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Socioeconomic Disadvantage, School Attendance, and Early Cognitive Development: The Differential Effects of School Exposure

Douglas D. Ready[1]

Abstract

Over the past several decades, research has documented strong relationships between social class and children's cognitive abilities. These initial cognitive differences, which are substantial at school entry, increase as children progress through school. Despite the robust findings associated with this research, authors have generally neglected the extent to which school absenteeism exacerbates social class differences in academic development among young children. Using growth-curve analyses within a three-level hierarchical linear modeling framework, this study employs data from the Early Childhood Longitudinal Study (ECLS-K) to examine the links between children's social class, school absences, and academic growth during kindergarten and first grade. Results suggest that the effects of schooling on cognitive development are stronger for lower socioeconomic status (SES) children and that the findings associated with theories of summer learning loss are applicable to literacy development during early elementary school. Indeed, although they continue to achieve at lower absolute levels, socioeconomically disadvantaged children who have good attendance rates gain more literacy skills than their higher SES peers during kindergarten and first grade.

Keywords

social class, inequality, achievement, attendance

Over the past several decades, hundreds of empirical studies have documented the associations between social class and children's cognitive abilities. Perhaps the least disputed conclusion to emerge from educational research over the past half-century is that socioeconomically disadvantaged children are less likely to experience school success. Low-income students enter kindergarten academically behind their more advantaged peers (Entwisle, Alexander, and Olson 1997; Lee and Burkam 2002; Mayer 1997), and these initial cognitive differences increase as children progress through school (Downey, von Hippel, and Broh 2004; Phillips, Crouse, and Ralph 1998; Reardon 2003). Myriad explanations have been offered for this inequality, including disparities in family, school, and neighborhood resources; the persistent associations between social class and race; and sociocultural disconnects between home and school environments (see Duncan and Magnuson 2005; Lareau 2003; Rothstein 2004).

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Despite the robust findings associated with this research, authors have generally neglected the extent to which school absenteeism explains social class differences in cognitive development, particularly among young children. Due largely to the effects associated with residential mobility and children's health, disadvantaged children are more likely to be chronically absent from school. This has important implications for educational equity, as formal schooling matters more to disadvantaged than advantaged children's academic achievement (Downey et al. 2004; Raudenbush 2009). The research presented here extends this line of reasoning to posit that school absences have stronger negative effects for socioeconomically disadvantaged children than for their more advantaged peers. Using three-level growth-curve analyses within a hierarchical linear framework, this study examines the multiplicative effects of children's social class and school absences on early cognitive development.

BACKGROUND

School absences can be categorized as either legitimate or illegitimate (Kearney and Bensaheb 2006). Examinations of illegitimate absences—particularly at the high school level—tend to focus on "school refusal" behaviors. For example, a large body of research investigates adolescent drop-out and graduation rates, often through the lens of student oppositional behavior and clashes with school social and organizational cultures (see Fine 1991; Riehl 1999). Many of these studies link absenteeism to increased at-risk behaviors, such as alcohol and drug use and unsafe sexual and behavioral practices (see Eaton, Brener, and Kann 2008; Hallfors et al. 2002). It is unclear, however, whether findings regarding high school truancy and drop-out rates shed light on the effects of early elementary school absences, which are far more likely to be "legitimate" (de la Torre and Gwynne 2009). Studies of secondary school attendance assume at least a degree of student agency in decisions about school participation and completion. With early elementary school children, however, oppositional behavior is rare and individual autonomy is usually limited; few primary school students "drop out" and young children rarely skip school on their own accord (Epstein and Sheldon 2002). Rather, school absences more often flow from illness and health-related matters, residential mobility resulting from housing instability, and other challenges associated with access to child care. Central to this study is the fact that such concerns are considerably more common among socioeconomically disadvantaged children.

Family Background, Children's Health, and School Attendance

Compared to more affluent students, children living in poverty are 25 percent more likely to miss three or more days of school per month (National Center for Education Statistics [NCES] 2006a). This link between family income and children's school attendance is the product of complex and interconnected relationships. Children born to teenage unmarried mothers, a demographic group strongly associated with childhood poverty, are more likely to be chronically absent from early elementary school (Romero and Lee 2008). Adult composition of the home is also strongly related to both economic resources and children's cognitive development (Blank 1997; Bumpass and Lu 2000; Bumpass and Raley 1995; Cancian and Reed 2001; Ellwood and Jencks 2004), which are in turn associated with student mobility: Disadvantaged children are considerably more likely to change schools during the school year (de la Torre and Gwynne 2009; Hanushek, Kain, and Rivkin 2001; Rumberger 2003). This is important, as student mobility is linked to both children's cognitive development and school attendance. For example, homeless children and those with unstable housing situations are far more likely to be absent from school (Rafferty 1995). In short, socioeconomically disadvantaged children are less likely to have regular school attendance.

In addition to family sociodemographic characteristics, the link between social class and school attendance also operates through young children's health (Case, Lubotsky, and Paxson 2002; Romero and Lee 2008). Low socioeconomic status (SES) children are more likely to experience serious health problems (Hughes and Ng 2003; Rothstein 2004). As a result, they are three times more likely to be chronically absent from school due to illness or injury (Bloom, Dey, and Freeman 2006). Specifically, children living in poverty suffer much higher rates of asthma, heart and kidney disease, epilepsy, digestive problems, as well as vision, dental, and hearing disorders (Case et al. 2002; Halfon and

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Newacheck 1993; Moonie et al. 2006). These ailments—particularly those related to respiratory disorders—are often exacerbated by parental behaviors, including elevated use of tobacco, and by environmental factors associated with poverty, including substandard housing and increased exposure to pollutants and lead (Currie et al. 2007; Gilliland et al. 2001; Hughes and Ng 2003; Malveaux and Fletcher-Vincent 1995; Rothstein 2004). Moreover, poor children are far less likely to have private health insurance and access to medical care (Bloom et al. 2006). Thus, relatively minor ailments often persist, leading to even more serious conditions.

