CHILD DEVELOPMENT

Child Development, xxxx 2012, Volume 00, Number 0, Pages 1–17

Academic Achievement Trajectories of Homeless and Highly Mobile Students: Resilience in the Context of Chronic and Acute Risk

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Analyses examined academic achievement data across third through eighth grades (N = 26,474), comparing students identified as homeless or highly mobile (HHM) with other students in the federal free meal program (FM), reduced price meals (RM), or neither (General). Achievement was lower as a function of rising risk status (General > RM > FM > HHM). Achievement gaps appeared stable or widened between HHM students and lower risk groups. Math and reading achievement were lower, and growth in math was slower in years of HHM identification, suggesting acute consequences of residential instability. Nonetheless, 45% of HHM students scored within or above the average range, suggesting academic resilience. Results underscore the need for research on risk and resilience processes among HHM students to address achievement disparities.

Homelessness and high residential mobility among low-income families pose serious threats to learning and achievement and occur on a widespread scale that endangers efforts to address achievement disparities (National Research Council & Institute of Medicine, 2010; Obradović et al., 2009). About 1.9 million low-income students between the ages of 9 and 11 move each year (Wight & Chau, 2009), whereas 794,617 homeless students attended public school during the 2007–2008 school year (National Center for Homeless Education [NCHE], 2009).

Homeless and highly mobile (HHM) students are conceptualized as falling on the high end of a continuum of risk, beyond stably housed, low-income children (Masten, Miliotis, Graham-Bermann, Ramirez, & Neemann, 1993). HHM students also tend to experience high levels of family adversity and other risks for poor developmental outcomes like educational, social-emotional, and health problems (Buckner, 2008; Haber & Toro, 2004; Masten et al., 1993; Samuels, Shinn, & Buckner, 2010). Children who move frequently are more likely to experience poverty, homelessness, and other risk factors, whereas children who experience homelessness are more likely

This research was supported in part by predoctoral fellowships awarded to Dr. Cutuli from the Center for Neurobehavioral Development (CNBD) at the University of Minnesota and from the National Institute of Mental Health (NIMH; 5T323MH015755), and by the Fesler-Lampert Chair and grants to Dr. Masten from the National Science Foundation (NSF; 0745643) and the Center for Urban and Regional Affairs at the University of Minnesota. Christopher David Desjardins' work was supported by a fellowship from the Interdisciplinary Education Sciences Training Program (IES Award R305C050059; University of Minnesota PRF 473473). Any opinions, conclusions, or recommendations expressed in this article are those of the authors and do not necessarily reflect the views of the CNBD, NIMH, NSF, or IES.

We would like to thank the staff of the Minneapolis Public Schools, and particularly Margo Hurrle for sharing her invaluable perspective and dedication to the needs of HHM children.

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DOI: 10.1111/cdev.12013

than others to have changed residences frequently and have high levels of other adversities (Rog & Buckner, 2007; Wood, Halfon, Scarlata, Newacheck, & Nessim, 1993). Perhaps, because of an accumulation of risk factors or due to the disruption of the experience itself, HHM status represents additional risk to developmental outcomes beyond those associated with poverty more generally (Rafferty & Shinn, 1991; Scanlon & Devine, 2001).

Study goals were twofold. First, we examined whether HHM status represents risk to achievement and growth in reading or mathematics beyond the risks associated with poverty. Second, we examined whether risk among HHM students is episodic in nature. Five years of longitudinal standardized test data from a large, urban school district were used to investigate whether HHM status is related to lower levels of initial achievement (beginning in third grade) and differential growth among children who were identified as HHM.

Academic Achievement Gaps Related to Poverty, Homelessness, and High Residential Mobility

There are marked disparities in academic achievement among students from different socioeconomic status (SES) and ethnic backgrounds. As a group, children who experience poverty underperform academically compared to students from higher SES families (McLoyd, 1998; Sirin, 2005). Pungello, Kupersmidt, Burchinal, and Patterson (1996) found that low-income students had lower reading and math achievement longitudinally across second through seventh grades. Caro, McDonald, and Willms (2009) found an SES-related gap in math achievement that widened with age from 7 through 15. Furthermore, ethnic minority children are overrepresented among low-family income groups, and these income differences relate to Black–White achievement gaps (Magnuson & Duncan, 2006). The risk associated with HHM status seemingly contributes to income and Black–White achievement gaps, as low-income and minority students are overrepresented among HHM groups (Obradović et al., 2009).

Residential mobility is linked with lower levels of academic achievement, more problems at school, and increased rates of grade retention. Ingersoll, Scamman, and Eckerling (1989) found that students with a higher number of residential or school moves over the past school year had lower levels of reading and math achievement in Grades 1 through 12. This difference persisted when controlling for student SES. Among 1st through 12th graders, children who moved three or more times were 60% more likely to repeat a grade, controlling for poverty and other sociodemographic risks. They also were much more likely to have additional school-related problems such as expulsion or suspension (Simpson & Fowler, 1994). Considering just the children between the ages of 6 and 17 in the same sample, those who moved six or more times were 35% more likely to have repeated a grade, controlling for a more comprehensive list of risk factors such as poverty, single-parent family, low parental education, gender of the child, and other risks (Wood et al., 1993). In another study, Adam and Chase-Lansdale (2002) linked a greater number of residential moves over the preceding 5 years with lower current grades in school among a sample of low-income adolescent girls, after controlling for sociodemographic risk (e.g., caregiver's education, age, and marital status) and perceived current environment (e.g., quality of social support). How this risk operates is still a matter for further research, but residential mobility is a risk factor for lower academic achievement in low-income groups, beyond the effects of poverty (Scanlon & Devine, 2001).

Results from studies of children experiencing homelessness are mixed, but the preponderance of findings suggests that homelessness is associated with low achievement in analyses that include control variables or poverty control group comparisons. Fantuzzo and Perlman (2007) found that homelessness predicted lower levels of literacy and science achievement among 11,835 students from a second grade cohort in a large, urban school district. This finding persisted when controlling for gender, ethnicity, out-of-home placement, child maltreatment, and any birth-related risk (inadequate prenatal care, premature birth, or low birth weight). Children who had experienced homelessness had lower levels of academic achievement, even while accounting for other salient social risk factors.

Other studies have compared homeless children with nonhomeless, low-income peers on measures of achievement. Rubin et al. (1996) contrasted homeless and housed school-age children from the same classroom. Math, spelling, and reading achievement scores were lower for the homeless group, a disparity that was only partially explained by differences in school attendance. San Agustin et al. (1999) found that homeless school children in New York City shelters had more academic problems in reading, math, and spelling compared to a control sample of classmates. Rescorla, Parker, and Stolley (1991) failed to find a difference on an individually administered achievement test in a smaller sample of homeless school children compared to children on public assistance. However, homeless children did have lower vocabulary scores. Buckner, Bassuk, and Weinreb (2001) investigated academic achievement among 60 sheltered homeless children and 114 children receiving aid for low-income families. None of the children in the control group were staying in shelter, but a number were "doubled up" and staying with other families. Whether the child was staying in a shelter did not predict academic achievement beyond race, gender, and age. Meanwhile, the number of schools attended in the past year was related to achievement. Although the findings in these studies are mixed, most of the evidence suggests that homelessness represents a risk for academic achievement beyond poverty. However, the mechanisms of this risk are likely to be related to a complex interplay of multiple factors over time.

