregated predictors. At the school level, predictors included aggregated student demographics that represent the subgroups considered in school accountability calculations (percentages of African American, Latino, and economically disadvantaged students) and aggregated risk factors to represent the percentage of children within the third-grade cohort at each school who experienced each risk. The grade cohort was used because it represents the group of children spending the largest amount of time in proximal contact with one another—in classes, at lunch, during recess, etc. As opposed to concentrations of student characteristics at the school, aggregated student demographics and risk factors among a grade cohort in regular contact with one another would likely have the greatest influence on important educational well-being indicators. These school aggregated predictors were scaled such that a one unit increase was equivalent to a 10 percentage point increase (e.g., 10% increase in the concentration of homeless students).

Reading and mathematics achievement. The School District of Philadelphia provided achievement outcome data. Children's standardized reading and mathematics achievement was assessed by the Complete Battery Plus version of the *TerraNova—Second Edition* (CTB/McGraw-Hill LLC, 1997). The TerraNova demonstrates acceptable internal consistency, extensive external validity, and evidence of construct validity (see technical report, CTB/McGraw-Hill LLC, 2001). Items were carefully reviewed to ensure adequate content validity, comparisons with the *Test of Cognitive Skills* (2nd ed.) and with InView (CTB/McGraw-Hill LLC, 2001) indicate evidence of construct validity, and correlations between subtests and total scores support criterion-related validity. The Reading Composite includes measures of essential reading skills such as children's vocabulary, drawing conclusions, and making inferences. The Mathematics Composite assesses mathematics computation, mathematical concepts, and the application of concepts and computation through word problems.

Attendance rate. School district administrative records included the number of unexcused absences for every child. These records were used to calculate an annual percentage of daily attendance for each student in third grade.

Data Analysis

Multilevel linear modeling was used to estimate the effects of school concentrations of early risk factors on student educational well-being using PROC MIXED in SAS 9.3 (SAS Institute Inc., 2011). Multilevel modeling is particularly suitable because, assuming independence of the covariate and random effects, it accounts for the clustering of children within schools while avoiding aggregation bias and misestimation of standard errors for parameter estimates (Raudenbush & Bryk, 2002). Full maximum likelihood estimation was used because it allows for statistical comparison of fit for nested models with fixed effects (Singer & Willett, 2003). In this study, we estimated a series of five models for each outcome—reading achievement, mathematics achievement, and attendance rate. The appendix provides the equations for each estimated model.

Model 1 was unconditional (no predictors included) in order to determine whether there was significant variation in outcome residuals at Level 1 (σ^2) and Level 2 (τ_{00}). Model 2 was estimated adding Level 1 predictors including demographics (gender, race/ethnicity, and economic disadvantage) and risk factors (preterm or low birth weight, inadequate prenatal care, teen mother, high

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Table 3
Descriptive Statistics for Student- and School-Level Third-Grade Outcome Variables

	Student Level		School Level	
	M	*SD*	*M*	*SD*
Reading achievement (*n* = 10,145)	607.50	38.58	608.2	14.2
Mathematics achievement (*n* = 10,117)	569.96	43.09	570.6	17.3
Attendance rate (*n* = 10,166)	95.3	5.9	95.6	2.5

lead exposure, substantiated maltreatment, low maternal education at birth, and homeless shelter stay). All Level 1 predictors were binary and were not centered. As with grand-mean centering, this centering decision adjusts the Level 2 variation in educational well-being indicators for Level 1 covariates (Raudenbush & Bryk, 2002). The variation in the relations between Level 1 predictors and educational well-being indicators across schools was constrained to the same fixed value; therefore, the parameter estimates represent the association between each predictor and the educational outcome of interest averaged across schools. Models 3 and 4 estimated the unique associations of school-level demographics and risk factors, respectively, while adjusting for the Level 1 predictors in Model 2. All school-level predictors were grand-mean centered. These separate models were estimated to provide a comparison of the additional intercept variation explained in each outcome by the set of aggregated student demographics (Model 3) and the set of aggregated risk factors (Model 4). Model 5 was the final model and included all Level 1and Level 2 predictors.