School Attendance and Academic Outcomes

Surprisingly few researchers have explicitly examined the associations between elementary school attendance and children's cognitive development. This is partly a function of the fact that until recently, nationally representative longitudinal data on young children were not available. Cross-sectional analyses of data from the National Assessment of Educational Progress (NAEP) suggest that only 21 percent of eighth graders who missed more than three days of school per month scored at or above basic levels, compared to 45 percent of children who missed no days of school (NCES 2007). Other cross-sectional studies, using student measures aggregated to the school level, also report negative relationships between student absences and academic performance (see Caldas 1993; Lamdin 1996). However, school-level studies lose a considerable amount of within-school variability in terms of student achievement, attendance, and socioeconomic background. Moreover, they ignore the hierarchical nature of the data (i.e., children are nested within schools), which raises both conceptual and statistical concerns (Raudenbush and Bryk 2002; Snijders and Bosker 1999).

The Differential Effects of School Exposure

Because traditionally disadvantaged children are less likely to experience cognitively rich home and neighborhood environments, the proportional influence of formal schooling on their academic development is generally stronger (Alexander, Entwisle, and Olson 2001; Downey et al. 2004; Raudenbush 2009). A central explanation for this phenomenon is that in the United States, variability in learning environments is greater between families than between schools (see Downey et al. 2004). Specifically, differences between low- and high-quality schools are generally smaller than differences between homes that provide low and high levels of social and academic support. As such, a low SES child who attends a high-quality school may benefit more than a socially advantaged child in the same school. Support for these assertions stems from a large body of research concluding that socioeconomically disadvantaged children gain fewer academic skills during the summer when school is not in session (Alexander et al. 2001; Burkam et al. 2004; Heyns 1978). While formal schooling may not eradicate social class differences in academic performance among young children, it likely reduces the rate at which such inequalities grow. If the theory behind these "summer learning loss" studies holds true during the school year as well, the link between school absences and academic development should differ by socioeconomic status.

Although social class disparities in cognitive ability widen faster during the summer months, these inequalities can grow during the school year as well (Downey et al. 2004). This school year disadvantage may flow partly from the fact that socioeconomically disadvantaged children are disproportionately assigned to ability groups and programs that afford limited resources and opportunities to learn (Entwisle et al. 1997; Farkas 2003; Hallinan 1987; Sørensen and Hallinan 1977; Tach and Farkas 2006). For example, lower SES children are more likely to experience larger class sizes (Loeb, Darling-Hammond, and Luczak 2005; Ready and Lee 2007) and remedial coursework that involves rote teaching and low-level academic content (Levin 2007; Oakes, Gamoran, and Page 1992). Disadvantaged children are also more likely to experience teachers who themselves have lower test scores and who lack certification and graduate degrees (Lankford, Loeb, and Wyckoff 2002; NCES 1997; Oakes 1990). Moreover, studies have found positive links between peer ability levels and student learning (Hanushek et al. 2003; Hoxby 2000; Zimmer and Toma, 2000), which is important considering that lower SES children more often

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encounter low-achieving peers (Mayer 2002; Rumberger and Palardy 2005).

The Focus of Early Instruction

The associations between school attendance and student learning will be stronger with academic subjects that are the focus of classroom instruction. For example, research on high schools suggests that mathematics learning is more dependent on the processes and content of formal schooling than is literacy development. Arguments supporting this conclusion note that students have little access to advanced mathematics concepts outside of school—few parents spend time at home working on trigonometry with their teenagers (see Lee et al. 1998). In contrast to high schools, the overwhelming instructional focus of kindergarten and first grade is literacy development. Two out of three full-day kindergarten teachers allocate one hour or more per day to literacy instruction, while only 21 percent use a similar portion of the school day for mathematics instruction (Walston and West 2004). Disparities in instructional focus are equally strong in first grade, when almost 90 percent of teachers spend at least one hour per day on literacy instruction, compared to 30 percent who do so with mathematics (NCES 2006b). Considering how little time kindergarten and first-grade teachers spend on mathematics instruction, we would expect to find weaker associations between school attendance rates and young children's mathematics learning.

Research Focus

Researchers have clearly established that disadvantaged children enter school with fewer academic skills and that these disparities widen further over time. This article examines the extent to which social class differences in literacy and mathematics learning are related to differential school attendance rates. As noted earlier, the benefits of formal schooling may be greater for socioeconomically disadvantaged children. Hypothetically, for such students school absences will have a disproportionately negative effect. The analyses described in this study were designed to address three specific questions:

Research Focus 1: Descriptively, how can we characterize the relationship between social class and student attendance during kindergarten and first grade?

Research Focus 2: To what extent is early academic development a function of school attendance rates, and how do these associations differ across literacy and mathematics?

Research Focus 3: Does the link between social class and cognitive development *depend* on school attendance? In other words, are socioeconomic inequalities in academic performance exacerbated by schooling's disproportionate influence on disadvantaged children's learning?

