Are student absences worth the worry in U.S. primary schools?

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Abstract

Student absences are a potentially important, yet understudied, input in the educational process. Using longitudinal data from a nationally-representative survey and rich administrative records from North Carolina, we investigate the relationship between student absences and academic performance. Generally, student absences are associated with modest but statistically significant decreases in academic achievement: a one standard deviation (SD) increase in absences is associated with decreases in achievement of 0.04 and 0.02 math and reading test-score SD, respectively. Chronically absent students, defined as those above the 95th percentile of the absences distribution, score 0.05 to 0.11 test-score SD lower than their counterparts in the middle of the distribution. In North Carolina, the harm associated with student absences is greater among both low-income students and English language learners, particularly for reading achievement. Also unexcused absences are twice as harmful as excused absences. Policy implications and directions for future research are discussed.

Keywords: Student absences, attendance, achievement gaps, education production function

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1. Introduction

The achievement gap between students of different socioeconomic status (SES) has grown over the past several decades, despite substantial efforts to close such gaps (Reardon, 2011). Understanding the source(s) of the achievement gap is crucial to devising an appropriate policy response (Fryer & Levitt, 2004). Student attendance is a potentially important, yet understudied, input in the educational process, as absences disrupt learning, weaken schools' and classrooms' sense of community, and reduce students' exposure to classroom instruction (Gottfried, 2009). By reducing student exposure, student absences also undermine investments in school and teacher quality. Accordingly, student absences potentially contribute to the achievement gap in two ways. First, absence rates are higher among low-SES students (Ready, 2010). Second, absences may cause greater harm to students who reside in low-SES households, as such households may be less able to compensate for lost instructional time than their more advantaged counterparts (Chang & Romero, 2008). It is particularly important that policy makers and educators understand the consequences of primary school student absences, as children's socio-behavioral (i.e., non-cognitive) skills are affected by their early environment (Heckman, Stixrud, & Urzua, 2006) and problems of chronic absence and school disengagement manifest as early as first grade (Alexander, Entwisle, & Kabbani, 2001; Schoeneberger, 2012).

The relationship between student attendance and academic achievement is relatively understudied, particularly at the primary level (Ready, 2010). Much of the existing literature on the relationship between attendance and academic performance is correlational and the few studies that have attempted to identify causal effects of absences are limited to single urban districts (e.g., Gottfried, 2009, 2011; Morrissey et al., 2013). We begin to fill this gap in the literature by investigating the influence of primary-school student absences on academic achievement using survey data from the nationally representative Early Childhood Longitudinal Study-Kindergarten Cohort (ECLS-K) and longitudinal student-level administrative data on the population of primary-school students in North Carolina's public schools. We do so by including absences as a current input in value-added models (VAMs) of the education production function that condition on classroom fixed effects. Specifically, we examine the functional form of the relationship between student absences and academic achievement, test for heterogeneity across students and absence type in the relationship between student absences and academic achievement, and examine the sensitivity of our results to the choice of VAM specification and estimation method.

The ECLS-K and North Carolina data are complementary in that they each have unique strengths and weaknesses, which we discuss in a later section. Thus, it is reassuring that the two datasets provide largely similar results. Namely, the harmful effects of student absences are statistically significant for math and reading and modest in size: a one standard deviation (SD) increase in absences is associated with decreases in reading and math achievement of 0.02 to 0.04 test-score SD, respectively. These effects are arguably practically significant, as they are similar in magnitude to the effect of a one SD increase in teacher absences (Clotfelter, Ladd, & Vigdor, 2009; Herrmann & Rockoff, 2012) and constitute about one third of the effect of a one SD increase in teacher effectiveness (Hanushek & Rivkin, 2010; Kane, Rockoff, & Staiger, 2008).

The paper proceeds as follows: Section 2 reviews the existing literature on student absences. Sections 3 and 4 describe the data and methods used in the current study, respectively. The results are reported in section 5 and section 6 concludes with a discussion of policy implications and implications for future research.

2. Literature Review

If student absences harm achievement and disadvantaged students are absent at higher rates than their more advantaged counterparts, differential rates of student attendance may contribute to achievement gaps. A small number of studies have investigated the household-level correlates of primary-school student absences in the U.S. (e.g., Morrissey et al., 2013; Ready, 2010). Ready (2010) shows that household SES, as measured by an index composed of parents' income, educational attainment, and occupational prestige, is strongly negatively correlated with student absences in the nationally representative ECLS-K. Romero and Lee (2008) note that children of young mothers are more likely to be chronically absent and a National Center for Education Statistics report (NCES, 2006) indicates that poor children are about 25% more likely than their wealthier peers to be absent three or more times per month.[1]

Gottfried (2009) provides a more nuanced analysis of the predictors of second through fourth graders' absences in Philadelphia Public Schools by distinguishing between excused and unexcused absences. Perhaps unsurprisingly, Gottfried finds that as students' total absences increase, so too does the percentage of absences that are unexcused. Similarly, Gottfried finds that students who either have behavioral problems or are eligible for reduced-price lunch programs experience significantly more total absences and unexcused absences, yet fewer excused absences. Together, these findings suggest that a sizable percentage of chronically absent students' absences are discretionary and thus potentially avoidable.

From the standpoint of education policy, the importance of student absences depends upon the relationship between student absences and children's cognitive and social development.

[1] Definitions of "chronically absent" vary across states and districts, but the modal definition is being absent on at least 10 percent of school days (or about 18 absences per year, or two to three absences per month) (Bruner, Discher, & Chang, 2011).

The early literature on the relationship between student attendance and academic performance largely focused on high-school students. For example, Monk and Ibrahim's (1984) analysis of student-level data from one school in upstate New York generally found student absences to be negatively associated with performance on ninth-grade Algebra exams. However, absences may affect the educational achievement of older students differently than they affect elementary-school students for at least three reasons. First, parents may be less able to assist older students make up more advanced work. Second, the underlying causes of absences may be different for older students. Third, elementary-school students in self-contained classrooms may have an easier time making up missed work, as doing so requires coordinating with one self-contained classroom teacher. Early empirical studies of the relationship between primary school attendance and academic performance used cross-sectional school-level data to show a negative and statistically significant correlation between schools' average daily attendance and performance on standardized tests (e.g., Caldas, 1993; Roby, 2004).

More recently, scholars have recognized the benefits of using student-level longitudinal data to investigate the relationship between absences and academic performance among primary school students, as school-level analyses ignore potentially substantial within-school and within-student variation in absence rates (Ready, 2010). Two of these studies were conducted by Gottfried (2009, 2011), who estimated lagged test score VAMs of the education production function that included student absences as a contemporaneous input using data on second through fourth graders in Philadelphia Public Schools. Gottfried found that a one SD increase in absences lowered test scores by about one tenth of a test-score SD, that students with higher ratios of excused to unexcused absences performed better, and that conditioning on family fixed effects slightly *increased* the estimated magnitude of absences' effect on academic performance.

Similarly, Noell et al. (2008) controlled for student absences in value-added analyses of teacher preparation programs in Louisiana and found a statistically significant negative coefficient on absences. Finally, Ready (2010) estimated growth-curve models of students' academic performance in kindergarten and first grade using the ECLS-K, paying particular attention to the effects of absences, an SES index, and SES-absence interactions. Ready found a statistically-significant negative relationship between absences and literacy development during kindergarten and first grade that was stronger among low-SES students.

The current study contributes to the existing literature on the relationship between student absences and academic achievement in U.S. primary schools in several ways. First, we extend Gottfried's analyses of a high-poverty, largely minority, urban school district by conducting rigorous value-added analyses that condition on classroom fixed effects, unobserved student heterogeneity, and the endogeneity of student absences in the larger and more diverse contexts of North Carolina and the 1998-99 cohort of U.S. kindergarteners. Second, we extend Ready's analysis of heterogeneity in the relationship between student absences and academic performance by considering sources of heterogeneity over and above SES, such as by absence type and by students' gender, grade level, English language proficiency, poverty status, special-education classification, and prior achievement. Third, we investigate the functional form of the relationship between absences and performance by testing for nonlinearities in the relationship between student absences and achievement. Finally, we conduct a thorough sensitivity analysis to investigate the results' robustness to the choice of VAM specification and estimation method.

3. Data

The current study investigates the relationship between student absences and academic achievement using two complementary datasets, each with their own strengths and limitations. In this section we describe each in turn, and conclude by comparing the two.

