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Absenteeism in Head Start and Children's Academic Learning

Arya Ansari
University of Virginia

Kelly M. Purtell
The Ohio State University

Using nationally representative data from the Family and Child Experiences Survey 2009 cohort (n = 2,842), this study examined the implications of 3- and 4-year-old's absences from Head Start for their early academic learning. The findings from this study revealed that children who missed more days of school, and especially those who were chronically absent, demonstrated fewer gains in areas of math and literacy during the preschool year. Moreover, excessive absenteeism was found to detract from the potential benefits of quality preschool education and was especially problematic for the early learning of children who entered the Head Start program with a less developed skill set. Implications for policy and practice are discussed.

Despite the increased interest in early childhood programs as a means of minimizing long-term academic disparities (Duncan & Magnuson, 2013), there is a widespread belief among parents that early childhood programs are not school or are less important than later schooling (Ehrlich, Gwynne, Pareja, & Allensworth, 2013). Reflecting these notions, recent estimates from urban communities reveal that absenteeism is rampant among preschoolers (Dubay & Holla, 2015; Ehrlich et al., 2014). To date, however, the focus of the school attendance literature has generally been on the K-12 educational system, and thus, we know little about the implications of preschool absences. Given the large investments being made in early childhood programs both in the United States and globally (Duncan & Magnuson, 2013), we need to consider the ramifications of absenteeism for children's early learning, especially in programs such as Head Start, the largest federally funded preschool program in the United States. As brief background, Head Start is a government program that was established in 1965 as part of President Lyndon B. Johnson's War on Poverty. Although Head Start began as an 8-week summer demonstration project, it has since expanded to a 9-month part- and full-day preschool program serving roughly 1 million 3- and 4-year-olds per year. Since its inception, Head Start was designed to "promote the school readiness of low-income children by enhancing their cognitive, social, and emotional development" (Head Start Act, 2007). To do so, Head Start takes a whole child model to early childhood education and provides comprehensive educational, nutritional, and social services to low-income children and their families (Zigler & Muenchow, 1992).

Despite the dearth of empirical inquiry regarding preschool absences, research on elementary school absenteeism has consistently found that children who miss more days of school perform more poorly in areas of academic achievement as compared with their classmates with a better school attendance record (Chang & Romero, 2008; Gershenson, Jacknowitz, & Brannegan, 2015; Gottfried, 2009, 2010, 2011; Morrissey, Hutchison, & Winsler, 2014; Ready, 2010). These pervasive negative associations are multifactorial: Children who are frequently absent are (a) more often from disadvantaged households and at risk for less optimal academic achievement (Morrissey et al., 2014; Ready, 2010), and (b) exposed to fewer days of instructional environments (Arbour et al., 2016). The elementary school literature also highlights the fact that school absences are influenced by numerous factors that cut across different layers of the family, community, and school context, and are not solely determined by child health (Gottfried, 2015b). Accounting for these

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Correspondence concerning this article should be addressed to Arya Ansari, Center for Advanced Study of Teaching and Learning, University of Virginia, PO Box 800784, Charlottesville, VA 22908-0784. Electronic mail may be sent to aa2zz@eservices.virginia.edu.

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ecological factors may be even more necessary when examining absenteeism in preschool, as parents are less likely to view preschool attendance as critical, compared with attendance in elementary school years (Ehrlich et al., 2014). However, we know little about preschool absences. This is, in part, due to the fact that unlike the K-12 educational system, school attendance is not mandated by law for preschoolers and, thus, is not always tracked at the child-level by preschool programs like Head Start. Although kindergarten is also not mandated by law in most states, there are typically administrative records of kindergartner's school absences, as it is part of the formal schooling system.

Two recent studies from Baltimore (Connolly & Olson, 2012) and Chicago (Ehrlich et al., 2014) are of note, however, as they have provided some of the first empirical evidence that indicate that absenteeism is especially high (20%–27% in Baltimore and 36%–45% in Chicago) and particularly problematic during the preschool year. Specifically, data from these two communities indicate that a sizable number of children who were chronically absent—defined as missing 10% of the school year (Balfanz & Byrnes, 2012)—as early as preschool were documented as chronically absent throughout elementary school. These community efforts also revealed that preschool absenteeism was associated with lower academic test scores through the end of second grade, with effect sizes ranging from roughly 5% to 15% of a standard deviation.

