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Assessing the Effect of School Days and Absences on Test Score Performance*

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Abstract

While instructional time is viewed as crucial to learning, little is known about the effectiveness of reducing absences relative to increasing the number of school days. Using administrative data from North Carolina public schools, this paper jointly estimates the effect of absences and length of the school calendar on test score performance. We exploit a state policy that provides variation in the number of school days prior to standardized testing and find substantial differences between these two effects. Extending the school calendar by ten days increases math and reading test scores by only 1.7% and 0.8% of a standard deviation, respectively. A similar reduction in absences would lead to gains of 5.5% in math and 2.9% in reading. We perform a number of robustness checks including utilizing flu data to instrument for absences, family-year fixed effects, distinguishing between excused and unexcused absences, and controlling for a contemporaneous measure of student disengagement. Our results are robust to these alternative specifications. In addition, our findings indicate considerable heterogeneity across student ability, suggesting that targeting absenteeism among low performing students could aid in narrowing current gaps in performance.

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1 Introduction

During the last decade, the U.S. federal government and many states have taken a series of steps to improve educational outcomes in elementary, middle, and high school. To this end, many programs have been implemented[1] whose primary aim is to hold schools accountable for the performance of their children. More recently, policy makers have renewed their attention towards[2] the actual number of days that students spend at school. For example, while the federal government is aiming for an extension of the school calendar,[3] many states and cities have already increased the number of school days.[4] Despite these initiatives, little is known about the effectiveness of this type of interventions relative to other possible competing policies. For instance, reducing absenteeism may constitute an alternative avenue for policy as it would target specific students who would benefit the most from being in the classroom. Indeed, there is significant room for improving student attendance; Balfanz and Byrnes (2012) estimate that 5 million to 7.5 million students are missing nearly a month of school. Absences are a pervasive problem present at all schooling levels, even the initial ones. For example, at least 10 percent of kindergartners and first graders miss 10 percent or more of the school year [see, Chang and Romero (2008)]. The impact of these absences -even those in early grades- can have long term effects; chronic absenteeism constitutes an early predictor of dropping out of school [see, Romero and Lee (2007); Connolly and Olson (2012); Attendance Works & Healthy Schools Campaign (2015)]. In addition, absences are costly for schools' and districts' budgets. For instance, in California, absences cost public schools $3.5 billion in state funding based on daily attendance between 2010/11 and 2012/13 [see, Harris (2014)]. Given these large costs, recent initiatives have been designed to reduce chronic absenteeism such as "NYC Success Mentor Corps"[5] and "WakeUp! NYC"[6] which were recently launched in New York City.[7]

[1]For example, the federal government implemented No Child Left Behind beginning in 2001 and North Carolina introduced Accountability for Basic skills and for local Control (ABCs) in 1997.

[2]In 1983, the report "A Nation at Risk" issued by the National Commission on Education Excellence, compared the U.S. school year of 180 days to the longer school calendars in Europe (190 to 210 days) as justification for an increase in school time.

[3]In 2009, President Obama said that the "challenges of a new century demand more time in the classroom" (The New York Times, August 22, 2011). Similarly, the U.S. Secretary of Education, Arne Duncan has stated that "the school day is too short, the school week is too short, and the school year is too short" (Time Magazine, April 15, 2009).

[4]North Carolina recently added five days to the public school calendar.

[5]The NYC Success Mentor Corps is a research-based, data-driven mentoring model that seeks to improve attendance, behavior, and educational outcomes for at-risk students in low-income communities citywide. For more information see http://www.nyc.gov/html/truancy/downloads/pdf/nyc_success_mentor.pdf

[6]Students receive phone calls with pre-recorded wake up messages from Magic Johnson, Jose Reyes, and Mark Texeira, among others.

[7]According to Balfanz and Byrnes (2013), these programs constitute cost-efficient strategies. They found that students in poverty at schools that were targeted by these initiatives were 15% less likely to be chronically absent than

In this regard, the goal of this paper is to quantify the relative effectiveness of reducing absences with respect to extending the school calendar on test score performance based on a sample of elementary school students. While most studies have analyzed the importance of absences or days of class separately,[8] this analysis provides an approach that allows for both effects to be examined simultaneously. We believe that, from a policy perspective this is key, given that extending the school year or reducing absences are likely to affect students at different margins. For example, missing a day of school due to an absence may be more detrimental to a student's performance since they will need to make up for missed work later. Moreover, catching up is likely to be more difficult for low performing students, resulting in larger gaps in academic performance within the classroom. To examine possible heterogeneous effects of absences and days of class, we analyze whether children from relatively low income families, or those who perform poorly, benefit comparatively more from spending increased time at school. Similarly, we try to identify whether the loss of a school day has differential effects depending on the school grade, and whether absences' effects persist in subsequent school years. We believe that providing a detailed analysis of heterogeneous effects will inform the policy discussion in terms of identifying specific groups of the population that may benefit the most from particular interventions. Finally, we investigate the effect of teacher and school quality on absences. We study to what extent attending (having) a better school (teacher) could lead to a decrease in the number of days absent.

Contrary to most of the literature that has considered countries, states, counties, or schools as the unit of analysis,[9] we make use of detailed longitudinal data at the individual level from North Carolina public schools. This allows us to control for students', teachers', and schools' observable and unobservable characteristics. Therefore, this paper is able to analyze the importance of time spent at school from several perspectives (i.e. absences and days of class), as well as to implement a rigorous econometric strategy to address problems of endogeneity in a number of ways. In order to deal with the various threats to identification, such as health shocks, disengagement effects, and omitted variable bias, we employ several different identification strategies. First, we use previous year test scores, student, teacher and school fixed effects, and measures of overall school performance to control for heterogeneity. Second, we control for a contemporaneous measure of student disengagement (i.e. school suspensions). Third, we utilize flu data at the county level to instrument for absences. Fourth, we employ family-year fixed effects to account

similar students at comparison schools. Moreover, they show that those who exited chronic absenteeism experienced significant improvements in their academic performance, leading to important reductions in dropout rates.

[8]See Section 2 for a discussion of the related literature.

[9]For example, Lee and Barro (2001), Pischke (2007), and Marcotte and Hemelt (2008), among others.

for any time-varying family specific shocks. Finally, we examine unexcused absences to take into account any illnesses or other excused events that may affect both absences and grades.[10] Reassuringly, our results are consistent across specifications.

Estimating models with three-way high-dimensional fixed effects when the sample size is large is not a trivial matter. In our case, it requires to estimate an extremely large number of parameters[11] (i.e. 701,166 students; 33,051 teachers; and 1,364 schools), therefore an iterative algorithm is implemented in order to overcome computational issues.

Results show substantial differences between the effect of absences and days of class on test score performance. Our preferred specification indicates that extending the school calendar by ten days would increase math and reading test scores by 1.7% and an insignificant 0.8% of a standard deviation, respectively,[12] while a similar reduction in absences would lead to an increase of 5.5% in math and of 2.9% in reading scores.[13] Estimation results show that absences have an even larger negative effect among low performing kids, suggesting that the costs of catching up are higher among those who show greater difficulties at school. In addition, we analyze whether spending more time at school (i.e. fewer absences or a longer academic calendar) has a larger effect on students in later grades. While being ten days absent in grade 3 leads to a decrease of 2% of a standard deviation in math test scores, in grade 5 the effect is 8.1%. Moreover, we present evidence indicating persistent effect of absences in subsequent grades, particularly in math. Finally, we show that attending (having) a school (teacher) in the 75th percentile of the fixed effect distribution decreases absences by 0.14 (0.14) days relative to the 25th percentile; a relatively large result given that the average number of absences is 6.28 days.[14] Overall, the results point towards the presence of an important asymmetry between the effects of expanding total time spent at school through a reduction of absences or through an extension of the school calendar. However, we should emphasize that expanding or missing instructional time in elementary school are likely to have different implications than, for example, in college. Therefore, these findings should be circumscribed to students that are attending the first years of their schooling careers.

[10]Excused absences are those that are originated by an illness or injury; quarantine; medical appointment; death in the immediate family; called to court under subpoena or court order; religious observance; educational opportunity (prior approval is needed); local school board policy; absence related to deployment activities. A student's absence from school for any reason other than those previously listed is considered as an unexcused absence.

[11]Given that part of our empirical strategy makes use of all fixed effects in a later analysis, we need to recover all the fixed effect parameters (i.e. demeaning the sample is not a feasible alternative in this case).

[12]Sims (2008) also finds no significant effect on reading scores.

[13]The magnitude of these effects are approximately one-third of the size of a one standard deviation increase in teacher effectiveness. (Hanushek and Rivkin, 2010).

[14]These calculations are based on the fixed effects from the math test score regression.

The financial resources required to extend the school calendar are large due to the high fixed cost of operating a school.[15] This fact combined with our findings showing a larger effect of absences than days of class on test score performance are likely to have important policy implications. While policymakers in many countries are discussing changes to the school calendar,[16] making better use of the existing time schemes by reducing absences constitutes an avenue for policy that deserves greater attention. A possible (inexpensive) example of an intervention that reduces absences is the Education Act of 1996 in the United Kingdom. This policy empowers head teachers to issue Penalty Notices for unauthorized absences from school. This means that when a pupil has five or more days of unauthorized absences in any term (where no acceptable reason has been given for the absence), or if their child persistently arrives late for school after the close of registration, their parents or guardians may receive a Penalty Notice of £60 if paid within 21 days, rising to £120 if paid within 28 days. A report on the effectiveness of these fines [Crowther and Kendall (2010)], found that 79% of local authorities said penalty notices were "very successful" or "fairly successful" in improving school attendance.[17] Finally, an alternative path to reduce absenteeism has been suggested by Cuffe, Bignell, and Waddell (2014), who show that increasing participation in extracurricular activities (e.g. athletic competitions) leads to a reduction in unexcused absences for high schoolers.[18]

The remainder of this paper is organized as follows. Section 2 places our work in context with the related literatures on student absences and school length. Section 3 details the data used in the empirical analysis. Section 4 outlines the econometric strategy. Section 5 describes the results. Section 6 presents a series of robustness checks. Section 7 examines the heterogeneous effects of absences and days of class by several student characteristics. Section 8 concludes.

[15] Many calculations indicate that a ten percent increase in time would require a six to seven percent increase in cost (Chalkboard Project (2008), Silva (2007)), this would approximately imply an increase of $527 dollars per pupil in North Carolina.