DATA AND METHOD

This study employs data from the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K). Sponsored by the National Center for Education Statistics, these data are ideal for studying the relationship between social class, school attendance, and children's academic development, particularly with the statistical methods discussed in the following. The ECLS-K collection of base year (1998) data followed a stratified design structure. The primary sampling units were geographic areas consisting of counties or groups of counties from which about 1,000 public and private schools offering kindergarten programs were selected. A target sample of about 24 children was then selected from each school. This study draws from the first four data waves of ECLS-K, which include information on the same children in the fall and spring of kindergarten (waves 1 and 2) and the fall and spring of first grade, with a random subsample in the fall (waves 3 and 4).

Sample and Measures

Analytic sample. From the full ECLS-K sample, the analytic sample was constructed in several stages. The initial step selected children who had a nonmissing weight, advanced to the first grade following the 1998-1999 kindergarten year, did not change schools during kindergarten or first grade, and had test scores for at least two of the four literacy and mathematics assessments.[1] The second stage of sample selection focused on schools, selecting those with a nonmissing weight, that offered kindergarten and first grade, enrolled at least three ECLS-K children, and were not year-round (e.g., they had a traditional nine-month

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academic year). The final analytic sample includes 42,229 literacy and mathematics test scores nested within 13,613 children, who are nested within 903 public and private schools.

Assessment outcomes. The ECLS-K cognitive assessments were administered individually, with an adult assessor spending between 50 and 70 minutes with each child at each data collection wave. The literacy assessments measured both basic literacy skills (print familiarity, letter recognition, beginning and ending sounds, rhyming sounds, and word recognition) as well as more advanced reading comprehension skills (initial understanding, interpretation, personal reflection, and ability to demonstrate a critical stance). The mathematics items, which measured conceptual and procedural knowledge and problem solving, assessed the ability to identify and count numbers and geometric shapes, complete simple multiplication and division exercises, and recognize more complex mathematical patterns (NCES 2000).[2]

Child characteristics. The ECLS-K data include separate measures indicating the number of days students were absent in kindergarten and first grade. Due to their non-normal distributions, the multilevel analyses use log-transformed versions of these measures, which were then standardized (z scored) to ease comparison with both the SES measure and the SES by school absence interaction terms. The ECLS-K data also provide a continuous measure of children's socioeconomic status, which is a composite of parents' income, education, and occupational prestige (z scored, $M = 0$, $SD = 1$). As covariates, the child-level analyses incorporate a dummy-coded gender measure (girls = 1, boys = 0) and dummy variables indicating whether the child is black, Asian, Hispanic, Native American, or multiracial, with whites serving as the uncoded comparison group in the multivariate analyses. The models further account for children's age (in months), single-parent status (yes = 1, no = 0), whether a language other than English was the primary home language (yes = 1, no = 0), and whether the child was repeating kindergarten (yes = 1, no = 0) or attended full-day kindergarten (yes = 1, no = 0). All child-level measures are group-mean centered.

Weights. As with other longitudinal NCES data sets, analyses using ECLS-K require the use of weights to compensate for unequal probabilities of selection within and between schools and for nonresponse effects. The descriptive and analytic analyses employ child-level (C124CW0) and school-level weights (S2SAQW0). Both weights are normalized to a mean of 1 to reflect the actual (smaller) sample sizes. Although the multilevel models examine achievement across four waves of ECLS-K, the "1234" ECLS-K panel weights are only defined on children in the sample at time 3. Hence, the use of those weights automatically restricts the sample to that small subgroup. Instead, the analyses are weighted using the "124" panel weights, which retain the larger sample.

Analytic Approach

The primary analyses employ hierarchical linear modeling (HLM) within a three-level growth-curve framework (Raudenbush and Bryk 2002; Singer and Willett 2003). Specifically, the models nest learning trajectories within children, who are nested within schools. The Level-1 HLM models estimate children's individual learning trajectories. At Level 2, these learning trajectories are modeled as a function of children's social and academic background, with a particular focus on the interactions between child socioeconomic status and school absences. Unlike many studies that employ HLM, these analyses do not explore cognitive development as a function of school characteristics. Rather, the models investigate the links between school attendance and socioeconomic disadvantage among children attending the same school. The HLM models are thus analogous to fixed effects models that remove the influences of unobserved differences between schools on children's learning.

Conceptualizing time with ECLS-K. The ECLS-K data present a unique challenge to researchers interested in modeling children's cognitive growth over time. Longitudinal studies of student learning generally consider the timing of events as constant across cases (i.e., "third grade" represents an identical value or construct). However, the dates on which the ECLS-K cognitive assessments were administered varied considerably across children, both within and between schools. This is understandable given the enormity of the data collection involved with ECLS-K and the time each one-on-one assessment required. In addition to variability in testing dates, the starting and ending dates of academic years also varied across schools.

The result of this variability in school exposure at each assessment is that children's opportunities to learn differed both within and between schools.

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For example, the time children were in school between the fall and spring kindergarten assessments ranged from almost four to over eight months, averaging about six months (although the school year is nine months). For some children, the fall assessments took place months into the school year and the spring assessments occurred several months before the end of the school year. As such, the assessments do not represent comparable events in time across children. Further complicating the analyses, on average, children were in school for approximately half of the "summer vacation" between the spring kindergarten and fall first-grade assessments. Considering the rapid learning rates among young children, researchers who employ the ECLS-K data must take these concerns into account.