Although these two studies have greatly contributed to the discourse surrounding absenteeism prior to the start of formal schooling, there has not been a national analysis of preschool attendance. Studying preschool attendance, especially among low-income preschoolers, is crucial as many early childhood programs operate under the compensatory hypothesis (Sameroff & Chandler, 1975), which argues that at-risk children can benefit most from their participation. Supporting these theories, a number of studies on Head Start have revealed that children who start school with a less developed skill set benefit more from preschool than children with a more developed skill set (Choi, Elicker, Christ, & Dobbs-Oates, 2016; Puma, Bell, Cook, & Heid, 2010). Less often discussed is that, by missing school, these children who begin the year with the lowest skills have fewer opportunities to make ground on their more skilled peers. In this way, absenteeism may be particularly problematic for children who enter the program with the lowest skills (for similar analyses with elementary school absences, see Chang & Romero, 2008).

Understanding the role of children's absenteeism in early childhood programs also has important implications for policy and practice as preschool absences may be one of the key reasons why prior evaluations of Head Start (Puma et al., 2012) and meta-analyses of classroom quality (Keys et al., 2013) have yielded only small academic benefits for children. Reflecting these possibilities, a recent experimental evaluation of preschool programs in Chile (Arbour et al., 2016) found that children who were less likely to be absent from school made greater academic gains as a result of their participation in the preschool intervention as compared with children who were more likely to be absent. Such studies, however, are few and far between.

Yet, such possibilities are supported by theories of social integration and intergenerational bonding, which argue that, beyond the parent–child relationship, one of the most important relationships children develop are those with their teachers (Crosnoe, Johnson, & Elder, 2004). This relationship is a source of support that develops from the daily interactions with children, which in turn, can facilitate children's early learning (Hatfield, Burchinal, Pianta, & Sideris, 2016). Thus, in addition to missing instructional interactions, the development of supportive relationships between teachers and children may be particularly impacted by children's school absences because it limits how often children can interact with their teachers.

Thus, the goal of this report was to address these gaps in knowledge. To this end, we address the following three research questions: (a) What are the implications of absenteeism for children's early academic learning over the course of the Head Start year? (b) Are children with lower academic skills at the start of preschool more susceptible to the influence of absenteeism? (c) Does absenteeism attenuate the academic benefits of quality classroom environments? We hypothesized that all children would perform more poorly over time in areas of early academics when they were more frequently absent from Head Start; however, those who entered school with the lowest skills would be more likely to be negatively affected. We also expected that school absences would minimize the potential benefits of quality preschool environments.

Method

The Family and Child Experiences Survey (FACES) 2009 cohort followed a nationally representative sample of 3,349 3- and 4-year-old first time Head

Start attendees across 486 classrooms (for sampling information, see Malone et al., 2013). With a response rate of roughly 94%, children and families were followed through the end of the kindergarten year (Fall 2009, Spring 2010, Spring 2011, and for 3-year-olds, Spring 2012) across all 50 states and the District of Columbia. FACES 2009 was funded by the Administration for Children and Families and collected by Mathematica Policy Research and their partners. The data collection includes surveys with Head Start teachers and directors, parent surveys, direct child assessments, and classroom observations (West, Tarullo, Aikens, Malone, & Carlson, 2011). For the purposes of the current investigation, we focus on the first two waves of data collection (Fall 2009 and Spring 2010), as these waves capture the Head Start year. We excluded 444 children who did not have a valid longitudinal weight for these two waves. However, all analyses include the longitudinal weight, which accounts for participants' nonresponse at the second wave of data collection. We also excluded 63 children who were in a home-based program, resulting in a final analytic sample of 2,842 children. On average, our final sample of children (50% female) were 3.84 years of age ($SD = 0.55$, range = 2.66–5.00 years of age) with the majority coming from ethnic minority households (36% Latino, 34% Black, 8% Asian or other). The remaining 21% of children were identified as White by their parents. Over half of children came from a household without two parents (53%) and with an unemployed mother (52%), and on average, mothers had a high school diploma (for other sample descriptives, see Table 1).