[16] For example, France has recently extended the length of the school week. See "French Plan to Add to Already Lengthy School Days Angers Parents and Teachers," The New York Times, February 11th, 2013.

[17] Given that for the sample we analyze (i.e. students in grades 3 to 5), parents play a key role in whether or not their child(ren) will attend school, penalty notices are expected to have an effect on reducing unexcused absences.

[18] It is important to distinguish between policies that aim to increase overall attendance from those that try to inhibit chronic absenteeism. While increasing participation in athletic competitions or implementing penalty notices likely intend to promote overall student attendance, programs such as the NYC Success Mentor Corps (see footnote 5) mainly target chronic absenteeism on a specific group of students. The study of the relative effectiveness of these type of polices is a matter that goes beyond the scope of this paper.

2 Background

The length of the school year and a student's total number of absences combine to determine the total amount of instructional time a student receives in a given year. Despite this, their effects on student performance have largely been examined independently; likely due to the lack of available data on absences and the limited variability on school year length.

2.1 Absences

A common finding in the literature is that students with greater attendance than their classmates perform better on standardized achievement tests, and that schools with higher rates of daily attendance tend to have students who perform better on achievement tests than do schools with lower daily attendance rates [Roby (2004); Sheldon (2007); Caldas (1993)]. These correlations present a challenge in estimating the effect of absences on student performance; more able and motivated students are both more likely to attend school and to perform well in their courses and on standardized tests. Therefore, without adequate controls for personal characteristics, part of any estimated effects of absences will reflect a downward ability bias due to endogenous selection.

The literature has addressed this issue in a variety of ways. Devadoss and Foltz (1996) used survey responses to obtain information on student effort and motivation. Dobkins, Gil, and Marion (2010) exploited data generated from a mandatory attendance policy for low-scoring college students. Stanca (2006), Martins and Walker (2006), and Arulampalam, Naylor, and Smith (2012) also examined college student attendance utilizing panel data to try to control for unobserved characteristics correlated with absence, finding that attendance does matter for academic achievement. However, missing a school day at university level may have substantially different effects than in elementary school.

Fewer studies have exploited panel data to examine the effects of absences at the elementary school level. Notable exceptions include Gershenson, Jacknowitz, and Brannegan (2014), Goodman (2014), and Gottfried (2009; 2010; 2011).[19] However, relative to these papers, we are able to jointly control for student, teacher, and school fixed effects.[20] School fixed effects enable us to control for the common influences of a school by capturing systematic differences

[19]Gershenson, Jacknowitz, and Brannegan (2014) and Gottfried (2009; 2011) find results similar to ours.

[20]While Gershenson, Jacknowitz, and Brannegan (2014), Goodman (2014) and, Gottfried (2009; 2011) also control for school fixed effects, family fixed effects or classroom fixed effects, none of them jointly account for student, teacher, and school fixed effects. Due to the large number of fixed effects that we aim to recover estimating this model is not trivial. In this regard, we implement an interative fixed effect estimator that circumvents the data dimensionality problem (see Section 4).

across institutions.[21] This includes curriculum, hiring practices, school neighborhood, and the quality of leadership. Teacher fixed effects control for the common influences of a given teacher, and student fixed effects control for student observed and unobserved heterogeneity. We are also able to identify siblings, allowing us to control for family-year fixed effects combined with previous year test scores.[22] This controls for family-specific shocks such as a death in the family or divorce when estimating the effect of absences.

We utilize North Carolina flu data to instrument for absences and we also examine a specification that includes controls for a contemporaneous measure of student disengagement.[23] Goodman (2014) uses snowfall amounts in Massachusetts to identify the effect of time spent at school on test score performance. However, his findings in math are substantially larger than the ones shown in this paper. For example, in his preferred specification, he finds that ten days of absences induced by bad weather reduce math achievement by 50% of a standard deviation, while our findings range between 5% and 10% of a standard deviation depending on the specification.[24] Finally, he finds that school closure due to snowfall has no effect on test score performance, while we find positive and significant effects of an extra day of class. Differences in the results may be due to several factors. First, we control for a larger set of fixed effects (i.e. student, teacher and school fixed effects). Second, we use flu data to instrument for absences, while he uses snowfall, leading to possible different local average treatment effects. Third, the marginal absence providing identification in Goodman (2014) is one induced by bad weather; which is not likely to be the main driver of student absences like it could be illness. Fourth, instructional loss due to weather is unlikely to be totally exogenous. In Massachusetts, snow is a normal winter occurrence and as such, schools may already be accounting for cold weather related absences when setting their yearly school calendar. Finally, certain features of the North Carolina data make this database more suitable for this type of analysis than the Massachusetts data. Namely, administrative records in Massachusetts provide data on days absent and number of school days for the whole school year, rather than until the day of the exam, as is the case for our sample; and schools in Massachusetts can endogenously reschedule test dates in reaction to winter conditions, while North Carolina does not reschedule end of grade (EOG) testing.[25]

[21] 19.16% of students that are in the sample for more than one year are observed at multiple schools.

[22] Gottfried (2011) also employs a family-year fixed effect approach in analyzing student performance in the School District of Philadelphia.

[23] Other studies implement alternative instruments. For example, Gottfried (2010) uses distance from school to identify the effect of attendance on test scores and finds a positive relationship.

[24] His results without instrumenting for absences and incorporating student fixed effects are smaller, although still larger than our results (approximately 30% larger than our preferred specification).

[25] These different features of the data could explain why he did not find positive statistical effects of an extra day of class while we do find positive effects.

2.2 Length of the School Year

A number of previous studies have examined the effects of length of the school year on student achievement. Several studies on school quality in the United States include term length as one of the regressors [see, e.g., Grogger (1996) and Eide and Showalter (1998)] but typically find insignificant effects. The biggest stumbling block to uncovering the impact of school days on student performance is the lack of variation in the total number of school days in an academic year. We overcome this problem thanks to a specific North Carolina policy that provides variation in the number of instructional days across schools before the day of the exam.[26]

Most studies examining the length of the school year use state or country level data [see, e.g., Card and Krueger (1992); Betts and Johnson (1998); Lee and Barro (2001)]. Card and Krueger (1992) and Betts and Johnson (1998) found positive and significant effects of length of the school year on earnings for birth cohorts in the first half of the 20th century, which had more variability in the number of school days.[27] Lee and Barro (2001) utilized cross-country data and examined the correlation of student performance and measures of school resources, including the number of class days. They found that more time in school increased mathematics and science scores, but lowered scores in reading, which is largely consistent with our findings for math; however, we find a positive effect on reading. Differently from previous papers, we are able to use within school variation in days of class. Moreover, we use microlevel data at the student level which allows us to explore policy relevant heterogeneous effects of increasing school days.

Other studies have exploited quasi-experimental variation to identify the effect of additional days of class. Marcotte and Hemelt (2008) examined the effect of fewer days of class resulting from snow-related school closures on test score performance and found that the pass rate for third grade math and reading assessments falls by more than a half percent for each school day lost due to an unforeseen closure. Hansen (2011) examined both school closures due to weather in Colorado and Maryland as well as state-mandated changes in test-date administration in Minnesota. He found that in both cases more instructional time prior to test administration increases student performance. Pischke (2007) utilized variation introduced by the West-German short school years in 1966-67, which exposed some students to a total of about two-thirds of a year less of schooling while enrolled. He found that the short school years increased grade

[26] More specifically, North Carolina allows for flexibility in the setting of the testing date, which is when academic achievement is measured. See Section 3 for a more detailed discussion.

[27] Card and Krueger (1992) presented additional results including a state fixed effect; the positive effect of term length vanished within states and conditional on other school quality variables.

repetition in primary school and led to fewer students attending higher secondary school tracks.[28] Relative to Pischke, we examine a smaller change in the number of days of class; however, it is of the approximate size considered by policy makers.[29] Finally, Fitzpatrick, Grissmer, and Hastedt (2011) exploit quasi-randomness in the timing of assessment dates to examine the effect of days of class on test score performance in kindergarten. Their estimates suggest that an additional day of school results in gains of about 0.05 standard deviations in both reading and math test scores. However, as in Pischke (2007), the time gap in tests they exploit for their analysis is larger (i.e. some students had only 60 days of class until the day of the exam while others had over 200).

Our paper is most similar to Sims (2008), who studied the effect of days of class, using the implementation of a Wisconsin state law that restricted districts to start dates after September 1st to identify the effects of this extra time on student achievement. He found that an additional week of class was associated with an increase of 0.03 standard deviations in math scores for fourth graders, but he found no effect on average reading and language scores. We find smaller effects of additional days on scores. This difference can be attributed to our use of a different econometric strategy and of individual level data.

3 Data and Descriptive Statistics

3.1 Data

The North Carolina education data is a rich, longitudinal, administrative data set that links information on students, teachers, and public schools over time. This database is maintained by the North Carolina Education Research Data Center (NCERDC), which is housed at Duke University.

Students in North Carolina have to take (standardized) exams in math and reading at the end of the school year, with the aim to assess whether they have met grade-level expectations.[30] Performance in these tests is comparable across time and grades through the use of a developmental scale, where each point on this scale measures the same amount of learning. For example, a student who shows identical growth on this scale in two consecutive grades is interpreted as having learned equal amounts in each year.[31] Due to this institutional setting, our longitudinal

[28] Pischke (2007) found no effect on earnings.

[29] In North Carolina, the school year was recently extended by 5 days. In contrast, Pischke's findings are due to a change in about 100 days of schooling.

[30] All students in North Carolina take the same test conditional on school grade.

[31] Tests are administered by the classroom teacher, while the test coordinator (who is chosen by the superintendent

database provides information on mathematics and reading test scores for each student in elementary,[32] middle, and high school. Since the availability of some of the data varies over time, the analysis is restricted to the years 2006 to 2010[33] and grades 3 to 5.[34] The nature of the dataset makes it possible to track the progress of an individual student over their educational careers and link students to their teachers[35] and school in each year, provided they stay within the universe of North Carolina public schools.

NCERDC records also include extensive information on student, teacher, and school characteristics. Data on students include ethnicity, gender, whether or not they participated in the federal free and reduced price lunch subsidy program, geocoded address, number of days suspended from school, days in membership and absences. Days in membership is used to calculate the number of days of class prior to the exam.[36] It is defined as the number of days the student was on the roster in a particular school; a student is in membership even when absent. Note that days in membership only includes days of instruction, but not designated teacher work days.[37] Absences data include both the total number of days, as well as disaggregated data by excused and unexcused absences. All absences and days in membership data are collected at the time of end of grade (EOG) testing.

