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

Preliminary and Incomplete

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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. This paper constitutes the first attempt to jointly estimate the relative effectiveness of reducing absences to extending the school calendar on test score performance. Using administrative data for North Carolina public schools, we exploit a state policy that provides variation in the number of days prior to standardized testing and find substantial differences between these effects. Extending the school calendar by ten days increases math and reading test scores by only 0.8% and 0.2% of a standard deviation, respectively; a similar reduction in absences would lead to gains of 5.8% and 3% in math and reading. Our findings indicate substantial heterogeneity across student ability, suggesting that targeting absenteeism among low performing students would aid in narrowing current gaps in performance. Finally, we analyze whether different institutional settings could affect how school administrators and teachers respond to possible

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extensions of the school calendar. Our findings suggest that low performing schools value an extra day of class more when monetary bonuses are in place.

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. In this regard, 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 (once again)[2] focused on 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 these type of interventions relative to other competing policies. For instance, reducing absenteeism may constitute a more effective and less expensive intervention as it would target specific students who would benefit the most from being in the classroom. Recent examples of this type of initiative are "NYC Success Mentor Corps,"[5] and "WakeUp! NYC"[6] which was launched in New York City with the goal to reduce chronic absenteeism.[7]

The goal of this paper is to quantify the relative effectiveness of reducing absences to extending the school calendar on test score performance. While most studies have analyzed the importance of absences or days of class separately,[8] this paper constitutes the first attempt to provide 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.

[1]For example, while the program No Child Left Behind has been implemented by the federal government since 2001; 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]On 2009, President Obama said that the "*challenges of a new century demand more time in the classroom*" (The New York Times, August 22, 2011). In a similar vein the U.S. Secretary of Education, Arne Duncan has claimed 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 5 days or 25 hours 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.

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

[7]Chronic absenteeism is typically defined as missing more than 10 percent school in a year.

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

For example, missing a day of school (due to absence) may be more detrimental to a student's performance since they will need to (later) make up missed work. Moreover, catching up is likely to be more difficult for low performing students, resulting in larger gaps in academic performance within the classroom. To this end, we examine possible heterogeneous effects of absences and days of class. Specifically, we analyze whether children from (relatively) low income families, or those who perform poorly, benefit comparatively more from spending more time at school. Similarly, we try to identify whether the loss of a school day has differential effects depending on the school grade. For example, a fifth grade class is likely to cover more material than in third grade; the consequence of which is students in higher grades find it more difficult to catch up. Finally, how teacher and school quality affect absences is also investigated. We study whether attending (having) a better school (teacher) leads to a decrease in the number of days absent at school. 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.

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 not only able to analyze the importance of time spent at school from several perspectives (i.e. absences and days of class), but it also implements a rigorous econometric strategy that will deal with problems of endogeneity in several ways. We not only make use of student, teacher, and school fixed effects, but we also provide robustness checks by controlling for previous year test scores and family fixed effects. In addition, with the aim to avoid possible students behavioral responses, we focus on students between grades 3 and 5, and we distinguish between excused and unexcused absences. Estimating models with triple fixed effects when the sample size is large is not a trivial matter. In our case, it requires us to estimate more than 413,351 parameters[10] (i.e. 382,835 students; 29,202 teachers; and 1,305 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

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

[10]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).

on test score performance. Our preferred specification indicates that extending school calendar by ten days would increase math and reading test scores by around 0.8% and 0.2% of a standard deviation, respectively; while a similar reduction in absences would lead to increases of 5.8% and 3% in math and reading. Moreover, estimation results show that absences have even larger negative effects among low performing kids, suggesting that catching up is costly especially among those who show greater difficulties at school.

Our findings also indicate that spending more time at school (i.e. less absences or longer academic calendar) have larger effects on later grades. For example, while being 10 days absent in grade 3 leads to a decrease of 2.5% of a standard deviation in math test scores, in grade 5 the effect is 8.9%. This result is consistent with the concept that the amount of material covered per day in later years is larger; therefore catching up could become more problematic. Finally, we show that attending (having) a school (teacher) one standard deviation better decreases absences by 0.6 (0.5) days; a large result given that that the average number of days absent is 6. Our findings suggest 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. Therefore, a successful strategy that decreases absences may have substantially larger effects than that of extending the school calendar. Moreover, the fact that this type of intervention may benefit low achieving students the most, suggests that it may also help to narrow current gaps in academic performance.

While the results show small effects of extending the school calendar, it remains an open question as to whether different institutional settings could affect how school administrators and teachers respond to possible extensions of the school calendar. North Carolina provides a testing window (last three/four weeks of class) during which schools administer the end of grade exams, providing schools with some flexibility in when their students are tested. Depending on the incentives that are in place (e.g. monetary bonus based on students performance), school administrators may act strategically by increasing/decreasing the total number of school days prior to the date of the test.[11] Elimination of teachers' incentive pay in the later years of the sample provides an opportunity to analyze school administrator and teacher behaviors before and after the removal of monetary bonuses. In order to formalize how incentives may shape the

[11]Test scores must be submitted before a given deadline established by the North Carolina Testing and Accountability Programs, potentially generating a cost of delaying the day of the exam (i.e. schools will have less time to grade the exams). Therefore, it is expected that not all schools will make full use of the testing window.

behavior of educators, we present a simple theoretical framework. The model provides two main conclusions. First, teachers effort and the number of days of class (before the day of the exam) determined by the school principal are negatively related to the performance of the students in the preceding year. Second, removal of the financial incentives leads to a decrease in teacher effort and fewer days of class (before the exam). Consistent with these conclusions, the empirical evidence shows that low performing schools are more likely to make extensive use of the testing window when monetary bonuses are in place; this behavior disappears after changes to the scheme of incentives (e.g. elimination of monetary bonuses). Overall, these results suggest that different institutional settings will affect how educators make use of available school time.

The remainder of the 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 and describes the results. Section 5 which will examine the heterogeneous effects of absences and days of class by several student characteristics. Section 6 presents a theoretical framework with which to analyze strategic behavior in the setting of the testing date by schools. The results of an empirical specification examining this behavior are also presented. Section 7 concludes.

2 Background

The length of the school year and absences combine to determine the total amount of instructional time for a student 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 both absences and length of the school year.