Measures

Below, we describe our focal measures. The reliability estimates for all of the child outcomes come from the FACES 2009 User's Guide (Malone et al., 2013).

Absenteeism

During the spring of 2010, parents were asked, "Approximately how many days has [CHILD] been absent since the beginning of the school year?" Responses were continuously measured and ranged from 0 to 20. Because not all parents reported on their children's absences at the same time point (52% in March, 28% in April, and 20% in May), and because some programs operated for four rather than 5 days per week, we created an indicator of the proportion of days missed as a fraction of the days children were enrolled in school.

To create this measure, we first used parents date of assessment during the spring term to gauge how long children were enrolled in Head Start and divided the number of days children were absent by the number of months they were enrolled in school. This measure provided us with the number of days children were absent per month. Next, we multiplied the number of days children were absent per month by nine (i.e., the months of the school year). Finally, we divided this estimate by the number of days the program was in operation, which provided us with the proportion of the school year children were absent (see Figure S1 for a histogram of the distribution of children's school absences). Chronic absenteeism was defined as missing 10% or more of the school year (Balfanz & Byrnes, 2012). As a precaution, we also used the raw number of days children were absent and the results were the same as those presented below.

Academic Achievement

Three domains of children's academic achievement were directly assessed at the beginning (Fall 2009) and end (Spring 2010) of the school year. First, children's *language skills* were measured using the Peabody Picture Vocabulary Test (Dunn & Dunn, 1997; Fall $\alpha = .97$ and Spring $\alpha = .95$). To capture children's language skills, assessors asked children to point to one of four pictures that best illustrated the meaning of a word that was said aloud by the assessor. Because the *W* scores, which provide information on children's absolute performance at any given time point and captures growth in children's learning and development, were not available for the Spanish version of the Peabody Picture Vocabulary Test, we used the standard scores. Next, two subscales from the Woodcock–Johnson (Woodcock, McGrew, & Mather, 2001), the Letter Word Identification (Fall 2009: $\alpha = .85$ and Spring 2010: $\alpha = .83$) and Spelling Word (Fall 2009: $\alpha = .79$ and Spring 2010: $\alpha = .83$), were administered to children to capture their *literacy skills*. These assessments captured children's ability to identify and write letters. Because the pattern of findings were the same across both the Woodcock–Johnson subscales, we created an overall composite of literacy achievement using the *W* scores, allowing us to assess growth over time. Finally, children's *math skills* were directly assessed with the Woodcock–Johnson Applied Problems subscale (Woodcock

Table 1
Descriptive Statistics for Study Variables

	M (SD) or proportion	Bivariate correlations	
		Absenteeism	Chronic absenteeism
Child/household characteristics			
Percent of days absent	5.48 (4.30)	—	—
Chronically absent	0.12	—	—
Child is male	0.50	.04	.00
Child race			
White	0.21	—	—
Black	0.34	−.26***	−.16***
Latino	0.36	−.15***	−.11***
Asian/other	0.08	−.09*	−.04
Child age (months)	46.09 (6.65)	−.04	−.05*
Child health[a]	4.29 (0.90)	−.04*	−.03
Four-year-old cohort	0.43	−.01	−.03
Months between fall and spring child assessments	5.85 (1.47)	.02	.02
Language of assessment (fall–spring)			
English–English	0.84	—	—
Spanish–Spanish	0.07	.01	.01
Spanish–English	0.09	−.03	−.02
Mothers' marital status			
Married	0.29	—	—
Single	0.18	−.05	−.02
Not two-parent household	0.53	−.09***	−.05*
Mothers' years of education	12.00 (1.84)	.01	.01
Mothers' age	28.83 (5.89)	−.04	−.04
Household size (children and adults)	4.61 (1.61)	−.06**	−.05*
Mothers' employment			
Full time	0.27	—	—
Part time	0.21	.06	.05
Unemployed	0.52	.08***	.08***
Mothers' depressive symptoms[b]	4.89 (5.82)	.09***	.07***
Ratio of income to poverty[c]	2.52 (1.36)	.04	.01
Number of moves in the last 12 months	0.49 (0.83)	.03	.02
Cognitive stimulation[d]	0.79 (0.16)	.02	.01
Frequency parent spanked child	0.67 (1.26)	.04*	.01
English household language	0.76	−.02	−.01
Classroom characteristics			
Child/teacher ratio	8.55 (2.25)	−.05**	−.04*
Child/adult ratio	7.36 (2.13)	−.06**	−.06**
Class size	17.28 (2.17)	−.07**	−.07***
Hours of school per week	26.36 (11.49)	−.10***	−.12***
Program meets 5 days a week	0.75	−.10***	−.10***
Full-day program	0.60	−.11***	−.11***
Other languages used in the classroom (yes)	0.34	−.04*	−.04*
Quality of teacher–child interactions (CLASS)	4.07 (0.49)	−.02	−.03
Global classroom quality (ECERS–R)	4.27 (0.77)	.01	.00
Teacher characteristics			
Depressive symptoms[b]	4.25 (4.60)	.01	.00
Years teaching	12.71 (8.68)	−.03	−.01
Years of education	14.99 (1.79)	−.06**	−.01
Degree in early childhood education	0.92	−.01	−.00
Hourly salary	14.11 (4.79)	−.11***	−.06**
Number of benefits[e]	6.55 (2.39)	.06*	.05