These analytic challenges that accompany the ECLS-K data actually provide a unique methodological opportunity. The Level-1 models include three time-varying covariates that indicate individual children's exposure to school at each assessment: (1) months of exposure to kindergarten, (2) months of exposure to summer between kindergarten and first grade, and (3) months of exposure to first grade.[3] These three measures of school exposure—each linked to the four assessment dates—permit the modeling of four distinct parameters: (1) *initial status*, or children's achievement as they began kindergarten (literally, predicted achievement with exposure to zero days of kindergarten, zero days of summer, and zero days of first grade). Rather than initial *status*, the three remaining parameters are linear *learning* rates or slopes over: (2) *the kindergarten year*, (3) *the summer between kindergarten and first grade*, and (4) *the first-grade year*.[4] The variance components for each of the four parameters are included in the appendix.

Problems of Selection Bias

Although modeling the associations between student attendance and academic growth is seemingly straightforward, such efforts are fraught with methodological challenges. Any nonexperimental study that seeks to attribute academic development to formal schooling faces serious questions of selection and unmeasured variable bias. With the analyses presented here, estimates of the effects of school absences on student learning may be spurious, reflecting instead other influences unrelated to school attendance. For instance, students with poor attendance may also experience less stable and cognitively less stimulating home and neighborhood environments—differences that the models may not fully consider. Such confounding influences would be evident in models suggesting that *school year* attendance rates impact *summer* learning. These results would suggest unmeasured variable bias, hinting instead at family and neighborhood effects, or child health effects that are constant regardless of school attendance. Conversely, the finding that school attendance rates influence kindergarten and first-grade learning—but *not* learning during the summer months—provides stronger evidence that school attendance is indeed linked to cognitive development and not to student characteristics that are simply associated with both school attendance and student academic performance. Fortunately, the analytic approach and data structure employed here distinguish learning that occurs during the school year (when school *and* family and neighborhood influences are present) from learning during the summer months (when school effects are removed).

RESULTS

This section presents both descriptive and analytic results. The descriptive analyses address the first research question regarding the relationship between socioeconomic status and school absence rates. Group mean differences were examined for statistical significance with ANOVAs (for continuous variables) and chi-squares (for categorical variables). The within-school findings, which represent the focus of this study, describe the relationships between social class, school absences, and academic development during kindergarten and first grade. The multilevel results are presented in a points-per-month of learning metric, although some coefficients are converted into effect size (standard deviation) units, which is important given the large sample size and the statistical power it affords (see J. Cohen 1988).

Descriptive Results

Table 1, which presents information about students organized by school absence rates, provides clear answers to the first research question: Student attendance and social class are clearly related. A one-third standard deviation SES gap

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Table 1. Student Sociodemographic Characteristics by Kindergarten and First-Grade Attendance Rates (n = 13,613 children within 903 schools)

	Kindergarten attendance[a]			First-grade attendance		
	Good (n = 2,891)	Average (n = 6,820)	Poor (n = 3,902)	Good (n = 3,532)	Average (n = 6,878)	Poor (n = 3,203)
Socioeconomic status (z scored)	0.077***	–0.015***	–0.289	0.020***	–0.034***	–0.273
Percentage female	48.2	48.4	49.2	47.4***	47.5***	52.1
Percentage single parent	20.0***	22.4***	36.8	23.1***	23.3***	36.0
Percentage white	67.2***	67.7***	49.7	62.5***	66.5***	52.4
Percentage black	15.5***	15.3***	19.9	17.2	15.5***	19.0
Percentage Hispanic	11.2***	11.2***	21.8	13.7***	12.0***	20.5
Percentage Asian	3.5*	3.0	2.5	4.1***	2.8*	2.1
Percentage Native American	0.7***	0.9***	3.5	0.9***	1.0***	3.8
Percentage multiracial	1.9*	1.9*	2.6	1.6	2.3	2.2
Percentage non–English speaking household	7.1***	6.8***	11.4	9.2*	6.7***	10.7
Percentage kindergarten repeater	3.2***	3.5***	5.8	3.2***	4.1**	5.3
Percentage full-day kindergarten	56.5**	55.7***	59.8	59.3*	56.3	56.7
Age (in months)	66.3**	66.1	65.9	66.2	66.1	66.1

a. Children with average attendance (3.5 to 10 absences) and good attendance (< 3.5 absences) are statistically compared to children with poor attendance (> 10 absences).
*$p < .05$. **$p < .01$. ***$p < .001$.

separates children with good versus poor kindergarten attendance (effect size [ES] = 0.366; $p < .001$), while a slightly smaller social class disparity distinguishes children with good from those with poor first-grade attendance (ES = 0.293; $p < .001$). School attendance rates are related to other important sociodemographic characteristics as well. More than one out of three children with poor kindergarten and first-grade attendance rates lived in a single-parent home compared to less than one out of four children who had average or good attendance ($p < .001$). Students who missed more than 10 days of kindergarten and first grade were also more likely to speak a language other than English at home ($p < .05$).

Further reflecting the interconnected nature of sociodemographic disadvantage, we also find links between school attendance rates and race/ethnicity. White and Asian children are less often chronically absent compared to non-Asian minority children. In kindergarten and first grade, two out of three children with good or average attendance rates were white, compared to roughly one in two children with poor attendance. Although kindergarten repeaters were disproportionately represented among chronically absent children, the relationship between full-day kindergarten attendance and attendance rates is less clear. Full-day kindergarteners were somewhat more likely to have poor attendance, but the following year the relationship is actually reversed. These descriptive results indicate no (or very weak) relationships between school attendance and gender and attendance and children's age.