3.1 ECLS-K Data

The Early Childhood Longitudinal Study-Kindergarten Cohort (ECLS-K) is a longitudinal data set collected by the National Center for Education Statistics (NCES). The original sample of approximately 21,400 children from about 1,000 schools was designed to be nationally representative of kindergartners during the 1998-99 academic year. Because some demographic groups were intentionally oversampled, we weight all subsequent analyses of the ECLS-K data using sampling weights provided by the NCES.[2] The ECLS-K data include information collected from children, parents, teachers, and school administrators during the fall and spring of the kindergarten and first-grade academic years as well as the spring of third, fifth, and eighth grades. The primary analyses use both kindergarten waves and the spring first-grade wave of data, as test scores are available for the full sample of children at the beginning and end of kindergarten and at the end of first grade. Students who experienced a mid-year classroom change, repeated a grade, or changed schools during either kindergarten or first grade are excluded from the analysis, as are students who are missing demographic, total absence, or test-score data. These exclusions result in a baseline analytic sample of 11,650 student-year observations.[3]

[2] Specifically, we use the C#CW0 longitudinal weight, where # is wave number.
[3] All ECLS-K sample sizes are rounded to the nearest 50 in accordance with NCES guidelines for restricted data.

Importantly for the current study, the majority of schools surveyed by the ECLS-K reported administrative student-level attendance and school lateness (tardy) records in the spring survey waves and 7,600 student records in the baseline analytic sample (about 65%) distinguish between excused and unexcused absences. Missing data on excused versus unexcused absences in the ECLS-K is generally a school-level phenomenon. The absences survey instrument specifically asks that the student record form be completed after the last day of school, so ECLS-K attendance records contain students' total absences for the entire school year. Unfortunately, the dates of specific absences are unobserved, which prevents restricting the analysis to absences that occurred prior to year-end tests or before the kindergarten fall assessment.

The ECLS-K directly measured cognitive development by administering age-appropriate reading and mathematics tests in each wave of the survey. In kindergarten and first grade, math examinations tested children's abilities on the following subjects: numbers and shapes, relative size, ordinality and sequence, addition and subtraction, and multiplication and division. The reading examinations tested kindergartners and first-graders on letter recognition, beginning sounds, ending sounds, sight words, and words in context. Because achievement tests used a two-stage assessment approach, all children did not take the same exam. Hence, the ECLS-K computed scaled test scores based on the full set of test items using Item Response Theory (IRT) (NCES, 2002).

Because a small number of NCES employees administered the ECLS-K assessments to students individually, students in the same school and even in the same classroom did not necessarily take the ECLS-K tests on the same day (NCES, 2002). However, Fitzpatrick et al. (2011) find that ECLS-K test dates are essentially randomly distributed across students, suggesting that differences in ECLS-K assessment dates do not invalidate the current study, especially after conditioning on observed student characteristics and classroom fixed effects. Thus it is unnecessary to control for assessment dates.

In addition to being nationally representative of the 1998-99 U.S. kindergarten cohort, a second advantage of the ECLS-K data over state or district administrative data is the availability of detailed information on the composition and characteristics of students' households over and above what is typically found in administrative data. In addition to information on race/ethnicity, gender, poverty status, whether the child spoke English at home, and whether the child had an Individualized Education Program (IEP), the ECLS-K contains information on three household characteristics that may jointly predict academic achievement and school attendance: the number of adults living in the student's household, mothers' employment status, and mother's marital status.[4] For example, the presence of multiple household adults might increase achievement by providing additional tutoring support at home and increase absences by ensuring that an adult is available to care for children who do not attend school. Alternatively, the presence of multiple household adults may decrease absences by increasing the likelihood that someone is available to facilitate attendance. Similar arguments apply to mother's employment.

3.2 North Carolina Data

A limitation of the ECLS-K is that only a small number of students were sampled in most classrooms, which results in limited within-classroom variation in student absences with which to identify the relationship between student absences and student achievement. Accordingly, we augment analyses of the ECLS-K data with similar analyses of longitudinal administrative data on the population of third through fifth graders who attended North Carolina's public schools

[4] IEPs are an important part of the 2004 Individuals with Disabilities Education Act (IDEA). Specifically, IEPs document the goals and support systems in place for children with learning disabilities. Parents and educators work together to develop an appropriate IEP.

between the 2005-06 and 2009-10 school years. These student-level data are maintained and provided by the North Carolina Education Research Data Center (NCERDC).[5] The NCERDC data contain administrative records on students' race, gender, poverty status, limited English proficiency (LEP) status, whether the student had administratively classified math or reading learning disabilities, total absences, whether the absence was excused or unexcused, total tardies, student-classroom links, and end-of-grade math and reading test scores.[6] The baseline analytic sample is comprised of fourth and fifth graders.

Students who experienced a mid-year classroom change, repeated a grade, or changed schools during third, fourth, or fifth grade, are excluded from the analysis, as are students who are missing total absence, test score, or demographic data. These exclusions result in a sample of 903,314 student-year observations, which we subsequently refer to as the full sample. Like in the ECLS-K, however, only about two thirds (634,013) of these student-year records distinguish between excused and unexcused absences and again data on absence type are generally missing at the school level. Data on tardies are frequently missing as well, mostly at the school level for the 2008-09 and 2009-10 academic years, and are only available for 587,919 student-year observations. The distinction between excused and unexcused absences is made for all students for whom tardies are observed. Accordingly, we treat students for whom test-score, background characteristics, classroom identifiers, and absence and tardy data are observed as the baseline analytic sample, both because we are interested in estimating the relationship between tardies

[5] See http://www.childandfamilypolicy.duke.edu/project_detail.php?id=35 for additional information.
[6] North Carolina's end-of-grade tests are state mandated, criterion referenced, vertically aligned, and are given to all students in the spring of third, fourth, and fifth grades.

and student achievement and because models that exclude tardies will yield biased estimates if tardies are correlated with absences and influence achievement.[7]

3.3 Sample Characteristics

Table 1 provides summary statistics for the ECLS-K and North Carolina (NC) analytic samples. In this and all subsequent analyses test scores in both datasets are standardized by subject, grade, and year to have mean zero and standard deviation one (Ballou, 2009). Standardized test score means and standard deviations are not precisely zero and one in the analytic samples because they were standardized using all available test scores. The average student was absent six to eight times and when the distinction was made, which is an important caveat, excused absences are more common in both datasets. Tardies are less frequent than absences in both datasets.

Table 1 also shows that the NC data are comprised of more black and low-income students than the nationally representative ECLS-K, which is to be expected given North Carolina's demographics. The ECLS-K and NC analytic samples are approximately evenly split between kindergarteners and first graders, and fourth and fifth graders, respectively. About 7 percent of sampled kindergarteners are "redshirts" who delayed kindergarten entrance by one year. Boys and girls are equally represented in both data sets. About 5 percent of children in the ECLS-K reported not speaking English at home and one percent of children in NC were administratively classified as LEP. Intuitively, the latter rate is lower because some children of first-generation immigrants speak English proficiently but speak the parents' native language at

[7] However, we conduct sensitivity analyses using the full sample of 903,314 student-years for which absences are observed and show in appendix table A.1 that the average characteristics of students for whom tardies are observed are similar to those for whom tardies are unobserved to assuage concerns that the results are influenced by endogenously missing data on student tardies.

home. About 6 percent of students had an IEP in the ECLS-K and 3.5 percent of students were categorized as having a learning disability in either math or reading in NC. Years are equivalent to grade levels in the ECLS-K, and are thus not reported in table 1, because the survey follows one cohort of children over time and grade skippers and repeaters are excluded from the analytic sample.

As discussed in the introduction, differential rates of student absences may contribute to achievement gaps even if absences uniformly harm all students' achievement. Tables 2 and 3 examine differences in student absence and tardy rates by grade level, gender, poverty status, English language proficiency, and learning disabilities in the ECLS-K and NC data, respectively. Table 2 finds a small but statistically significant difference of about one additional absence for kindergarteners, children who do not speak English at home, and children who have an IEP, but no difference between boys and girls. The most striking difference in table 2 is by poverty status, as students living in households below the poverty line experienced nearly five more absences than their counterparts in households at or above the poverty line defined by the ECLS-K. This is an arguably practically significant difference, which corresponds to half the sample standard deviation reported in table 1. Similar patterns are observed for tardies, excused absences, and unexcused absences. It is also worth noting that the distinction between excused and unexcused absences by SES may not be meaningful. Specifically, SES might be correlated with the probability that parents take/have the time to write/call the school to officially excuse an absence. In table 3, the differences in total absences in the NC data are all strongly statistically significant, which is at least partly due to the large sample size. However, the practical importance of these differences is limited, as the largest differences are about one absence per year.