Residuals from each model were used to calculate an intraclass correlation coefficient (ICC) that specifies the proportion of variation in the outcome that exists at the school level. ICC estimates were compared across nested models to determine the amount of residual variation in the outcome that was explained by the inclusion of each new set of additional predictors. Chi-square difference tests on the deviance statistics using parameters as the degrees of freedom were conducted to test whether each new estimated model fit the data significantly better than the preceding nested model (Singer & Willett, 2003). The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were also reported, as they are more conservative adjustments of the deviance statistic that correct for the number of parameters in the model (Singer & Willett, 2003).

Results

The multilevel analysis results are presented in Tables 3 through 6. The unconditional models (Model 1) are presented in the first column of each table. The ICC for reading achievement was 0.13, indicating that 13% of the total variability in reading achievement was between schools and the corresponding Level 2 variance component was statistically significant. The Level 2 variance components and corresponding ICC estimates for mathematics achievement and attendance were slightly higher and statistically significant, with percentages of variance between schools of 15% and 16%, respectively. This indicated that schools were somewhat more diverse in their average mathematics achievement scores and attendance rates than they were in average reading achievement scores.

Model 2 for each outcome adjusted for student-level demographics and risk factors. The results are presented in the second column of Tables 4 through 6. On average, males performed significantly worse than females by a difference of –0.22 *SD* in reading achievement and –0.10 *SD* in mathematics achievement. African American and Latino students performed worse than White students in reading by about a quarter of a *SD* and mathematics by approximately –0.40 *SD*. Students experienced significantly poorer reading and mathematics achievement as well as lower attendance rates if they were economically disadvantaged (–0.17 *SD*, –0.15 *SD*, and –0.34 *SD*, respectively), had a mother without a high school degree (–0.16 *SD*, –0.13 *SD*, and –0.27 *SD*, respectively), or were maltreated (–0.15 *SD*, –0.13 *SD*, and –0.25 *SD*, respectively). Students had significantly lower attendance rates only if they experienced sociofamilial risk factors—having a teen mother (–0.17 *SD*) and a homeless shelter stay (–0.19 *SD*). Although statistically significant relations were evident among health-related risk factors (preterm or low birth weight, inadequate prenatal care, high lead exposure) and academic achievement, all differences were less than 0.10 *SD*. The inclusion of these Level 1 predictors reduced the between-school intercept variability (τ_{00}) in reading achievement, mathematics achievement, and attendance rates by 28% to 44%. However, the residual Level 2 variance components for all three educational well-being indicators remained significant in Model 2, indicating there was still between-school variation to explain.

Model 3 results are presented in the third column of each table and show the reduction in between-school variation in educational well-being indicators as a function of school-level demographics after accounting for student-level demographics and risk factors. For every 10% increase in the school percentage of African American and Latino students, the average student reading and mathematics scores decreased by 0.05 *SD*. On average, students also demonstrated an approximately 0.05 *SD* decrease in reading, mathematics, and attendance rates for every 10% increase in the economically disadvantaged student population. Relative to Model 2, adding these school-level demographics reduced the between-school residual variance in educational well-being intercepts an additional 2% to 13%.

Model 4 results (fourth column) show the associations between school concentrations of student risk factors and educational well-being. Attending schools with a 10% higher concentration of

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Table 4
Multilevel Modeling Results for Reading Achievement (N = 10,145)