Analytic Results

Kindergarten literacy development. Table 2 presents the within-school HLM models estimating literacy development across four separate parameters: initial status (achievement at kindergarten entry), kindergarten learning, first-grade learning, and summer learning between kindergarten and first grade. For each parameter, Model 1 provides the parameter-specific unadjusted associations between social class and literacy ability (for the initial status parameter) or literacy development (for the remaining three parameters). Model 2 then introduces the school absences measure, while Model 3 incorporates the SES by absence interaction term. Model 4 represents the full model, which adjusts the Model 3 coefficients for additional child-level academic and sociodemographic characteristics.

The first panel in Table 2 displays the estimates of children's literacy ability at kindergarten

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Table 2. Social Class, School Attendance, and Early Literacy Development (n = 13,613 children within 903 schools)

	Model 1	Model 2	Model 3	Model 4 (adjusted[a])
Initial status				
Socioeconomic status (SES)[b]	0.1719***	0.1700***	0.1690***	0.1604***
Kindergarten absences[c]		−0.0170**	−0.0167**	−0.0145**
SES × Kindergarten Absences			0.0045	0.0036
Intercept	−1.2963***	−1.2964***	−1.2964***	−1.2971***
Kindergarten				
SES	−0.0027***	−0.0026***	−0.0030***	−0.0033***
Kindergarten absences		−0.0016**	−0.0016*	−0.0015*
SES × Kindergarten Absences			0.0012**	0.0013**
Intercept	0.1017***	0.1017***	0.1017***	0.1018***
First grade				
SES	−0.0028***	−0.0030***	−0.0031***	−0.0030***
First-grade absences		−0.0016***	−0.0012***	−0.0014***
SES × First-grade Absences			0.0005*	0.0006*
Intercept	0.0983***	0.0983***	0.0983***	0.0982***
Summer				
SES	0.0034*	0.0034+	0.0038+	0.0046*
Kindergarten absences		−0.0005	−0.0004	−0.0003
SES × Kindergarten Absences			−0.0003	−0.0003
Intercept	0.0031	0.0030	0.0031	0.0035

Note: Kindergarten, first-grade, and summer coefficients are in a points per month of learning metric. All measures are group-mean centered. *SD*s for all parameters are available in the appendix.

a. Full model includes controls for race/ethnicity, gender, age, language and single-parent status, full-day kindergarten, and kindergarten repetition.

b. Measure is z scored.

c. Log transformed, then z scored,

$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

entry and highlights the considerable socioeconomic inequalities that characterize early academic ability. Model 1 indicates that a one standard deviation increase in SES translates into a roughly 0.17 point (or 13 percent) advantage in initial literacy skills (ES = 0.33; $p < .001$). Model 2, which is solely descriptive, suggests that children who experience increased absences in kindergarten also typically begin kindergarten with fewer literacy skills (ES = 0.03; $p < .01$). As indicated by the nonsignificant interaction term in Model 3, this relationship between school absences and entering literacy ability does not vary by children's social class. Model 4 adjusts these coefficients for children's racial/ethnic backgrounds, gender, age, full-day kindergarten attendance, kindergarten repetition, and language and single-parent status. These child attributes explain a small portion of the initial disparities tied to SES and school absences.

Rather than inequalities at kindergarten entry, the remaining models explore the multiplicative influences of SES and school absences on children's academic growth. The intercept in Model 1 in the second panel of Table 2 indicates that an average SES child gains roughly one-tenth of a point per month during kindergarten ($p < .001$).[5] The small negative SES coefficient suggests that kindergarten serves a somewhat compensatory role in terms of children's literacy skills, with lower SES children narrowing the initial gap somewhat with their higher SES peers (by roughly 0.003 points per month; $p < .001$).[6] If we extrapolate this over a 9.5-month academic year, the initial inequality between average and low SES children (–1 *SD* SES) narrows by roughly

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0.029 points during kindergarten. Although a welcome finding, this equalizing effect clearly does not eliminate the much larger 0.17 point gap that separated these hypothetical children at kindergarten entry.

Model 2 incorporates the kindergarten absence measure and addresses the second research question regarding the link between school absences and academic growth. We find a negative association between absenteeism and kindergarten literacy development, with a one standard deviation increase in absences tied to a roughly 1.5 percent monthly reduction in literacy development (ES = 0.04; $p < .01$). Put another way, even after controlling for SES, children who are chronically absent—those with absence rates one standard deviation above the mean—gain roughly 14 percent fewer literacy skills during the 9.5-month kindergarten year compared to children with average school attendance rates.

This study's third research question asks whether this link between school absences and academic development varies by children's socioeconomic status. Model 3 introduces the SES by kindergarten absences interaction term and reveals that the relationship between school absences and literacy learning does indeed differ by socioeconomic status ($p < .01$). The positive coefficient indicates that the negative effects of increased absenteeism are *stronger* for lower SES children. Specifically, the negative impact of a similar increase in kindergarten absences is 75 percent larger for a low SES compared to an average SES child. The final model adjusts these coefficients for additional sociodemographic characteristics. The negative relationship between school absences and literacy development and the differential effects of absences by children's social class remain robust from Model 3 to Model 4.