Table 1
Continued

	M (*SD*) or proportion	Bivariate correlations	
		Absenteeism	Chronic absenteeism
Children's outcomes			
Language (fall)	81.62 (19.76)	.07***	.05*
Language (spring)	86.12 (16.85)	.06**	.04
Letter word identification (fall)	304.98 (24.37)	−.02	.01
Letter word identification (spring)	322.75 (27.86)	−.08***	−.05*
Spelling (fall)	344.02 (29.31)	−.03	−.02
Spelling (spring)	363.34 (30.32)	−.08***	−.09***
Math (fall)	373.42 (25.70)	−.03	−.03
Math (spring)	386.93 (24.77)	−.06**	−.05*

Note. [a]Children's health was reported by parents using a 5-point Likert scale (1 = *poor*, 5 = *excellent*). [b]Both parents' and teachers' depressive symptoms were measured via 12 questions from the short form of the Center for Epidemiological Studies Depression Scale (α = .91; Radloff, 1977) with scores ranging from 0 to 36. [c]The ratio of income to poverty measure was quasi-continuous with scores ranging from 1 (< 50% of the federal poverty line [FPL]) to 6 (> 200% of the FPL). [d]The cognitive stimulation measure was a composite of 12 items that captured parents' household investments during the past week (e.g., told child a story, taught child letters or numbers). [e]Teachers benefits (e.g., paid vacation, sick leave) was based on a 0–9 scale. *p < .05. **p < .01. ***p < .001.

et al., 2001; Fall 2009: α = .87 and Spring 2010: α = .89). We used the *W* score for this assessment, which captured growth in children's ability to analyze and solve simple math problems.

For all assessments, children who came from non-English-speaking homes were assessed with the Simon Says and Art Show subscales of the Preschool Language Assessment Survey (preLAS; Duncan & De Avila, 1998; α = .88–.90). The Simon Says screener assessed children's English receptive vocabulary (e.g., children were asked to touch their toes), whereas the Art Show assessed children's English-expressive language skills (e.g., children were asked to identify what was in each picture). The preLAS was used to determine whether children from non-English speaking homes had the English language skills necessary to take the assessment in English. Those who failed the test were assessed with the Spanish version of the assessments (roughly 95% of children who failed the screener at the start of the year spoke Spanish). For these children, we used their scores on the Spanish assessments, which demonstrated similar levels of internal consistency as the English measures (Malone et al., 2013). For the small number of non-Hispanic children who did not speak Spanish at home and who failed the language screener, test score data from the first wave were imputed using missing data procedures. It is important to note that (a) almost all of the non-Hispanic children who did not speak Spanish passed the language screener during the spring semester, and thus, had valid scores at the end of the year, and (b) our results were not sensitive to the inclusion (or exclusion) of these children. All analyses included an indicator of children's assessment language (84% English–English, 7% Spanish–Spanish, and 9% Spanish–English).