Parameter	Model 1 Parameter Estimate	Model 1 *SE*	Model 2 Parameter Estimate	Model 2 *SE*	Model 3 Parameter Estimate	Model 3 *SE*	Model 4 Parameter Estimate	Model 4 *SE*	Model 5 Parameter Estimate	Model 5 *SE*
Fixed effect										
Intercept	608.16***	1.03	628.63***	1.52	624.71***	1.54	625.28***	1.42	624.25***	1.50
School-level predictors										
Gender (male)					–0.90	0.90			–0.36	0.80
African American					–1.83***	0.35			–0.70	0.38
Latino					–2.23***	0.51			–0.94	0.50
Asian/Other					–0.18	0.92			1.13	0.88
Economically disadvantaged					–2.02***	0.46			–0.28	0.45
Preterm or low birth weight							0.20	0.87	–0.07	0.88
Inadequate prenatal care							–2.32**	0.77	–2.28**	0.79
Teen mother							–1.66*	0.73	–0.99	0.81
High lead exposure							–1.97*	0.80	–0.80	0.93
Substantiated maltreatment							0.16	1.23	0.50	1.24
Mother without a high school degree							–2.67***	0.60	–2.83***	0.73
Homeless shelter stay							–1.84*	0.88	–1.84*	0.86
Student-level predictors										
Gender (male)			–8.44***	0.71	–8.38***	0.71	–8.40***	0.71	–8.38***	0.71
African American[a]			–8.49***	1.36	–4.82**	1.48	–6.00***	1.36	–4.86**	1.48
Latino[a]			–10.48***	1.62	–6.90***	1.71	–8.38***	1.59	–6.92***	1.70
Asian/Other[a]			0.03	2.03	1.65	2.08	1.63	2.01	1.56	2.08
Economically disadvantaged			–6.55***	0.84	–5.96***	0.85	–6.28***	0.84	–6.20***	0.85
Preterm or low birth weight			–2.93***	0.88	–2.93***	0.88	–2.83**	0.89	–2.86**	0.89
Inadequate prenatal care			–3.02***	0.78	–2.91***	0.78	–2.49**	0.78	–2.49**	0.78
Teen mother			–0.51	0.89	–0.36	0.89	–0.13	0.90	0.08	0.90
High lead exposure			–3.91***	0.93	–3.72***	0.93	–3.36***	0.93	–3.42***	0.93
Child maltreatment			–5.96***	1.18	–5.85***	1.18	–5.63***	1.19	–5.64***	1.19
Mother without a high school degree			–6.18***	0.89	–5.97***	0.89	–5.23***	0.90	–5.21***	0.90
Homeless shelter stay			–0.71	1.25	–0.67	1.25	–1.19	1.26	–1.14	1.26
Variance component										
Level 1 (σ^2)	1,308.76	18.57	1,263.04	17.94	1,263.67	17.94	1,264.46	17.96	1,264.19	17.95
Level 2 (τ_{00})	187.25	21.69	105.78	14.11	69.11	9.92	42.33	7.34	41.22	7.26
Percentage τ_{00} explained			44		63		77		78	
Model statistics										
AIC	102,015		101,493		101,389		101,312		101,276	
BIC	102,022		101,499		101,396		101,319		101,283	
Deviance	102,011		101,489		101,385		101,309		101,273	

[a]Reference group is White.
*$p < .05$. **$p < .01$. ***$p < .001$.

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students whose mothers did not have a high school degree was associated with significantly worse reading (–0.07 *SD*) and mathematics achievement (–0.05 *SD*) as well as lower attendance rates (–0.10 *SD*) on average. Students experienced a decrease in reading (–0.06 *SD*) and mathematics (–0.05 *SD*) achievement scores on average with every 10% increase in the school concentration of students with inadequate prenatal care. A 10% increase in the school concentration of students with teen mothers was associated with poorer average performance in mathematics by –0.05 *SD*. Attending schools with a 10% increase in the homeless student body was associated with –0.05 *SD* in reading achievement and –0.10 *SD* in attendance rates. And being in a school with a 10% increase in the student body experiencing substantiated maltreatment was associated with –0.15 *SD* in the average student's attendance rate. The inclusion of school concentrations of risk factors in Model 4 reduced the between-school residual variance in educational well-being intercepts by 5% to 26%.