4. Identification Strategy

We investigate the relationship between student absences and academic achievement by including absences as a contemporaneous input in value-added models (VAMs) of the education production function. Intuitively, VAMs exploit longitudinal student data by using lagged test scores to proxy for the unobserved histories of educational and familial inputs received by each child. Todd and Wolpin (2003), Harris, Sass, and Semykina (2014), and Guarino, Reckase, and Wooldridge (2013) provide thorough discussions of the empirical difficulties created by a lack of data on historical inputs, derivations of lagged test-score VAM specifications from a structural education production function, and the assumptions required for consistent estimation of various VAM specifications. Following Guarino et al. (2013), we model the test score (*y*) of student *i*, in classroom *j*, grade *g*, and year *t* as

$$y_{ijgt} = \alpha y_{i,t-1} + f\left(A_{it}\right) + \boldsymbol{\beta}\mathbf{x}_{it} + \eta_{jgt} + u_{ijgt}, \tag{1}$$

where $f(A)$ is a general function of absences; $\mathbf{x}$ is the vector of student and household characteristics summarized in table 1, some of which vary over time; η is a classroom fixed effect (FE); and u is a composite error term that contains student *i*'s time-invariant unobserved ability and idiosyncratic shocks to achievement.[8]

The year, grade, and school FE commonly included in VAMs are subsumed by the classroom FE, which are crucial to our identification strategy. Specifically, the classroom FE control for the non-random sorting of teachers across schools and classrooms, as well as classroom-specific shocks that jointly influence both absences and achievement (e.g., a flu epidemic or a particularly effective teacher) (Monk & Ibrahim, 1984). As a result, our estimates of absences' effect on performance rely on within-classroom variation in student absences,

[8] In the ECLS-K, which is a cohort survey, the grade and year subscripts are redundant, as grade skippers and repeaters are excluded from the analytic sample.

holding past achievement constant. Standard errors are clustered by school district, which makes statistical inference robust to the presence of arbitrary heteroskedasticity and arbitrary serial correlation within districts, schools, *and* students over time because the analytic sample is restricted to students who did not change schools during the study's time period and schools are nested within districts (Angrist & Pischke, 2009, p. 319).[9] Ordinary Least Squares (OLS) is taken as the preferred estimator of (1), as Guarino et al. (2013) find this approach the most robust to a variety of potential non-random student-teacher assignment scenarios. This is potentially important in North Carolina, as Rothstein (2010) provides evidence that North Carolina's student-teacher assignments are not random.

Having chosen an appropriate VAM specification and estimator, a related question regards the functional form of the relationship between absences and achievement ($f(A)$ in (1)). For example, the effect of absences may be nonlinear either because absences below some minimal threshold are relatively harmless or because the effect is cumulative. Similarly, the effect of absences may vary by absence type (Gottfried, 2009) or by observed student characteristics, as households likely vary by SES in their ability to support "catch up" following an absence spell (Chang & Romero, 2008; Ready, 2010), females may have stronger non-cognitive skills (Bertrand & Pan, 2013; Jacob, 2002), and teachers may struggle to assist exceptional students (i.e., students with disabilities and English language learners) in catching up following absence spells (Jones, Buzick, & Turkan, 2013). Incorrectly assuming that $f(A)$ is linear or failing to properly model heterogeneity in the effect of student absences on achievement may obfuscate the empirical relationship between student absences and achievement.

[9] It is worth noting that the main results are robust to including "school changers" in the analytic sample and including a school-changer indicator in the vector of student controls. However, we exclude such students from the baseline sample to avoid conflating the effect of changing schools with the effect of absences, as the unobserved shock that led to a school change may also affect a student's attendance patterns.

Accordingly, we test for potential nonlinearities and heterogeneities by considering quadratic and step-function specifications of $f(A)$ and by interacting A with the subset of $\mathbf{x}$ described above.

5. Results

5.1 Baseline Analysis of the ECLS-K

Table 4 reports baseline estimates of the effect of kindergarten and first-grade student absences on math and reading achievement using data from the ECLS-K. Each panel of table 4 reports estimates for a different specification of $f(A)$. Column 1 reports estimated effects on math achievement and column 2 reports estimated effects on reading achievement. The linear specifications estimated in panel 1 suggest that an additional student absence reduces both math and reading achievement by 0.002 test-score standard deviations (SD). These estimates are statistically significant at 5% significance and suggest that a one SD increase in absences (9.5) decreases math and reading achievement by about 0.02 test-score SD. The partial effect of student tardies on math achievement is even smaller in magnitude and insignificant at traditional significance levels, while tardies' effect on reading achievement is slightly larger and strongly statistically significant. The adjusted R^2 values and estimated coefficients on tardies are essentially identical across the five specifications considered in table 4, and are thus omitted from panels 2 through 5.

Panel 2 of table 4 tests for nonlinear effects of student absences on achievement by modeling $f(A)$ as a quadratic function of absences in the baseline specification of (1). For both math and reading, the linear and squared absence terms are individually and jointly statistically significant, as are the estimated average partial effects (APE) of -0.004 and -0.003, respectively. The quadratic APE estimates reported in panel 2 are larger than the linear partial effects reported in panel 1. However, the estimated partial effects of absences in the quadratic specifications are approximately constant over the range of absences observed in the data.

Panel 3 of table 4 considers an alternative nonlinear relationship between student absences and achievement in the form of a step function where students are coded as having fewer than three absences, three to 9.5 absences (omitted reference category), 10 to 21 absences, or more than 21 absences. These cutoffs correspond to the 25th, 75th, and 95th percentiles of the observed distribution of annual absences among kindergartners and first graders in the ECLS-K, and the highest threshold of 21 absences is close to the point at which many states consider a student to be "chronically absent" (Bruner et al., 2011). The estimates of this specification suggest that there is no significant difference in the achievement of students who are absent fewer than three times and those who are absent between three and ten times. Students in the 25th through 75th percentiles of the absence distribution scored 0.03 math test-score SD lower than students who were absent less often, but no such difference is observed for reading achievement. Chronically absent students score significantly lower than students who had fewer than 10 absences on both math and reading tests, however, by 0.09 and 0.05 test-score SD, respectively. These are substantive differences.

Given the harm associated with frequent (more than 21) absences observed in panel 3 of table 4, we next examine the robustness of the linear estimates reported in panel 1 by estimating the linear specification on a restricted sample that excludes students who were absent more than 21 times. These estimates are reported in panel 4 of table 4, and are quite similar to those reported in panel 1, suggesting that the linear-specification estimates were not driven by chronically absent students. Accordingly, the linear specification estimates in panel 1 are taken as the preferred baseline estimates both for their simplicity and to facilitate the straightforward estimation of interaction specifications that allow for heterogeneous effects of student absences.

Panel 5 of table 4 tests whether excused and unexcused absences differentially affect student achievement using the subsample for which this information is available. Somewhat surprisingly, the point estimate on excused absences is larger than that on unexcused absences for both math and reading achievement, though neither difference is statistically significant at traditional significance levels.

Table 5 continues to test for heterogeneity in the relationship between student absences and academic achievement by estimating augmented versions of the baseline linear specification that interact student absences with six observed student characteristics: grade level, a poverty indicator, gender, an indicator equal to one if child does not speak English at home, an indicator equal to one if child has an individualized education plan (IEP), and the student's lagged test score. Specifically, columns 1 and 2 report estimates for math achievement, where the lagged-achievement interaction effect is restricted to equal zero in column 1.

In column 1 of table 5, the estimated marginal effect of an additional absence on math achievement for a male kindergartener who is not below the poverty line, speaks English at home, and does not have an IEP is identical to the baseline specification's estimate that assumes homogeneous effects of absences reported in panel 1 of table 4. This is unsurprising, as the five interactions terms in column 1 are individually and jointly statistically insignificant.[10] When the sixth interaction term, between lagged achievement and total absences, is added to the model estimated in column 2 of table 5 the other five interactions terms remain individually and jointly statistically insignificant. Interestingly, however, this interaction term is positive and marginally

[10] The first-grade, poverty, female, and English interaction terms are remain statistically insignificant when each is added individually to the baseline specification.

statistically significant, suggesting that absences are marginally less harmful to students with higher previous achievement.