Longitudinal studies of academic achievement among homeless children are scarce. To our knowledge, only two analyses have investigated the impact of homelessness on children's achievement over time, and these studies have produced conflicting results. Rafferty, Shinn, and Weitzman (2004) found lower levels of math and reading achievement in the year following a shelter stay for homeless students compared to low-income, housed school-aged children. This difference disappeared 5 years later, after the homeless group had been rehoused.

In contrast, a more recent study found effects consistent with a continuum of chronic risk. Obradović et al. (2009) employed a cohort-based methodology, examining growth across 2 school years within cohorts of students who were initially in Grades 2 through 5 at the outset of testing. This approach limited the conclusions that could be made about student growth across the full grade span. The data were drawn from the same district as the present study, but at an earlier point in time. Achievement level and growth was compared for three levels of risk: HHM, poverty (qualified for free meals [FM] or reduced price meals [RM], but not HHM), and "advantaged" (not low income or HHM). They found effects consistent with a continuum of chronic risk: Children identified as HHM at any point had lower initial levels of achievement relative to those in the poverty group, and those in the poverty group had lower initial achievement scores relative to those who had been neither poor nor HHM. Differences in achievement growth over time were less consistent, appearing for two cohorts. However, when they did occur, students in the poverty and HHM groups showed slower growth.

HHM as Acute or Chronic Risk?

Although there appear to be achievement gaps for children identified as HHM compared to lower risk students, it is unclear whether these differences widen or close over time, or depend on the timing of a homeless episode. Pertinent data addressing these issues are scarce: More studies with repeated assessments of achievement are necessary to assess growth, studies of timing effects are rare, and extant longitudinal findings are inconsistent. The current study addressed these issues, extending what we know about HHM students' achievement over time.

The risk associated with HHM status can be thought of in two different ways with respect to time: HHM status may either (a) represent experiences that disrupt growth in achievement around the time of the HHM episode (the acute-risk hypothesis) or (b) represent higher levels of stable, cumulative risk that accompany very low levels of income, regardless of when the HHM episode occurs (the chronic-risk hypothesis). These views are not mutually exclusive, as students at a higher level of chronic risk may have experiences punctuated by episodes of acute risk. Elaborating on whether chronic and acute mechanisms contribute to lower achievement can assist in policy and practice decisions for HHM students.

If the HHM episode disrupts achievement in an acute way, one would expect slower growth in achievement following the HHM episode relative to other times when the same student is not HHM. Rafferty et al. (2004) lend support to this view as homeless students underperformed relative to peers around the time they were homeless, but not after they had been rehoused for a number of years. Conversely, if HHM status simply indicates which children experience higher levels of more chronic risk, such as those typically indexed by high levels of poverty, one would expect the timing of the episodes to have less influence on achievement. This assumption was implicit in the approach taken by Obradović et al. (2009), when they examined differences in academic achievement along a continuum of risk. Students were considered to be in the HHM group if they received the HHM flag *at any point* across the period of the study, regardless of whether they were HHM at one point and not others. However, it remains unclear if the risk associated with HHM status operates exclusively in this chronic or more stable fashion, or if it intensifies following HHM episodes.

Resilience Among HHM Students

Despite the risk associated with homelessness and residential mobility at the group level, there is clear variability in individual students' achievement. Many students do well. Students are considered resilient when they show competence despite experiencing risk (Luthar, 2006; Masten, Cutuli, Herbers, & Reed, 2009; Ungar, 2011; Yates, Egeland, & Sroufe, 2003).

Many students identified as HHM show academic resilience. Obradović et al. (2009) found that about 58%–63% of reading and math score trajectories fell within or above 1 *SD* of national test norms, respectively. Factors such as differences in attendance rates, gender, race, and receiving special services were sometimes related to achievement differences among HHM students. However, a great deal of variability in achievement remained even when these factors were accounted for. Most HHM students showed competent levels of academic achievement (in the average range or higher), and factors like having better attendance, female sex, being of the majority racial group, and not qualifying for English language learning (ELL) services *only partly* accounted for the observed variability in achievement. These factors are important, but they are not the whole story when it comes to academic resilience. This is not surprising as resilience is viewed as the product of complex processes that involve individual factors, family functioning, aspects of culture, and the child's broader ecology throughout development (Luthar, 2006; Masten, 2007; Masten et al., 2009; Ungar, 2011; Yates et al., 2003). Specifically among homeless children, these factors include self-regulation (Buckner, Mezzacappa, & Beardslee, 2003; Obradović, 2010), parenting quality (Miliotis, Sesma, & Masten, 1999), health (Cutuli, Herbers, Rinaldi, Masten, & Oberg, 2010), and complex interplay among factors (Herbers et al., 2011).

The Present Study

The current study had two primary aims: The first was to examine HHM status as a risk factor for math and reading achievement over time, beyond the risk associated with poverty. The second aim was to examine whether this risk includes aspects that are chronic, acute, or both. Longitudinal achievement data span 5 years of assessment, beginning in the fall of 2005. The analyses employed an accelerated longitudinal design (Pungello et al., 1996; Raudenbush & Chan, 1992) and used linear mixed modeling (LMM; Fitzmaurice, Laird, & Ware, 2004) to examine differences in initial achievement and growth over third through eighth grades.

Data were analyzed in two steps reflecting the two aims. First, HHM status was treated as a time-invariant (or static) predictor, and all available district data were analyzed to investigate whether HHM status operates as a chronic-risk factor beyond poverty. We hypothesized that SES and HHM risk would help predict differences in reading and math achievement. We expected the existence of a risk gradient in which lower levels of academic achievement at third grade would correspond to progressively higher levels of risk. The expected risk gradient included four levels of risk (from highest to lowest risk): (a) students identified as HHM, (b) students who were not HHM but who qualified for the federal FM program, (c) students who were not HHM but qualified for federal RM, and (d) students not identified as HHM who never qualified for any of these income-based programs. In other words, we expected that groups with incrementally lower levels of income would show incrementally lower levels of achievement, and HHM students would be at the highest level of risk demonstrated by the lowest levels of achievement. These differences were expected to be evident by third grade (intercept effects) and to increase over time due to differential growth among groups, with more disadvantaged groups showing slower growth than lower risk groups (trajectory effects). We expected differences to persist when other risk factors were controlled: minority status, poor attendance, special education, ELL, and gender.

In addition, we investigated the form of the growth curves. Longitudinal studies of achievement have yielded mixed results with regard to the shape of growth curves. Studies considering relatively short spans of time (e.g., a few years) in certain developmental periods (e.g., adolescence) tend to show linear growth (Obradović et al., 2009; Shin, Davison, & Long, 2009). Studies with a longer time span over different developmental periods (e.g., early or middle childhood) tend to show nonlinear growth (Ding, Davison, & Petersen, 2005; Kowaleski-Jones & Duncan, 1999). With this in mind, we examined the plausibility of linear versus nonlinear growth curves, with the latter being either a quadratic polynomial, or a more parsimonious model using the log transformation of time (Long & Ryoo, 2010).

Second, we tested the hypothesis that HHM status represents an acutely disruptive episode, even in the presence of chronic risk. HHM episodes would have greater negative effects on achievement around the time that HHM occurs. This second set of analyses involved only students identified as HHM at least once during the course of the study. LMM analyses with HHM as a dynamic variable were conducted to compare achievement and growth during the years following an episode of HHM, compared to those years when the student did not experience HHM. Growth in achievement was expected to slow during the disrupted period.