Classroom Quality

During the spring of 2010, all Head Start classrooms were observed and rated on the Classroom Assessment Scoring System (CLASS; Pianta, La Paro, & Hamre, 2008). The CLASS is based on a 7-point Likert scale (1–2 = *low* to 6–7 = *high*) and was used to measure instructional and socioemotional aspects of the classroom with a focus on teacher–child interactions.

Covariates

To reduce the possibility of spurious associations, both our main effect and interaction models adjusted for a full set of covariates that were derived from the fall of the Head Start year and reported on by either parents or teachers (see Table 1). It is important to note that all analyses also accounted for children's school entry skills (i.e., lagged dependent variables), which are recognized as one of the strongest adjustments for omitted variable bias (National Institute of Child Health and Human Development Early Child Care Research Network & Duncan, 2003). In doing so, our analyses consider the extent to which absenteeism was associated with changes in children's academic achievement across the Head Start year.

Analysis Plan

All focal analyses were estimated within a regression framework using the *Mplus* program and included all covariates listed in Table 1 (Muthén & Muthén, 1998-2013). To examine the associations between absenteeism and children's early academic learning, we estimated three separate models individually predicting children's language, literacy, and math skills (Model 1). However, it might be that one additional absence may not greatly matter for children's early learning, and instead, it is chronic levels of absences that impact children's academic development, thus, we also estimated similar models with a dichotomous indicator of chronic absenteeism replacing the continuous absenteeism variable (Model 2). Next, to test for moderation, we interacted absenteeism with each of the moderators, one at a time (Model 3: children's initial skill, Model 4: classroom quality). For these moderation analyses, we used the continuous version of absenteeism. If there was evidence for moderation, we plotted the interactions by calculating the predicted outcome scores for different combinations of absenteeism and the moderator using standard deviation (*SD*) cut points (Aiken & West, 1991). Specifically, we used + and −1 *SD*s for our thresholds.

Standard errors were adjusted in all models by clustering at the classroom level in order to account for dependence in child outcomes and all regression models were weighted to be nationally representative. Item-level missing data were minimal (average 6%, range = 0%–19%) and were addressed with full information maximum likelihood estimation. Finally, all continuous variables were standardized ($M = 0$, $SD = 1$), and thus, our parameter estimates indicates how many *SD*s children's early academic skills would change per *SD* increase in absenteeism. It should be noted that in discussing our results, we focus on the general pattern of findings without a *p*-value adjustment for multiple comparisons; however, we also present results adjusting for multiple comparisons using the Benjamini adjustment (Benjamini & Hochberg, 1995) for each predictor. We note when results were discrepant between the adjusted and nonadjusted models.

In addition to the regression models discussed earlier, we also estimated supplementary propensity score models (Rosenbaum & Rubin, 1985), which are often used to minimize selection bias. Specifically, we estimated three sets of propensity score models, namely: (a) weighted models with the propensity score covariate (PSC), (b) unweighted models with the PSC, and (c) models with propensity score matched (PSM) samples that were weighted with the propensity score weight. We included both PSM and the PSC models because PSM is generally used for dichotomous predictors, whereas the PSC approach can be used with both dichotomous and continuous predictors (Austin, 2011). We estimated both weighted and unweighted PSC models because the unweighted model parallels our PSM model that are not nationally representative, whereas the weighted approach best parallels our weighted regression models that are nationally representative. All propensity scores were generated within an unweighted logit (chronic absenteeism) or ordinary least squares regression (absenteeism) framework. Additionally, all propensity score analyses included the covariates listed in Table 1 (doubly robust estimation; Funk et al., 2011).

Results

We begin by discussing the descriptive patterns of absenteeism and the bivariate associations between the sample characteristics and children's school absences. For the bivariate correlations, we focus on the general patterns that emerged among our covariates and both absenteeism and chronic absenteeism. Then, we address our focal three research objectives before we close with a brief description of our propensity score models.

Descriptives and Bivariate Correlates of School Absences

As can be seen in Table 1, children in Head Start missed approximately 5.5% of the school year ($SD = 4.3\%$, range = 0.0%–23.8%), and roughly 12% of the full sample of children was chronically absent. Translated into days of school missed, these estimates indicate that on average, children in Head Start were absent for roughly 8 days of the year. Children who were chronically absent missed an average of 22 days.