Columns 3 and 4 of table 5 estimate the same two specifications for reading achievement. Again, most of the interaction terms are individually statistically insignificant. The poverty interaction term in column 3 is statistically significant at 5% significance, however, which suggests that the harmful effect of absences on reading achievement is twice as large in low-income households as in households above the poverty line. This difference is consistent with the hypothesis that while reading skills are primarily developed at home (Currie & Thomas, 2001), they are more effectively developed in high-SES households that are able to invest more time reading to children (Baydar & Brooks-Gunn, 1991; Guryan, Hurst, & Kearney, 2008), which causes low-income households to struggle to compensate for the lost instructional time associated with student absences. However, the poverty-absences interaction terms loses its statistical significance when the lag-score interaction is added to the model in column 4. Like in the case of math achievement, the absences-lag score interaction effect in column 4 of table 5 suggests that the harmful effect of absences is significantly smaller for students who performed better in the previous year.

5.2 Baseline Analysis of North Carolina

Table 6 reports baseline estimates of the effect of fourth and fifth graders' absences on math and reading achievement using data from North Carolina. Each panel of table 6 reports estimates of (1) assuming a different specification of $f(A)$. Column 1 reports estimated effects on math achievement and column 2 reports estimated effects on reading achievement. The linear specifications estimated in panel 1 suggest that an additional student absence reduces math and reading achievement by 0.007 and 0.004 test-score SD, respectively. These estimates are statistically significant at 1% significance and suggest that a one SD increase in absences (5.7) decreases academic achievement by about 0.02 to 0.04 test-score SD, effect sizes that are similar in magnitude to the baseline ECLS-K estimates reported in section 5.1. The partial effects of student tardies on math and reading achievement are smaller in magnitude and once again statistically significant at 1% significance. Like in the analysis of the ECLS-K data, the estimated effects of tardies are essentially identical across the five specifications considered in table 6, and are thus not reported in panels 2 through 5.

Panel 2 of table 6 tests for nonlinear effects of student absences on achievement by modeling $f(A)$ as a quadratic function of absences in the baseline specification of (1). The linear and squared absence terms are jointly statistically significant, as are the estimated average partial effects (APE), for both math and reading. However, because the quadratic specifications' estimated APE are identical to those of the linear specification reported in panel 1 and the estimated quadratic partial effects are approximately constant over the ranges of absences observed in the data, we prefer the linear specification as the baseline in subsequent analyses.

Panel 3 of table 6 considers an alternative nonlinear relationship between student absences and achievement in the form of a step function where students are coded as having fewer than three absences, three to 9 absences (omitted reference category), 10 to 17 absences, or more than 17 absences. These cutoffs correspond to the 25th, 75th, and 95th percentiles of the observed distribution of annual absences among fourth and fifth graders in the NC analytic sample. During the time period of this study North Carolina mandated a minimum of 180 instructional days, so the "more than 17 absences" category closely corresponds with the "10%"

definition of chronic absence (Bruner et al, 2011).[11] Estimates of this specification suggest that students who are absent fewer than three times score 0.04 and 0.02 SD higher on math and reading standardized tests, respectively, than those who are absent three to nine times during the course of the school year. Meanwhile, students who were absent ten or more times scored significantly lower than other students in both math and reading. Specifically, students who are absent between 10 and 17 times scored approximately 0.05 test-score SD lower in math and 0.02 test-score SD lower in reading. Chronically absent students performed even worse, earning math scores more than one tenth of a test-score SD lower than their counterparts in the 25th through 75th percentiles of the absences distribution. The reading scores of chronically absent students were more than 0.06 test-score SD lower than those of students in the 25th through 75th percentiles of the absences distribution.

Given the significantly lower performance of chronically absent students observed in panel 3 of table 6, we examine the robustness of the linear estimates reported in panel 1 by estimating the linear specification on a restricted sample that excludes students who were absent more than 17 times (the 95th percentile of the absences distribution). These estimates are reported in panel 4 of table 6, and are nearly identical to those reported in panel 1, suggesting that the linear-specification estimates were not driven by chronically absent students. Accordingly, the linear specification estimates in panel 1 are taken as the preferred baseline estimates both for their simplicity and to facilitate the straightforward estimation of interaction specifications that enable tests for heterogeneous effects of student absences. Panel 5 of table 6 tests for differences in the effect of excused versus unexcused absences on math achievement. As expected, the estimated effect of unexcused absences on math achievement is twice as large

[11] Chronic absence is typically defined as being absent on 10% or more of school days. In 2011 North Carolina increased the legal minimum to 185. See http://www.ncpublicschools.org/fbs/accounting/calendar/.

as that of excused absences. Similarly, the estimated effect of unexcused absences on reading achievement is twice as large as that of excused absences. Both differences are statistically significant at 1% significance.

Table 7 continues to test for heterogeneity in the relationship between student absences and academic achievement by estimating augmented versions of the baseline linear specification that include interactions of student absences with six observed student characteristics: grade level, a poverty indicator, gender, an indicator equal to one if the student is administratively classified as having Limited English Proficiency (LEP), an indicator equal to one if the student is administratively classified as having a math or reading learning disability, and the student's lagged test score.

Columns 1 and 2 of table 7 test for heterogeneity in the relationship between student absences and math achievement, where the lagged-achievement interaction effect is restricted to equal zero in column 1. There is no evidence that the effect of absences on math achievement varies by grade level, though absences are marginally less harmful to girls than boys. The poverty-absences interaction term is small and negative, yet is only statistically significant in column 2, which includes the lag-score interaction term. Absences are about 30% more harmful to LEP students' math achievement, and this difference is statistically significant at 5% significance, perhaps because language difficulties create an additional hurdle to students seeking to make up missed work or because the parents of LEP students are less able to help children with schoolwork at home. Somewhat surprisingly, absences are less harmful to the math achievement of students who have a math learning disability, though this difference becomes statistically insignificant after controlling for the lag-score interaction term. This could arise from schools' provision of additional support to students with learning disabilities. The lag-score interaction term itself is negative and statistically significant, which contradicts the ECLS-K result and suggests that absences are marginally more harmful to previously high-achieving students. Overall, the interaction terms are jointly statistically significant in columns 1 and 2 of table 7, suggesting that the relationship between absences and math achievement varies by observed student characteristics.

Columns 3 and 4 of table 7 estimate the same two specifications for reading achievement. The sources of heterogeneity in the relationship between absences and achievement are largely similar for both math and reading. For example, absences are again marginally more harmful to the reading achievement of female, low-income, and LEP students. Intuitively, the harmful effect of absences among LEP students is stronger, in both absolute and percentage terms, on reading achievement than on math achievement.

5.3 Sensitivity Analysis

OLS estimates of (1) are potentially biased for two reasons. First, time-invariant unobserved student heterogeneity in the composite error term of (1) may jointly predict both achievement and absences. Second, even after conditioning on time-invariant student heterogeneity, the possibility remains that time-varying student-specific shocks jointly determine absences and achievement. In this section we consider some alternative estimators that condition on unobserved student heterogeneity and examine the robustness of the main results more generally. Table 8 does so for the ECLS-K data. Column 1 reproduces the baseline estimates of panel 1, table 4, to facilitate comparisons. In column 2 we show that the baseline estimates are robust to not weighting the regressions, as suggested by Solon, Haider, and Wooldridge (2013). Column 3 contains estimates of an extensive specification that, in addition to the baseline student characteristics, conditions on mothers' employment status, mothers' marital status, and the number of adults residing in the household. The estimated effect of absences on math achievement actually increases, and the estimated effect on reading achievement remains the same. Moreover, both estimates remain strongly statistically significant, suggesting that the baseline estimates are not biased by changes in household structure that jointly determine absences and achievement.

Unobserved time-invariant student heterogeneity is another potential source of endogeneity. This is easily removed from the baseline specification by first differencing (FD) equation (1). Because OLS estimates of the resulting FD equation are biased (Nickell, 1981), we apply the instrumental variables (IV) procedure proposed by Anderson and Hsiao (1982), in which twice-lagged achievement instruments for the first-differenced lag score.[12] These FD estimates are reported in column 4 of table 8.[13] The FD estimate of the effect of absences on math achievement is actually larger than the corresponding OLS estimates and remains statistically significant at 5% significance, though is less precisely estimated. This finding is consistent with Gottfried's (2011) finding that conditioning on family FE yields larger estimates of the effect of absences on achievement and indicates that the baseline math results are not driven by unobserved student heterogeneity. The corresponding FD estimate for reading is approximately zero and imprecisely estimated. However, it is difficult to attach much meaning to the reading estimate, as the estimated coefficient on the lag score (α) is close to one, which is suggestive of a weak-IV problem (Wooldridge, 2010, p. 374).