Method

Analyses were based on all available data routinely collected by the Minneapolis Public School (MPS) district. This included 5 years of achievement data for third- through eighth-grade students from 2005–2006 through the 2009–2010 school years. All identifiable information was removed from the records prior to analyses. Standardized achievement tests were administered to all third- through seventh-grade students in the fall of each school year starting in 2005. All eighth graders were administered the same achievement tests beginning in fall 2007. Six years of enrollment data spanning 2003–2004 through 2008–2009 were available for the analyses. Enrollment data included grade, gender, ethnicity, attendance rates, HHM status for each year, and whether the child qualified for any of the following services or programs: special education, English proficiency or ELL services, or federal reduced price or free meals.

The accelerated longitudinal design included all available information and minimized selection biases. The number of data points for an individual ranged from 1 to 5. LMM includes students with at least one observed score, but predictor scores must not be missing. Valid inferences are predicated on the type of missing data mechanism, described below.

Measures

Risk groups. The MPS district determined HHM status for each student at the time of enrollment and continuously throughout each school year. Criteria for HHM status were based on the language of the McKinney Vento legislation, reauthorized in 2001 as Title X of the No Child Left Behind Act of 2001 (2002). Children qualified as HHM if they lived in any of the following conditions: (a) in a shelter, motel, vehicle, or campground; (b) on the street; (c) in an abandoned building, trailer, or other inadequate accommodation; or (d) doubled up with friends or relatives because they could not find or afford housing. HHM students were identified at a Student Placement Center, in schools, or while staying in shelters. Also, school enrollment forms included a screening question to help identify students as they entered the district or changed schools. When endorsed, families and youth completed a more detailed self-identification questionnaire to determine HHM status. Prior to the 2006–2007 school year, students reporting three or more changes in residence in a 12-month period received the HHM designation. About 80% of all children who qualified for HHM status were identified while staying in shelter. Students identified as HHM at any point during a school year were included in the HHM group for that year.

Classification in any of the three other risk groups was based on eligibility for the National School Lunch Program. Students qualified for FM if their family income was below 130% of the poverty line, as indicated by U.S. Department of Agriculture guidelines. Students from families with incomes below 185% of the poverty line (but not below 130%) qualified for RM. For chronic-risk analyses, students were grouped with priority to the assumed highest level of risk that they experienced in the data set, in the following order (high to low): HHM, FM, RM, and General. Each student was included in only one risk category. Thus, a student who at any time qualified for HHM was classified in that group, one who qualified for FM but not HHM was classified in the FM group, and one who qualified for RM but not FM or HHM was classified as RM. All remaining students were included in the General group.

Academic achievement. Students completed the reading and math portions of the Computer Adaptive Levels Tests (CALT; Northwest Evaluation Association, 2005), a nationally normed adaptive test calibrated to each student's achievement level. The CALT consists of three testlets of 13 multiple-choice items each, separately for reading and for math. The difficulty level is further calibrated to the student's performance: Students who do well on a testlet are administered more difficult items; students who do poorly on a testlet receive less difficult items subsequently. Students receiving services for limited English proficiency were allowed to take the paper version of the math section translated into Hmong, Spanish, or Somali.

In fall 2009, the district began to administer the Measures of Academic Progress (MAP) reading and math assessments to replace the CALT. The MAP is also a nationally normed adaptive test developed by the Northwest Evaluation Association that dynamically adapts to a student's response in a similar way to the CALT. Raw scores on the CALT and MAP are converted to scale scores via item response theory scaling procedures. A recent technical study (Chan, 2010) demonstrated the statistical equivalence between the MAP and the CALT.

Demographic and enrollment characteristics. Demographic and school-based variables were collected as part of the routine MPS enrollment and record-keeping process. Parents or guardians completed enrollment forms to indicate the child's gender and primary ethnicity (American Indian, African American, Asian, Hispanic, and White). Assistance was available for HHM students to help ensure accurate and complete information.

About a quarter (27.0%) of students in the district data set qualified for ELL services. Eligibility was based on district assessment of English language proficiency at intake or in response to teacher recommendations. About 19% of students qualified for special education services. A student is determined eligible for special education under the Response to Intervention procedures approved by the Minnesota Department of Education. There are more than a dozen different special education disability categories with specific eligibility criteria determined by the State of Minnesota Special Education rules.

Attendance records for each student are maintained by MPS. Teachers take attendance every day, and an attendance clerk at each school ensures that complete attendance information is entered into a district-wide information system. Given our emphasis on HHM students, we computed a variable reflecting the overall proportion of days attended (total number of days attended/total number of days enrolled). This approach is employed by MPS research staff to reflect students' attendance without overpenalizing HHM students who are more likely to move into or away from the district during the school year.

Data Analyses

The hypotheses were evaluated using LMM (Fitzmaurice et al., 2004). A number of covariates were included in all models to control for factors related to both achievement and risk (National Research Council, 2002; Obradović et al., 2009; Sirin, 2005). With the exception of the continuous attendance variable, all of the covariates were represented by dummy codes. Dichotomous variables had a single dummy code with the first listed option serving as the reference group: gender (male, female), ELL status (no ELL, ELL), and eligible for special education (no special education, special education). Several factors were used for ethnicity (White, American Indian, African American, Asian, Hispanic), and risk group (HHM, FM, RM, General), with White being the reference group for ethnicity and HHM being the risk reference group. Follow-up tests compared the other three risk groups to estimate the magnitude of difference between those groups (FM, RM, and General). The dynamic HHM variable was dichotomously dummy coded (not HHM, HHM) and was allowed to vary from grade to grade. Preliminary analyses not presented showed individual variation in intercepts and growth trajectories, consistent with past work on academic achievement in elementary and middle school (Kowaleski-Jones & Duncan, 1999; Obradović et al., 2009). Random effects for intercept and slope accounted for this variation.

We used a multimodel inference approach in which a number of alternative models were compared to determine relative fit and plausibility (Anderson, 2008; Burnham & Anderson, 2004). Nine models were considered to examine the shape of the growth curve (linear, quadratic, or a log transformation of grade) and the effects of risk on intercept and growth. Models differed by whether they contained control variables only (intercept and slope), included additional risk effects for intercept only, and included additional risk effects for the intercept and the growth curve (slope or trajectory). These three configurations were used in models that considered growth as a linear, a quadratic, and a log function, simultaneously examining the shape of growth. This resulted in four groups of nine models, with nine models compared for each type of risk (static, dynamic) on each outcome (math, reading).

We evaluated model fit (plausibility) based on the Akaike's information criterion (AIC; Akaike, 1973, 1974). In a model set, the model with the lowest AIC has the best fit, and differences in AIC reflect relative goodness of fit. The weight of evidence was calculated, which denotes the probability that a model is the most plausible of the set. The weight of evidence for the kth model (W_k) is computed as $W_k = \frac{\exp(-.5\Delta_k)}{\sum_l^L \exp(-.5\Delta_k)}$, where L is the total number of models, and $\Delta_k = \text{AIC}_k - \text{AIC}_{\min}$, with $\text{AIC}_{\min}$ being the minimum AIC in the set. The best fitting model has the largest weight. Models with high weights are the most plausible, and multiple models should be considered when each has a sizeable weight (Burnham & Anderson, 2004). Analyses were performed using R base version 2.9.2 (R Development Core Team, 2009), with the packages lme4 (Bates & Maechler, 2009), bbmle (Bolker, 2010), and ggplot2 (Wickham, 2009).