A number of our child, household, and classroom factors were also related to children's school absences (see Table 1). Specifically, Black and Latino children were less likely to be absent and chronically absent from Head Start than White children, as were children who came from households without two parents (vs. households with married parents). In contrast, children were more likely to be absent from Head Start when their mothers exhibited more depressive symptoms and were unemployed (vs. employed full time). In terms of classroom characteristics, we found that children who were enrolled in larger classrooms, bilingual classrooms, and classrooms that operated for more hours per week (e.g., part vs. full day) were less likely to be absent from school. Children were also less likely to be absent from Head Start when their teachers received a higher hourly wage (for other associations that emerged for only one of our two absenteeism measures, see Table 1).

Absenteeism and Children's Early Learning

Although absenteeism was not associated with children's language development in our multivariate models (see Table 2), children who were more frequently absent demonstrated smaller gains in literacy and math with effect sizes corresponding with 5%–6% of a *SD* (see Table S1 for the associations between the covariates and outcomes). Findings for chronic absenteeism were stronger, with children who were chronically absent exhibiting even smaller gains, with effect sizes of 13%–14% of a *SD*. In practical terms, the effect sizes for chronic absenteeism translate to roughly 2 (math) to 3 (literacy) months of lost academic skill gains (calculated by dividing the standardized difference in test scores by the regression slope for children's age; Bradbury et al., 2011).

Moderators of Absenteeism and Children's Early Learning

As can be seen in Table 2, results from our multivariate analyses also suggested that children's school entry skills were fairly stable, and although missing school was generally associated with less optimal academic achievement for all children, it was most problematic if children started school with the lowest language and literacy (but not math) skills. For example, the negative associations between absenteeism and children's literacy development were 16% of a *SD* greater for children who entered the Head Start program with low as opposed to high literacy skills.

Finally, although all children exhibited greater gains in areas of early literacy when they experienced higher quality interactions with their teachers, these associations were larger when children were less frequently absent (see Figure 1; this estimate was only marginally significant with a Benjamini adjustment). Although not reaching conventional standards of significance in either our adjusted or nonadjusted models ($p = .06$), similar—albeit slightly smaller—patterns emerged for children's language development. Thus, these results indicate that high-quality programs were associated with improvements in children's early language and literacy skills, but children who were more frequently absent did not reap the maximum benefit.

Propensity Score Models

After balancing the comparison conditions (results are available upon request), we found that our propensity score models confirmed the conclusions discussed above (see Table S2). As stated earlier, children who were more frequently absent

Table 2
Multivariate Results of Children's Academic Achievement as a Function of Absenteeism

	Child outcomes[a]		
	Language	Literacy	Math
Main effects of absenteeism			
Absenteeism (Models 1, 3, and 4)	−.00 (.02)	**−.05 (.02)****	**−.06 (.02)****
Chronic absenteeism (Model 2)	−.03 (.05)	**−.14 (.05)****	**−.13 (.06)***
Main effects of moderators			
School entry skills (Models 1–4)	**.62 (.02)*****	**.60 (.02)*****	**.54 (.02)*****
Quality of teacher–child interactions (Models 1–4)	.01 (.02)	**.10 (.02)*****	−.02 (.03)
Interaction terms[b]			
Absenteeism × School Entry Skills (Model 3)	*.06 (.03)**	**.04 (.01)****	.04 (.03)
Absenteeism × Quality of Teacher–Child Interactions (Model 4)	*−.03 (.02)†*	*−.03 (.01)**	−.00 (.02)

Note. Coefficient in bold were statistically significant at $p < .05$ and coefficients in italics were significant at $p < .10$ with a Benjamini false discovery adjustment. All continuous variables were standardized within wave ($M = 0$, $SD = 1$), and therefore the unstandardized regression coefficients in this table correspond to effect sizes. [a]All models controlled for the covariates listed in Table 1 and were clustered at the classroom level. [b]Because the variables above have a mean of 0, the main effect coefficients were the same across both the interaction and main effect models. Separate models were estimated for each individual interaction.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

