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The Impact of Teacher Absences on Student Achievement

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July 2006

ABSTRACT

In this paper, we report the results of a study to estimate the causal impact of teacher absences on the mathematics achievement of urban elementary school students. In our analyses, we make use of two years of data on fourth grade teachers in a large urban school district and information on the students whom they teach. We use three identification strategies to account for a potential correlation between the number of days that a teacher is absent from school and her unobserved skill level. Our first strategy specifies fixed effects for teachers. Our second strategy uses indicators of weather conditions in the vicinity of a teacher's home, the length of a teacher's home-to-school commute, and interactions between them as instruments for teacher absence. Our third strategy combines the first two strategies. Our results indicate that the first ten days of teacher absence cause students' mathematics achievement to decline by 0.15 of a standard deviation.

The Impact of Teacher Absences on Student Achievement

I. INTRODUCTION

Over the 13 years between the start of kindergarten to the end of grade 12, the typical American public school student spends almost one entire academic year in a classroom from which the regularly assigned teacher is absent (Billman, 1994; Nidds & McGerald, 1994; Ostapczuk, 1994). The financial costs of teacher absences, measured in terms of salaries for substitute teachers and associated administrative spending, amount to $4 billion annually (The District Management Council, 2004). Much less is known about the impact of teacher absences on student achievement.

This paper reports the results of a study to estimate the causal impact of teacher absences on the mathematics achievement of elementary school students. We make use of two years of data on fourth grade teachers in a large urban school districts and information on the students whom they teach. We use three identification strategies to account for a potential correlation between the number of days that a teacher is absent from school and her unobserved skill level. Our first strategy specifies fixed effects for teachers. Our second strategy uses indicators of weather conditions in the vicinity of a teacher's home, the length of a teacher's home-to-school commute, and interactions between them as instruments for teacher absence. Our third strategy combines the first two strategies. Our results indicate that the first ten days of teacher absences cause students' mathematics achievement to decline by 0.15 standard deviations.

II. HOW TEACHER ABSENCE MAY AFFECT STUDENT ACHIEVEMENT

There are several ways in which teacher absences may affect student achievement. First, instructional intensity may be radically reduced when a regularly assigned teacher is absent (Capitan & et al., 1980; Gagne, 1977; Varlas, 2001). Substitute teachers showing movies is a time-honored illustration. Low skill levels of substitute teachers may contribute to the reduction in instructional focus. Nineteen states do not require that substitutes hold a Bachelor's degree (Henderson, Protheroe, & Porch, 2002), a standard requirement for regular teachers. Furthermore, the *No Child Left Behind Act* of 2001 specifically exempts substitutes from its otherwise ambitious requirements for teacher quality (US Department of Education, 2004).

The second way that teacher absences may affect student achievement is through the disruption of the regular flow of classroom events. Students may have difficulty forming meaningful relationships with multiple, mobile substitutes. Even if substitutes manage brilliant isolated lessons, they may not be able to implement a regular teacher's long-term instructional strategies. Also, substitutes' lack of detailed knowledge of students' skill levels makes it difficult to provide differentiated instruction that addresses the needs of individual students.

Finally, teacher absences may negatively impact student achievement by inhibiting attempts by school faculties to implement consistent instructional practices across classrooms and grades, and to collaborate on improving instruction.

III. PREVIOUS RESEARCH

Measurement of Teacher Absences

Teachers are absent from school for a variety of reasons. Some absences are unavoidable, a result of illnesses and family emergencies. Others absences are avoidable, and motives range from the responsible—jury duty or attending a professional development workshop—to the irresponsible—painting the house or fishing. Researchers generally use the term *absenteeism* to describe avoidable absences, regardless of motivation (Chadwick-Jones, Nicholson, & Brown, 1982; Rhodes & Steers, 1990; Winkler, 1980). Researchers interested in employee absences tend to focus on absenteeism. This focus makes sense in that employers have little ability to combat truly unavoidable absences. In contrast, employers can combat absenteeism by manipulating relevant employment policies.

A number of studies show that teacher absences are sensitive to the details of employment policies. For example, teachers' rates of absence are positively associated with the generosity of leave provisions, such as the number of contractually allowed days of paid sick- or personal-leave (Educational Research Service, 1980; Ehrenberg, Ehrenberg, Rees, & Ehrenberg, 1991; Winkler, 1980). Rates of absence drop when incentive schemes like buy-backs of unused sick-leave or bonuses for exceptional attendance are implemented (Boyer, 1994; Ehrenberg, Ehrenberg, Rees, & Ehrenberg, 1991; Winkler, 1980; Freeman & Grant, 1987; Jacobson, 1990; Skidmore, 1984; White, 1990).

Teachers who are required to report absences directly to their principal by telephone are absent less often than teachers who can report their absences indirectly via a centralized reporting center or a school-based message machine (Farrell & Stamm, 1988; Winkler, 1980).