The final estimated model (Model 5) included all Level 1 and Level 2 predictors and the results are presented in the last column of Tables 4 through 6. Compared to Model 3, the associations between school-level demographics and educational well-being indicators were substantially reduced. These associations were no longer significant for both reading achievement and attendance rates, and only one, the percentage of African American students, was still significant at the $\alpha = .05$ level in the mathematics achievement model. Among the school-level risk factors, schools with high concentrations of students experiencing homelessness, inadequate prenatal care, substantiated maltreatment, and whose mothers did not have a high school degree remained significantly associated with at least one of the three student educational well-being indicators. A chi-square difference test between Model 4 and Model 5 found that the added school-level demographics did not indicate a significantly better fit to the data than the model with just school-level risk factors for reading achievement, $\chi^2(5) = 1$, $p > .05$, mathematics achievement, $\chi^2(5) = 2$, $p > .05$, and attendance rates, $\chi^2(5) = 5$, $p > .05$. These model fit estimates correspond to 0% to 1% changes in the reduction of between-school residual variance in educational well-being indicators.

Discussion

The present study documents that school concentrations of distinctive risk experiences are associated with important educational well-being indicators. Findings showed that very little unexplained variation remained in academic achievement and attendance rates between schools once accounting for (a) school concentrations of children experiencing publicly monitored risk factors, (b) school concentrations of racial and low-economic subgroups of students, and (c) student-level demographics and risk factors. Even in this study of a single large urban district in which the average school had 68% of its children qualifying for free and reduced lunch, 12% to 16% of the variation in student achievement and attendance was found to exist between schools. This variation is consistent with other studies examining school effects (Konstantopoulos & Hedges, 2008; Raudenbush & Bryk, 2002). School concentrations of student risk factors and demographics were able to reduce the unknown variation in educational well-being indicators that existed between schools by 56% to 78%, with school concentrations of risk factors accounting for more variance. The association between school concentrations of race and economic disadvantage and student educational well-being were substantially reduced once accounting for school concentrations of student risk factors. This study highlights the importance of including these concentrations of risk factors when trying to understand what accounts for variation in student educational well-being indicators.

The most harmful concentration of risk for all educational well-being indicators was low maternal education, after accounting for student-level risks and demographics. Attending a school with a high concentration of students whose mother did not complete high school was significantly related to poor reading, mathematics, and attendance. This research supports the low-maternal education research that associates this risk with significant disadvantage. In a large secondary analysis study of low-income families with young children (one third Black, Latino, and White), researchers found low-maternal education associated with unemployment, young maternal age, and involvement in federal assistance programs (citation removed). Mothers without adequate education may be experiencing more stress to support their families and less able to be involved in their child's school or other community-enriching activities with their children (Magnuson, 2003).

These school-level findings highlight the possible impact of the density of this risk on the well-being of a community of children attending school together. They indicate that children who attend school with peers who do not have opportunities associated with maternal education may be at greater risk of falling behind academically and less likely to attend school regularly. Similarly school concentrations of students who did not receive adequate prenatal care were associated with overall poor reading achievement. This may also reflect communities where mothers are not connected to public health services or who evidence social barriers to engagement and participation in other opportunities and services (Hohmann-Marriott, 2009; Sunil, Spears, Hook, Castillo, & Torres, 2010). High concentrations of children who may be disconnected from learning opportunities and needed health and social services may affect the school environment as a whole (i.e., both students and teachers).

Children's reading achievement and attendance rates were also lower for those attending school with large concentrations of children who were experiencing risk factors representing displacement and family instability—homelessness and child maltreatment. Homelessness is often associated with unpredictable moves that adversely affect the family support system and children's development and well-being (Buckner, 2007). Children who experience homelessness are also more likely to move between schools and enter and leave new classrooms in the middle of a school year, which creates more instability and unpredictability for teachers (Buckner, Bassuk, & Weinreb, 2001). Similarly children experiencing maltreatment are far more likely to be displaced from their homes by receiving intervention including foster care; this disruption in their living environment has been demonstrated to negatively affect their educational

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Table 5
Multilevel Modeling Results for Mathematics Achievement (*N* = 10,117)