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 generate students who perform better on achievement tests than do schools with lower daily attendance rates (Roby, 2004; Sheldon, 2007). This presents a challenge in estimating the effects of absences on student performance; more able and motivated students are both more likely to attend school and to score highly in their courses and on standardized tests. Therefore, without adequate controls for personal characteristics, part of any estimated effects of absences will reflect an downward ability bias due to endogenous selection. The literature has addressed this in a variety of ways. Devadoss and Foltz (1996) use survey responses to obtain information on student effort and motivation. Dobkins et al (2010) exploit data generated from a mandatory attendance policy for low- scoring students. The resulting discontinuity in attendance rates provides the basis for identifying causal effects of attendance on performance. They find that a 10 percentage point increase in a students overall attendance rate results in a 0.17 standard deviation increase in the final exam score without adversely affecting performance on other classes taken concurrently. Stanca (2006) and Martins and Walker (2006) utilize panel data to try to control for unobserved characteristics correlated with absence, finding that attendance does matter for academic achievement. Both panel studies utilize student fixed effects to control for unobservable heterogeneity. Unlike these papers, our data will allow us to additionally control for teacher and school fixed effects. We will also be able to identify siblings and control for sibling-year FE combined with previous year test-score.[12]

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. Various studies on school quality in the United States include term length as one of the regressors (for example, Grogger (1996) and Eide and Showalter (1998)) but typically found 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, a problem this study overcomes due to North Carolina policy.

Card and Krueger (1992) and Betts and Johnson (1998) analyzed the effect of state level school quality on earnings in earlier periods which had more variability in the number of school days. Both studies found positive and significant effects of term length on later earning when state effects are not controlled for. Card and Krueger (1992) also presented results with state fixed effect; the positive effect of term length vanished within states and conditional on other school quality variables. Lee and Barro (2001) utilized cross-county data and examine the correlation of student performance and measures for school resources, including the amount of time spent in school during

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

the year. They found that longer time in school increased mathematics and science scores, but lowered scores in reading. These studies use state or country level data, and in some cases, data on earlier periods. Given that North Carolina policy allows for some flexibility in setting the exam date, days of class will be measured at the school level. Combined with individual level data, will enable us to identify the effects for different groups in the student population which is important for effective policy deployment.

Other studies have exploited quasi-experimental variation to identify the effect of additional days of class. 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 repetition in primary school and led to fewer students attending higher secondary school tracks, but had no effect on earnings. Sims (2008), the paper most similar to our study in how the effect of days of class are identified, used 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 additional class days were associated with small increases in math scores for fourth graders, but not average reading or language scores.

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 data is maintained by the North Carolina Education Research Data Center (NCERDC), which is housed at Duke University. This longitudinal database contains mathematics and reading test scores for each student in elementary,[13] middle, and high school. Since the availability of some of the data varies over time, the analysis is restricted to the years 2006-2010[14] and grades 3 to 5.[15] Encrypted identifiers make it possible to track the

[13]More specifically, for grades 3 and above. Students in lower grades do not take end of grade (EOG) tests, but a test is administered in September as well as the end of grade 3. All other grades were tested in either May or June of that year.

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

[15]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.

progress of individual student over their educational careers and link students to their teachers[16] and school in each year, provided they stay within the universe of North Carolina public schools.

NCERDC records also include extensive information on student 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, days in membership and absences. The days in membership for a student is the number of days the student was on the roster in a particular school; a student is in membership even when absent. Absences data includes 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. Finally, school data includes the name, district, overall performance in fulfilling NCLB requirements as well as demographics of the student and teacher body.

Only counts of absence 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 absence are defined as one 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.[17] Aside from the distinction between excused and unexcused absences, no other details are provided as to the reasons for the absences.

In addition to the main sample of students, a sample of students who are siblings is also employed. Following Macartney and Caetano (2013), the geocoded address data is used to identify students living in the same household to create a family identifier. Observing households of children as they progressed through elementary school makes it possible to identify family fixed effects, as will be described in the next section. Students residing in the same family were identified through the geocoded address information. Thus, two or more students 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

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

[17] http://www.ncpublicschools.org/docs/fbs/accounting/manuals/sasa.pdf.

to be members of the same household.

Teachers that are matched with less than 5 students are not included in an effort to avoid special education (or other specialty) classes as well as minimize measurement error when estimating fixed effects. Moreover, teachers with more than 30 students in a school year were excluded due to possible data miscoding. The total number of student-year observations for 2006-2010 is more than 1,008,000 while the total number of teachers included is more than 29,000.

3.2 Descriptive Statistics

Table 1 presents descriptive information on the sample of students in grades 3 to 5. Students are absent on average 6.14 days of school prior to the exam; more than half of them excused absences. Students in middle school exhibit slightly more absences, largely driven by a greater number of the unexcused type. 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 of endogeneity. In addition, students in grades 3 to 5 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 generate students who perform better on achievement tests than do schools with lower daily attendance rates (Roby (2004), Sheldon (2007)). Table 2 examines absences by student characteristics, including quintile of last year's prior math score.[18] 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 between test scores and absences.[19] This suggests that students who are less capable are also more likely to miss school. Simple 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.

[18] Scores are comparable across time and grades through the use of a developmental scale. The developmental scale is created from the number of correctly answered questions on the standardized test. Each point of the developmental 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.

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

Table 1: Descriptive Statistics for North Carolina Public School Students

	Mean	SD
Absence Information:		
Total days absent	6.14	5.55
Excused absences	3.51	4.24
Unexcused absences	2.31	3.28
Days of Class	166.32	3.48
End of Grade Scores:		
Math	0.0260	0.9844
Reading	0.0201	0.9854
Math prior year	0.0405	0.9548
Reading prior year	0.0357	0.9614
Race (%):		
White	56.75	49.54
Black	25.50	43.59
Hispanic	10.34	30.45
Asian	2.30	14.98
Other	5.11	22.02
Gender (%):		
Male	49.99	50.00
Female	50.01	50.00
Other characteristics (%):		
Free/reduced lunch eligible	46.86	49.90
Special education	14.00	34.70
English language learner	6.42	24.52
N	1,008,575	

Source: NCERDC, 2006-2010. End of grade test scores are standardized by year and grade level. Samples are based on students having two or more observations with required test scores and total absences information, 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.

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 6.59 days a year. Blacks and Hispanics however, are absent 5.52 and 5.27 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.