Chronic-risk analyses. The first set of analyses focused on students who were identified as HHM at any point compared to students from families with different income levels. These analyses involved the entire sample of students who completed standardized achievement tests in reading (N = 26,501) or math (N = 26,474) in the 2005–2006 through 2009–2010 school years and had any enrollment data from 2003–2004 through 2008–2009. Students were divided into the four mutually exclusive risk groups described earlier: (a) HHM (13.8% of the sample), (b) FM (57.2%), (c) RM (3.7%), and (d) General (25.3%). Demographics and enrollment characteristics are provided in Table 1.

The largest proportion of missing data was due to the accelerated longitudinal design. However, data were missing for a variety of other reasons, as would be the case with any urban district that contains a sizable proportion of low income and mobile students. Taking into account missingness by design, about 72% of possible data points for students in the sample were observed (not missing) and included in the analyses (61,262 of a possible 85,864 for reading achievement; 60,989 of 84,336 for math achievement models). The HHM group had the smallest number of complete cases (41.4% for reading; 38.5% for math), followed by the FM group (56.7% reading; 54.6% math), the RM group (60.6% reading; 57.2% math), and the General group (71.2% reading; 70.1% math). The overall number of observed data points is listed by risk group and grade in Table 2. LMM allows for valid inferences under the assumption that the missing mechanism is missing at random or missing completely at random (Little & Rubin, 1989). Additional analyses (coefficients not provided) suggest that missingness is not likely to be contingent on either reading or math test scores and, therefore, lead us to believe that the missing at random assumption is supported.

Acute-risk analyses. The second set of analyses involved examining the dynamic impact of HHM on achievement. These analyses considered only students who were identified as HHM during the 2004–2005 through 2008–2009 school years with corresponding achievement data (N = 3,442 for reading achievement; N = 3,436 for math). HHM status was tied to achievement scores taking a 1-year lag approach. Given the goal of testing for time-related disruption in achievement, it was

Table 1
Demographic Characteristics

									Special		
	Gender (%)		Ethnicity (%)							Attendance (%)	
Group	*N*	Female	AI	AA	AS	HI	WH	ELL (%)	Education (%)	*M*	*SD*
General											
Reading	6,702	49.1	1.5	13.0	6.0	5.0	74.4	2.9	11.0	96.5	2.9
Math	6,708	49.1	1.6	13.0	5.9	5.2	74.3	3.0	11.1	96.4	3.0
Reduced price meals											
Reading	968	50.5	4.6	36.6	10.7	9.9	38.1	14.2	15.7	95.6	3.4
Math	970	50.9	4.5	36.7	10.9	9.8	38.0	14.1	15.7	95.7	3.3
Free meals											
Reading	15,181	48.8	5.0	46.8	11.9	25.8	10.5	41.3	20.3	94.4	4.6
Math	15,152	48.7	5.0	46.8	11.9	25.8	10.5	41.3	20.4	94.4	4.6
HHM											
Reading	3,650	50.1	9.7	68.7	6.7	9.2	5.8	15.2	30.7	90.6	7.0
Math	3,644	49.9	9.7	68.7	6.7	9.1	5.8	15.1	31	90.6	7.0
Total											
Reading	26,501	49.1	4.7	40.9	9.6	17.7	27.1	27.0	19.2	94.4	4.9
Math	26,474	49.1	4.7	40.9	9.6	17.7	27.1	27.0	19.3	94.4	5.0

Note. HHM = Homeless or highly mobile; AI = American Indian; AA = African American; AS = Asian; HI = Hispanic; WH = White; ELL = qualified for English language learner services.

Table 2
Number of Observations by Grade

	General		Reduced price meals		Free meals		Homeless or highly mobile		Total	
Grade	Reading	Math	Reading	Math	Reading	Math	Reading	Math	Reading	Math
3	3,542	3,552	448	448	6,394	6,393	1,301	1,293	11,685	11,686
4	3,258	3,259	393	390	6,372	6,325	1,372	1,370	11,395	11,344
5	3,028	3,019	365	363	6,124	6,084	1,373	1,363	10,890	10,829
6	2,679	2,668	365	358	5,848	5,794	1,305	1,290	10,197	10,110
7	2,490	2,477	369	361	5,308	5,762	1,320	1,306	9,987	9,906
8	1,612	1,624	261	262	4,309	4,298	926	930	7,108	7,114
Total	16,609	16,599	2,201	2,182	34,855	34,656	7,597	7,552	61,262	60,989

important to ensure that the HHM experience occurred before the achievement testing. This 1-year lag approach has been used successfully in past work considering achievement in highly mobile students (Ingersoll et al., 1989). About 62% of the possible data points were observed in this subsample (7,076 of 11,462 possible observations for reading achievement; 7,029 of 11,256 for math). Forty-one percent of students had complete data for reading achievement, whereas 38.2% had complete data for math. Effects of the dynamic HHM variable were considered on both intercept and trajectory separately with respect to reading and math.

Results

Consistent with other large urban districts (Fantuzzo & Perlman, 2007), almost 75% of the students were in one of the three low-income groups, and 13.8% were HHM at some point across the 6 years considered in this analysis. Ethnic minority students were overrepresented in the low-income groups, as noted by the lower percentage of White students in relation to higher levels of risk; see Table 1. African American students, in particular, comprised the majority (68.7%) of the HHM group. Larger percentages of HHM students qualified for special education services. Not surprisingly, HHM students had a lower mean level of attendance with greater variance. Whereas district-wide attendance rates were 94.4% (*SD* = 4.9%), attendance for the HHM group was 90.6% (*SD* = 7.0%), as defined by the district.

Results reflecting the two primary aims are presented separately. First, we present results examining whether HHM status represents static risk beyond low income for reading and math achievement across third through eighth grades. Then, we present results for analyses testing for acute-risk effects associated with HHM status.

Static-Risk Models of Academic Achievement Among HHM and Different Income Groups

Model comparison results of static-risk analyses are provided in Table 3. For both math and reading, the best fitting models had the quadratic polynomial trend over time. The best fitting models also had both intercept and trajectory effects. Coefficients and standard errors for the best fitting models are provided in Table 4. Specific effects in Table 4 are discussed in terms of their relative effect size indicated by *t* values: estimate divided by its standard error.

Math achievement. The best fitting model had static risk differences for both intercept and trajectory. This model unequivocally had the best fit among the nine models (AIC = 446,121; weight of evidence >.99; minimum difference in AIC from the best fitting model: ΔAIC = 145).