While the FD estimates reported in column 4 of table 8 are robust to the presence of time-invariant unobserved student heterogeneity, they remain susceptible to unobserved time-varying

[12] See Guarino et al. (2013) for further discussion of this and related IV estimators in the context of VAMs.
[13] In the ECLS-K data, the instrument is twice-lagged achievement, which is the fall of kindergarten test score.

shocks that jointly predict student absences and achievement. While there is no perfect solution to this potential source of endogeneity in the current context, under the fairly restrictive assumption of sequential exogeneity the FD-IV procedure described in the preceding paragraph can be extended to also instrument for ΔA_t with lagged absences (A_{t-1}) (Wooldridge, 2010, p. 370). The consistency of this approach hinges on so called sequential exogeneity (Wooldridge, 2010, p. 368), which for our purposes means that conditional on a student FE and the covariates on the right hand side of (1), including the lag score and classroom FE, lagged absences do not affect current test scores. Sequential exogeneity is plausible in the current context, though it cannot be tested. Nonetheless, these FD-IV results are reported in column 5 of table 8. The coefficient on the lagged reading test score is again close to one, obfuscating the interpretation of the reading results. However, the estimated effect of absences on math achievement in column 5 is approximately zero and is no longer statistically significant, as the standard error is six times larger than that in the baseline specification. While the imprecision of the FD-IV estimates in column 5 is unsurprising, the insignificance of the math result suggests that the harmful effect of absences on academic achievement observed in previous specifications is potentially spurious. Specifically, absences might be acting as a proxy for other time-varying student or household characteristics that harm student achievement. Of course, these results should be interpreted with caution, as they hinge on the instrument's validity (i.e., sequential exogeneity).

We conclude with a somewhat similar sensitivity analysis of the North Carolina data, the results of which are reported in table 9. Column 1 reproduces the baseline estimates of panel 1, table 6, to facilitate comparisons. In column 2 we report estimates of the baseline specification, excluding tardies, for the full sample of 903,314 student-years for which all relevant variables *except* tardies are observed. The point estimates on absences are unchanged, suggesting that the results are not biased by omitting tardies from the model or by restricting the sample to observations for which tardies are observed. Column 3 again excludes tardies from the model, but now uses only the baseline analytic sample for which tardies *are* observed. Again, the point estimates on student absences remain unchanged, which suggests that the main results are not biased by non-randomly missing data on student tardies.

Columns 4 and 5 of table 9 contain FD and FD-IV estimates analogous to those reported in Columns 4 and 5 of table 8. The FD estimates in column 4 that remove the student effect from equation (1) are slightly smaller and less precisely estimated, but similar in magnitude to the baseline OLS estimates and remain statistically significant at 1% significance. This indicates that the baseline estimates were not driven by unobserved student heterogeneity. Interestingly, however, the estimated tardy coefficients lose their statistical significance. Finally, the FD-IV estimates reported in column 5 of table 9 instrument for first-differenced absences with lagged absences, as discussed above. Like in the ECLS-K data, this procedure yields estimates of the effects of absences on both math and reading achievement that are statistically indistinguishable from zero. Again, the FD-IV results should be interpreted with caution, as they rely on strong assumptions (i.e., sequential exogeneity).

Taken as a whole, the sensitivity analyses of both datasets reported in tables 8 and 9 suggest that the main finding of a significant negative relationship between student absences and academic achievement is robust to a number of modeling and sample restriction decisions, as well as conditioning on unobserved student heterogeneity. The FD-IV results do question whether this is a causal relationship, or if absences are simply correlated with time-varying unobservable shocks to student achievement. However, either case yields several policy implications that we discuss in detail below.

6. Discussion

The current study investigates the relationship between student absences and academic achievement by estimating value-added models that exploit within-classroom and within-student variation in absences using two longitudinal datasets: the ECLS-K, which is a nationally representative survey of the 1998-99 cohort of U.S. kindergarteners, and administrative data on the population of third through fifth graders who attended North Carolina's public schools between 2005-06 and 2009-10. Both data sets provide evidence of a modest but statistically significant negative relationship between student absences and both math and reading achievement: a one SD increase in absences is associated with decreases in achievement of 0.02 to 0.04 test-score SD. That the harmful effects of student absences are generally stronger on math achievement than on reading achievement is consistent with the general finding that educational inputs and policies have relatively greater impacts on math achievement (e.g., Hanushek & Rivkin, 2010; Jacob, 2005; Rivkin, Hanushek, & Kain, 2005; Rockoff, 2004), perhaps because children are more apt to learn and develop reading skills at home (Currie & Thomas, 2001).

The practical significance and policy relevance of these results are most easily observed by comparing these effects to those of other educational inputs that are considered to be practically significant. Specifically, these results suggest that a one SD increase in absences is roughly equivalent to between one third and one quarter of the effect of a one SD increase in teacher effectiveness (Hanushek & Rivkin, 2010; Kane, Rockoff, & Staiger, 2008). Other useful benchmarks for contextualizing the marginal effect of a student absence are the marginal effects of teacher absences and additional school days. Regarding the former, studies by Herrman and Rockoff (2012) and Clotfelter et al. (2009) find that a one SD increase in teacher absences similarly reduces student achievement by 0.02 to 0.04 test-score SD. Regarding the latter, a small literature is emerging that attempts to estimate the effect of school days on student achievement by exploiting plausibly random variation in school days caused by either inclement weather or changes in test dates. Marcotte and Hansen (2010) review the literature on snow days, which tends to find that each instructional day lost to snow decreases achievement by about 0.02 to 0.04 test-score SD. This effect is ten times larger than the harm associated with one student absence, perhaps because the average student is able to catch up following an absence, while snow days simply eliminate a day of learning that cannot be made up until after the spring test. Fitzpatrick et al.'s (2011) estimates of the effect of a school day are more in line, and perhaps more comparable, with our estimates because the authors exploit the quasi-randomness of test dates in the ECLS-K. Specifically, Fitzpatrick et al. (2011) estimate that each day in school is associated with an increase of 0.005 to 0.007 test-score SD, which are more in line with our estimates. Still, they are slightly larger than our ECLS-K estimates of the marginal effect of an absence. Again, this may be due to the fact that there is a mechanism in place to help students catch up following an absence, and the average student is able to do so, to some extent.

Heterogeneity in the relationship between student absences and achievement is the one area in which the ECLS-K and North Carolina analyses yield moderately different results, though this might partly be driven by the relative lack of power in the smaller ECLS-K sample. The harmful effect of absences on reading achievement is significantly stronger among low-income students in both samples, perhaps because reading skills are more effectively developed in high-SES households that are able to invest more time reading to children (Baydar & Brooks-Gunn, 1991; Guryan et al., 2008) and are thus better able to help children "catch up" following an absence spell. In North Carolina, there is an even larger difference between the effect of absences on the math and reading achievement for LEP and non-LEP students. This difference is particularly large for reading achievement, as the harmful effect of absences on reading achievement for LEP students is more than twice that for non-LEP students. Again, this may be partly due to LEP students' parents being less able to help with reading assignments at home.

The last notable difference between the two datasets is that no statistically significant difference between the effects of excused and unexcused absences was found in the ECLS-K, while unexcused absences were found to be twice as harmful as excused absences in North Carolina. Again, the lack of differential effects by absence type in the ECLS-K analysis could be due to a lack of statistical power in the substantially smaller ECLS-K analytic sample. Alternatively, the different results could be driven by differences in the grade levels contained in the two datasets or perhaps differences in the compositions of the ECLS-K and NC analytic samples. We further investigate the grade-level question by estimating the ECLS-K interaction specifications reported in table 5 on a balanced panel of kindergarten through fifth-grade students using the third- and fifth-grade waves of the ECLS-K. The first-, third-, and fifth-grade interactions reported in appendix table A.2 are neither individually nor jointly statistically significant, suggesting that the relationship between absences and achievement is approximately constant between kindergarten and fifth grade of the ECLS-K sample. However, it is worth stressing that this result should be interpreted with caution given that the third and fifth grade estimates use first and third grade lag scores, respectively.