Only counts of days absent are provided for each student and each academic year; it is not possible to specifically discern when a student was absent. The NCERDC data categorizes absences as either excused or unexcused; excused absences are defined as the ones due to illness or injury; quarantine; medical appointment; death in the immediate family; called to court under subpoena or court order; religious observance; educational opportunity (prior approval is needed); local school board policy; absence related to deployment activities. All other absences are categorized as unexcused.[38] Aside from the distinction between excused and unexcused

of the district) oversees the grading, which is done at the local education agency level.

[32]More specifically, for grades 3 and above. Students in lower grades do not take end of grade (EOG) tests. Pupils in grades 4 to 5 are tested only at the end of the academic year (i.e. May or June). However, students in grade 3 take the "previous year/baseline" test at the beginning of the academic year, and the EOG test in May or June of that same academic year.

[33]School years are referred to by the year the school year ended. For example, the 2005/06 school year is year 2006.

[34]Younger students are less likely to skip school without parental knowledge, limiting issues of endogeneity. In addition, students in upper grades can take courses with multiple teachers, making the estimation of teacher fixed effects problematic.

[35]The data does not identify student's teachers directly, but rather identifies the individual who administered the end of grade exams. In elementary school, classrooms are largely self-contained with the classroom teacher proctoring the exam.

[36]In practice, days of class is the modal days in membership at the school level.

[37]This implies, for example, that days that a school (or district) sets aside for teacher training in which students have the day off are not considered as days of class. However, if a teacher is absent to attend a training course, a substitute would fill in for the teacher and it would be counted as a day of class.

[38]More information on North Carolina's attendance policies can be found at: http://www.ncpublicschools.org/docs/fbs/accounting/manuals/sasa.pdf.

absences, no further details are provided as to the reason for the absence.[39]

In addition to the main sample, the sample of students who are siblings is also employed. Following Caetano and Macartney (2013), the geocoded address data are used to identify students living in the same household to create a family identifier. Two or more children who share the same home address in a given academic year are considered to be part of the same household. Even if the address changed between years, as long as the students remain together at the new address, they are considered to be members of the same household. As a result, the ability to observe children's addresses as they progressed through elementary school makes it possible to identify family-year fixed effects.

Teachers that are matched with less than five students are not included in an effort to avoid special education (or other specialty) classes as well as minimize sampling error when estimating fixed effects. Moreover, teachers with more than 30 students in a school year are excluded due to possible data miscoding.[40] The total number of student-year observations for 2006-2010 is more than 1,302,000 while the total number of teachers included is more than 33,000.

3.2 Descriptive Statistics

Table 1 presents descriptive information on the sample of students in grades 3 to 5. Students are absent on average 6.28 days of school prior to the exam. Figure 1 depicts the distribution of absences in the data. While the distribution is centered around five days of class, a sizable proportion of students are absent for much longer; 25% percent of students miss nine days (just under two weeks) of class and 10% miss 13 days or more, each year, prior to the day of the exam. Interpretation of results typically focuses on the effect of the average number of absences on performance. However, it is important to recognize that, for a sizable share of the sample, reducing absences would have a much larger impact.

North Carolina has an ethnically diverse student body with 25.9% of students identifying as black and over 10% as Hispanic. Relative to the United States in the 2010 Census, North Carolina has a greater share of black school-age children and a slightly smaller Hispanic population. Males and females are equally represented in the data. Just under half of elementary school students are eligible for the free or reduced price lunch subsidy program, a measure of low-income status. In addition, 13.98% of students are categorized as special education students and 7% are classified as having limited english proficiency. Finally the proportion of students

[39]Note that number of excused and unexcused absences are attached to the students records (i.e. exam scores).

[40]Teachers can be followed over many periods. Therefore, we can know, for example, whether they have changed schools or not.

that has ever been suspended is 6.79%, where the average length of suspension is 3.18 days. Note that North Carolina ranks third nationally in the rate of school suspensions behind South Carolina and Delaware.

Table 1: Descriptive Statistics for North Carolina Public School Students, Grades 3-5

	Mean	s.d.
Days Absent	6.28	5.66
Days of Class	166.17	3.61
Suspensions:		
Ever Suspended (%)	6.79	25.16
Days Suspended*	3.18	4.22
Race (%):		
White	55.93	49.65
Black	25.86	43.79
Hispanic	10.60	30.79
Asian	2.38	15.24
Other	5.23	22.26
Gender (%):		
Male	50.21	50.00
Female	49.79	50.00
Other characteristics (%):		
Free/reduced lunch eligible	47.90	49.96
Special education	13.98	34.68
Limited english proficiency	7.04	25.58
N	1,302,037	

Source: NCERDC, 2006-2010. End of grade test scores are standardized by year and grade level. The sample is based on students having required test scores and total absences information, and are linked to a teacher with at least 5 and no more than 30 students. Final analytical samples also require non-missing information for all included variables.

*Conditional on suspension.

As younger students are less likely to skip school without parental knowledge, by limiting the sample of analysis to grades 3 to 5 we are able to minimize issues related to this source of endogeneity.[41] In addition, students in these grades are more likely to enjoy self-contained classrooms and therefore the link between teachers and students is more reliable as compared to those in higher grades.

Researchers have demonstrated that students with greater attendance than their classmates perform better on standardized achievement tests, and that schools with higher rates of daily attendance tend to have students who perform better on achievement tests than do schools with lower daily attendance rates [Roby (2004); Sheldon (2007)]. Table 2 examines absences by

[41]In the NCERDC data, middle school students do exhibit slightly more absences, driven largely by a greater number of the unexcused type.

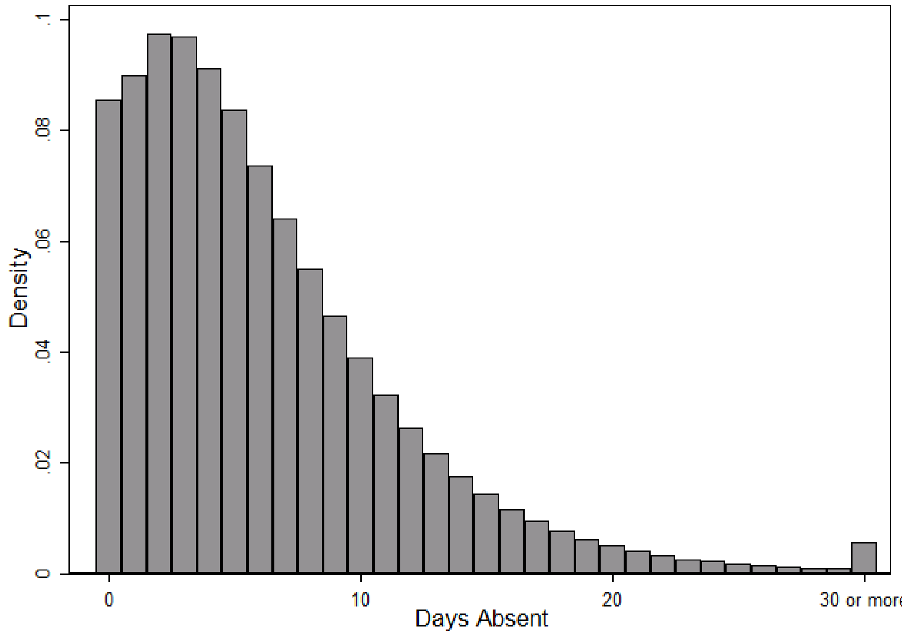

Figure 1: Distribution of Absences

student characteristics, including quintile of last year's prior math score. Students with lower prior year test scores generally have a greater number of absences. This result is largely driven by unexcused absences, which exhibits a stronger negative relationship with lagged math test scores.[42] This suggests that students who are less capable are also more likely to miss school. Simple ordinary least squares (OLS) will therefore result in biased coefficient estimates; without adequate controls, part of any estimated effects of absences will reflect a downward ability bias due to endogenous selection.

Table 2 also highlights racial and gender differences in total number of absences as well as their distribution between excused and unexcused types. White students have a greater number of absences than other racial groups with an average of 6.73 days a year. Blacks and Hispanics are absent 5.72 and 5.42 days respectively. However, a greater share of absences are excused for white students relative to both the other two racial groups. Males have slightly more absences than do females due to a greater number of unexcused absences. There does not appear to be any time trend in absences.

Although students may have varying quantities of instructional time prior to EOG tests resulting from absences, schools also differ in the number of actual class days prior to exam administration. During the sample period, the Department of Education mandated 180 days

[42]This pattern holds when examining absences relative to prior reading score.

Table 2: Average Number of Absences

	Total Absences		Excused Absences		Unexcused Absences	
	Mean	s.d.	Mean	s.d.	Mean	s.d
Grades 3-5						
Average:	6.28	5.66	3.55	4.30	2.41	3.40
Prior Math Score:						
Lowest Quintile	6.91	6.28	3.62	4.51	3.08	4.01
Second Quintile	6.43	5.83	3.60	4.36	2.67	3.56
Third Quintile	6.24	5.59	3.65	4.35	2.39	3.28
Fourth Quintile	5.96	5.28	3.62	4.19	2.10	2.95
Highest Quintile	5.50	4.92	3.40	4.02	1.72	2.55
Sex:						
Male	6.34	5.73	3.55	4.32	2.47	3.46
Female	6.21	5.59	3.54	4.27	2.35	3.33
Race:						
Asian	4.06	4.33	2.16	3.25	1.46	2.52
Black	5.72	5.68	2.59	3.75	2.79	3.84
Hispanic	5.42	5.06	2.60	3.54	2.63	3.50
White	6.73	5.70	4.22	4.56	2.20	3.13
Year:						
2006	6.34	5.80	3.64	4.40	2.43	3.43
2007	6.66	5.87	3.54	4.51	2.20	3.34
2008	6.20	5.68	3.68	4.23	2.50	3.44
2009	5.87	5.40	2.91	3.59	2.73	3.46
2010	6.32	5.54	3.19	3.72	2.61	3.19

Source: NCERDC, 2006-2010. Samples are based on students having required test scores and total absences information and are linked to a teacher with at least 5 and no more than 30 students. The sum of excused and unexcused absences do not sum to total absences as absence counts by type are only available for approximately two-thirds of the student-year observations. When missing, absences by type are generally missing at the school, rather than student, level.