The left side of Table 4 lists parameter estimates predicting math achievement. As expected, the income-based risk groups varied with respect to math achievement in third grade. The Reference row shows the HHM intercept adjusted for other variables in the model. The Risk portion of the table lists the added value for the comparison group. Focusing on the first column, each intercept estimate is positive, indicating that each comparison group had a higher intercept than the HHM group. The intercept for a group is computed as the sum of the estimate in the Reference row and in the row of interest. For example, the estimated intercept for the General risk group is 159.06 + 9.60 = 168.66. The General group had the highest intercept, followed by the Reduced group and then the Free group. Estimates of the linear and quadratic polynomials reflected trajectory differences among the

Table 3
Fit Statistics and Relative Model Fit Weights of Evidence

Risk effect	Curve	Math achievement AIC	Math achievement ΔAIC	Math achievement Weight	Reading achievement AIC	Reading achievement ΔAIC	Reading achievement Weight
Static-risk models							
None	Linear	451,450	5,329	<.01	462,835	5,163	<.01
None	Log	447,976	1,855	<.01	459,566	1,894	<.01
None	Quadratic	447,662	1,541	<.01	459,392	1,720	<.01
Intercept	Linear	450,132	4,011	<.01	461,182	3,510	<.01
Intercept	Log	446,592	471	<.01	457,878	206	<.01
Intercept	Quadratic	446,266	145	<.01	457,680	8	.02
Intercept, trajectory	Linear	449,968	3,847	<.01	461,177	3,505	<.01
Intercept, trajectory	Log	446,465	344	<.01	457,872	200	<.01
Intercept, trajectory	Quadratic	**446,121**	**0**	**>.99**	**457,672**	**0**	**.98**
Dynamic-risk models							
None	Linear	53,030	472	<.01	55,212	361	<.01
None	Log	52,621	63	<.01	54,926	75	<.01
None	Quadratic	52,573	15	<.01	54,861	10	.01
Intercept	Linear	53,016	458	<.01	55,201	350	<.01
Intercept	Log	52,609	51	<.01	54,915	64	<.01
Intercept	Quadratic	52,561	3	.18	**54,851**	**0**	**.71**
Intercept, trajectory	Linear	53,012	454	<.01	55,199	348	<.01
Intercept, trajectory	Log	52,608	50	<.01	54,916	65	<.01
Intercept, trajectory	Quadratic	**52,558**	**0**	**.82**	54,853	2	.29

Note. All models included the same set of control effects and only the risk effects as indicated. Adopted models are noted in bold. AIC = Akaike's information criterion; ΔAIC = difference in AIC relative to the best fitting model; Weight = weight of evidence.

groups. Most notably, the General group had a much faster linear increase than the HHM group ($t = 2.00$) and a less concave quadratic effect ($t = 1.80$). The General group linear term is $13.53 + 0.54 = 14.07$, and the General quadratic term is $-2.01 + 0.09 = -1.92$. Smoothed (LOWESS) curves for the groups are presented in Figure 1 (no adjustment for covariates). For reference, Figure 1 also depicts the national norm means.

Reading achievement. For reading achievement, the best fitting model included static risk differences for intercept and trajectory. This model produced the best fit (AIC = 457,672, weight = .98, ΔAIC = 8). At third grade (intercept), the General group had the highest intercept, followed by the Reduced group, the Free group, and then the HHM group.

Regarding the polynomials, the Linear Slope column in the Risk portion indicates all added values are negative, meaning that the groups had a slower linear increase than the HHM group. However, the General and Reduced groups had larger quadratic terms than the HHM group, indicating curves that did not slow down as quickly over time ($t = 0.83$ and $t = 1.50$, respectively). Figure 2 displays smoothed curves for each group and the national norm means.

Post hoc analyses among African American students. We completed a post hoc analysis that repeated the above static-risk model comparisons for reading and math achievement using only the African American students. This was done to further investigate the contributions of HHM and low-income status apart from other factors associated with ethnicity. Results did not change for math achievement (weight of evidence > .99 for model with intercept and quadratic trajectory effects of risk group: weights of all other models considered: < .01). For reading achievement, the model that contained intercept and quadratic trajectory effects of risk group was again adopted (weight = .74). The model that contained only an intercept effect of risk group with quadratic change had a higher weight when only African American students were considered (weight = .26). All other models provided poor relative fit (all weights < .01).

Variability in Academic Achievement and Dynamic-Risk Models Among HHM Students

There was considerable variability among HHM students with respect to both math and reading achievement, with individual patterns of reading

Table 4
Parameter Estimates (Standard Errors) for Adopted (Best Fitting) Static-Risk Models

	Math achievement			Reading achievement		
	Fixed effects			Fixed effects		
	Intercept	Linear slope	Quadratic trajectory	Intercept	Linear slope	Quadratic trajectory
Risk						
HHM vs. general	9.60 (0.39)	0.54 (0.27)	0.09 (0.05)	14.24 (0.48)	−0.57 (0.32)	0.05 (0.06)
HHM vs. reduced	5.70 (0.56)	−0.16 (0.40)	0.09 (0.08)	8.16 (0.71)	0.74 (0.46)	0.12 (0.08)
HHM vs. free	2.80 (0.31)	−0.06 (0.22)	−0.01 (0.04)	4.13 (0.39)	−0.09 (0.25)	−0.04 (0.04)
Free vs. general[a]	6.80 (0.28)	0.60 (0.20)	0.10 (0.04)	10.11 (0.36)	−0.48 (0.23)	0.09 (0.04)
Free vs. reduced[a]	2.90 (0.50)	−0.10 (0.35)	0.09 (0.07)	4.04 (0.63)	−0.65 (0.41)	0.16 (0.08)
Reduced vs. general[a]	3.90 (0.51)	0.70 (0.36)	0.00 (0.07)	6.08 (0.65)	0.18 (0.41)	−0.07 (0.08)
Ethnicity (White vs. . . .)						
American Indian	−6.66 (0.49)	−0.03 (0.34)	−0.08 (0.07)	−7.98 (0.61)	0.04 (0 39)	0.02 (0.07)
African American	−8.61 (0.29)	−0.61 (0 20)	−0.07 (0 04)	−9.46 (0.36)	0.05 (0 23)	−0.04 (0.04)
Asian	−3.06 (0.42)	0.24 (0.29)	0.01 (0.06)	−4.10 (0.53)	−0.09 (0.33)	0.06 (0.06)
Hispanic	−5.13 (0.38)	0.45 (0.26)	−0.20 (0.05)	−7.13 (0.43)	0.94 (0.30)	−0.12 (0.06)
Sex (male vs. female)	−1.31 (0.19)	−0.32 (0.13)	0.03 (0.03)	1.72 (0.23)	−0.43 (0.15)	0.06 (0.03)
ELL (no vs. yes)	−6.21 (0.31)	−0.99 (0.22)	0.15 (0.04)	−12.22 (0.39)	0.61 (0 25)	0.02 (0.05)
Special ed. (no vs. yes)	−8.98 (0.24)	−0.92 (0.17)	−0.05 (0.03)	−15.15 (0.31)	−0.35 (0.19)	0.15 (0.04)
Attendance[b]	37.50 (2.48)	−2.79 (1.83)	1.32 (0.34)	33.29 (3.08)	−4.94 (2.08)	1.03 (0.37)
Reference	159.06 (2.32)	13.53 (1 72)	−2.01 (0.32)	156.93 (2.89)	14.57 (1.96)	−1.74 (0.35)
	Variance components			Variance components		
Intercept (*SD*)	111.82 (10.57)			191.41 (13.84)		
Linear slope (*SD*)	8.55 (2.92)			17.78 (4.22)		
Quadratic slope (*SD*)	0.23 (0.48)			0.42 (0.65)		
Intercept, quadratic slope covar.	0.01			0.12		
σ^2	28.75 (5.36)			32.98 (5.74)		
	Model fit			Model fit		
Akaike's information criterion	446,121			457,672		

Note. HHM = homeless or highly mobile; ELL = qualified for English language learner services.
[a]Parameters based on follow-up tests. [b]Attendance was continuous.

and math achievement varying greatly among HHM students in the district. This variability in individual achievement trajectories is illustrated in Figures 3 and 4. Underscoring this variability, 1,644 (45.0%) of the HHM students demonstrated resilience as defined by scoring within or above 1 *SD* below the mean of the CALT national reading achievement norms for all available data points, 1,453 (39.8%) students scored below that threshold for all data points, and 553 (15.2%) students had scores that were above and below this threshold at different points in time. Similar ratios emerge when this threshold was applied to math achievement: 1,637 (44.9%) HHM students consistently scored within or above 1 *SD* below the national norms, 1,454 (39.9%) scored below that mark for all available test scores, and 553 (15.2%) students had at least one score above and one score below this mark at different points in time.