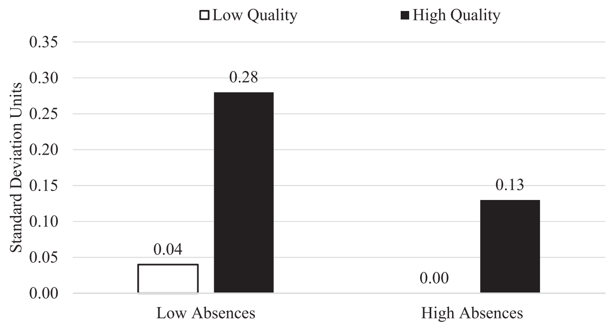

Figure 1. An illustration of the conditional effects of quality teacher–child interactions on children's literacy skill gains as a function of their absences from school. *Note*. Low absences correspond to roughly 2 days (1.18% of the school year; roughly 11% of the sample were at or above this threshold), whereas high absences correspond to approximately 15 days (9.78% of the school year; roughly 13% of the sample were at or above this threshold). Low quality corresponds to a score of 3.58 on the Classroom Assessment Scoring System (CLASS; roughly 15% of the sample were at or above this threshold) and high quality corresponds to 4.56 on the CLASS (roughly 18% of the sample were at or above this threshold). To facilitate interpretation of the interaction, the high absences and high quality group has been set as the referent.

exhibited fewer gains in math and literacy (but not language skills) over the course of the Head Start year, and these associations were stronger at chronic levels of school absences.

Discussion

Despite the growing investments in early childhood programs (Duncan & Magnuson, 2013), children's school attendance has been largely ignored and remains unmeasured in most early care and education programs (Mendez, Crosby, & Helms, 2016). Thus, the purpose of this research brief was to provide a preliminary exploration of the implications of absenteeism for children's early academic achievement using a nationally representative Head Start sample. Drawing on data from the FACES 2009 cohort, this study sought to illustrate the importance of measuring absenteeism in preschool while also encouraging new work in an area that has remained relatively underdeveloped. The results of our study have four take-home messages.

First, our descriptive results suggest that children missed roughly 8 days of the school year, and 12% of children were chronically absent and, therefore, missed an average of 22 days. We also documented a few potential determinants of school absences; for example, minority children were less likely to be absent as compared with White children, as were children who were enrolled in school for longer hours and in larger and bilingual classrooms. When taken together, these descriptive results indicate that absenteeism is a prevalent in Head Start but that certain groups of children are at greater risk of missing time than others. Future programs designed to increase attendance may be strengthened by tailoring their efforts to these subgroups.

Second, results from our focal multivariate models confirmed some of what is known about the relations between absenteeism and achievement during the primary school years and beyond, and suggest that these patterns hold true in preschool (Gottfried, 2009, 2011; Gershenson et al., 2015; Morrissey et al., 2014; Ready, 2010). Children who missed more days of preschool demonstrated fewer gains in literacy and mathematics, and the detrimental effects were greater among children who were absent for more than 10% of school year (chronic absenteeism; Chang & Romero, 2008; Ready, 2010). Put in context with other influences on children's early learning, the associations between chronic absenteeism and children's early learning were roughly three to four times as large as that of meta-analyses of classroom quality (meta-analytic effect size [E.S.] of classroom quality [Keys et al., 2013]: .03–.05 *SD*s vs. chronic absenteeism E.S.: .13–.14 *SD*s). Within the context of our study, the effects of chronic absenteeism were roughly 1.4 (literacy: $E.S._{quality} = .10$ vs. $E.S._{chronic\ absenteeism} = .14$) to 6.5 (math: $E.S._{quality} = .02$ vs. $E.S._{chronic\ absenteeism} = .13$) times larger than the effects of classroom quality and amounted to 2–3 months of math and literacy development. Despite the links between absenteeism and children's early literacy and math development, preschool absences were not associated with children's language development. This finding parallels prior work that shows that preschool programs often do not influence children's language skills but do influence their early literacy (National Early Literacy Panel, 2008). Thus, these findings suggest that future evaluations of Head Start should consider a treatment-on-the-treated model that incorporates children's absenteeism to estimate the full potential of the program.