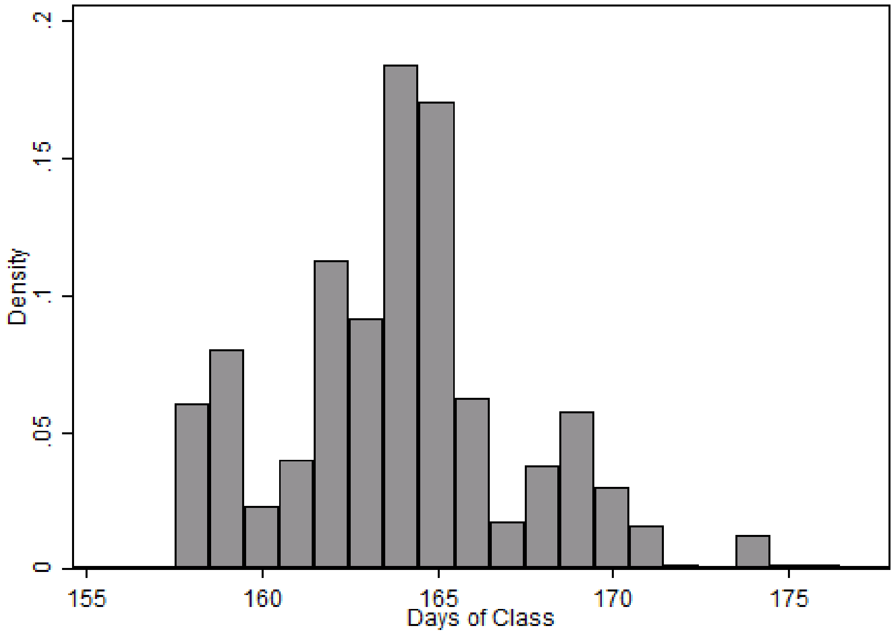

Figure 2: Variation in Days of Class across Schools

of class.[43] However, the North Carolina Department of Public Instruction dictates a window of time for exam administration with the specific testing date chosen by the local education agency (LEA).[44] As a result, students at different schools may have had a differing number of instructional days at the time academic performance was measured, as can be seen in Figure 2.[45] While schools are not actually extending the school year, the number of instructional days prior to the test are adjusted when the LEA sets the school's EOG testing date.[46,47] This variation in instructional days,[48] coupled with data on absences allows for the separate identification of

[43]Only two districts, Forsyth and Guilford Counties, had additional days of class.

[44]http://www.ncpublicschools.org/accountability/calendars/archive lists the testing windows for all tests administered in North Carolina since 2001. A LEA in North Carolina is typically a county.

[45]Figure 3 in appendix A shows variation in days of class within school over time. Given that the econometric strategy makes use of school fixed effects, this is the relevant variation in our analysis.

[46]The North Carolina Department of Public Instruction provides a testing window during which schools administer the end of grade exams, giving some flexibility as to when schools test their students. School district authorities (not the school principal) are responsible for setting the testing dates (within the testing window) for a given school. Therefore, given this institutional setting and the fact that our empirical strategy includes several controls for peers and schools' lagged performance in addition to school, teacher and students fixed effects, we believe that our estimates on the effect of days of class do not to suffer from omitted variable bias.

[47]The fact that the North Carolina Department of Public Instruction dictates a window of time for exam administration leads to some concerns regarding cheating (i.e. schools that take the exam earlier may provide information about the test to schools that take it later). While NC public school system has adopted many measures to avoid this type of behavior, it is difficult to completely rule out this possibility. However, if cheating was driving our results, then we would expected large effects on days of class (i.e. taking the exam later), but this is not the case as we show in the results section.

[48]The number of days of class prior to the EOG exam varies between 158 and 180 days.

the effect of absences from additional days of schooling.[49]

4 Methodology

The data enables us to observe the EOG test scores, the number of class days, and the absences of students in each year for grades 3 to 5 until the day of the test. Our primary aim is to estimate the causal effect of both an absence and an additional day of instruction on performance. The number of instructional days prior to the exam varies across schools and years and therefore enables the identification of the effect of absences separately from additional instructional time.

In analyzing the effect of absences on performance, there are potential problems of endogeneity bias. As shown in Table 2, more able and motivated students appear more likely to both attend school and score highly in their courses and on standardized tests. Therefore, without adequate controls, part of any estimated effects of absences will reflect a downward bias due to endogenous selection. This bias could be minimized with good proxies for ability, engagement/motivation, or other individual characteristics.[50]

Our first strategy to deal with the potential problem of omitted variable bias exploits the panel properties of the data. Student fixed effects are used to control for all observed and unobserved student characteristics that are constant over time. This potentially includes student effort, motivation and ability, as well as familial factors such as parental willingness for their child to miss school or their efforts to help with school work at home.

School fixed effects are also included in the model to control for the common influences of a school by capturing systematic differences across institutions. These include curriculum, hiring practices, school neighborhood, and the quality of leadership. These effects are identified by teachers who switch schools during grades 3 through 5. Teacher fixed effects are included to control for the common influences of a teacher. Finally, fixed effects for grade and year parse out the effect of schools and teachers from other common influences that occur across the population in a given year and for a given cohort.

The main equation of our model is:

$$y_{igkst} = \beta_0 + \beta_1 a_{it} + \beta_2 d_{ist} + \beta_3 X_{it} + \beta_4 G_{ig} + \beta_5 T_t + \beta_6 E_{st} + \alpha_i + \theta_k + \delta_s + \epsilon_{igkst} \quad (1)$$

[49] The exam date is set at the beginning of the school year. Therefore, schools cannot extend the number of days of class prior to the exam based on shocks that occur during the academic year.

[50] The data contain information on the students' prior year test score which is also included in several specifications of the model.

where y_{igkst} denotes the test score of student i, in grade g, teacher k, school s, and year t where the test score is standardized by grade, year and subject. The explanatory variables of interest are a_{it} and d_{ist}; a_{it} is the number of absences over the course of the school year up to the day of the exam; d_{ist} is the number of days of instruction prior to the examination day. X_{it} is a vector of student covariates, G_{ig} are grade fixed effects, T_t are time fixed effects, and E_{st} is a vector that controls for average absences of peers (to account for spillover effects), proportion of students in the school that achieved proficiency during the previous academic year, and average performance of peers in the prior year. α_i, θ_k, and δ_s denote student, teacher, and school fixed effects respectively. Given the large number of student (701,166), teacher (33,051) and school (1,364) fixed effects that we are trying to recover, estimating equation (1) is not trivial. In this regard, we employ an iterative fixed-effects estimator introduced by Arcidiacono, Foster, Goodpaster, and Kinsler (2012) to reduce the computational cost of estimating the multi-level fixed effects model of student achievement.[51].

A value-added model of student achievement is also implemented. The feature of including a lagged achievement score at the individual level implies, according to the literature of teacher value added [Todd and Wolpin (2003)], that it is no longer necessary to incorporate additional measures of ability or previous years inputs (i.e. previous year test score serves as a sufficient statistic for unobserved input histories).

5 Baseline Results

Table 3 presents the regression results for math and reading, based on Equation (1). Specification (1) is a simple OLS regression of standardized test scores[52] without any fixed effects or controls for student ability. The coefficients on absences for both math and reading are negative, significant and large in magnitude. However, since there are no controls for unobserved individual characteristics, which are in all probability negatively correlated with absences, the absolute value of the coefficient is likely to be biased upward. We expect that once adequate controls are included, the absolute value of this coefficient will decrease. Similarly, the coefficient of days of class shows the opposite sign of what was hypothesized and it is likely to suffer from omitted variable bias.

Specification (2) includes student fixed effects, thereby controlling for observed and unobserved student characteristics that are constant over time. An additional absence results in

[51]Appendix B describes the algorithm that we use to estimate equation (1)
[52]Test scores are standardized at grade-year level.

Table 3: Baseline Regression

	Math Test Score							Reading Test Score						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Days Absent	-0.0198***	-0.0067***	-0.0066***	-0.0057***	-0.0055***	-0.0076***	-0.0076***	-0.0113***	-0.0036***	-0.0036***	-0.0031***	-0.0029***	-0.0039***	-0.0039***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0001)
Days of Class	-0.0073***	0.0001	-0.0002	0.0006**	0.0017***	0.0011**	0.0015***	-0.0051***	0.0001	-0.0001	0.0001	0.0008	0.0017***	0.0018***
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0004)	(0.0003)
Student FE	No	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	No	No
School FE	No	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Teacher FE	No	No	No	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes
Controls	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes	No	Yes
Lagged Student Score	No	No	No	No	No	Yes	Yes	No	No	No	No	No	Yes	Yes
N	1,302,037	1,302,037	1,301,254	1,248,497	814,127	878,586	814,128	1,302,037	1,302,037	1,301,254	1,248,497	814,127	878,586	814,128

Source: NCERDC, 2006-2010, grades 3-5. Dependent variable is standardized by grade and year. All specifications include dummy variables for grade, year, and free/reduced price lunch status. Specifications without student fixed effects also include dummy variables for race and gender. Controls include average absences of peers, proportion of students in the school that achieved proficiency level in the previous academic year, and lagged average performance of peers, Bootstrapped standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

math (reading) scores declining by 0.67% (0.36%) of a standard deviation. Therefore, a student with the average number of absences[53] would see their math (reading) score decline by 4.21% (2.26%) of a standard deviation. Additional days of class has a positive, but insignificant effect on both math and reading performance. The inclusion of school fixed effects (specification (3)) has little effect on the magnitude of the coefficient of interest for either subject.[54]

Specification (4) includes three-way high-dimensional fixed effects and finds significant, although slightly smaller coefficients on days absent relative to the previous specifications. Reducing absences by the average (6.28 days) results in scores declining 3.58% and 1.95% of a standard deviation respectively for math and reading. Additionally, the effect of days of class on math test scores is now significant, although smaller in magnitude relative to absences, with test scores increasing 0.38% of a standard deviation for an equivalent increase in school days.

In addition to the three-way high-dimensional fixed effects, specification (5), our preferred specification, includes average peer absences (in order to capture possible spillover effects), and more importantly, it incorporates controls for school lagged performance (i.e. average performance of classmates on the previous year's exam, and the percent of students in the school who achieved proficiency in the prior academic year). The results show a similar pattern as before, where the absolute effect of being absent is almost three times larger than the effect of an extra day of class.[55] Notice that the sample size decreases due to the addition of extra controls (estimating specification (4) with the sample from specification (5) produces similar results).