Figure 1 depicts the distribution of absences in the data. While the distribution is centered around 5 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%

Table 2: Average Number of Absences

	Total Absences		Excused Absences		Unexcused Absences	
	Mean	SD	Mean	SD	Mean	SD
Grades 3-5						
Average:	6.14	5.55	3.51	4.24	2.31	3.28
Prior Math Score:						
Lowest Quintile	6.80	6.20	3.55	4.44	2.99	3.91
Second Quintile	6.31	5.71	3.54	4.27	2.61	3.49
Third Quintile	6.16	5.50	3.62	4.28	2.32	3.19
Fourth Quintile	5.90	5.21	3.59	4.16	2.06	2.88
Highest Quintile	5.46	4.88	3.38	4.00	1.69	2.51
Sex:						
Male	6.20	5.62	3.51	4.26	2.36	3.33
Female	6.08	5.48	3.51	4.22	2.26	3.23
Race:						
Asian	3.96	4.27	2.10	3.20	1.39	2.44
Black	5.54	5.53	2.53	3.66	2.69	3.72
Hispanic	5.27	4.96	2.55	3.50	2.51	3.36
White	6.60	5.60	4.18	4.50	2.12	3.03
Year:						
2006	6.07	5.50	3.55	4.25	2.26	3.23
2007	6.55	5.76	3.50	4.45	2.13	3.24
2008	6.10	5.59	3.66	4.19	2.43	3.35
2009	5.76	5.30	2.90	3.60	2.62	3.31
2010	6.25	5.54	3.16	3.76	2.55	3.15

Source: NCERDC, 2006-2010. Samples are based on students having two or more observations with required test scores and total absences information, linked to a teacher with at least 5 and no more than 30 students.

miss 13 days or more. 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.

Although students may have varying quantities of instructional time prior to end of grade 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 of class; only two districts had additional days, most likely for cost containment reasons.[20] North Carolina Department of Public Instruction dictates a window of time for exam administration.[21] As a result, students at different schools may have had differing number of instructional days at the time academic performance

[20]Forsyth and Guilford Counties had more than 180 days of class.

[21]http://www.ncpublicschools.org/accountability/calendars/archive lists the testing windows for all tests administered in North Carolina since 2001.

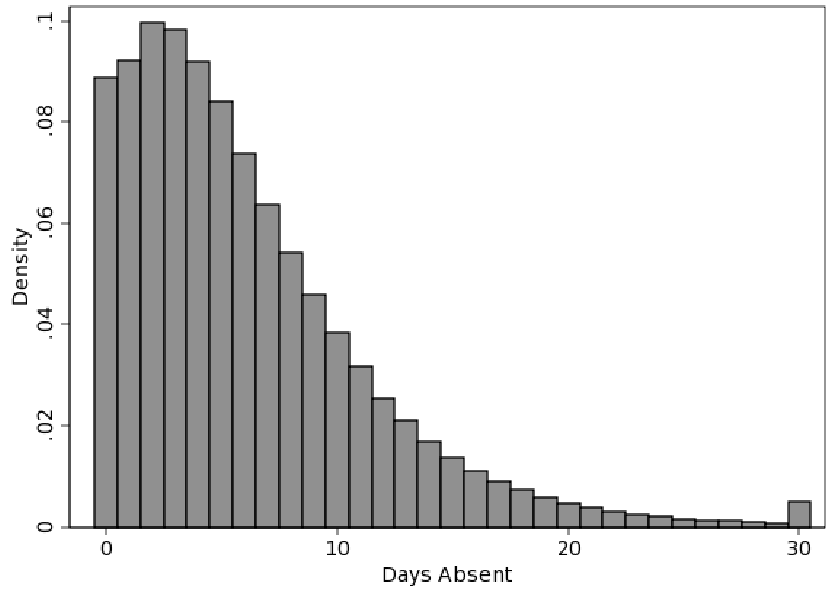

Figure 1: Distribution of Absences

was measured. While schools are not actually extending the school year, they are effectively adjusting their school year length by choosing when to administer the EOG test. This variation in instructional days, coupled with data on absences allows us to separately identify the effect of absences from additional days of schooling.[22]

4 Instructional Time

4.1 Methodology

The data enable us to observe the EOG test score, the number of class days, and the absence of students in each year for grades 3 through 5. Our primary aim is twofold; to estimate the causal effect of both absence and an additional day of instruction on performance. The dependent variable y_{igkst} is the i^{th} student's end-of-grade performance with teacher k and in school s which is standardized by year t and grade g. The main 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 end of year examination. The number of instructional days prior to the exam varies across schools and years and therefore enables the identification

[22]The number of days of class prior to the EOG exam only varies between 158 and 180 days. Therefore, this analysis can only provide an estimate of an additional day within this range.

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 was shown in Table 1, more able and motivated students appear more likely to both attend school and to score highly in their courses and on standardized tests. Therefore, without adequate controls part of any estimated effects of absences will reflect a downward ability bias due to endogenous selection. This 'ability bias' could be minimized with good proxies for ability or other individual characteristics. The data contains information on the students' prior year test score which is included in some specifications of the model.

Our main strategy for dealing with the potential problem of ability bias is to use the panel properties of the data. Student fixed effects are employed for control of all observed and unobserved student characteristics that are constant across 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. This includes curriculum, hiring practices, school neighborhood, and the quality of leadership. These effects are identified off of students who switch schools during grades 3 through 5. Teacher fixed effects are included to control for the common influences of a teacher. These effects are identified off of students who have different teachers; all teachers included in the estimation must be connected through at least one student in order to recover the fixed effects. Finally, fixed effects for grade and year will 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.

Given the large number of students (382,835), teachers (29,202) and schools (1,305) in our data, after using student fixed effects to control for individual heterogeneity among students, incorporating a dummy variable for each teacher and for each school would be infeasible. We employ an iterative fixed-effects estimator introduced by Arcidiacono et al. (2012) to reduce the computational cost of estimating the multi-level fixed effects model of student achievement.

The main estimating equation is:

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

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. a is the number of days absent from the start of school until the day of the exam, d is the number of school days until the day the exam is administered, X is a vector of student covariates, G is a vector of grade dummy variables, and T are school year dummy variables. α_i, θ_k, and δ_s denote student, teacher, and school fixed effects respectively.

A value-added model of student achievement is also implemented. The feature of including a lagged achievement score at the individual level means, that under the assumptions of the model, it is no longer necessary to incorporate additional measures of ability or a full historical panel of information on any particular student.