The empirical finding of a practically significant and robust negative relationship between student absences and student achievement has implications for education and social policy. However, the optimal policy response depends upon precisely how and why student absences affect achievement, and whether absences have a direct causal effect on achievement or simply correlate with unobserved determinants of achievement. The results of the sensitivity analyses conducted in section 5.3 are mixed. On the one hand, the estimated coefficients on absences are robust to conditioning on a rich set of time-varying statistical controls and unobserved student heterogeneity. These results suggest that student learning can be increased by reducing either the frequency or deleterious effects of student absences. The former suggests the importance of future research that examines how household and neighborhood characteristics, as well as school and classroom policies, influence student attendance. Low-cost policies that nudge parents to facilitate regular attendance may be especially cost effective. The latter suggests the potential benefits of programs that assist students who are frequently absent to "catch up" through some combination of compensating for lost instructional time and ensuring that absent students receive prompt and complete information on missed lessons and assignments.

On the other hand, however, the FD-IV estimates that instrument for absences (reported in column 5 of tables 8 and 9) suggest that the observed relationship between absences and achievement may be spuriously driven by time-varying unobservables that jointly predict absences and achievement. Taken at face value, this is an interesting and policy-relevant result, despite the implication of no direct causal link between absences and achievement. Specifically, this finding suggests that student absences are easily observable indicators of students who are at risk of experiencing developmental setbacks. Moreover, absences, or more specifically, increases in absences from the past year, might be used as indicators in an early-warning system designed to identify students experiencing difficulties outside of the traditional school day that are affecting both attendance and achievement. Effectively identifying such students has at least two direct policy implications, regardless of whether the observed relationship between absences and achievement is causal. First, outreach to the parents of such students might yield useful information regarding the challenges that the household or student is facing outside of school, and how the harmful impacts of such challenges on the student's learning might be minimized. Second, in-school and after-school tutoring, counseling, and related support programs might be targeted to students who are absent more frequently than in previous school years.

The results of the current study also have implications for value-added estimates of teacher effectiveness, as student attendance is an educational input that is at least partially outside of teachers' control. Accordingly, failing to control for student absences in value-added models (VAMs) may yield biased estimates of teacher effects. However, if teachers influence attendance, controlling for student absences in VAMs will effectively penalize teachers who indirectly increase student performance by increasing student attendance. These issues, and the extent to which teachers affect student attendance more generally, are further investigated in Gershenson (2014).

Finally, we consider absences' ability to explain the achievement gap between students of different SES. Simple comparisons of means show unconditional math achievement gaps between students below and above the poverty line of about 0.6 and 0.7 test-score SD in the ECLS-K and North Carolina data, respectively. Because the harmful effects of absences on math achievement were only marginally stronger among low-income students, the current back-of-the-envelope analysis considers only how differences in the frequency of absences are likely to contribute to the achievement gap, which provides conservative estimates of the absences' contributions to achievement gaps. The average differences reported in tables 2 and 3 suggest that only about 1% of the achievement gap is attributable to differential rates of student absences. However, the baseline results indicate that reducing impoverished students' absences by 10 relative to non-poor students would reduce the achievement gap by 5 to 10 percent; similarly, the step-function specification estimates suggest that moving a chronically-absent student to the middle of the absences distribution might reduce the achievement gap by about 15%.

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Table 1. Descriptive statistics of analytic samples

	ECLS-K			North Carolina		
	Mean	SD	N	Mean	SD	N
Standardized test scores						
Math	0.19	0.88	11,650	0.06	0.98	903,314
Reading	0.21	0.78	11,650	0.05	0.98	903,314
Absences & tardies						
Total absences	7.97	9.54	11,650	6.22	5.66	903,314
Total tardies	3.33	7.16	11,650	1.94	5.37	587,919
Excused absences	6.63	6.43	7,600	3.40	4.23	634,013
Unexcused absences	1.80	7.95	7,600	2.35	3.32	634,013
First grade	45.6%		11,650			
Fifth grade				50.1%		903,314
Child race/ethnicity						
Non-Hispanic white	70.6%		11,650	56.7%		903,314
Non-Hispanic black	12.6%		11,650	26.0%		903,314
Hispanic	10.3%		11,650	9.8%		903,314
Other	6.6%		11,650	7.5%		903,314
Female	50.9%		11,650	50.0%		903,314
Below poverty level	12.8%		11,650	47.2%		903,314
No English at home/LEP	4.7%		11,650	1.3%		903,314
Student has an IEP	5.8%		11,650			
Math disability				1.5%		903,314
Reading disability				3.0%		903,314
Any learning disability				3.5%		903,314
Kindergarten redshirt	7.1%		11,650			
Mother's education						
No HS diploma	8.0%		11,650			
HS graduate	29.9%		11,650			
Some college	35.3%		11,650			
Bachelor's or more	26.8%		11,650			

Notes: ECLS-K means and standard deviations (SD) are weighted by ECLS-K provided sampling weight C#CW0. Kindergarten and fourth grade are the omitted grade categories in the ECLS-K and NC data, respectively. The ECLS-K asks whether English is spoken in the student's home. The NC data classifies children as having limited English proficiency (LEP). Individualized Education Plans (IEP) identify students who have learning disabilities in the ECLS-K. The redshirt variable indicates whether the family of a kindergarten-aged child delayed entry into kindergarten. ECLS-K sample sizes are rounded to the nearest 50 to conform to NCES regulations.

Table 2. Conditional descriptive statistics of ECLS-K analytic sample

		Total absences	Total tardies	Excused absences	Unexcused absences
	Mean	8.4	3.1	6.5	1.9
Kindergarten	SD	(11.0)***	(7.1)***	(6.4)***	(9.1)***
	N	6,300	6,300	5,400	5,360
	Mean	7.4	3.6	7.2	2.5
First grade	SD	(7.4)	(7.2)	(6.4)	(4.8)
	N	5,300	5,300	2,100	1,350
	Mean	7.9	3.2	6.6	2.0
Male	SD	(9.6)	(6.8)**	(6.3)**	(9.1)
	N	5,650	5,650	3,700	3,300
	Mean	8.1	3.5	6.9	2.0
Female	SD	(9.4)	(7.5)	(6.5)	(7.7)
	N	5,950	5,950	3,800	3,400
	Mean	7.4	3.1	6.4	1.6
At or above poverty level	SD	(8.0)***	(6.8)***	(6.0)***	(6.5)***
	N	10,250	10,250	6,550	5,800
	Mean	11.9	5.0	8.5	4.6
Below poverty level	SD	(15.9)	(9.2)	(8.3)	(15.2)
	N	1,400	1,400	950	900
	Mean	7.9	3.3	6.7	2.0
Speaks English at home	SD	(9.4)***	(7.1)	(6.4)***	(8.3)
	N	10,950	10,950	7,050	6,350
	Mean	9.2	3.9	8.1	2.5
No English at home	SD	(12.3)	(8.3)	(7.3)	(10.8)
	N	700	700	450	400
	Mean	7.9	3.3	6.7	2.0
Student has no IEP	SD	(9.6)**	(7.2)	(6.4)	(8.6)
	N	11,050	11,050	7,100	6,400
	Mean	8.9	3.4	7.2	2.1
Student has IEP	SD	(7.9)	(6.2)	(6.4)	(5.2)
	N	600	600	400	350

Notes: Means and standard deviations (SD) are weighted by ECLS-K provided sampling weight C#CW0. Sample sizes are rounded to the nearest 50 to conform to NCES regulations. Mean difference t-tests were performed to compare kindergarteners and first graders, males and females, students above and below poverty line, English speakers and non-English speakers, and students without and with individualized education plans (IEP).
*** p<0.01, ** p<0.05, * p<0.1.