Dynamic-Risk Analyses

The second aim examined within-individual variability in achievement to determine if HHM status operated solely as a marker of chronic risk, or if achievement varied from year to year as a function of HHM status. These analyses involved the subset of HHM students in the district from the 2004–2005 to 2008–2009 school years. Nine models were compared to determine the nature of achievement trajectories (linear, log, or quadratic function) and whether or how HHM status might operate as a dynamic source of risk (no effect, intercept or mean level effect, or growth effect; see Table 3).

Dynamic risk and math achievement. Parameter estimates for the adopted model predicting math achievement are provided on the left side of Table 5. The Reference row shows the parameter estimates when an individual was not classified as HHM the previous school year. The HHM Dynamic Effects row shows the parameter estimates when an individual was classified as HHM the previous

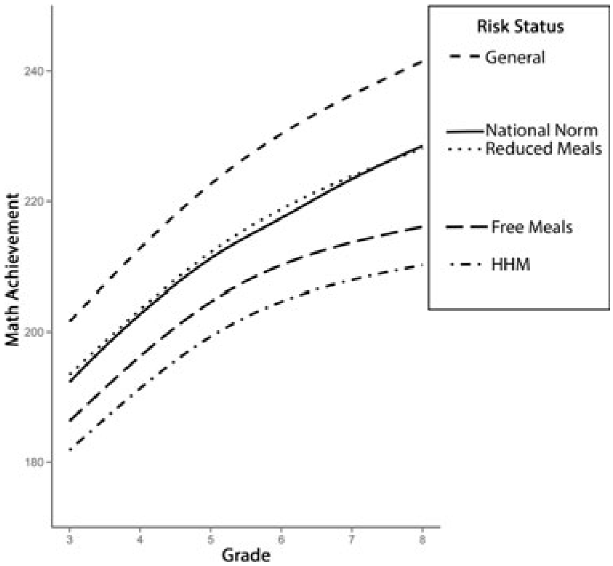

Figure 1. Math achievement by static-risk group for the district sample.
Note. Lines represent LOWESS functions of observed data by group, plus the test national norms for math achievement.

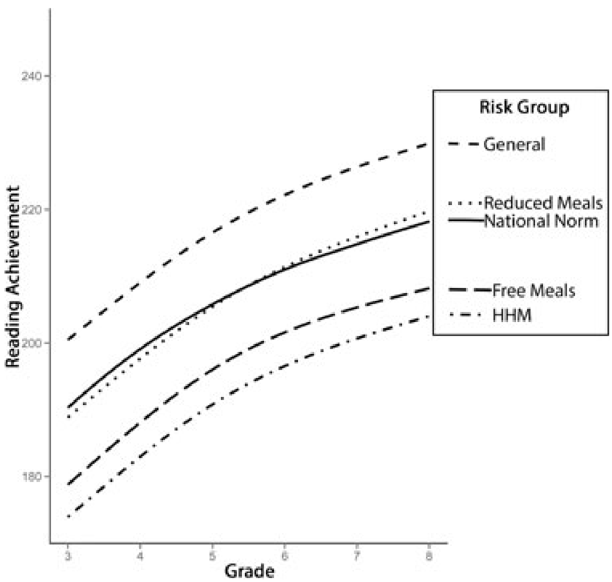

Figure 2. Reading achievement by static-risk group for the district sample.
Note. Lines represent LOWESS functions of observed data by group, plus the test national norms for reading achievement.

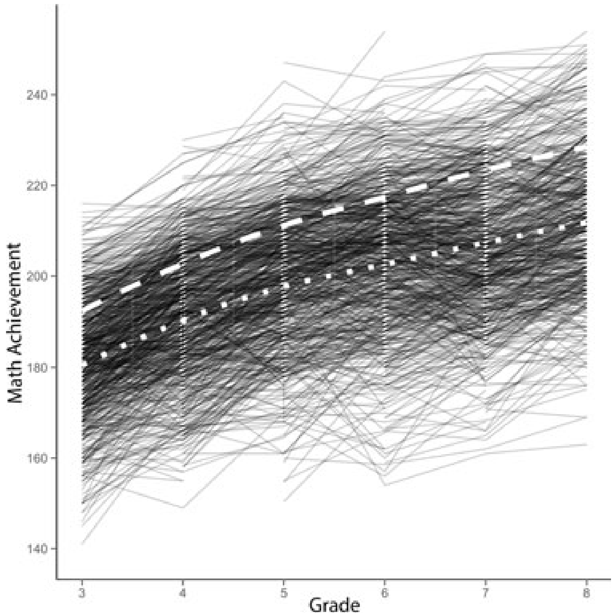

Figure 3. Variability among homeless and highly mobile (HHM) students for math achievement.
Note. Individual math achievement trajectories of HHM students are depicted in black. The white dashed line represents the mean level of math achievement based on national norms. The white dotted line is 1 *SD* below the national norm mean.

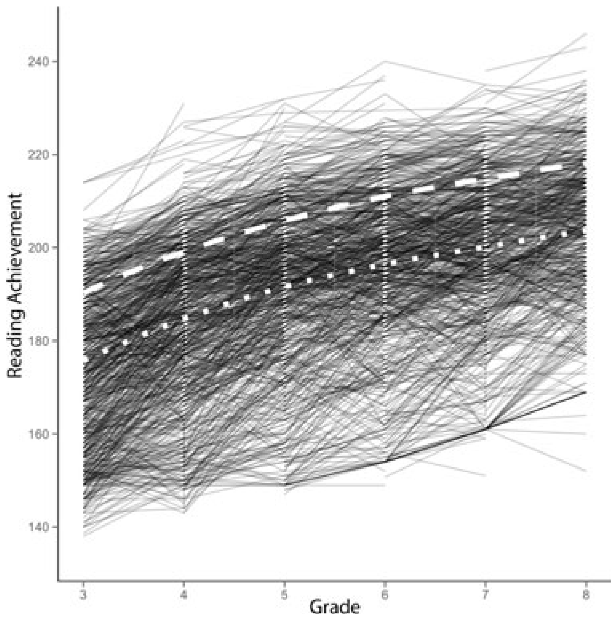

Figure 4. Variability among homeless and highly mobile (HHM) students for reading achievement.
Note. Representative individual reading achievement trajectories of HHM students are depicted in black. The while dashed line represents the mean level of reading achievement based on national norms. The white dotted line is 1 *SD* below the national norm mean.