The death of a family member or a prolonged illness would be expected to have a direct effect on test scores in addition to increasing absences. As a check to ensure that the results from estimation Equation 1 are not being driven by these major events, we reestimate Equation 1 with absences disaggregated by type. Both illness and family emergencies are excused absences. If these major events are driving our results, then we would anticipate that the coefficient on excused absences would be more negative relative to unexcused absences.

4.2 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 without any fixed effects or controls for student ability.[23] The coefficients on absences for both math and reading are negative, significant and large in magnitude. However, since there are no controls for individual ability which is likely to be negatively correlated with absences, the coefficient is biased downward; we expect that once adequate controls are included, the coefficient on absences will increase. Similarly, the coefficient on days of class is the opposite sign from what was hypothesized and likely also suffers 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 math (reading) scores declining by 0.66% (0.35%) of a standard deviation. Therefore, the average student's math (reading) score declines by 4.05% (2.15%) of a

[23] In addition to the regressors specified in Equation 1, controls for gender and ethnicity are also included.

Table 3: Baseline Regression

	Math Test Score					Reading Test Score				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Days Absent	-0.0198***	-0.0066***	-0.0065***	-0.0058***	-0.0067***	-0.0107***	-0.0035***	-0.0034***	-0.0030***	-0.0026***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Days of Class	-0.0081***	0.0002	0.0000	0.0008**	0.0010**	-0.0059***	0.0003	0.0001	0.0002	0.0016***
	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0005)	(0.0005)
Student FE	No	Yes	Yes	Yes	No	No	Yes	Yes	No	No
School FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Teacher FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Lagged Student Score	No	No	No	No	Yes	No	No	No	No	Yes
N	1,001,032	1,001,024	1,001,024	1,000,896	872,863	1,001,032	1,001,024	1,001,024	1,000,896	872,863

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. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

standard deviation.[24] Additional days of class has a positive, but insignificant effect on both math and reading performance. The addition of school fixed effects (specification (3)) has little effect to the magnitude of the coefficient of interest for either subject.

Specification (4), our preferred specification, includes triple fixed effects and finds significant, although slightly smaller coefficients on days absent relative to the previous specifications, with scores declining 3.56 and 1.84 percent of a standard deviation respectively for the average student in math and reading. Specifications (5) examines a model with lagged achievement, and teacher and school fixed effects; the results are qualitatively similar to the preferred specification.

Thus far we have been assuming that family inputs that are correlated with absences and affect performance are constant across time and therefore taken care of with the inclusion of student fixed effects. However, these estimates may still be biased if there are potentially unobserved family factors that may be influencing both student absences and testing performance. As mentioned previously, the geocoded address data was used to construct a family ID variable. Table 4 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 different incidence of absences within that year for a family.[25] 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 attend the same school, the coefficient on days of class cannot be well identified. The coefficient on absences indicates that an additional absence decreases scores by 0.76% and 0.42% for math and reading respectively.

With the exception of specification (1), all estimates of the effect of an absences on the end of grade exam are similar in magnitude. Adding additional days of class also seems to have an effect on math scores, although not reading, and is much smaller in magnitude than that of an absence. This is consistent with the notion that children are exposed to reading and literacy outside of school, especially at home where parents may read to their children. Math, meanwhile, is primarily learned in school.

On average, absenteeism affects test score performance negatively, although each day of absence may differ in its impact. While losing a day or two over the course of a school year may not have a significant effect on performance, missing many days may be

[24]The average student in grades 3-5 is absent 6.14 days of school.

[25]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.

Table 4: Siblings Fixed Effects Regression

	Math Score	Reading Score
Days Absent	-0.0076***	-0.0042***
	(0.0007)	(0.0007)
Sibling Year FE	Yes	Yes
Lagged Student Score	Yes	Yes
N	659,805	658,456

Source: NCERDC, 2006-2009, grades 3-5. Dependent variable is standardized by grade and year. All specifications include dummy variables for grade and year. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

more disruptive; perhaps because material builds upon prior course work, particularly in math, making it difficult for students to catch up. To explore the potential nonlinearities of the effect of absences on student performance, Equation 1 with student fixed effects (specification (1)) is rerun with dummy variables for each day absent from 1 to 30 and another for 31 or more.[26] The coefficients on each of the days absent dummies are plotted in Figure 2. The pattern of the coefficients suggests that the effect of absences on test scores is in fact roughly linear through 30 absences. While consecutive absences may be especially disruptive, the data does not allow us to disentangle isolated absences from longer term incidents.

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 death in the family or a major illness; both of which are excused absences and might be expected to have direct effects 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.[27] Specification (4) of Table 5 presents results disaggregating absences by type. An additional excused absence lowers math (reading) scores by 0.45% (0.46%) of a standard deviation. Unexcused absences has a much more negative effect: 0.73% and 0.22% of a standard deviation for math and reading respectively. Specification (5) examines specification (1) but with the sample of students for which there is data on absences disaggregated by type. The results are similar for absences, but becomes insignificant for days of class.

[26] More than 30 absences in a school year results in a review of whether or not the student should be promoted to the next grade level.

[27] 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.

Table 5: Absences Regression

	Math Test Score					Reading Test Score				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Days of Class	0.0008**	0.0006		-0.0004	-0.0003	0.0002	0.0001		0.0001	0.0002
	(0.0004)	(0.0004)		(0.0009)	(0.0008)	(0.0005)	(0.0005)		(0.0009)	(0.0010)
Days Absent	-0.0058***		-0.0057***		-0.0055***	-0.0030***		-0.0030***		-0.0031***
	(0.0002)		(0.0002)		(0.0002)	(0.0002)		(0.0002)		(0.0002)
Excused Absences				-0.0045***					-0.0022***	
				(0.0002)					(0.0003)	
Unexcused Absences				-0.0073***					-0.0046***	
				(0.0003)					(0.0004)	
Student FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,000,896	1,000,896	1,000,896	583,112	583,112	1,000,896	1,000,896	1,000,896	583,112	583,112

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. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