Table 3. Conditional descriptive statistics of North Carolina analytic sample

		Total absences	Total tardies	Excused absences	Unexcused absences
Fourth grade	Mean	6.2	2.0	3.4	2.3
	SD	(5.6)***	(5.5)*	(4.2)**	(3.3)***
	N	450,714	292,838	315,753	315,753
Fifth grade	Mean	6.3	1.9	3.4	2.4
	SD	(5.8)	(5.2)	(4.3)	(3.4)
	N	452,600	295,081	318,260	318,260
Male	Mean	6.3	1.9	3.4	2.4
	SD	(5.7)***	(5.3)	(4.3)***	(3.4)***
	N	451,895	293,735	317,042	317,042
Female	Mean	6.1	1.9	3.4	2.3
	SD	(5.6)	(5.4)	(4.2)	(3.2)
	N	451,419	294,184	316,971	316,971
At or above poverty level	Mean	5.7	1.8	3.4	1.8
	SD	(5.0)***	(5.1)**	(4.1)	(2.7)***
	N	476,775	313,601	346,220	346,220
Below poverty level	Mean	6.8	2.1	3.4	3.0
	SD	(6.3)	(5.7)	(4.4)	(3.9)
	N	426,539	274,318	287,793	287,793
Not LEP	Mean	6.2	2.0	3.4	2.3
	SD	(5.7)***	(5.4)***	(4.2)***	(3.3)***
	N	891,125	578,207	622,961	622,961
LEP	Mean	5.3	1.3	2.5	2.6
	SD	(5.0)	(3.9)	(3.4)	(3.5)
	N	12,189	9,712	11,052	11,052
Math or reading learning disability	Mean	7.3	2.2	3.8	2.9
	SD	(6.4)***	(6.0)**	(4.6)***	(3.9)***
	N	31,807	22,017	24,544	24,544
No math or reading learning disabilities	Mean	6.2	1.9	3.4	2.3
	SD	(5.6)	(5.3)	(4.2)	(3.3)
	N	871,507	565,902	609,469	609,469

Notes: Mean difference t-tests were performed to compare fourth and fifth graders, males and females, students above and below poverty line, students without and with limited English proficiency (LEP), and students without and learning disabilities.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4. ECLS-K estimates of absences' effect on student achievement

	Math achievement	Reading achievement
	1	2
1. Baseline linear specification (N = 11,650)		
Total Absences (TA)	-0.002	-0.002
	(0.001)**	(0.001)**
Total Tardies	-0.001	-0.003
	(0.001)	(0.001)***
Adjusted R^2	0.44	0.47
2. Quadratic specification (N = 11,650)		
TA	-0.004	-0.003
	(0.001)***	(0.001)***
TA^2	0.00003	0.00002
	(0.00001)**	(0.00001)***
Average partial effect (APE)	-0.004	-0.003
	0.001***	0.001***
3. Step function specification (N = 11,650)		
0 to 2.5 TA	0.0001	0.019
	(0.016)	(0.014)
3 to 9.5 TA	(omitted reference category)	
10 to 21 TA	-0.030	0.001
	(0.015)**	(0.013)
More than 21 TA	-0.088	-0.053
	(0.031)***	(0.025)**
4. Baseline, excluding chronically absent students (above 95th percentile) (N = 10,950)		
TA	-0.003	-0.002
	(0.001)*	(0.001)**
5. Baseline, by type of absence (N = 7,500)		
Excused absences	-0.003	-0.002
	(0.002)*	(0.001)**
Unexcused absences	-0.002	-0.001
	(0.001)*	(0.002)
Differential effect *t* test	p = 0.68	p = 0.34

Notes: Regressions are weighted by ECLS-K provided weight, C#CW0. Sample sizes are rounded to the nearest 50 to conform to NCES regulations. Each model controls for lagged achievement, classroom fixed effects, child race/ethnicity, child redshirt status, child gender, poverty status, English speaking status, individualized education plans (IEP), and total tardies (results shown for specification 1). Standard errors are robust to clustering at the school level. Adjusted R^2 range from 0.43 to 0.49 in specifications 2-5. In specifications 2 and 3, the absence terms are jointly statistically significant at $p < 0.05$. In specification 5 the absence terms are jointly significant at $p<0.05$ for math, but are not jointly significant for reading. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5. ECLS-K estimates of heterogeneity in absences' effect on student achievement

	Math achievement		Reading achievement	
	(1)	(2)	(3)	(4)
Lagged test score	0.700	0.686	0.716	0.683
	(0.011)***	(0.015)***	(0.010)***	(0.012)***
Total absences (TA)	-0.002	-0.003	-0.002	-0.003
	(0.001)*	(0.001)**	(0.001)*	(0.001)***
Total tardies	-0.001	-0.001	-0.003	-0.003
	(0.001)	(0.001)	(0.001)***	(0.001)***
Female	-0.035	-0.036	0.038	0.040
	(0.015)**	(0.015)**	(0.012)***	(0.012)***
Below poverty level	-0.053	-0.062	0.000	-0.014
	(0.027)*	(0.027)**	(0.021)	(0.022)
Does not speak English at home	0.021	0.018	0.013	0.004
	(0.039)	(0.038)	(0.036)	(0.036)
Student has an IEP	-0.093	-0.097	-0.206	-0.208
	(0.047)*	(0.047)**	(0.035)***	(0.035)***
First grade*TA	-0.001	-0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Poverty*TA	0.0003	0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.001)**	(0.001)
Female*TA	0.001	0.001	-0.0001	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)
Does not speak English*TA	0.001	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Student has an IEP*TA	-0.006	-0.005	0.002	0.002
	(0.004)	(0.004)	(0.003)	(0.003)
Lagged score*TA		0.002		0.004
		(0.001)*		(0.001)***
Joint significance of interactions	$p = 0.67$	$p = 0.33$	$p = 0.13$	$p < 0.001$
Adjusted R^2	0.44	0.44	0.47	0.47

Notes: Regressions are weighted by ECLS-K provided weight, C#CW0. N = 11,650, which is rounded to the nearest 50 to conform to NCES regulations. Each model controls for classroom fixed effects, child race/ethnicity, child redshirt status, child gender, poverty status, English speaking status, individualized education plans (IEP), and total tardies. Standard errors are robust to clustering at the school level. In addition to the variables in the table, each model controls for child race/ethnicity, maternal education, and child redshirt status. Standard errors, in parentheses, are clustered at the school level.
*** p<0.01, ** p<0.05, * p<0.1.

Table 6. North Carolina estimates of absences' effect on student achievement

	Math achievement	Reading achievement
	1	2
1. Baseline linear specification (N = 587,919)		
Total Absences (TA)	-0.007	-0.004
	(0.0002)***	(0.0001)***
Total Tardies	-0.001	-0.001
	(0.0001)***	(0.0001)***
Adjusted R^2	0.66	0.60
2. Quadratic specification (N = 587,919)		
TA	-0.008	-0.004
	(0.0002)***	(0.0001)***
TA^2	0.00004	0.00001
	(0.00001)***	(0.00001)
Average partial effect (APE)	-0.007	-0.004
	(0.0002)***	(0.0002)***
3. Step function specification (N = 587,919)		
0 to 2 TA	0.038	0.016
	(0.001)***	(0.002)***
3 to 9 TA	(omitted reference category)	
10 to 17 TA	-0.045	-0.024
	(0.002)***	(0.003)***
More than 17 TA	-0.110	-0.062
	(0.004)***	(0.004)***
4. Baseline, excluding chronically absent students (above 95th percentile) (N = 561,696)		
TA	-0.007	-0.003
	(0.0002)***	(0.0002)***
5. Baseline, by type of absence (N = 587,919)		
Excused absences	-0.005	-0.002
	(0.0002)***	(0.0002)***
Unexcused absences	-0.010	-0.006
	(0.0003)***	(0.0003)***
Differential effect t test	$p< 0.0001$	$p< 0.0001$

Notes: Each model controls for lagged achievement, classroom fixed effects, child race/ethnicity, child gender, poverty status, Limited English proficiency (LEP), subject-specific learning disabilities, and total tardies. Standard errors are robust to clustering at the school level. The estimated effects of tardies and the adjusted R^2 in specifications 2-5 are identical to those in specification 1. In specifications 2, 3, and 5 the multiple absence terms are jointly statistically significant at $p < 0.001$.
*** p<0.01, ** p<0.05, * p<0.1.