	Model 1		Model 2		Model 3		Model 4		Model 5	
Parameter	Parameter Estimate	*SE*	Parameter Estimate	*SE*	Parameter Estimate	*SE*	Parameter Estimate	*SE*	Parameter Estimate	*SE*
Fixed effect										
Intercept	570.19***	1.24	594.22***	1.73	590.78***	1.76	591.40***	1.69	590.48***	1.74
School-level predictors										
Gender (male)					–1.52	1.13			–1.27	1.10
African American					–1.82***	0.44			–1.11*	0.53
Latino					–2.16***	0.64			–1.03	0.69
Asian/Other					0.37	1.15			1.81	1.22
Economically disadvantaged					–1.79**	0.58			–0.21	0.63
Preterm or low birth weight							–0.90	1.22	–0.95	1.21
Inadequate prenatal care							–2.18*	1.08	–1.98	1.10
Teen mother							–2.22*	1.02	–1.62	1.12
High lead exposure							–1.36	1.11	0.62	1.30
Substantiated maltreatment							0.28	1.72	0.87	1.74
Mother without a high school degree							–2.29**	0.84	–2.28**	0.82
Homeless shelter stay							–1.33	1.51	–1.01	1.57
Student-level predictors										
Gender (male)			–3.79***	0.79	–3.72***	0.79	–3.77***	0.79	–3.72***	0.79
African American[a]			–18.05***	1.52	–14.83***	1.64	–15.93***	1.55	–14.85***	1.64
Latino[a]			–16.38***	1.80	–13.30***	1.89	–14.44***	1.81	–13.32***	1.89
Asian/other[a]			3.01	2.25	4.28	2.30	–4.32	2.25	4.21	2.30
Economically disadvantaged			–5.92***	0.92	–5.47***	0.94	–5.66***	0.93	–5.63***	0.94
Preterm or low birth weight			–3.87***	0.98	–3.88***	0.98	–3.77***	0.98	–3.79***	0.98
Inadequate prenatal care			–2.42**	0.86	–2.27**	0.86	–1.99	0.86	–1.99*	0.87
Teen mother			0.17	0.99	0.33	0.99	0.71	0.99	0.67	1.00
High lead exposure			–1.45	1.03	–1.22	1.03	–1.03	1.03	–1.09	1.03
Child maltreatment			–5.07***	1.32	–4.93***	1.31	–4.81***	1.32	–4.81***	1.32
Mother without a high school degree			–4.95***	0.99	–4.71***	1.00	–4.21***	1.00	–4.17***	1.00
Homeless shelter stay			–1.30	1.39	–1.26	1.39	–0.93	1.40	–0.99	1.40
Variance component										
Level 1 (σ^2)	1,593.93	22.64	1,551.73	22.08	1,551.27	22.06	1,551.16	22.06	1,551.08	22.06
Level 2 (τ_{00})	277.97	31.29	158.53	20.01	121.20	15.96	108.62	14.73	104.37	14.44
Percentage τ_{00} explained			43		56		61		62	
Model statistics										
AIC	103,763		103,321		103,242		103,204		103,163	
BIC	103,770		103,328		103,249		103,211		103,170	
Deviance	103,759		103,317		103,238		103,200		103,159	

[a]Reference group is White.
**p* < .05. ***p* < .01. ****p* < .001.

well-being (Department of Health and Human Services, 2012). Findings from the current study extend this research by documenting the negative impact of these homeless and maltreatment experiences on the other children who attend school with these peers but are not, themselves, experiencing these two risk factors associated with displacement. Results

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Table 6
Multilevel Modeling Results for Attendance Rate (N = 10,166)