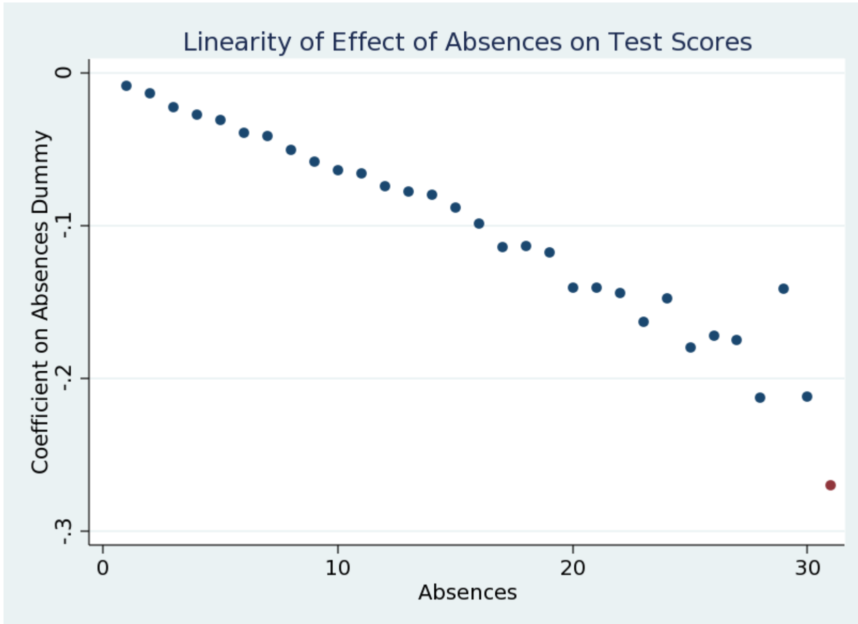

Figure 2: Coefficients on Days Absent Dummy Variables

5 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 effects of an additional instructional day differ by student ability, students are grouped based on their test score from the prior year. Table 6 shows the regression results with absences interacted with a dummy for the quintile of the prior year's score. These results indicate that the students in the lowest quintile are most adversely affected by an additional absence in both math and reading; consistent with the hypothesis that lower ability students have a harder time making up missed work. However, the top of the distribution has similarly negative effects on math scores. Table 7 provides a robustness check using student fixed effects rather than prior scores to proxy for ability; the effects of both absences and additional days of class are muted for higher ability students.

Table 6: Differences by Ability

	Math Test Score	Reading Test Score
Days Absent x Score 1	-0.0092***	-0.0059***
	(0.0003)	(0.0003)
Days Absent x Score 2	-0.0080***	-0.0040***
	(0.0003)	(0.0003)
Days Absent x Score 3	-0.0079***	-0.0038***
	(0.0002)	(0.0003)
Days Absent x Score 4	-0.0080***	-0.0036***
	(0.0003)	(0.0003)
Days Absent x Score 5	-0.0093***	-0.0038***
	(0.0003)	(0.0003)
Days of Class x Score 1	0.0067***	0.0062***
	(0.0007)	(0.0007)
Days of Class x Score 2	0.0036***	-0.0027***
	(0.0008)	(0.0008)
Days of Class x Score 3	-0.0002	0.0005
	(0.0006)	(0.0007)
Days of Class x Score 4	-0.0035***	-0.0005
	(0.0006)	(0.0007)
Days of Class x Score 5	0.0007	-0.0036***
	(0.0006)	(0.0007)
Score 2	1.0787***	1.1773***
	(0.1248)	(0.1302)
Score 3	2.1693***	1.9989***
	(0.1110)	(0.0889)
Score 4	3.1577***	2.5895***
	(0.1022)	(0.0986)
Score 5	3.2613***	3.5990***
	(0.1179)	(0.0985)
School FE	Yes	Yes
Teacher FE	Yes	Yes
N	705,784	705,784

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, and ethnicity. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

Table 8 further explores the relationship between absences and the quality of students, teachers and schools by regressing the three fixed effects from our preferred specification of the baseline regression (Specification (4)). As expected from our previous results, lower ability students have more absences than their higher ability peers. However, worse schools (teachers) also increase absences; a one standard deviation increase in school (teacher) quality decreases absences by 0.63 (0.50) days. This is a large

Table 7: Differences by Ability: Student Fixed Effect

	Math Test Score	Reading Test Score
Days of Class	0.0007*	-0.0000
	(0.0004)	(0.0005)
Days of Class x Student FE	-0.0005**	-0.0011***
	(0.0002)	(0.0002)
Days Absent	-0.0057***	-0.0029***
	(0.0002)	(0.0002)
Days Absent x Student FE	0.0005***	0.0007***
	(0.0001)	(0.0001)
N	1,000,896	1,000,896

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. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

Table 8: Days Absent

	Math Test Score	Reading Test Score
Student FE	-0.2653***	-0.1338***
	(0.0055)	(0.0045)
School FE	-0.6304***	-0.6691***
	(0.0291)	(0.0356)
Teacher FE	-0.5004***	-0.5216***
	(0.0245)	(0.0325)
N	1,000,896	1,000,896

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

effect given the sample average of 6 absences.

As a student advances in their educational career, it is likely that an increasing amount of material is covered in a given school day. For example, one might expect that more subject matter is taught in grade 5 than in grade 3. As a result, catching up could be more difficult in the higher grades. Table 9 examines the differences by grade of an absence. Indeed, 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 0.25% (0.15%) of a standard deviation in grade 3, by grade 5 each absences has almost four times the impact.

Lower income students may also experience different effects relative to their wealthier classmates. This may be due to parents not having the same amount of time and/or ability to help their child with homework or reading with them. Examining the effects by free/reduced price lunch subsidy program status in Table 10, we find that an addi-

Table 9: Differences by Grade

	Math Test Score	Reading Test Score
Absences x Grade 3	-0.0025***	-0.0015***
	(0.0002)	(0.0002)
Absences x Grade 4	-0.0054***	-0.0030***
	(0.0002)	(0.0002)
Absences x Grade 5	-0.0089***	-0.0042***
	(0.0002)	(0.0003)
Days of Class x Grade 3	-0.0007	-0.0015**
	(0.0008)	(0.0007)
Days of Class x Grade 4	0.0010**	0.0004
	(0.0005)	(0.0006)
Days of Class x Grade 5	0.0019***	0.0012
	(0.0006)	(0.0008)
Student FE	Yes	Yes
School FE	Yes	Yes
Teacher FE	Yes	Yes
N	1,000,895	1,000,895

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. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

tional absence has larger deleterious effects on test scores for low income students; an additional absences decreases math (reading) test scores by 0.12% (0.17%) of a standard deviation. Additional days of class also has a bigger impact on low income students with an extra day of class increasing scores for math and reading by 0.08% and 0.28% respectively. The much larger effect on reading for additional class days suggests that these students may not be getting the same reading enrichment at home as their wealthier peers.