First-grade literacy development. The third panel in Table 2 displays the multilevel results for first-grade literacy learning. Mirroring the kindergarten estimates, first grade also appears to play a somewhat equalizing role, with lower SES children gaining somewhat more skills than their higher SES peers (although they continue to score considerably lower in absolute terms). Moreover, as with kindergarten, Model 2 points to negative associations between school absences and first-grade literacy learning (ES = 0.05; $p < .001$), or a roughly 1.6 percent disadvantage in literacy learning per month for each additional one standard deviation increase in school absences. Model 3 indicates that these negative effects of increased absenteeism are roughly 40 percent stronger for lower SES children (i.e., –1 *SD* SES; $p < .05$). As with kindergarten, these findings hold through Model 4 as well.

Summer literacy development. The kindergarten models were also used to estimate literacy development during the summer between kindergarten and first grade. The findings in the bottom panel of Table 2 highlight the phenomenon of summer learning loss. The nonsignificant intercept indicates that the typical average SES child gains no literacy skills during the summer months. In contrast to kindergarten and first grade, however, we find an advantage for higher SES children, who continue to gain literacy skills during the summer months, while lower SES children fall further behind. Note that this summer advantage for higher SES children is quite similar to (though slightly smaller than) the school year advantage enjoyed by lower SES children. In short, kindergarten and first grade appear to have some compensatory effects for socioeconomically disadvantaged children. During the summer, however, when school is not in session, academic disparities tied to socioeconomic disadvantage widen further.

Although these summer learning findings are important in their own right, the analyses were conducted for reasons unrelated to social class differences in summer literacy development. Namely, the reported associations between social class, school absences, and literacy development during kindergarten and first grade may be spurious, reflecting instead the effects of unmeasured sociodemographic child characteristics. Despite a host of statistical controls and the use of analytic methods that estimate learning among children in the same school, the school year models may suffer from selection bias. Indeed, this is a central concern with any nonexperimental study that seeks to attribute cognitive development to schooling—or in this instance, *reduced* schooling resulting from absenteeism. A finding that school year absences were negatively associated with summer learning would likely indicate such selection bias.

Model 2 in the bottom portion of Table 2 indicates that kindergarten absences are unrelated to summer learning ($p > .05$). Moreover, the SES coefficients in Models 1 and 2 are identical; children's school year absences are unrelated to the positive summer learning effects for higher SES

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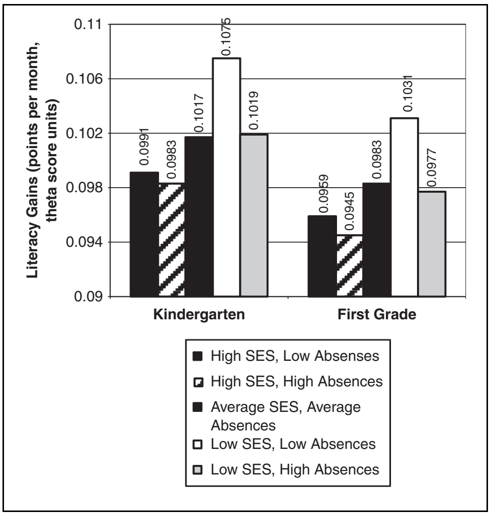

Figure 1. Social class, school absences, and early literacy development
Note: High and low defined as +1 *SD* above and –1 *SD* below the means, respectively. Calculations use coefficients from Model 3, Table 2.

children. An additional set of analyses (not shown here) regressed summer learning on first-grade absences. Although clearly illogical in its temporal ordering, the child and family characteristics present during first grade likely exist during the immediately prior summer. The first-grade absence measures were also unrelated to summer learning. These results provide relatively robust support for the links between school absences and literacy learning in kindergarten and first grade.

Summary of literacy findings. Figure 1 uses the coefficients from Model 3, Table 2 to graphically display the estimated monthly literacy gains for five groups of children. Most striking here is the fact that low SES children who attend school regularly appear to benefit the most academically from early schooling. Compared to high SES children with good attendance, low SES children with good attendance gain almost 8 percent more literacy skills per month during kindergarten and almost 7 percent more per month during first grade. This substantively important compensatory effect flows from two phenomena—the generalized (but slight) narrowing of initial socioeconomic inequalities in literacy ability during the school year and the fact that school exposure has stronger effects for lower SES children. Put another way, the initial difference in literacy skills between low and high SES children with good attendance narrows by roughly one-third by the end of first grade. Conversely, the gap between low SES children with poor attendance and their more affluent peers with good attendance narrows by less than 8 percent during the first two years of formal schooling.

Mathematics development. The literacy models discussed previously were also used to estimate the associations between social class, school absences, and children's mathematics learning. As with literacy, time in school was positively related to mathematics skills development, and monthly learning rates were considerably lower during the summer compared to the school year, suggesting that early schooling does indeed influence children's mathematics learning. Moreover, school absences were related to first-grade mathematics learning, with a one standard deviation increase in absences associated with a –0.0011 point-per-month (1.26 percent) decrease in first-grade mathematics learning ($p < .05$), based on an average monthly gain of 0.0872 points. Calculated using a 9.5-month school year, each one standard deviation increase in absences is associated with a roughly 12 percent reduction in mathematics development over the course of first grade. However, the mathematics and literacy results differed in most other respects. In particular, the findings indicated no relationship between school absences and kindergarten mathematics learning. Furthermore, the association between school absences and first-grade mathematics leaning did not vary as a function of social class—the negative effects of increased absences were not stronger for socioeconomically disadvantaged children.