Parameter	Model 1 Parameter Estimate	Model 1 *SE*	Model 2 Parameter Estimate	Model 2 *SE*	Model 3 Parameter Estimate	Model 3 *SE*	Model 4 Parameter Estimate	Model 4 *SE*	Model 5 Parameter Estimate	Model 5 *SE*
Fixed effect										
Intercept (γ_{00})	93.25***	0.19	95.27***	0.29	95.06***	0.30	94.82***	0.28	94.96***	0.28
School-level predictors										
Gender (male)					0.08	0.24			0.15	0.20
African American					–0.06	0.08			0.18	0.09
Latino					–0.13	0.12			0.17	0.11
Asian/Other					–0.11	0.20			0.18	0.19
Economically disadvantaged					–0.30**	0.11			0.05	0.10
Preterm or low birth weight							0.02	0.20	–0.03	0.20
Inadequate prenatal care							–0.25	0.18	–0.32	0.19
Teen mother							0.00	0.17	–0.02	0.19
High lead exposure							–0.27	0.19	0.09	0.22
Substantiated maltreatment							–0.89**	0.29	–0.87**	0.30
Mother without a high school degree							–0.61***	0.14	–0.63***	0.17
Homeless shelter stay							–0.57*	0.26	–0.56*	0.27
Student-level predictors										
Gender (male)			–0.04	0.13	–0.04	0.13	–0.03	0.13	–0.04	0.13
African American[a]			–0.32	0.25	–0.42	0.27	–0.41	0.25	–0.43	0.27
Latino[a]			0.00	0.30	0.17	0.31	0.31	0.30	0.16	0.31
Asian/Other[a]			2.68**	0.37	2.77***	0.38	2.90***	0.37	2.78***	0.38
Economically disadvantaged			–1.99***	0.15	–1.93***	0.15	–1.94***	0.15	–1.95***	0.15
Preterm or low birth weight			–0.04	0.16	–0.04	0.16	–0.04	0.16	–0.03	0.16
Inadequate prenatal care			–0.13	0.14	–0.12	0.14	–0.07**	0.14	–0.07	0.14
Teen mother			–1.00***	0.16	–0.98***	0.16	–0.93***	0.16	–0.93***	0.16
High lead exposure			–0.13	0.17	–0.12	0.17	–0.10	0.17	–0.09	0.17
Child maltreatment			–1.50***	0.22	–1.50***	0.22	–1.43***	0.22	–1.43***	0.22
Mother without a high school degree			–1.57***	0.16	–1.55***	0.16	–1.44***	0.16	–1.44***	0.16
Homeless shelter stay			–1.15***	0.23	–1.15***	0.23	–1.08***	0.23	–1.08**	0.23
Variance component										
Level 1 (σ^2)	44.00	0.62	41.99	0.60	41.98	0.59	41.99	0.60	41.99	0.60
Level 2 (τ_{00})	6.55	0.75	4.73	0.57	4.60	0.56	2.88	0.39	2.88	0.39
Percentage τ_{00} explained			28		30		56		56	
Model statistics										
AIC	67,746		67,196		67,173		67,087		67,071	
BIC	67,752		67,203		67,180		67,094		67,078	
Deviance	67,741		67,192		67,169		67,083		67,067	

[a]Reference group is White.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

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suggest that the instability associated with homelessness and maltreatment translated into a disruptive school environment for classmates and threatened their reading achievement and attendance rates.

As a group these risks are indicators of families with fewer opportunities and greater family instability and stress. Schools with higher concentrations of students from these families may have overall school climates that reflect this disadvantage, stress, and instability. Greater disconnection and displacement may be associated with more challenges for teachers to adjust their instruction in order to supply missing prerequisite skills for students who have had fewer home-based learning opportunities. The nature of these problems may also result in greater residential instability and school mobility. Unpredictable movement of students in and out of the school can contribute to disruptions and instability in the school environment that may compromise the educational experiences for all the children in the school, even those not directly affected by these risks.