As seen in Table 2, the number of absences varies by both gender and race. Black and Hispanics are less likely to be absent in elementary school but are much more likely to miss days of instruction in higher grades. Table 11 examines how this effects math and reading scores. The results indicate that there is no significant differential effect across races for either excused or unexcused absences.

6 Strategic Behavior

North Carolina has a long history with accountability programs. In 1997, ABCs (Accountability for Basic skills and for local Control) was introduced with the aim of

Table 10: Differences by Free/Reduced Price Lunch Status

	Math Test Score	Reading Test Score
Absences	-0.0049***	-0.0022***
	(0.)	(0.0003)
Absences x FRL	-0.0012***	-0.0017***
	(0.)	(0.0005)
Days of Class	-0.0006	-0.0011
	(0.)	(0.0008)
Days of Class x FRL	0.0008	0.0028***
	(0.)	(0.0007)
Student FE	Yes	Yes
School FE	Yes	Yes
Teacher FE	Yes	Yes
N	583,121	583,121

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. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

Table 11: Race Regression by Race and Gender: Absences

	Math Test Score			Reading Test Score		
	Black	Hispanic	White	Black	Hispanic	White
Excused Absences	-0.0039***	-0.0016	-0.0037***	-0.0012*	-0.0056**	-0.0019***
	(0.0009)	(0.0023)	(0.0005)	(0.0010)	(0.0022)	(0.0005)
Male x Excused Absences	-0.0018	-0.0004	-0.0009	-0.0011	0.0045	-0.0001
	(0.0011)	(0.0033)	(0.0007)	(0.0011)	(0.0033)	(0.0006)
Unexcused Absences	-0.0060***	-0.0051**	-0.0068***	-0.0046***	-0.0033*	-0.0035***
	(0.0009)	(0.0022)	(0.0008)	(0.0011)	(0.0023)	(0.0008)
Male x Unexcused Absences	-0.0015	-0.0032	-0.0012	-0.0021	-0.0018	-0.0003
	(0.0011)	(0.0028)	(0.0009)	(0.0014)	(0.0036)	(0.0011)
Days of Class	-0.0019	-0.0038	0.0003	0.0011	0.0040	-0.0001
	(0.0014)	(0.0041)	(0.0012)	(0.0019)	(0.0037)	(0.0011)
Male x Days of Class	0.0007	0.0003	0.0007***	-0.0008	-0.0011***	-0.0007***
	(0.0005)	(0.0004)	(0.0001)	(0.0005)	(0.0004)	(0.0002)
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes	Yes	Yes
N	147,433	47,791	326,450	147,433	47,791	326,450

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. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

holding schools accountable for their value added. The main objective of this policy is to quantify how much children improve while being enrolled in a given school. To this end, teachers and staff at schools that raise student achievement above a certain threshold receive salary bonuses.[28] In the 2002-2003 academic year, No Child Left Behind (NCLB) was layered on top of the ABCs program. NCLB mandates that all students be

[28]Bonuses range from $500 to $1,500.

proficient by 2014, and that each school must make Adequate Yearly Progress (AYP) towards meeting this objective, not only overall, but also for a set of demographic subgroups within each school. Schools failing to achieve AYP for two consecutive years begin to face sanctions, where their severity can increase depending on past history. Two main differences distinguish these accountability programs. ABCs focuses on average gains in test scores, and its structure of incentives affects directly teachers behavior (i.e. monetary bonus). In contrast, NCLB evaluates schools based on proficiency levels, and the scheme of incentives is designed to mainly affect schools principal behavior.

North Carolina uses end of grade (EOG) testing in both math and reading for grades 3 through 8 to quantify student's improvement and determine whether or not a school has met its expected growth and proficiency levels. The state provides a testing window during which schools administer the end of grade exams. The EOG tests were required to be administered during the last three or four weeks of classes,[29] providing schools with some flexibility as to when they test their students.[30] However, making full use of the testing window may be costly, given that test scores must be submitted before a given deadline established by the North Carolina Testing and Accountability Programs. Therefore, this generates a cost of delaying the day of the exam given that schools will have less time to grade the exams. It is therefore expected that those schools who could benefit the most from an extra day of class prior to the exam are the ones who will set a later testing date.

Beginning in 2009, two main changes to the scheme of incentives were introduced. First, ABCs discontinued incentive pay to teachers. Second, students that performed below, but close to proficiency levels in a given subject,[31] were required to retake the test. The higher of the two grades is considered for accountability purposes. The combination of no monetary bonuses with the fact that schools may want to have extra time to focus on those students who need to retake the exam may have substantially changed how schools set the exam day within the testing window. Therefore, changes in the structure of incentives are likely to affect how schools value an extra day of class before the exam. In this regard, the aim of this section is to analyze this type of strategic

[29] http://www.ncpublicschools.org/accountability/calendars/archive lists the testing windows for all tests administered in North Carolina since 2001.

[30] Superintendents and principals were responsible for setting the testing dates for an individual district and school.

[31] NCLB divides student performance into 4 categories. Levels 3 and 4 denote proficient or more, while levels 1 and 2 indicate a student is not proficient in that subject. Since 2009, students who achieve level 2 have been required to retake the test.

behavior in order to shed some light on how schools may respond to possible extensions of the school calendar when different institutional settings are in place.[32] Next, we present a simple theoretical framework that intends to formalize these concepts.

6.1 Theoretical Framework

Consider the following scenario where a school principal has to set the number of schools days before the day of the exam, and a teacher that has to decide the amount of effort that she will exert conditional of the number of instructional days and the scheme of incentives that are in place. Moreover, assume that test score production function of student i, with teacher k, in grade g, in school s, during year t is given by the following expression:

$$Test_{igkst} = s_i + e_{gkt}d_{st} + \varepsilon_{igkst}$$

where s_i denotes student ability, e_{gkt} level of effort per unit of time exerted by the teacher, d_{st} total number of school days in school s, and ε_{igkst} denotes an error term. For simplicity, we impose that e_{gkt} and $d_{st} \in (0, 1]$.