Specification (6) examines a model with lagged achievement, and teacher and school fixed effects.[56] The coefficient on days absent is slightly larger in magnitude relative to the preferred specification; where reducing absences by the average results in scores declining by 4.77% and 2.45% of a standard deviation for math and reading respectively. The equivalent increase in school days would increase math scores by 0.69% and reading scores by 1.07% of a standard deviation. Finally, specification (7) mimics specification (6) but it adds the same three controls as in specification (5) (i.e. average peer absences, average performance of classmates on the previous year's exam, and percent of students in the school who achieved proficiency in the

[53]The average student in grades 3-5 is absent 6.28 days of school.

[54]Table 13 (in appendix C) provides an alternative specification where number of days absent divided by days of class is included as an independent variable. Results remain very similar.

[55]Results do not change if instead of controlling for average peer absences, we control for average lagged peer absences.

[56]The sample size is smaller in this specification because, for a given year, we do not have data on previous year test scores for students (except in grade 3). Running a specification with three-way high-dimensional fixed effects on this sample provides similar results as the ones currently reported in specification 4 (i.e. the change in the sample size is not driving the difference in results).

prior academic year), which results in little change to the coefficients of interest.[57]

In summary, the absolute value of the effect of each additional absence on test scores appears to be larger relative to an extra day of class.[58] The fact that absences have a greater effect on math achievement than on reading achievement is consistent with the general finding that educational inputs and policy have relatively larger impact on math achievement [Hanushek and Rivkin (2010); Jacob (2005); Rivkin, Hanushek, and Kain (2005)], perhaps because children are more likely to be exposed to reading and literacy outside of school, particularly at home where parents may be more apt to help their children learn and develop reading skills [Currie and Thomas (2001)].

6 Robustness Checks

Despite the set of controls that have been included in Table 3 (i.e. student, teacher, and school fixed effects, previous year test score, school lagged performance, peer absences, and free/reduced price lunch status), our results may still be driven by confounding effects. For example, student engagement may not be fixed over time or family/health shocks could affect absences and test score performance in a way that may not be captured by our extensive set of controls. In this section we provide a series of robustness checks.

6.1 Student Disengagement

The fact that students may lose interest in classroom activities during their schooling career suggests that the dynamic component of this type of behavior cannot be captured by the addition of student fixed effects. This may cause concern that our results for absences are in fact driven by a correlation between "lack of interest in school" and the decision to not attend class. To this end, we present several pieces of evidence that assess the importance of this potential threat to our identification strategy.

First, recall that our sample corresponds to students from grades 3 to 5. Therefore, the decision to be absent from school needs to be (at least tacitly) supported by their parents. This

[57]The number of observations in specification (5) is smaller than in specification (7) because we are additionally controlling for student fixed effects.

[58]Given that the math and reading tests are common across schools and designed around the representative length of the school calendar, then it is possible to argue that a more curriculum-independent test might have been needed in order to pick up school calendar effects. While we cannot fully discard this possibility, many students in North Carolina do not perform particularly well in the end of grade exams. For example, 26.4% of them do not even achieve proficiency level. Therefore, it is apriori expected that more days of class should have an impact in test score performance even if the test is not changed.

Table 4: Student Disengagement Regression

	Math Test Score		Reading Test Score	
Days Absent	-0.0051***	-0.0049***	-0.0027***	-0.0025***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Suspensions		-0.0057***		-0.0045**
		(0.0014)		(0.0021)
Student FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	364,448	364,448	364,448	364,448

Source: NCERDC, 2006-2008, grades 3-5. Dependent variable is standardized by grade and year. All specifications include days of class and dummy variables for grade, year, and free/reduced lunch participation. Controls include average absences of peers, proportion of students in the school that achieved proficiency in the previous academic year, and lagged average performance of peers. Bootstrapped standard errors are reported in parenthesis. The sample is smaller than our main estimating sample as suspensions are only available until year 2008 and for approximately two-thirds of the student-year observations. Suspensions are generally missing at the school level. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

suggests that endogeneity issues should be of less concern relative to a sample of high school students.

Second, we include a proxy for student disengagement to our baseline specifications. More specifically, total days suspended is added as a measure of misbehavior. The total days of suspension is the sum of in-school and out-of-school suspensions.[59] If student disengagement is affecting our results, we should expect a decline in the effect of absences once controlling for suspensions. Table 4 shows that the coefficients on absences are in fact fairly constant across specifications. The first column for both math and reading corresponds to the baseline specification in Table 3.[60] For math (reading), the effect on absences only changes from -0.0051 (-0.0027) in our baseline specification to -0.0049 (-0.0025) after controlling for suspensions (see columns 2 and 4).

Finally, we employ an instrumental variables approach, in which we instrument the number of absences with data on flu outbreaks at the county level in North Carolina. The flu is a contagious respiratory illness that affects all ages; however, school-aged children are the group with the highest rates of flu illness.[61] We use data from the North Carolina Disease Event

[59] In-school suspensions are usually served in an in-school suspension classroom. When a school does not have an in-school suspension program or when offenses are more serious or chronic, they may be dealt with through short-term, out-of-school suspensions. Long-term suspensions are more than ten days in length may be used for more serious offenses and are served out-of-school. Approximately 6.79% of students in our sample have been suspended at some point in time.

[60] The sample size is smaller as data on suspensions is only reported until 2008.

[61] Center for Disease Control, http://www.cdc.gov/flu/school/guidance.htm

Tracking and Epidemiologic Collection Tool (NC DETECT) provided by the North Carolina Division of Public Health[62] which has been collecting the number of influenza-like illnesses (ILI) affecting kids between the age of 5 and 12 years since January of 2008.[63,64]

In order for a measure of flu activity to be an appropriate instrument for absences, it must be correlated with absences and only impact test score performance through missing days of schooling. While one may be concerned that the flu has a direct impact on EOG scores, the flu season commonly peaks in January, February, or March[65] well before the EOG tests are administered.[66] Moreover, our data show low flu activity during the months exams take place.[67] Therefore, this is not likely to be an important threat to our identification strategy. However, even though our data correspond to flu cases in children between the ages of 5 and 12, a possible concern is that flu outbreaks may also affect teacher attendance, and therefore may confound the effects of student and teacher absences. Unfortunately, we only have data on teacher absences due to sickness through the 2008 school year, while our data on flu outbreaks start in January of 2008. However, as we show in appendix D (Table 14), adding teacher sick days to our baseline specification does not affect our coefficient on either days absent or school days.[68] Furthermore, it does not have a substantial effect on students' performance. This result is consistent with the fact that the availability of substitute teachers in North Carolina is likely to lessen the potential harm from teacher absences.[69]

[62]NC DETECT is an advanced, statewide public health surveillance system. NC DETECT is funded with federal funds by North Carolina Division of Public Health (NC DPH), Public Health Emergency Preparedness Grant (PHEP), and managed through a collaboration between NC DPH and the University of North Carolina at Chapel Hill Department of Emergency Medicine's Carolina Center for Health Informatics (UNC CCHI).

[63]ILI cases are reported by N.C. hospital emergency departments.

[64]More specifically, NC DETECT has provided the total number of ILI cases per month in each N.C. county affecting kids between the age of 5 and 12 (the total number of counties in N.C. is 100). If the number of cases in a given county-month data cell is greater than zero but less than ten, then the information is censored. We use multiple imputation techniques [Royston (2007)] in order to deal with those values that we do not observe but we know are in the range between one and nine visits. Results are similar, if instead of using multiple imputation techniques, we just replace the censored values with specific numbers (i.e. one, five, or nine). Finally, we aggregate the data at the academic year level (i.e. August to June). The resulting proportion of ILI cases that are imputed is small (i.e. 7.9% across both the 2008/09 and 2009/10 seasons).

[65]According to CDC, in the last thirty years flu activity most often peaked in February (45% of the time), followed by December, January and March (which each peaked 16% of the time). It has never peaked after March. Source: http://www.cdc.gov/flu/about/season/flu-season.htm

[66]EOG tests are generally administered at the end of May or later. The inclusion of controls for ILI activity in May and June in our baseline regressions do not alter the results.

[67]6.3% of yearly flu visits occurred in May and 5.8% in June.

[68]The results do not change across specifications (with or without teacher sick days) but the coefficient on school days becomes insignificant due to fewer years of data that we can use in this regression (i.e. only years 2006-2008), therefore leading to less variability over time.

[69]Finally, another potential threat to identification is if students that get the flu are not a random subset of the population due to the effect of the flu vaccine. However, the chances of showing flu symptoms after being vaccinated are still large. CDC (Centers for Disease controls and Prevention) claims that an important role in determining the likelihood that flu vaccine will protect a person from flu illness is the similarity or "match" between the flu viruses the flu vaccine is designed to protect against and the flu viruses spreading in the community. More specifically, they

We define the instrument as:

$$IV_{flu,c,yr} = \left(\frac{\sum\limits_{m} ILI_{c,m}}{\frac{N_{c,yr}}{10{,}000}} \right)$$

where $ILI_{c,m}$ is the number of influenza-like illness cases in county c in month m (the analysis uses data from August to June, which corresponds to the academic year) and $N_{c,yr}$ is the number of elementary school students in county c during the academic year yr.[70] The IV then is the number of ILI cases per 10,000 school-aged children.[71,72]

Table 5 shows the results of OLS (benchmark case) and IV regression specifications for math and reading.[73] Columns (2) and (4) indicate that the effect of absences after instrumenting with flu outbreaks is larger than days of class.[74,75] More specifically, a one day reduction in absences would lead to increases of 1% and 1.8% of a standard deviation in math and reading (though the coefficient in the math specification is not statistically significant), respectively. This is approximately similar to our benchmark OLS specification result for math in column (1), but the IV results for reading are almost five times larger than its corresponding benchmark (i.e. -0.0182 compared to -0.0043). Given that IV recovers LATE effects, it is not surprising that the magnitude of the coefficients is larger than in the OLS specifications.[76]

In summary, the fact that including suspensions and instrumenting absences with flu data are not affecting our main results (i.e. the effect of absences is larger than that for days of class) suggest that disengagement effects are not likely to be driving our results.

state that "during years when the flu vaccine is not well matched to circulating viruses, it's possible that no benefit from flu vaccination may be observed (...) Even during years when the vaccine match is very good, the benefits of vaccination will vary across the population, depending on characteristics of the person being vaccinated and even, potentially, which vaccine was used." (Source: http://www.cdc.gov/flu/about/qa/vaccineeffect.htm). In this regard, according to CDC, vaccine effectiveness during the 2007/2008 season was only 37%.