DISCUSSION AND CONCLUSIONS

For decades, sociologists of education have examined inequality in children's cognitive development through the lens of summer learning loss theory (see Alexander et al. 2001; Burkam et al. 2004; Downey et al. 2004; Heyns 1978). This body of research contends that formal schooling has a stronger influence on the academic growth of socioeconomically disadvantaged children. During the summer months, when the equalizing benefits of schooling are removed, cognitive disparities widen further between disadvantaged

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children and their more affluent peers. The study presented here applied these constructs to the school year to examine the extent to which reduced schooling (in the form of school absences) differentially influences young children's literacy and mathematics development. In terms of children's literacy development, the results lend considerable support to the assertion that the effects of school exposure vary by children's socioeconomic backgrounds. Specifically, the findings described previously suggest a small compensatory effect of early schooling for socioeconomically disadvantaged children, with initial social class disparities in literacy ability narrowing slightly during kindergarten and first grade. During the summer, however, higher SES children gain literacy skills at a faster rate than their lower SES counterparts, thus exacerbating the considerable inequalities present at kindergarten entry.

These equalizing effects of schooling, however, are intimately dependent on school attendance rates. Importantly, low SES children—those who benefit most from school attendance—are also most likely to suffer chronic absences. Thus, if public schools are charged with narrowing socioeconomic disparities in academic outcomes, one potential solution is to increase attendance rates among lower SES children. It is important to stress again that these results reflect average within-school relationships. As such, they are somewhat conservative, as the bond between socioeconomic disadvantage and literacy learning is stronger in the broader student population than it is within individual schools; the persistence of socioeconomic segregation suggests that children are more likely to attend school with socioeconomically similar peers.

In contrast to literacy development, the results indicate weak links between school absences and early mathematics learning. Although increased absences are negatively related to mathematics learning in first grade, no such associations were found in kindergarten. These patterns closely reflect those reported by Downey et al. (2004). Moreover, the results presented here suggest that the relationship between school absences and first-grade mathematics development does not vary by student social class. Considering that the overwhelming focus of kindergarten and first grade is literacy instruction, this finding is not altogether surprising. Given the appropriate data, future studies might examine whether the links between attendance and literacy learning hold for older children in mathematics. In theory, mathematics development should become more closely tied to school attendance as curricula and classroom instruction focus more strongly on mathematics.

Additional Considerations

This study did not address two important issues surrounding socioeconomic disadvantage and school attendance. The first relates to how teachers and students use the time they are allotted. Authors have estimated that no more than 40 percent of the school day is actively devoted to teaching and learning (Berliner 1984). However, tremendous variability exists in how effectively teachers manage their classrooms and how efficiently they structure classroom activities (D. K. Cohen, Raudenbush, and Ball 2003). As such, the links between school exposure and student learning likely vary across teachers. Future analyses might reveal even stronger links between school absences and socioeconomic disadvantage among children fortunate enough to experience high-quality teachers and schools.

The implications of chronic elementary school absences likely reach beyond low SES children's academic development. Poor attendance may also negatively impact school fiscal recourses (when funding is tied to school enrollments) and the outcomes associated with high-stakes accountability systems that take student attendance into account. Moreover, student absences may well influence learning among students who do attend school regularly. For example, teachers likely lose instructional time due to administrative tasks surrounding student absences and to efforts to reintroduce academic material to students who fall behind due to missed school days. Although clearly beyond the scope of this study, one might also expect children's school-based social and affective relationships to suffer as a result of sporadic school attendance.

As sociologists of education have asserted for decades, schools may need to rethink the services that they provide their neediest children. For example, increasing attendance among low SES children may necessitate efforts that improve both the quality and availability of day care, medical services, and community outreach programs (see Epstein and Sheldon 2002). This all reinforces the notion that schools cannot, by themselves, eliminate

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educational inequality. Rather, more collective efforts will be required to ensure that the students who benefit the most from attending school are actually able to do so.

APPENDIX

Appendix. Variance Components for Literacy and Mathematics Initial Status and Kindergarten, Summer, and First-Grade Gains (n = 42,229 test scores, 13,613 children, 903 schools)

	Standard Deviation	Variance	Degrees of Freedom	Chi-square
Initial literacy status	0.52445	0.27505	10,770	92,970***
Kindergarten literacy gains	0.04486	0.00201	11,594	39,601***
Summer literacy gains	0.09002	0.00810	11,594	20,777***
First-grade literacy gains	0.03468	0.00120	11,594	36,119***
Initial mathematics status	0.50488	0.25491	10,770	74,806***
Kindergarten mathematics gains	0.03830	0.00147	11,594	27,915***
Summer mathematics gains	0.08929	0.00797	11,594	21,422***
First-grade mathematics gains	0.03182	0.00101	11,594	28,915***

Note: Variance components are taken from a fully unconditional hierarchical linear modeling model. Gains are in a points per month of learning metric.
***$p < .001$.