6.1.1 Teachers Maximization Problem

We assume that teachers derive utility from the average performance of the students in their classroom, and from a monetary bonus that depends on the gains in student performance:

$$U = \underbrace{\overline{Test}_{gkst}}_{\text{Classroom average performance}} + \underbrace{\alpha_4 \left[\frac{\overline{Test}_{gkst} - \overline{Test}_{gkst_{-1}}}{\overline{Test}_{gkst_{-1}}} \right]}_{\text{Bonus}} \tag{2}$$

where $\overline{Test}_{gkst}$ denotes the average test performance in the classroom in year t, and $\alpha_4 \left[\frac{\overline{Test}_{gkst} - \overline{Test}_{gkst_{-1}}}{\overline{Test}_{gkst_{-1}}} \right]$ represents the bonus that a teacher gets if her students improve their performance. If we replace $\overline{Test}_{gkst}$ by its definition in Equation 2, then we have:

$$U = \underbrace{\frac{1}{N} \sum_{i=1}^{N} [s_i + e_{gkt}d_{st} + \varepsilon_{igkst}]}_{\text{Classroom average performance}} + \underbrace{\alpha_4 \left[\frac{\frac{1}{N} \sum_{i=1}^{N} [s_i + e_{gkt}d_{st} + \varepsilon_{igkst}] - \overline{Test}_{gkst_{-1}}}{\overline{Test}_{gkst_{-1}}} \right]}_{\text{Bonus}}$$

[32]Other papers examining strategic behavior of schools in the presence of accountability include Jacob and Levitt (2003) and Macartney (2013).

Notice that teachers can only choose the level of effort per unit of time, and days of class are taken as given. Finally, we assume the following functional form for the teachers effort cost function:

$$C(e_{gkt}) = \alpha_1 \left[e_{gkt} d_{st}\right] + \alpha_2 \left[e_{gkt}^2 d_{st}\right] + \alpha_3 \left[e_{gkt} d_{st}^2\right]$$

Therefore, teachers' problem can be written as follows:

$$\begin{aligned} \max_{e_{gkt}} U &= \max_{e_{gkt}} \underbrace{\frac{1}{N}\sum_{i=1}^{N}[s_i + e_{gkt}d_{st} + \varepsilon_{igkst}]}_{\text{Average performance of classroom}} + \underbrace{\alpha_1 \left[\frac{\frac{1}{N}\sum_{i=1}^{N}[s_i + e_{gkt}d_{st} + \varepsilon_{igkst}] - \overline{Test}_{gkst_{-1}}}{\overline{Test}_{gkst_{-1}}}\right]}_{\text{Bonus}} \\ &\quad - \underbrace{\left[\alpha_2 \left[e_{gkt}d_{st}\right] + \alpha_3 \left[e_{gkt}^2 d_{sy}\right] + \alpha_4 \left[e_{gkt} d_{st}^2\right]\right]}_{\text{Effort cost function}} \end{aligned}$$

The first order condition w.r.t. e_{gkt} is given by:

$$\frac{1}{2\alpha_3}\left[1 + \frac{\alpha_1}{\overline{Test}_{gkst_{-1}}} - \alpha_2 - \alpha_4 d_{st}\right] = e_{gkt}^*$$

where $\alpha_n \geq 0$ with $n = \{1, 2, 3, 4\}$, and $\alpha_2 + \alpha_4 < 1$. Therefore, the optimal level of effort is increasing in the "price" (i.e. α_1) of the monetary bonus, but decreasing on the total instructional time, and the average performance of the class in the previous year.

6.1.2 School Principal Problem

The school principal has to determine the number of school days prior the exam (i.e. d_{st}), where the optimal effort exerted by the teachers (i.e. e_{gkt}^*) is taken as given. We assume a benevolent principal who only cares about the average performance of the students in the classroom. Therefore, the objective function is given by:

$$\max_{d_{st}} U = \max_{d_{st}} \underbrace{\frac{1}{N}\sum_{i=1}^{N}[s_i + \frac{1}{2\alpha_3}\left[1 + \frac{\alpha_1}{\overline{Test}_{gkst_{-1}}} - \alpha_2 - \alpha_4 d_{st}\right] d_{st} + \varepsilon_{igkst}]}_{\text{Average performance of classroom}}$$

where $\frac{1}{2\alpha_3}\left[1 + \frac{\alpha_1}{\overline{Test}_{gkst_{-1}}} - \alpha_2 - \alpha_4 d_{st}\right] = e_{gkt}^*$. The first order condition w.r.t. d_{st} is given by:

$$\frac{1}{2\alpha_4}\left[1 - \alpha_2 + \frac{\alpha_1}{\overline{Test}_{gkst_{-1}}}\right] = d_{st}^*$$

This implies that the optimal number of school days before the exam is negatively correlated with the performance of the classroom in the previous year. Moreover, the model shows that optimal instructional time would decrease and would be similar across schools if monetary bonuses were eliminated (i.e. $\frac{\alpha_1}{\overline{Test}_{gkst_{-1}}} = 0$).

Two main conclusions can be obtained from the model. First, teacher effort and the number of days of class (before the day of the exam) determined by the school principal are negatively related to student performance in the previous year. Second, removal of financial incentives leads to a decrease in teacher effort and fewer days of class (before the exam). While the model is not able to capture the role that re-testing may have on teachers and school administrators' behavior, it is expected that this may lead to a further decrease in the instructional time.

6.2 Empirical Strategy

In order to test whether low performing schools act strategically by making a more extensive use of the testing window when monetary bonuses were in place, we exploit the fact that beginning in 2009, ABCs discontinued incentive pay to teachers and re-testing results were allowed to be use for accountability purposes. In this regard, we estimate the following difference-in-difference specification:

$$D_{ust} = \beta_0 + \overline{Test}_{ust_{-1}} + \beta_2 Post + \beta_3 Post \times \overline{Test}_{ust_{-1}} + \beta_4 Year_t + \beta_5 X_{st} + \epsilon_{ust} \quad (3)$$

where D_{ust} is the percentile rank of total that number of class days prior the EOG exam in subject u at school s in year t. $Post$ is a dummy variable equal to one for years 2009 and 2010; the years incentive pay was not in place. $\overline{Test}_{ust_{-1}}$ is the average school test score in the previous year, $Year_t$ is a vector of year dummy variables, X_{st} is a vector of school covariates. If schools were strategically setting testing dates so as to increase the likelihood of improved student performance and enable monetary rewards for the teachers and staff, then schools with the lowest test scores would be most likely to increase the number of instructional days prior to the test, suggesting a negative coefficient on lagged test score. Barring the incentive, schools would then be expected to have fewer instructional days; implying a negative coefficient on the post dummy variable.[33]

[33] However, schools still face sanctions. If a school misses AYP for two consecutive years in the same

Table 12 presents the results from the difference-in-difference specifications with school percentile rank of the number of class days prior the EOG exam as the dependent variable. As hypothesized, columns (1) and (2) of Table 12 show that the signs on lagged scores for both math and reading are negative and significant. More specifically, schools with a lagged math score 1 standard deviation below the mean, would increase their percentile rank by 10 percentage points; where the results are even stronger for reading. However, estimation results show that after the elimination of monetary bonuses high and low achieving schools do not show substantial differences in their number of school days ranks. These results are consistent with the predictions of our theoretical framework, suggesting that low performing schools value an extra day of class more when monetary bonuses are binding.