[70] The number of elementary school students in a county is the sum of all students in grades K to 8, which generally corresponds to ages 5 to 12.

[71] The IV variable is defined per 10,000 school-aged children to be consistent with the rest of the literature which typically defines ILI rates per 10,000 or 100,000 population.

[72] Note that we are only instrumenting for number of days absent.

[73] All 2SLS specifications in this paper have very strong first stages (see Table 15 in appendix E). The coefficient on the instrument has a p-value of 0.000 in all specifications. Figure 4 (in appendix E) shows the presence of substantial variability in the number of flu cases across counties.

[74] The sample size is smaller than in previous specifications given that flu data is only available from 2008.

[75] The exam date is set at the beginning of the school year. Therefore, schools cannot extend the number of instructional days prior to the exam in response to a severe flu season.

[76] For example, if compliers are students who benefit the most from attending school, then instrumental variables estimates should exceed the fixed effects ones.

Table 5: IV Regression

	Math	Math	Reading	Reading
	(1)	(2)	(3)	(4)
Days Absent	-0.0093***	-0.0102	-0.0043***	-0.0182*
	(0.0003)	(0.0121)	(0.0002)	(0.0097)
Days of Class	0.0003	0.0003	0.0038***	0.0041***
	(0.0006)	(0.0006)	(0.0004)	(0.0005)
Specification	OLS	IV	OLS	IV
N	284,651	284,651	284,651	284,651

Source: NCERDC, 2009-2010, grades 3-5. Dependent variable is standardized by grade and year. All specifications include lagged test score, lagged peer score, and lagged school percent proficient in the given subject as well as dummy variables for grade, year, gender, race, and free/reduced-price lunch status. Notice that the sample size is smaller because we only have flu data for the years 2009-2010. Columns (1) and (3) show OLS results (serving as a benchmark case), while columns (2) and (4) show the IV regression results. Standard errors clustered at the classroom-year level are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

6.2 Family Shocks

Our baseline specifications thus far have been assuming that family shocks/inputs that are correlated with absences and affect performance are constant across time and therefore the inclusion of student fixed effects accounts for them. However, these estimates may still be biased if there are potentially time varying unobserved family factors that may be influencing both student absences and testing performance. As previously mentioned, we follow Caetano and Macartney (2013) in utilizing the geocoded address data to construct a family identifier. Table 6 incorporates a family-year fixed effect, which captures all observed and unobserved characteristics that are common to a family-year and is identified off of differing incidence of absences within a family in a given year.[77] Lagged test score is incorporated in the specification as a proxy for ability as that is likely to be different even across siblings. The family-year fixed effects specification controls for any family shock, such as parental divorce or a death in the family, that impacted both absences and test scores. Since siblings generally attend the same school, the coefficient on days of class cannot be well identified. The coefficient on absences in Table 6 indicates that an additional absence decreases scores by 0.70% and 0.37% of a standard deviation for math and reading respectively, which is similar to our previous findings from Table

[77] The information in the data does not provide the biological relationship between children living in the same household. Regardless, since the students are residing in the same household and are therefore exposed to shared family characteristics, children living at the same address will be considered family. There are 38,074 sibling groups that are observed in grades 3-5 in the same year. For those sibling groups of size two (93% of the siblings sample) observed in the same year, the mean absolute value of the difference in days absent is 3.32 days, with a standard deviation of 3.95 days.

Table 6: Siblings Fixed Effects Regression

	Math Score	Reading Score
Days Absent	-0.0070***	-0.0037***
	(0.0006)	(0.0007)
Sibling Year FE	Yes	Yes
Lagged Student Score	Yes	Yes
Controls	Yes	Yes
N	104,831	104,831

Source: NCERDC, 2006-2010, grades 3-5. Dependent variable is standardized by grade and year. All specifications include dummy variables for grade. Controls include peer absences and lagged peer score. Standard errors are reported in parenthesis. The sample is smaller than our main estimating sample as identification relies on observing at least two children from the same family in a given year. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

3. This suggests that family specific shocks are not driving the results.[78]

6.3 Health Shocks

Even after all of the controls to guard against endogeneity concerns, fixed effects do not guard against absences that are, for example, the result of a major/chronic illness; which is an excused absence and might be expected to have a direct effect on test scores. If this was driving our results, then after disaggregating absences into the two types, excused absences would be expected to be more negative relative to unexcused absences.[79] Given that data by type of absences is only available for the years 2006-2008, column (1) of Table 7 replicates specification (4) from Table 3 (i.e. the benchmark specification) but only using data prior to 2009. Results show comparable patterns across tables.[80] Specifications (2) and (3) disaggregate absences by type, where the former does not include controls for school performance and peer absences. Both specifications show very similar results. An additional excused absence lowers math (reading) scores by 0.41% (0.18%) of a standard deviation–according to specification (3)–while unexcused absences have an effect of 0.7% (0.4%) of a standard deviation. Therefore, these results indicate that health problems do not seem to bias our results.

[78]To the extent that absences for children in grades 3 to 5 are mainly driven by parental decisions that may be changing over time, then controlling for family-year fixed effects should address concerns regarding this type of endogeneity.

[79]Gottfried (2009) also examines disaggregated absences and finds that students with a higher proportion of unexcused absences places them at academic risk, particularly in math achievement.

[80]As mentioned previously, absences by type are not available for the full sample during the years 2006-2008. They are generally missing at the school level. The inclusion of three-way high-dimensional fixed effects should address any possible missing data bias. Finally, notice that given that our specifications include school fixed effects the coefficient on days of class are less likely to be well identified due to the fact that we are only using only three years of the sample.

The evidence presented in this section indicates that our baseline findings on the effect of students' absences on test scores performance are robust to several specifications, suggesting that possible expected threats to our identification strategy are not driving the results.[81]

Table 7: Absences by Type Regression

	Math Test Score			Reading Test Score		
	(1)	(2)	(3)	(1)	(2)	(3)
Days of Class	-0.0004	-0.0005	-0.0005	0.0004	0.0003	0.0001
	(0.0006)	(0.0006)	(0.0009)	(0.0008)	(0.0008)	(0.0013)
Days Absent	-0.0055***			-0.0031***		
	(0.0002)			(0.0002)		
Excused Absences		-0.0043***	-0.0041***		-0.0022***	-0.0018***
		(0.0002)	(0.0003)		(0.0003)	(0.0004)
Unexcused Absences		-0.0074***	-0.0070***		-0.0046***	-0.0040***
		(0.0004)	(0.0004)		(0.0003)	(0.0005)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes
N	671,148	671,148	425,082	671,148	671,148	425,082

Source: NCERDC, 2006-2008, grades 3-5. Dependent variable is standardized by grade and year. All specifications include dummy variables for grade, year, and free/reduced price lunch status. Controls include average absences of peers, proportion of students in the school that achieved proficiency in the previous academic year, and lagged average performance of peers. Bootstrapped standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

7 Heterogeneous Effects

On average, absences have a negative effect on test scores, while the positive impact of an additional day of class within the observed range is much smaller. However, these effects may differ based on student characteristics. As noted earlier, catching up after an absence is likely to be more difficult for a low performing student. Understanding the heterogeneous effects of an absence will help to inform the policy discussion by identifying groups of the population that are likely to disproportionately benefit from particular interventions.

To examine how the effect of attending school differs by student ability, students are grouped based on their test score from the prior year. Table 8 shows the regression results with absences and days of class interacted with a dummy for the tercile of the prior year's score. Score 3 denotes the highest tercile. These results indicate that students in the lowest tercile are the most adversely affected by an additional absence; consistent with the hypothesis that lower

[81] We also explore the presence of non-linear effects. In this regard, we saturated the unexcused absences variable with dummies for each day absent from 1 to 30 and another for 31 or more. The coefficients on each of this dummy variables are plotted in Figure 5 (see appendix F). The pattern of the coefficients indicates that the effect on test scores is in fact roughly linear through 30 absences.

ability students have a harder time making up missed work. A similar pattern can be found when considering days of class, i.e. low achieving students benefit the most from spending more time at school. Finally, as was the case in our previous results, absences have a larger effect than days of class within achievement level. In summary, the findings in Table 8 suggest that policies aiming to extend time spent at school (either through reducing absences or extending the school calendar) are likely to have larger impact on low achieving students, helping to close current gaps in performance.

Table 8: Differences by Ability

	Math Test Score	Reading Test Score
Days Absent	-0.0102***	-0.0071***
	(0.0003)	(0.0002)
Days Absent x Score 2	0.0016***	0.0030***
	(0.0003)	(0.0004)
Days Absent x Score 3	-0.0000	0.0029***
	(0.0003)	(0.0003)
Days of Class	0.0059***	0.0050***
	(0.0006)	(0.0005)
Days of Class x Score 2	-0.0056***	-0.0039***
	(0.0006)	(0.0005)
Days of Class x Score 3	-0.0062***	-0.0069***
	(0.0006)	(0.0005)
School FE	Yes	Yes
Teacher FE	Yes	Yes
Controls	Yes	Yes
N	814,127	814,127

Source: NCERDC, 2006-2010, grades 3-5. Dependent variable is standardized by grade and year. All specifications include dummy variables for each quartile of prior year test score, gender, grade, year, free/reduced price lunch status, and race. Controls include average absences of peers, proportion of students in the school that achieved proficiency in the previous academic year, and lagged average performance of peers. Bootstrapped standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

Table 9 further explores the relationship between absences and the quality of students, teachers, and schools by regressing days absent on the three fixed effects obtained from one of our baseline regressions (specification (4) in Table 3).[82] As expected from our previous results, lower ability students have more absences than their higher ability peers. However, we also find that worse schools (teachers) have a positive relationship with absences. More specifically, an increase in school (teacher) quality from the 25th percentile to the 75th percentile is associated

[82]Given that the fixed effects from the math and reading regressions are different, we present two set of results (i.e. the first column includes fixed effects from the math specification while the second column includes the fixed effects from the reading specification).

Table 9: Days Absent

	Math Test Score	Reading Test Score
Student FE	-0.1767***	-0.0892***
	(0.0048)	(0.0045)
School FE	-0.5132***	-0.4702***
	(0.1275)	(0.1584)
Teacher FE	-0.4113***	-0.3820***
	(0.0676)	(0.0981)
N	1,248,496	1,248,496

Source: NCERDC, 2006-2010, grades 3-5. Dependent variable is days absent. Bootstrapped standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

with 0.14 (0.14) fewer days absent.[83] This is a relatively large effect given the sample average of 6.28 absences. In this regard, improving the quality of schools and teachers could not only benefit students by providing them with a better educational environment, but may also reduce the detrimental effects from absences.