Table 7. North Carolina estimates of heterogeneity in absences' effect on achievement

	Math achievement		Reading achievement	
	(1)	(2)	(3)	(4)
Lagged standardized score	0.782	0.788	0.744	0.748
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Total absences (TA)	-0.007	-0.006	-0.003	-0.003
	(0.0003)***	(0.0003)***	(0.0003)***	(0.0003)***
Total tardies	-0.001	-0.001	-0.001	-0.001
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
Female	-0.003	-0.003	0.013	0.012
	(0.002)	(0.002)	(0.002)***	(0.002)***
Below poverty level	-0.075	-0.071	-0.092	-0.089
	(0.003)***	(0.003)***	(0.004)***	(0.004)***
Limited English proficiency	-0.006	-0.006	-0.007	-0.006
	(0.010)	(0.010)	(0.012)	(0.012)
Learning disability	-0.208	-0.203	-0.185	-0.181
	(0.009)***	(0.009)***	(0.010)***	(0.010)***
Fifth grade*TA	-0.0003	-0.0003	0.001	0.001
	(0.0003)	(0.0003)	(0.0003)*	(0.0003)*
Female*TA	0.001	0.001	0.0004	0.0005
	(0.0002)**	(0.0002)**	(0.0003)	(0.0003)*
Poverty*TA	-0.0003	-0.001	-0.001	-0.001
	(0.0003)	(0.0003)***	(0.0003)***	(0.0003)***
Limited English proficiency*TA	-0.002	-0.002	-0.004	-0.004
	(0.001)**	(0.001)**	(0.002)**	(0.002)**
Learning disability*TA	0.002	0.001	0.001	0.001
	(0.001)**	(0.001)	(0.001)*	(0.001)
Lagged score*TA		-0.001		-0.001
		(0.0002)***		(0.0001)***
Joint significance of interactions	$p = 0.012$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
Adjusted R^2	0.66	0.66	0.60	0.60

Notes: N = 587,919. Each model controls for lagged achievement, classroom fixed effects, child race/ethnicity, child gender, poverty status, Limited English proficiency (LEP), subject-specific learning disabilities, and total tardies. Standard errors are robust to clustering at the school level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. ECLS-K sensitivity analysis

	Baseline	Un-weighted	Statistical controls	FD	FD IV
	1	2	3	4	5
			Math achievement		
Lag score	0.700	0.700	0.697	0.745	0.745
	(0.011)***	(0.009)***	(0.012)***	(0.113)***	(0.114)***
Total absences	-0.002	-0.003	-0.003	-0.007	0.0005
	(0.001)**	(0.001)***	(0.001)**	(0.003)**	(0.006)
Total tardies	-0.001	-0.001	-0.001	-0.005	-0.006
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Adjusted R^2	0.44	0.44	0.44	-1.64	-1.65
			Reading achievement		
Lag score	0.717	0.717	0.712	0.969	0.966
	(0.010)***	(0.008)***	(0.010)***	(0.146)***	(0.145)***
Total absences	-0.002	-0.002	-0.002	-0.00004	-0.006
	(0.001)**	(0.001)*	(0.001)***	(0.004)	(0.007)
Total tardies	-0.003	-0.003	-0.002	-0.004	-0.004
	(0.001)***	(0.001)***	(0.001)***	(0.003)	(0.003)
Adjusted R^2	0.47	0.47	0.46	-1.95	-1.94
N	11,650	11,650	11,200	2,850	2,850

Notes: Except for column 2, all regressions are weighted by ECLS-K provided weight, C#CW0. Sample sizes are rounded to the nearest 50 to conform to NCES regulations. Each model controls for lagged achievement, classroom fixed effects, child race/ethnicity, child redshirt status, child gender, poverty status, English speaking status, individualized education plans (IEP), and total tardies. Standard errors are robust to clustering at the school level. Column 3 additionally controls for mother's employment status, mother's marital status, and the number of household adults. The first-differenced (FD) models in columns 4 and 5 use twice-lagged test scores as instrumental variables (IV) for the lagged gain scores. Column 5 also instruments for first-differenced absences with lagged absences. *** p<0.01, ** p<0.05, * p<0.1.

Table 9. North Carolina sensitivity analysis

	Baseline	Full sample	Analytic sample	FD	FD IV
	1	2	3	4	5
			Math achievement		
Lag score	0.782	0.782	0.782	0.128	0.127
	(0.003)***	(0.002)***	(0.003)***	(0.015)***	(0.015)***
Total absences	-0.007	-0.007	-0.007	-0.005	0.001
	(0.0002)***	(0.0001)***	(0.0001)***	(0.0004)***	(0.001)
Total tardies	-0.001	.	.	-0.001	-0.001
	(0.0001)***			(0.0003)	(0.0003)***
Adjusted R^2	0.66	0.66	0.66	-0.22	-0.22
			Reading achievement		
Lag score	0.744	0.751	0.744	0.052	0.051
	(0.003)***	(0.002)***	(0.003)***	(0.012)***	(0.012)***
Total absences	-0.004	-0.004	-0.004	-0.003	-0.001
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0004)***	(0.001)
Total tardies	-0.001	.	.	-0.0005	-0.006
	(0.0001)***			(0.0003)	(0.0003)*
Adjusted R^2	0.60	0.60	0.61	-0.13	-0.13
N	587,919	903,314	587,919	157,813	157,813

Notes: Each model controls for lagged achievement, classroom fixed effects, child race/ethnicity, child gender, poverty status, Limited English proficiency (LEP), subject-specific learning disabilities, and total tardies. Standard errors are robust to clustering at the school level. The first-differenced (FD) models in columns 4 and 5 use twice-lagged test scores as instrumental variables (IV) for the lagged gain scores. Column 5 also instruments for first-differenced absences with lagged absences.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.1. Descriptive statistics by tardy status in North Carolina

	Tardies observed	Tardies missing
	Mean	Mean
Standardized math score	0.05	0.08
Standardized reading score	0.04	0.06
Math lag score	0.07	0.09
Reading lag score	0.06	0.08
Total absences	6.27	6.12
Non-Hispanic white	56.3%	57.6%
Non-Hispanic black	26.7%	24.6%
Hispanic	9.6%	10.1%
Non-Hispanic other	7.4%	7.7%
Fifth grade	50.2%	49.9%
Female	50.0%	49.9%
Below poverty level	46.7%	48.3%
Limited English proficiency (LEP)	1.7%	0.8%
Learning disability – math	1.5%	1.4%
Learning disability – reading	3.3%	2.5%
2006	25.1%	9.9%
2007	27.6%	4.3%
2008	27.8%	5.3%
2009	13.2%	30.8%
2010	6.3%	49.7%
N	587,919	315,395

Notes: Excused and unexcused absences are only observed for 46,094 cases when data on tardies are missing. All differences are statistically significant at 1% significance.

Table A.2. Results from balanced ECLS-K K-5 regressions including interaction terms

	Math achievement		Reading achievement	
	(1)	(2)	(3)	(4)
Lag score	0.446	0.433	0.399	0.399
	(0.016)***	(0.020)***	(0.019)***	(0.025)***
Total absences (TA)	-0.005	-0.006	0.0003	0.0003
	(0.007)	(0.007)	(0.005)	(0.005)
Total tardies	-0.003	-0.003	-0.004	-0.004
	(0.002)	(0.002)	(0.002)**	(0.002)**
Female	-0.139	-0.134	0.066	0.066
	(0.042)***	(0.043)***	(0.039)*	(0.039)*
Below poverty level	-0.232	-0.240	-0.275	-0.275
	(0.076)***	(0.075)***	(0.072)***	(0.072)***
Does not speak English at home	0.159	0.160	0.006	0.006
	(0.090)*	(0.089)*	(0.126)	(0.126)
Individualized Education Plan (IEP)	-0.234	-0.232	-0.434	-0.434
	(0.120)*	(0.120)*	(0.135)***	(0.135)***
First grade*TA	0.002	0.003	0.003	0.003
	(0.008)	(0.008)	(0.005)	(0.006)
Third grade*TA	0.002	0.003	0.001	0.001
	(0.007)	(0.007)	(0.005)	(0.005)
Fifth grade*TA	0.003	0.005	0.003	0.003
	(0.006)	(0.006)	(0.004)	(0.004)
Poverty*TA	0.006	0.007	0.002	0.002
	(0.006)	(0.006)	(0.005)	(0.005)
Female*TA	0.0002	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.003)	(0.004)
No English at home*TA	-0.033	-0.033	-0.008	-0.008
	(0.007)***	(0.007)***	(0.024)	(0.023)
Student has an IEP*TA	-0.003	-0.003	0.005	0.005
	(0.007)	(0.007)	(0.014)	(0.013)
Lagged score*TA		0.002		-0.0001
		(0.002)		(0.003)
Joint significance of interactions	$p < 0.01$	$p < 0.01$	$p = 0.98$	$p = 0.99$
Adjusted R^2	0.03	0.03	-0.04	-0.04

Notes: Regressions are weighted by ECLS-K provided weight, C#CW0. N = 4,800, which is rounded to the nearest 50 to conform to NCES regulations. Each model controls for classroom fixed effects, child race/ethnicity, and child redshirt status. Standard errors are robust to clustering at the school level.
*** p<0.01, ** p<0.05, * p<0.1.