Table 12: Gaming: Difference-in-Difference

	(1)	(2)	(3)	(4)
	Math	Reading		
Post	-0.0430***	-0.0478***	-0.2776***	-0.0471*
	(0.0115)	(0.0115)	(0.0664)	(0.2120)
Lagged Score	-0.1081***	-0.1286**		
	(0.0173)	(0.0200)		
Lagged Score x Post	0.0819***	0.0933***		
	(0.0205)	(0.0160)		
Lagged Proficiency			-0.0026***	
			(0.0007)	
Lagged Proficiency x Post			0.0040***	
			(0.0009)	
High Status				-0.0464**
				(0.0219)
High Status x Post				0.1003***
				(0.0274)
Middle Status				-0.0183
				(0.0187)
Middle Status x Post				0.0765***
				(0.0232)
N	6,005	6,005	5,988	5,988

Source: NCERDC, 2006-2010. All specifications include year dummies, percent hispanic, percent black, percent free/reduced price lunch and school size. Standard errors are reported in parenthesis. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

In order to provide robustness checks, specifications (3) and (4) examine modified

subject, the district must offer transfers (with transportation) to higher-performing public schools in the same district. After three years, schools must offer supplemental education services. Subsequent failure to make AYP results in changes to leadership and/or staffing and restructuring of the school.

versions of Equation 3. Specification (3) examines the relationship between the share of students proficient in the prior year and instructional days. Consistent with the results in columns (1) and (2), schools with a larger proportion of proficient students are more likely to have fewer day of class before the exam. The removal of monetary incentives eliminates this effect. Similarly, specification (4) examines how last year's accountability status affects the number of school days before the exam. High status schools are those that received a status of honor school of excellence, school of excellence, or school of distinction in the prior year. Middle status are schools that received a status of school of progress or no recognition in the previous year. The excluded category are schools that received a status of low performing or priority school in the prior year. Consistent with our earlier findings, higher status schools had on average fewer days of class in the subsequent year, but this effect is offset with the change in the incentives.[34] The evidence indicates that different institutional settings do affect how schools value an extra day of class. Therefore, policies that aim to extend the school calendar would likely benefit by providing schools the right incentives to make each extra day more effective.

Previously, we mentioned that beginning in 2009, students that perform below but close to the proficiency threshold in a given subject (i.e. level 2)[35] were required to retake the test, where only the highest grade of both exams is considered for accountability purposes. Teachers may decide to act strategically by concentrating their efforts on those students with a higher probability of becoming proficient. To explore this hypothesis, we analyze whether conditional on previous year's performance those students who perform the best in the retesting also performed better in the previous year. We focus our analysis on the sample of level 2 students, and regress performance on the original test and the retest on quintiles of the previous year's performance, a dummy variable for retesting, and the interaction between this dummy and quintiles of previous year exam.

Table 13 shows that after controlling for the prior year's performance, students who most improve between the first test and the retest exam are those who had the highest scores in the previous year. Therefore, these results suggests that teachers may have concentrated their efforts on those students who had a higher chance of becoming

[34] How these statuses are grouped does not effect the qualitative results.

[35] NCLB divides student performance into 4 categories. Levels 3 and 4 denote proficient or more, while levels 1 and 2 indicate a student is not proficient in that subject. Since 2009, students who achieve level 2 have been required to retake the test.

Table 13: Gaming: Retesting

	Math	Reading
Quintile 2	-0.0697***	-0.0612***
	(0.0062)	(0.0052)
Quintile 3	-0.1044***	-0.0852***
	(0.0078)	(0.0064)
Quintile 4	-0.1334***	-0.1081***
	(0.0094)	(0.0075)
Quintile 5	-0.1973***	-0.1633***
	(0.0121)	(0.0096)
Retest	0.1248	0.2949***
	(0.1114)	(0.0959)
Retest x Quintile 2	0.1394***	0.1455***
	(0.0071)	(0.0061)
Retest x Quintile 3	0.2297***	0.2517***
	(0.0072)	(0.0063)
Retest x Quintile 4	0.3055***	0.3596***
	(0.0072)	(0.0062)
Retest x Quintile 5	0.4429***	0.5237***
	(0.0074)	(0.0063)
School FE	Yes	Yes
N	123,488	155,972

Source: NCERDC, 2006-2010, grades 4-5 conditional on level 2 on the first test. All specifications include dummies for hispanic, black, white, asian, male, free/reduced lunch, lagged score, grade and year are also included. Significance levels: $***$ denotes 1%; $**$ denotes 5%; $*$ denotes 10%

proficient. This is consistent with the findings of Neal and Schanzenbach (2010) who show that NCLB is likely to increase scores for marginal students.

7 Conclusions

This paper is the first attempt to jointly estimate 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 of school days is substantial. Our preferred specification indicates that extending school calendar by ten days would increase math and reading test scores by only 0.8% and 0.2% of a standard deviation, respectively; while a similar reduction in absences would lead to increases of 5.8% and 3% in math and reading. Second, results point to the presence of important heterogeneous effects. Missing a school day due to absence in grade 5 is 3.56 times more detrimental than in grade 3, 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 that initiatives targeting absenteeism could be more effective than just extending the school calendar, but also could contribute to narrowing current achievement gaps.

Estimation results also show that improving both school and teacher fixed effects by one standard deviation would decrease the average number of absences by 18%. 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.

Finally, we show that low performing schools seem to value an extra day of class more when monetary bonuses are binding. In this regard, the effectiveness of policies that aim to extend the school calendar are likely to vary depending on the scheme of incentives that are in place. Therefore, identifying the mechanisms that could lead to stronger complementarities between accountability programs and possible extensions of the school calendar could substantially contribute to make each extra day of class worth it.

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