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NOTES

1. After these selection criteria, approximately 16 percent of cases were missing kindergarten attendance data, and 15 percent were missing the first-grade attendance measures. Listwise, roughly 24 percent of cases were missing at least one attendance measure. Missing attendance data were estimated using multiple imputation, producing five complete data sets (see Little and Rubin 1987; Schafer 1997). Separate HLM analyses were then conducted using each of the five data sets. The coefficients reported here are averages from across the five sets of analyses. The standard errors are calculated via the methods suggested by Allison (2002). The fact that the analytic sample does not include children who changed schools during the academic year suggests that the estimates of socioeconomic disadvantage and attendance may be somewhat conservative. Children who changed schools between kindergarten and first grade are retained in the sample, although their learning is estimated for only one of the two years, due to the nested nature of the analyses. The fall first grade ECLS-K data collection effort involved only a 30 percent subsample of ECLS-K children. For children who changed schools between kindergarten and first grade and who had fall and spring first grade test scores, the models estimate their first-grade learning; kindergarten learning was estimated for the other students. The models were also reestimated without these children in the sample and produced results virtually identical to those presented here.
2. Researchers conducting growth-curve analyses using the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K) data have typically used the Item Response Theory (IRT) scale scores as outcomes. However, National Center for Education Statistics (NCES) and other researchers have concluded that the IRT scale scores are inappropriate for such purposes. This is particularly true for analyses that compare growth rates among groups with large initial cognitive differences (see LoGerfo, Nichols, and Reardon 2005; Reardon 2008). Unlike the IRT scale scores, which are somewhat arbitrary transformations of the theta scores, the theta scores are approximately interval scaled (a requirement for measuring change between populations over time; see Reardon and Raudenbush 2008), are normally distributed at

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each assessment wave, and are less dependent on the particular test items included on the assessment. More recent NCES publications state that the ECLS-K theta scores "are ideally suited for measuring growth from kindergarten through eighth grade" (NCES 2009). As such, the analyses presented here used the theta score versions of the ECLS-K cognitive tests as outcomes.

3. At the time of the first assessment the average child had been "exposed" to over 2 months of kindergarten but 0 months of summer and 0 months of first grade. With the second assessment, the average child had experienced over 8 months of kindergarten but no exposure to summer or first grade. At the third assessment, the average child had been exposed to 9.5 months of kindergarten (a full year), 2.7 months of summer (the traditional summer vacation), and over 1 month of first grade. At the point of the fourth and final assessment, the average child had been exposed to 9.5 months of kindergarten, 2.7 months of summer, and over 8 months of first grade.
4. Specifically, the models, similar to those employed by Downey, von Hippel, and Broh (2004), are described as:

$$\begin{aligned}
\text{Level 1}: Y_{tij} &= \pi_{0ij} + \pi_{1ij}(\text{TIME K}) \\
&\quad + \pi_{2ij}(\text{TIME Sum.}) \\
&\quad + \pi_{3ij}(\text{TIME 1st}) + e_{tij} \\
\text{Level 2}: \pi_{0ij} &= \beta_{00j} + \beta_{01j}(X_{ij} - \overline{X}_j) + \ldots + r_{0ij} \\
\pi_{1ij} &= \beta_{10j} + \beta_{11j}(X_{ij} - \overline{X}_j) + \ldots + r_{1ij} \\
\pi_{2ij} &= \beta_{20j} + \beta_{21j}(X_{ij} - \overline{X}_j) + \ldots + r_{2ij} \\
\pi_{3ij} &= \beta_{30j} + \beta_{31j}(X_{ij} - \overline{X}_j) + \ldots + r_{3ij} \\
\text{Level 3}: \beta_{00\text{j}} &= \gamma_{000} + \text{u}_{00\text{j}} \\
\beta_{10\text{j}} &= \gamma_{100} \\
\beta_{20\text{j}} &= \gamma_{200} \\
\beta_{30\text{j}} &= \gamma_{300}
\end{aligned}$$

where Y_{tij} is the predicted outcome at time t for child i in school j; π_{0ij} is the initial status for child ij (zero days of kindergarten, summer, or first grade); π_{1ij} is the kindergarten learning rate for child ij; π_{2ij} is the summer learning rate for child ij; π_{3ij} is the first-grade learning rate for child ij; π_{tij} is the error term associated with child ij at time t, assumed to be normally distributed with a mean of zero and a constant Level 1 variance, σ^2; β_{00j} is the mean initial status in school j; β_{01j} is the mean relationship between child characteristic X and initial status in school j; r_{0ij} is the random effect associated with initial status for child i in school j; β_{10j} is the average kindergarten monthly learning rate in school j; β_{11j} is the mean relationship between child characteristic X and kindergarten learning in school j; r_{1ij} is the random effect associated with the kindergarten learning rate for child i in school j; β_{20j} is the average summer monthly learning rate in school j; β_{21j} is the mean relationship between child characteristic X and summer learning in school j; β_{30j} is the average first-grade monthly learning rate in school j; β_{31j} is the mean relationship between child characteristic X and first-grade learning in school j; γ_{000} is the average initial status in the sample.
5. This estimate is quite consistent with the roughly 0.6 average theta score gain made between the fall and spring kindergarten literacy assessments. Recall that the models here estimate learning over the full 9.5 months of kindergarten and first grade. As noted, the average testing time gap was roughly 6 months between assessments, with the average student completing the fall assessment roughly 1.5 months into the academic year and the spring assessment roughly 1.5 months before the end of the school year.
6. Previous analyses using ECLS-K have employed a similar methodological approach and reported either small (positive) or no relationships between child socioeconomic status (SES) and literacy development during kindergarten and first grade (see Downey et al. 2004; Ready and Lee 2007). The small negative associations reported here between SES and academic growth relate to the use of the theta versions of the ECLS-K cognitive assessments, as opposed to the IRT scale scores (see note 2).

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