Table 10 examines heterogeneous effects by grade. Results indicate that absences appear to have a larger negative effect on both math and reading test scores at higher grades. While each additional absence decreases math (reading) scores by 0.20% (0.19%) of a standard deviation in grade 3, by grade 5 each absence has an impact about four (two) times larger. It is difficult to determine the exact mechanism behind this finding. However a possible explanation could be that school subjects are more complex in higher grades, therefore parents may become less able to help their child to catch up. Similarly, one might expect that more subject matter is taught in grade 5 than in grade 3, making more costly to learn the missed material.[84]

In order to further assess the effect of missing a school day at different stages of the schooling career, we examine "long-term" effects of absences (i.e. impact of school absences at an early grade on performance in subsequent grades). We study persistence effect of absences by following two different approaches. First, we obtain the ratio of coefficients (on absences) from regressions at different points in time [see Jacob, Lefgren, and Sims (2010)]. More specifically, we estimate the impact of previous year absences on contemporaneous test scores, and then in a second regression we estimate a similar specification but instead of including contemporaneous absences we include lagged absences. The ratio of the absences coefficient from the first regression to the analogous coefficient in the second regression provides a (simple) approximation of the one-

[83]This result corresponds to the specification that includes the fixed effects obtained from the regressions that use as dependent variable math test score.

[84]However, we should also acknowledge that students' capacity to learn also increases with age.

Table 10: Differences by Grade

	Math Test Score	Reading Test Score
Days Absent	-0.0020***	-0.0019***
	(0.0003)	(0.0005)
Days Absent x Grade 4	-0.0027***	-0.0008**
	(0.0003)	(0.0004)
Days Absent x Grade 5	-0.0061***	-0.0019***
	(0.0003)	(0.0004)
Days of Class	-0.0006	-0.0007
	(0.0014)	(0.0014)
Days of Class x Grade 4	0.0011	0.0006
	(0.0013)	(0.0014)
Days of Class x Grade 5	0.0039**	0.0029**
	(0.0016)	(0.0014)
Student FE	Yes	Yes
School FE	Yes	Yes
Teacher FE	Yes	Yes
Controls	Yes	Yes
N	814,127	814,127

Source: NCERDC, 2006-2010, grades 3-5. Dependent variable is standardized by grade and year. All specifications include dummy variables for grade, year, free/reduced price lunch status. Controls include peer absences, lagged peer score and lagged school percent proficiency. Bootstrapped standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

year persistence effect of absences.[85] In our second approach, we simultaneously control for contemporaneous absences and previous year absences. Table 11 shows the results from these specifications for math and reading, where our sample of analysis are fifth graders.[86] The ratio of the coefficients in columns (1) and (2) provides a measure of persistence based on the first approach, while column (3) shows "long-term" effects based on the second approach. Results indicate a likely persistent effect of absences in math, that ranges from 60% to 22%, while in reading the presence of "long-term" effects depends on the specification.[87] Overall, these results suggest that previous year absences are likely to have an impact in subsequent grades, providing an additional reason to focus on problems related to school attendance.

Finally, we analyze whether lower income students experience different effects from absences relative to their wealthier classmates. This may be due to parents not having the same amount of

[85] A similar approach has been followed by Chetty, Friedman, and Rockoff (2014) but in the context of analyzing long term effects of teacher value added. Note that in our case, the implicit assumption is that twice-lagged test score performance accounts for student unobserved heterogeneity.

[86] Note that the sample size is smaller than in Table 3 specification (7) due to the fact that Table 11 only includes students in grade 5.

[87] Due to little variation in days of class given the sample that we are using, the lag of the days of class coefficient does not provide any interesting result.

Table 11: Persistent Effect of Absences

	Math Test Score			Reading Test Score		
	(1)	(2)	(3)	(1)	(2)	(3)
Days Absent		-0.0100***	-0.0088***		-0.0042***	-0.0041***
		(0.0006)	(0.0007)		(0.0006)	(0.0007)
Lagged Days Absent	-0.0062**		-0.0020***	-0.0020***		-0.0001
	(0.0005)		(0.0006)	(0.0006)		(0.0007)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	47,736	47,736	47,736	47,736	47,736	47,736

Source: NCERDC, 2006-2010, grade 5. Dependent variable is standardized by year. All specifications include third grade standardized test score, free/reduced price lunch status in the third grade, as well as dummy variables for grade, year, gender and race. Controls include peer absences, lagged peer score and lagged school percent proficiency. Specifications (2) and (3) include days of class. Specifications (1) and (3) include lagged days of class. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

time and/or resources to help their child with homework. Examining the effects by free/reduced price lunch subsidy program status in Table 12, we find that missing school days have larger deleterious effects on test scores for low income students. For example, the effect of an absence (extra day of class) on a relatively poor student has an additional effect of -0.12% (0.15%) of a standard deviation in math.[88]

Overall, the results from this section show the presence of important heterogeneous effects of time spent at school. Low achieving students or those coming from less wealthy families would benefit the most from having fewer absences or attending school for a greater number of days during the year. Therefore, these findings indicate that increasing instructional time (mainly by decreasing absences) most likely will contribute to closing gaps in performance.[89]

8 Conclusions

This paper jointly estimates the relative effectiveness of reducing absences to extending the school calendar on test score performance. Despite the fact that many policy makers have focused their attention on extending the school calendar, the evidence presented in this manuscript indicates that targeting absenteeism could constitute a more effective intervention. First, our empirical strategy shows that the effect of reducing absences relative to extending the number

[88] We also studied heterogeneous effects across race and gender, but we did not find statistically significant results.

[89] Despite the fact that extending the number of school days does not show large effects on schooling outcomes, this does not preclude of possible complementarities between policies that simultaneously target absenteeism and the length of the school year. For instance, extending the school calendar could make possible the inclusion of more extracurricular activities that indirectly reduce absenteeism. See Cuffe, Bignell, and Waddell (2014) for an example on how extracurricular activities can reduce absenteeism.

Table 12: Differences by Free/Reduced Price Lunch Status

	Math Test Score	Reading Test Score
Absences	-0.0048***	-0.0025***
	(0.0003)	(0.0003)
Absences x FRL	-0.0012***	-0.0008***
	(0.0004)	(0.0003)
Days of Class	0.0010*	-0.0008
	(0.0006)	(0.0006)
Days of Class x FRL	0.0015***	0.0035***
	(0.0005)	(0.0005)
Student FE	Yes	Yes
School FE	Yes	Yes
Teacher FE	Yes	Yes
Controls	Yes	Yes
N	814,127	814,127

Source: NCERDC, 2006-2010, grades 3-5. Dependent variable is standardized by grade and year. All specifications include dummy variables for grade, year, free/reduced price lunch status. Controls include peer absences, lagged peer score and lagged school percent proficiency. Bootstrapped standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

of school days is substantially higher. Our preferred specification indicates that extending the school calendar by ten days would increase math and reading test scores by only 1.7% and 0.8% of a standard deviation, respectively; while a similar reduction in absences would lead to increases of 5.5% and 2.9% in math and reading, respectively. Moreover, we show that the large effect of absences on test score performance holds even after performing many robustness checks (i.e. use of family-year fixed effects, utilizing flu data to instrument for absences, distinguishing between excused and unexcused absences, and controlling for a contemporaneous measure of student disengagement). Second, results point to the presence of important heterogeneous effects. Missing a school day due to an absence in grade 5 is three times more detrimental than in grade 3 in math, and more importantly, low performing kids benefit the most from additional instructional time. The fact that reducing absenteeism can target specific students who would benefit the most from being in the classroom, not only suggests this type of initiative could be more effective than just extending the school calendar, but could also contribute to narrowing current achievement gaps.

Estimation results also suggest that improving both school and teacher quality from the 25th percentile to the 75th percentile would decrease the average number of absences by about 4.5%. Therefore, policies aiming to improve the quality of schools and teachers could not only benefit students by providing them with a better educational environment, but also by reducing the detrimental effects from absences.

The financial resources needed to extend the school calendar are high. Most calculations suggest that a ten percent increase in time would require a six to seven percent increase in cost [Chalkboard Project (2008), Silva (2007)]. This type of policy is even more difficult to implement in the context of decreasing per student public education spending.[90] Therefore, while many policymakers have focused their attention on extending the school calendar, the fact that a competing policy, like targeting absenteeism on specific groups of students may lead to large improvements in academic performance,[91] points towards an avenue of policy that deserves far greater attention.

Finally, we believe that future work should focus on understanding what type of interventions are the most effective at boosting school attendance. For example, it remains as an open question whether implementing extracurricular activities that engage students with school life [see, for example, Cuffe, Bignell, and Waddell (2014)] constitute a more effective policy than making phone calls to students with pre-recorded wake up messages from celebrities, like in the WakeUp! NYC program.

[90] Public Education Finances: 2011, U.S. Census Bureau, http://www.census.gov/govs/school/

[91] For example, the program "WakeUp! NYC" has been implemented using media tools (i.e. SchoolMessenger) that has already been incorporated in large number of schools for other purposes.