Overall, this study demonstrated the value of examining school-level effects of publicly monitored risk factors to extend our understanding of what's behind being behind. Although this is the first study to examine these monitored risks in such a comprehensive model and to differentiate school-level effects, the present study had noteworthy limitations that should be addressed in future research. First, this study was conducted in a large urban school district in which a large proportion of the student body is living in poverty and the findings should only be considered in light of this context. Future research should extend this inquiry to different populations of students. Also this study included no measures of school or family characteristics. Future inquiry should add measures of school quality and parental well-being as it is possible these factors mediate or moderate the relations between the risk factors and educational well-being indicators. For instance, it could be hypothesized that homeless or maltreated children who attend higher quality schools may demonstrate better academic achievement or attendance than maltreated children who attend a lesser quality school. Epidemiological extensions of this research could include other relevant public systems that capture information about salient parental factors at the school level (e.g., parental incarceration, depression, employment, social support, and involvement in their children's education). Second, this study looked at only the first state standardized tests in third grade. Research could use the longitudinal data contained in integrated data systems to examine the impact of individual and school concentrations of risks across testing periods from third through the transitions into middle and high school. Growth curve analyses could also be used to determine if school concentrations of risks relate differentially to growth in achievement or attendance and dropout patterns over time. Lastly, this study only explored the direct associations between student risks and school concentrations of student risk factors with each educational well-being indicator. Future research should build upon this work by considering whether the relations between student risks and educational well-being indicators vary as a function of school concentrations of risks.

Overall, this study demonstrates that poverty and race do not tell the whole story about what's behind being behind. It makes visible the challenges facing schools that predominately serve children from disadvantaged backgrounds and the inadequacy of accountability mandates based on undifferentiated categories of student demographics. Moreover, the primary national focus on racial and economic subgroups falls short of identifying mutable home or community risk factors that are associated with being left behind academically. In the present study, researchers worked in partnership with the local school district and city leadership to increase the school district's knowledge of the population of students they served. The use of integrated information across multiple public service agencies created an opportunity to go beyond variables of convenience in order to identify risks monitored by the local health and child welfare surveillance systems that have federal and state resources allocated for such use. Studying data across these agencies opens up the possibility of a wider conceptualization of integrated services to promote educational well-being for vulnerable children. We must expand our research capacities to study what's behind being behind and better identify concentrations of student risk factors in schools. We can target these schools through multisystem intervention and thus hold both the public education system and public service agencies accountable for the educational well-being of our youngest citizens.

Appendix

Model 1 Equation:

$$\text{Level 1}: Y_{ij} = \beta_{0j} + r_{ij},$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \mu_{0j},$$

$$\text{Combined}: Y_{ij} = \gamma_{00} + \mu_{0j} + r_{ij},$$

where Y_{ij} is the outcome for student i in school j; β_{0j} is the average expected outcome for school j; r_{ij} is the random variation in the outcome for student i in school j; γ_{00} is the grand mean of the outcome; and μ_{0j} is the random variation in the outcome for school j.

Model 2 Equation:

$$\text{Level 1}: Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij}) + r_{ij},$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \mu_{0j},$$

$$\beta_{1j} = \gamma_{10},$$

$$\text{Combined}: Y_{ij} = \gamma_{00} + \gamma_{10}(X_{ij}) + \mu_{0j} + r_{ij},$$

where β_{0j} now represents the mean outcome in school j adjusting for differences among schools in student-level demographics and risk factors (X_{ij}) while allowing school intercepts in outcomes to vary randomly (μ_{0j}).

Models 3–5:

$$\text{Level 1}: Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij}) + r_{ij},$$

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$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \gamma_{01}(W_j - \bar{W}\ldots) + \mu_{0j},$$

$$\beta_{1j} = \gamma_{10},$$

$$\text{Combined}: Y_{ij} = \gamma_{00} + +\gamma_{01}\left(W_j - \bar{W}\ldots\right) + \gamma_{10}(X_{ij}) + \mu_{0j} + r_{ij},$$

where W_j represents the set of predictors at Level 2. In Model 3, W_j included school-level concentrations of student demographics; in Model 4, the school-level concentrations of risk factors; and in Model 5, school-level concentrations of both student demographics and risk factors. These Level 2 predictors were centered around the grand mean ($\bar{W}$).

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Manuscript received August 23, 2012
Revisions received February 27, 2013,
and September 26, 2013
Accepted October 16, 2013

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