Table 5
Parameter Estimates (Standard Errors) for Adopted (Best Fitting) Dynamic-Risk Models for HHM Students

	Math achievement			Reading achievement		
	Fixed effects			Fixed effects		
	Intercept	Linear slope	Quadratic trajectory	Intercept	Linear slope	Quadratic trajectory
HHM dynamic effects	−1.78 (0.47)	1.18 (0.45)	−0.22 (0.09)	−0.80 (0.24)	-	-
Ethnicity (White vs. . . .)						
American Indian	−4.15 (1.48)	−0.17 (1.08)	0.12 (0.21)	−3.09 (1.84)	−0.29 (1.33)	0.07 (0.25)
African American	−5.79 (1.25)	−1.95 (0.91)	0.37 (0.17)	−4.52 (1.57)	−1.01 (1.12)	0.16 (0.20)
Asian	−9.59 (2.04)	−1.14 (1.48)	0.44 (0.28)	−12.23 (2.56)	−3.27 (1.82)	0.79 (0.33)
Hispanic	0.12 (1.80)	−0.95 (1.31)	012 (0.25)	−0.51 (2.25)	−0.85 (1.61)	0.26 (0.29)
Sex (male vs. female)	−0.63 (0.60)	0.01 (0.44)	−0.04 (0.08)	2.24 (0.75)	−0.61 (0.54)	0.10 (0.10)
ELL (no vs. yes)	−9.06 (1.30)	−0.76 (0.93)	0.19 (0.18)	−14.69 (1.62)	0.95 (1.15)	−0.11 (0 21)
Special ed. (no vs. yes)	−8.24 (0.66)	−0.94 (0.48)	−0.01 (0.09)	−14.90 (0.82)	−0.68 (0.60)	0.23 (0.11)
Attendance[a]	20.14 (5.23)	−0.83 (3.90)	0.79 (0.71)	16.92 (6.46)	0.23 (4.64)	−0.05 (0.82)
Reference	173.03 (5.00)	12.23 (3.72)	−1.80 (0.67)	168.11 (6.18)	11.09 (4.42)	−1.01 (0.78)
	Variance components			Variance components		
Intercept (*SD*)	114.52 (10.70)			186.16 (13.64)		
Linear Slope (*SD*)	8.17 (2.86)			27.25 (5.22)		
Quadratic Slope (*SD*)	0.06 (0.25)			0.54 (0.73)		
Intercept, Quadratic Slope Covar.	−0.73			−0.14		
σ^2	35.04 (5.92)			45.66 (6.76)		
	Model fit			Model fit		
Akaike's information criterion	52,558			54,851		

Note. HHM = homeless or highly mobile; ELL = qualified for English language learner services.
[a]Attendance was a continuous variable.

school year (controlling for the other variables). The comparison of the two rows illustrates how math achievement changed as HHM status changed. Focusing on the Intercept column, when HHM was occurring there was a decrease in the intercept of −1.78 (t = −3.79), indicating a deterioration in the overall level of the growth curve. As for the polynomials, although there was an increase in the linear component when HHM was occurring (1.18; t = 2.62), and there was a decrease in the quadratic component (−0.22; t = −2.44). The negative sign of the quadratic component indicated convexity, and the overall effect was a slowing (deceleration) of growth, especially for the latter grades (compare with Figure 1).

A number of static covariates also had sizable effects on math achievement, defined as coefficients with t values >2 in the adopted model. Relative to White students, American Indian (t = −2.80), African American (t = −4.63), and Asian (t = −4.70) students had lower math achievement at intercept. Students receiving special services similarly had lower initial levels of achievement (ELL: t = −6.97; special education: t = −12.48). Attendance was positively related to initial math achievement (t = 3.85). Relative to White students, African American students showed differences with respect to growth in math achievement over time (linear growth: t = −2.14; quadratic growth: t = 2.18).

Dynamic risk and reading achievement. Parameter estimates for the adopted reading achievement model are provided in the right side of Table 5. Similar to the results for math, the intercept was lower when HHM was occurring (−0.80; t = −3.33) indicating an overall deterioration. Unlike the results for math, the best fitting model did not have polynomial components that varied as a function of earlier HHM status.

Some static covariates had sizable effects on reading achievement in the adopted model. Relative to White students, African American students (t = −2.88) and Asian students (t = −4.78) had lower reading achievement at intercept, and Asian students showed differences in reading achievement quadratic growth (t = 2.39). Male students (t = −2.99), students receiving special services (ELL:

$t = -9.07$; special education: $t = -18.17$), and students with poorer attendance ($t = 2.62$) all had lower initial levels of reading achievement. Receiving special education services was also related to differences in quadratic growth ($t = 2.09$).

Discussion

Homelessness and high residential mobility represented a substantial risk for lower academic achievement among students in third through eighth grades in this large, urban school district. This was a salient issue with nearly 14% of all students in this district identified as HHM at some point over the course of 6 years. The risk associated with HHM status had a clear chronic component: Students who were ever HHM showed markedly lower achievement across third through eighth grades, with attenuated growth compared to students who were neither low income nor HHM. As a group, HHM students underperformed more stably housed peers in reading and math achievement over time. Gaps appeared and persisted for the HHM group even when compared to low-income peers. HHM status is a marker for high chronic risk to academic achievement.

Students who were ever identified as HHM showed lower levels of reading and math achievement when compared to groups of more stably housed students, including students who were never HHM, but had very low income (below 130% of the poverty line), had low income (below 185% of the poverty line), and were neither HHM nor low income. As expected, a risk gradient emerged in which students in the lower income groups showed progressively lower levels of achievement, and the HHM group underperformed even the lowest income group. These findings support the concept of a continuum of risk on which homelessness or high rates of residential mobility represents a greater level of risk beyond poverty alone (Masten et al., 1993; Samuels et al., 2010). The risk associated with HHM status was not attributable to other well-established risk factors for achievement, including attendance, ethnicity, gender, and qualifying for special services such as special education or ELL. The gaps for HHM students were already apparent in both reading and math achievement by third grade, the earliest year available on the achievement test in this district for the study period. Considering Figures 1 and 2, national norm lines appear to approximate the mean levels of achievement for the moderate-risk group of students. The mean achievement of the higher risk groups (HHM and FM) underperform relative to the norms whereas the lower risk group relatively overperforms. In addition to the above findings, this more qualitative evidence is consonant with the view of a continuum of risk where norms are based on a representative sample of children across all levels of risk.

Growth differences emerged for HHM and other groups across third through eighth grades, with the most pronounced effect for growth differences between the HHM and General groups in math, and between the HHM and RM groups in reading. The HHM group showed a widening of the gap over time compared to lower risk groups from third through eighth grades. There was no evidence of "catch-up" or narrowing of achievement gaps over time.

These results corroborate past findings showing lower levels of academic achievement for HHM students, either in a single grade or at a single point in time (Adam & Chase-Lansdale, 2002; Buckner, 2008; Fantuzzo & Perlman, 2007; Rubin et al., 1996) or when considered longitudinally as a marker of chronic risk (Obradović et al., 2009). The current study builds most directly on the work of Obradović et al. (2009), who compared standardized test scores and growth longitudinally over 20 months for groups of students (HHM, poverty, advantaged) using a cohort design. In contrast, we utilized a later and larger district data set to consider differences in achievement over a longer period of time (third through eighth grades) with a greater delineation between groups of students from low-income families (e.g., separating groups of students who qualify for FM from those who qualify for RM). An accelerated longitudinal design allowed us to confirm that students who were identified as HHM at any point showed lower mean levels of math and reading achievement across third through eighth grades. Furthermore, growth in achievement for the HHM group appeared slowed relative to lower risk groups. This echoes findings of Obradović et al. (2009) where slope effects emerged for several cohorts, albeit inconsistently.