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9 Appendix A

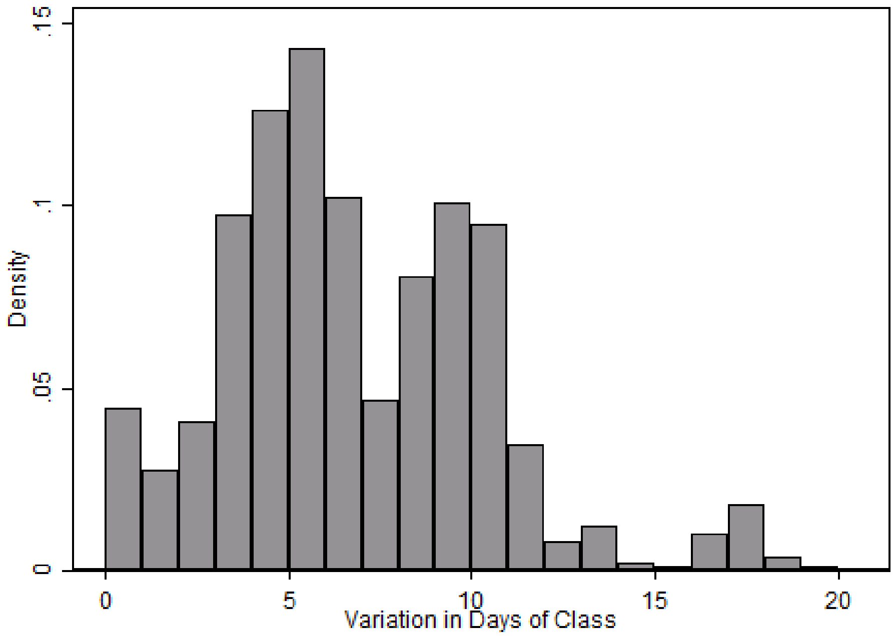

Figure 3: Variation in Days of Class within School

10 Appendix B

Estimating Equation (1) by ordinary least squares solves:

$$\min_{\beta_r,\alpha,\theta,\delta} \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{s=1}^{S}(y_{igkst}-\beta_0-\beta_1 a_{it}-\beta_2 d_{ist}-\beta_3 X_{it}-\beta_4 G_{ig}-\beta_5 T_t-\beta_6 E_{st}-\alpha_i-\theta_k-\delta_s)^2 \quad (2)$$

The following estimation method yields OLS estimates of the parameters of interest while circumventing the dimensionality problem. The algorithm begins with an initial guess of the parameters $\alpha_i^{(0)}, \theta_k^{(0)}, \delta_s^{(0)}$. It then iterates on the following steps with the m^{th} iteration:

- **Step 1:** Using the initial guesses for the student, teacher, and school fixed effects, calculate $Z_{igkst}^{(m)} = y_{igkst} - \alpha_i^{(m)} - \theta_k^{(m)} - \delta_s^{(m)}$ and solve the least squares problem:

$$\left\{\beta_0^{'(m)}, \beta_1^{'(m)}, \beta_2^{'(m)}, \beta_3^{'(m)}, \beta_4^{'(m)}, \beta_5^{'(m)}, \beta_6^{'(m)}\right\} =$$

$$\arg\min_{\beta} \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{s=1}^{S}(Z_{igkst}^{(m)}-\beta_0-\beta_1 a_{it}-\beta_2 d_{ist}-\beta_3 X_{it}-\beta_4 G_{ig}-\beta_5 T_t-\beta_6 E_{st})^2$$

- **Step 2:** Using $\left\{\beta_0^{'(m)}, \beta_1^{'(m)}, \beta_2^{'(m)}, \beta_3^{'(m)}, \beta_4^{'(m)}, \beta_5^{'(m)}, \beta_6^{'(m)}, \theta_k^{(m)}, \delta_s^{(m)}\right\}$ calculate $\alpha_i^{(m+1)}$ based on the following expression (n_i denotes number of observations for student i)

$$\alpha_i^{(m+1)} = \frac{1}{n_i}\left[\begin{array}{l}\sum_{k\in i}(y_{igkst} - \beta_0^{'(m)} - \beta_1^{'(m)}a_{it} - \beta_2^{'(m)}d_{ist} \\ \quad - \beta_3^{'(m)}X_{it} - \beta_4^{'(m)}G_{ig} - \beta_5^{'(m)}T_t - \beta_6^{'(m)}E_{st} - \theta_k^{(m)} - \delta_s^{(m)})\end{array}\right]$$

where the previous expression avoids the minimization over all the $\alpha_i's$. Notice that this expression is obtained from the first order condition of the least squares problem with respect to α_i

- **Step 3:** Using $\left\{\beta_0^{'(m)}, \beta_1^{'(m)}, \beta_2^{'(m)}, \beta_3^{'(m)}, \beta_4^{'(m)}, \beta_5^{'(m)}, \beta_6^{'(m)}, \alpha_i^{(m+1)}, \delta_s^{(m)}\right\}$ calculate $\theta_k^{(m+1)}$ in an analogous way to step 2.
- **Step 4:** Using $\left\{\beta_0^{'(m)}, \beta_1^{'(m)}, \beta_2^{'(m)}, \beta_3^{'(m)}, \beta_4^{'(m)}, \beta_5^{'(m)}, \beta_6^{'(m)}, \alpha_i^{(m+1)}, \theta_k^{(m+1)}\right\}$ calculate $\delta_s^{(m+1)}$ in an analogous way to step 2.
- **Step 5:** Repeat steps 1 to 4 until convergence of the parameters.

11 Appendix C

Table 13: Baseline Regression: Alternative Specification

	Math Test Score	Reading Test Score
Days Absent/Days of Class	-0.9141***	-0.4909***
	(0.0319)	(0.0416)
Days of Class	0.0015***	0.0007
	(0.0005)	(0.0007)
Student FE	Yes	Yes
School FE	Yes	Yes
Teacher FE	Yes	Yes
Lagged Student Score	No	No
N	814,127	814,127

Source: NCERDC, 2006-2010, grades 3-5. The dependent variable denotes number of days absent divided by days of class. This variable variable is standardized by grade and year. All specifications include peer absences, lagged peer score, and lagged school percent proficiency, as well as dummy variables for grade, year, and free/reduced price lunch status. Bootstrapped standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

12 Appendix D

Table 14: Baseline Regression: Teacher Absences

	Math Test Score		Reading Test Score	
Days Absent	-0.0047***	-0.0047***	-0.0027***	-0.0027***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Days of Class	0.0002	0.0002	-00016	-0.0016
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Teacher Sick Days		-0.0011***		-0.0007*
		(0.0003)		(0.0004)
School FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes
Lagged Student Score	Yes	Yes	Yes	Yes
N	370,438	370,438	370,438	370,438

Source: NCERDC, 2006-2008, grades 3-5. Dependent variable is standardized by grade and year. All specifications include dummy variables for grade, year, gender, race, and free/reduced price lunch status. Bootstrapped standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%. Notice that this specification only uses data from years 2006-2008, therefore there is less variability in the number of school days over time, explaining the lack of significance in "days of class."

13 Appendix E

Table 15: IV: First Stage

	Days Absent	
County ILI	0.0011***	0.0011***
	(0.0001)	(0.0001)
Lagged Math Score	X	
Lagged Reading Score		X
N	284,651	284,651

Source: NCERDC, 2009-2010, grades 3-5. Include lagged test score, days of class, lagged peer test score, lagged school percent proficiency, and dummy variables for grade, year, gender, race, and free/reduced price lunch status. Standard errors clustered at the classroom-year level are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%.

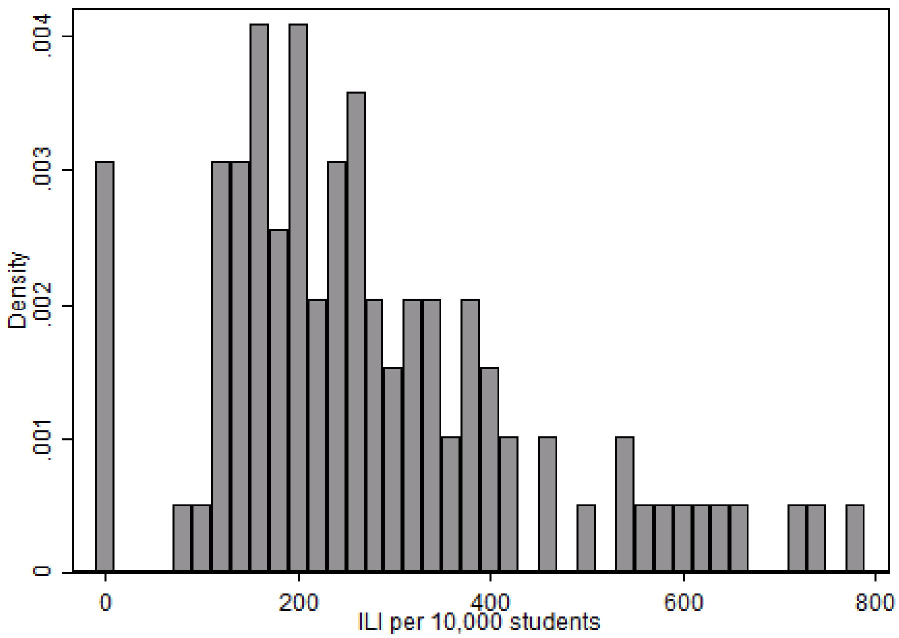

Figure 4: Distribution of County ILI per 10,000 Students, 2010

14 Appendix F

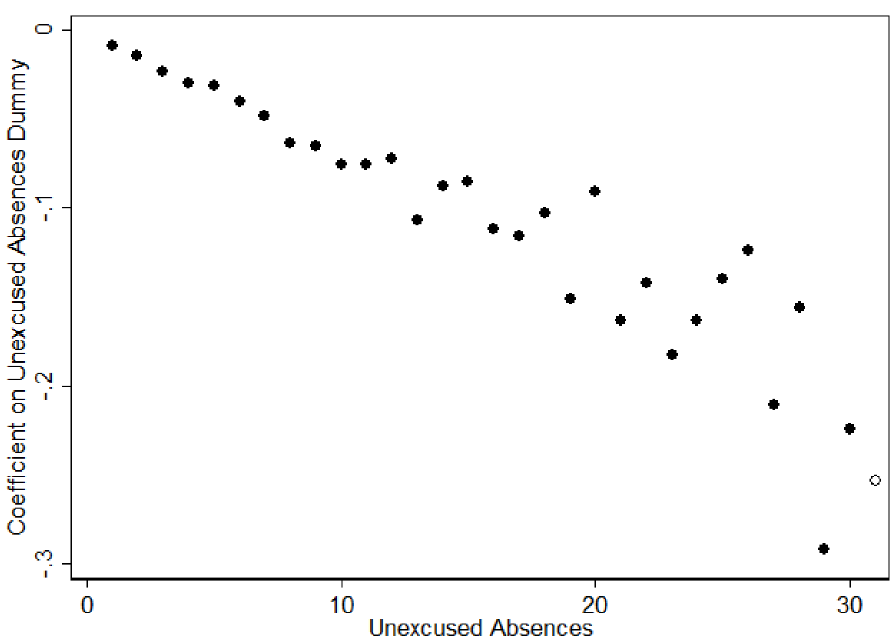

Figure 5: Coefficients on Unexcused Days Absent Dummy Variables.
These coefficients are obtained after controlling for student heterogeneity with math scores as the dependent variable. Similar results are obtained with reading scores. The last coefficient denotes 31 or more days absent.