Third, consistent with the compensatory model of education (Sameroff & Chandler, 1975) and Ready's (2010) study of absenteeism in kindergarten, preschool absences were most detrimental for children who entered the program with the lowest language and literacy skills. Although we did not see direct associations between absenteeism and language development, it may be that absences are more predictive for children who enter the classroom with low language skills, as they may be more dependent for classroom exposure to new language skills than their peers who enter school with higher language skills. Finally, consistent with the existing literature (Keys et al., 2013), results from this study revealed that the quality of teacher–child interactions facilitated children's literacy development. For the first time, however, our results show that these benefits were considerably larger for children who were infrequently absent. The implications of this finding are quite important in light of the fact that the benefits of quality preschool education have proven to be smaller than expected (Keys et al., 2013). The results of this study suggest that these patterns may partly be due to the attenuating effect of chronically absent children and, thus, should be considered in future studies of classroom quality.

Even though this study is the first national analysis of preschool absences, these general points of discussion need to be interpreted in light of a few limitations. The primarily limitation of our work is that of measurement. Unlike some studies on primary school absences that have been able to draw on data from school attendance records (Gershenson et al., 2015; Morrissey et al., 2014), we were restricted to parent reports of children's school attendance. Considering that attendance is rarely tracked at the preschool level, there are not many other options to estimate these associations. In fact, the FACES data set is one of two national early childhood data sets that have any information on children's preschool absences (Mendez et al., 2016). Even so, it is important to acknowledge that our estimates of preschool absences were lower than those of Ehrlich et al. (2014) and Connolly and Olson (2012), which may reflect social desirability. That is, there may be some bias due to parents' underreporting of children's preschool absences, which increase the risk of null findings. Despite this potential source of bias, the effect sizes reported in our study and the effect sizes reported in Chicago and Baltimore are of the same magnitude, suggesting that this bias is unlikely to affect the associations between the focal variables of interest. Moreover, our estimates of preschool absences are comparable to national estimates of kindergarten absences (Gershenson et al., 2015; Gottfried, 2015b), which is of note because kindergarten, like preschool, is not mandatory in most states. Next, we used a sample of Head Start children, which is an important strength as Head Start is the largest federally funded preschool program serving low-income children; however, this line of work should be extended to other types of preschool programs before we can generalize these patterns to other populations. Finally, although we (a) controlled for a rich set of covariates, and (b) we estimated propensity score models, these analyses do not imply cause and effect.

One purpose of a brief report is to provide new findings that extend the existing literature and spur future research. Our results inform the discourse surrounding absenteeism in preschool by illustrating the scope and consequences of school absences in Head Start for children living in poverty. When taken together, these results indicate that future researchers need to pay closer attention to the role of preschool absences in developmental and educational research. These findings also have practical implications and suggest that preschool teachers and administrators may want to exert some effort to reduce school absences. One important route may be to discuss challenges to attendance that parents are facing and work with them to reduce these barriers. Work with older children has shown that absenteeism is rarely due to one factor; thus, working with families to reduce multiple causes may be necessary (Teasley, 2004). One successful elementary model assigned monitors to engage with both families and school staff to increase attendance; this type of model may be particularly useful in Head Start, which already strives to increase parent center communication (Lehr, Sinclair, & Christenson, 2004). The early childhood field should also consider ways to make sure that parents understand that preschool is an educational program, not just a day care, and that school absences are problematic as recent research on prekindergarten has shown that these types of parental beliefs are critical to increasing school attendance (Katz, Johnson, & Adams, 2016). Setting and communicating clear attendance expectations and engaging parents in school are emerging as key ways to change parental beliefs and children's preschool absences (Katz et al., 2016).

Ultimately, if our results are confirmed with other samples of children and families from across the country, then we can draw more definitive conclusions regarding preschool absences as a source of inequality. In the meantime, however, an important first step is to ensure that future data collection efforts gather information on children's preschool absences. By using a large and nationally representative data set of Head Start children, this study pushes this agenda forward by providing some of the first insight into the harmful implications of absenteeism for low-income children's academic learning during the preschool year.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's website:

Table S1. Associations Between the Covariates and the Focal Child Outcomes

Table S2. Propensity Score Results of Children's Academic Achievement as a Function of Absenteeism

Figure S1. Illustration of the Distribution of the Proportion of Days Children Missed School