The second aim tested whether HHM status more strongly disrupted growth in achievement during periods when it was occurring in the student's life (the acute-risk hypothesis) as opposed to years when it was not occurring. The results indicate a general deterioration in achievement assessed during the fall following years that students are identified as HHM. For reading, achievement was lower following years when students were identified as HHM. For math, the intercept and trajectory change as HHM status changes. Specifically, growth in math slowed when students were identified as HHM the previous year.

These results are consistent with our expectation of acute effects of HHM status. Such effects were hypothesized based on the findings of Rafferty et al. (2004) who reported that homeless children had lower levels of both reading and math achievement, but only around the time they were in shelter. Differences disappeared after they had been rehoused for a number of years. The current findings provide partial support to Rafferty and colleague's assertion that HHM experiences disrupt achievement. For both reading and math, students showed lower levels of achievement the year following periods during which they were identified as HHM versus when they were not. Growth in achievement also slowed for math achievement during HHM periods. On the other hand, the results can be interpreted as showing an improvement following a previous year in which students were not HHM.

Similar to the current findings, other work with low-income students has reported specific effects of negative life events on growth in math achievement, but not growth in reading achievement. Pungello et al. (1996) found that low-income, ethnic minority students who experienced negative life events in the preceding 12 months showed slower growth in math achievement, but consistent growth in reading achievement over second through seventh grades. Negative life events may interfere with students' ability to attend to instruction, hampering achievement growth generally. Growth in math achievement may be more vulnerable to disruption because math instruction in elementary and middle school involves a number of qualitatively different operations. In contrast, reading instruction is more cumulative: Students acquire basic reading skills in the early grades and incrementally improve through practice. Life events, such as HHM experiences, may disrupt math achievement more acutely by interfering with mastery of novel content, whereas foundational reading skills could be consistently applied to new reading content. Future work is warranted to test this account.

Importantly, about 45% of HHM students showed academic resilience, defined as persistent achievement in the average or better range on the standardized tests over time. Although as a group HHM students were well below expected levels of achievement, a subset of these children managed to meet or exceed general expectations in the areas of math or reading achievement. A variety of factors were related to achievement, including attendance, qualifying for special services, ethnicity, and, in the case of reading achievement, gender. Even so, past efforts to substantially account for academic resilience using these factors have been largely unsuccessful. This suggests that the most influential protective factors and assets that might promote academic resilience in disadvantaged children are not among those routinely measured by school districts (Obradović et al., 2009). These include factors in the child's psychology and ecology, such as effective parenting, self-regulation skills, achievement motivation, or quality of teaching and relationships in classrooms (Luthar, 2006; Masten, 2007).

Diverse stakeholders stand to gain from a better understanding of the mechanisms and processes of academic risks related to HHM status and the variability within this high-risk group. Policies and practices designed to improve and reduce disparities in achievement must be grounded in an understanding of the processes that foster resilience (National Research Council & Institute of Medicine, 2010). Greater attention to the processes of risk and resilience can potentially inform intervention efforts for HHM students. The current findings affirm that HHM status represents substantial and persistent risk to learning, over and above poverty alone. In addition, HHM status confers an additional and more acute risk for disruption to achievement, and appears to have a negative impact on growth, at least for math achievement. Both chronic and acute processes appear to play roles in the academic risk and resilience of students who are identified as HHM. Nevertheless, many students identified as HHM do succeed.

Limitations and Future Directions

This study included all available data for third through eighth graders across 5 years of testing. However, missing data still posed an issue. HHM students had higher rates of missing data compared to other students. Missing data is an inherent problem in longitudinal work with students who, by definition, are mobile and thus difficult to track over time. Given the nature of LMM analyses, the differences found in the current study would likely be greater if all data were complete. It is important to investigate the impact of homelessness and high mobility using data from other sources that may have more complete observations, such as data from regional, state, or national tracking systems, or integrated data systems that may include more observations as the child or family interacts with multiple services in a locale.

Future research is needed to delineate the processes of risk and resilience among children who experience homelessness or high mobility. This study was limited to administrative data from a large, urban school district. Although the data represent a rare examination of growth in achievement for HHM students compared to others, the data precluded close examination of risk and protective processes that might explain differences. Psychosocial factors commonly associated with HHM status were not available (e.g., exposure to domestic violence or other trauma), nor were data on important potential protective factors in the child (e.g., cognitive functioning), home (e.g., high-quality parenting), or classroom (e.g., effective teaching or quality of teacher–child relationships). HHM status undoubtedly reflects multiple processes of risk and resilience that occur over time and operate at multiple levels of analysis. More work should focus on individual, relational, and contextual differences that may play vital roles in the academic resilience of HHM students, and how the processes of risk and protection unfold in context. Factors at the level of the individual, family, school, and neighborhood all likely influence whether the students can succeed in the context of homelessness or high residential mobility (Haber & Toro, 2004). An important strategy for future research will be to combine detailed data on potential protective or risk processes (e.g., psychosocial and contextual variables) with longitudinal administrative data sets.

An ecological-developmental perspective that acknowledges multiple levels of influence will help describe the processes of risk for HHM students (Haber & Toro, 2004). Factors at one level (e.g., lack of affordable housing; a move to shelter) may have different effects based on how they influence other, more proximal adaptive systems in the individual's life (e.g., family functioning; high-quality caregiving; higher quality schools; relationships with competent teachers). The risk associated with HHM status is probably only partly caused by the actual residential mobility or the shelter stay. The functioning of adaptive systems in the child's life, and how they support or impede success in key developmental tasks, will better account for differences in child success (Masten et al., 2009; Yates et al., 2003).

Homelessness and very high rates of residential mobility are almost always accompanied by other disruptions or stressful negative life events that may interfere with school and family systems that promote child competence. For example, when considering demographic and psychosocial factors, Masten et al. (1993) found that children living in emergency shelter differed from low-income, stably housed control children with respect to more recent negative life events and less income during the previous month. Children who experience residential mobility or homelessness experience disruptions in daily routines, lesson plans and assessments at new schools, social supports, relationships, and coping resources in community settings, and impairments in family functioning (Adam & Chase-Lansdale, 2002; National Research Council & Institute of Medicine, 2010). They are more likely to relocate to schools and neighborhoods with lower levels of resources and higher rates of mobility and turnover in residents. Such contexts provide students with less stability and fewer opportunities to navigate the challenges associated with HHM status and any concomitant risks. In sum, HHM status frequently represents multiple risks to development while also constraining the child's ability to adapt successfully.

It is also important to consider the remarkable variability among children in the HHM group. Research on children at high levels of risk has focused attention on the role of individual strengths, relationships, and other protective factors (Luthar, 2006). For HHM students, evidence suggests that protective factors, such as effective parenting, cognitive skills, and good self-regulation, operate to protect achievement (Herbers et al., 2011; Miliotis et al., 1999; Obradović, 2010). Factors such as these will likely illuminate keys to resilience: How a substantial portion of HHM students managed to show competent levels of achievement and growth. Understanding the processes that facilitate academic achievement among HHM and similar students is crucial for designing effective intervention and prevention programs. Results of this and related studies suggest that the national objective of reducing achievement disparities may require greater attention to the needs of HHM students who are not manifesting resilience, given their numbers and persistently low academic achievement. Promoting resilience in children and families at risk due to residential instability holds potential for reducing income-related disparities in reading and math achievement.

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