Two ubiquitous patterns provide evidence that absenteeism underpins some proportion of teacher absence. First, teachers are absent most frequently on Mondays and Fridays (Bundren, 1974; Capitan & Morris, 1978; Educational Research Service, 1980; Malick, 1997; Pennsylvania School Boards Association, 1978). This pattern suggests convenience and volition (Behrend, 1959) as such absences build longer blocks of leisure time (Rhodes & Steers, 1990). Second, a high proportion of teacher absences are of short duration (Educational Research Service, 1980). Because school districts generally require no medical certification for short-term illnesses—those of two days or less—high rates of short-term absence attributed to illness should be suspected of including avoidable absences (Rhodes & Steers, 1990).[1]

Predictors of Teacher Absences

State laws and district policies form a backdrop to school districts' experiences with teacher absences. For example, California law governing the State *Teachers Retirement System* was modified in 1997 to make more teachers eligible to purchase extra retirement benefits in proportion to their accumulated,

[1] The collective bargaining agreement in operation at our research site is not specific about the number of consecutive absences due to illness that necessitate documentation. Rather, the agreement notes that building administrators may demand documentation (e.g. a note from a doctor) after a "pattern of abuse" has been established.

unused sick-leave.[2] Such incentive schemes are negatively associated with absence rates (Boyer, 1994; Ehrenberg, Ehrenberg, Rees, & Ehrenberg, 1991). Also, school districts in different states are subject to different statutory requirements for minimum numbers of paid sick-leave days, and generosity of leave provisions is positively associated with rates of absence (Educational Research Service, 1980; Ehrenberg, Ehrenberg, Rees, & Ehrenberg, 1991; Winkler, 1980).[3]

Numerous attributes of individual teachers have also been linked to their absence. Female teachers tend to be absent more often than male teachers (Educational Research Service, 1980; Scott & Wimbush, 1991), and teachers with long commutes from home to school are absent more than those with short commutes (Beavers, 1981; Bridges & Hallinan, 1978; Educational Research Service, 1980; Scott & Wimbush, 1991; Winkler, 1980). Teacher age has a non-monotonic relationship with absence rates; the youngest and oldest teachers are absent more often than teachers of intermediate ages (Educational Research Service, 1980).

School characteristics have also been associated with teacher absence rates. Teachers in elementary schools tend to have higher rates of absence than those in secondary schools (Educational Research Service, 1980). Teachers in schools with large student enrollments tend to be absent more than those in schools with fewer students. (Educational Research Service, 1980).

[2] California Assembly Bill 1102, Knox, 1997.
[3] For example, in Fall River, Massachusetts, teachers are contractually allowed 22 days of paid sick-leave per year (Warren, 2004).

Teacher Absences and Student Achievement

A small body of research has examined the association of teacher absence and student achievement. Most of these studies have detected a negative relationship between teacher absences and student achievement (Bayard, 2003; Beavers, 1981; Boswell, 1993; Cantrell, 2003; Lewis, 1981; Madden & et al., 1991; Manatt, 1987; Pitkoff, 1989; Smith, 1984; Summers & Raivetz, 1982; Womble, 2001; Woods, 1990). However, not all have.[4]

These correlational studies do not provide compelling evidence of a causal link between teacher absence and student achievement. This is because they do not deal explicitly with the potential correlation between teacher absence and either unobserved teacher skill/effort or student skills. For example, a high rate of absence may signal a teacher's lack of skill or effort when she is in school. If this were the dominant pattern, then the observed negative relationship between teacher absences and student achievement would be an upwardly biased estimate of the causal impact of teacher absences on student achievement. Thus, the research challenge is to develop a strategy that permits unbiased estimation of the causal impact of teacher absences on student achievement.

[4] Studies that do not find a relationship between teacher absence and student achievement include (Ehrenberg, Ehrenberg, Rees, & Ehrenberg, 1991; Kirk, 1998; New York City Public Schools, 2000; Occhino, 1987).

IV. DATA

We obtained data on students and teachers for these analyses from the Ormondale School District (OSD),[5] a large, urban school district in the northern part of the United States. The district has nearly 80 elementary schools, with approximately 200 teachers and 4000 students at each elementary grade level. OSD has an electronic report card system in place that supports the matching of students to individual classroom teachers, and its Office of Human Resources was able to provide information on each of these teacher's demographic characteristics, home ZIP-Code, absences, experience, and employment status in the 2003 school year (SY03) and the 2004 school year (SY04). For the purpose of constructing a measure of the distance that a teacher commuted from home to school, we obtained the geographical locations of schools from the *Common Core of Data*, and purchased a commercial database that matched each ZIP-Code to the geographic latitude and longitude of its centroid.[6] We accessed information on the enrollment and aggregate student demographics within each school from the website of the State Department of Education and obtained daily weather information from the archives of *National Climatic Data Center* for the period and region studied.

Student-Level Data

Our analytic dataset contains detailed information on a sample of 6,166 students who were in the fourth grade in either SY03 or SY04. Our outcome

[5] In accordance with the wishes of district officials, Ormondale School District is a pseudonym.
[6] ZipCodeWorldTM Premium is published by Hexa Software Development Center (www.zipcodeworld.com).

variable is student achievement in mathematics, using scores obtained on state-sponsored assessments administered to fourth-grade students in early May. The dataset also includes students' mathematics and reading achievement prior to entering fourth grade, as measured by scores on *Stanford Achievement Tests* (Series-9) the students took while they were in third grade. We treated these prior measures as covariates in our regression analyses. For the eight percent of students in our sample who repeated 3^{rd} grade, we used their maximum score in each domain (mathematics, reading) to represent prior achievement in that domain.

Our dataset also contains a variety of student-level demographic and programmatic variables that we included as covariates in our analyses. Demographic controls include: (a) a vector of dichotomous indicators of student race/ethnicity (African-American, Asian, Hispanic, White), (b) student gender, (c) whether English was the student's first language, (d) whether the student received special education and related services, and (e) whether a student was eligible for free or reduced-price lunch. As indicated by the summary statistics presented in Table 1, our analytic sample primarily contains disadvantaged students. More than 80 percent of the students were eligible for a free or reduced price lunch, 32 percent had a first language other than English, and 13 percent received special education services. Our sample also consisted primarily of students of color: 47 percent of the students were African-American, 31 percent were Hispanic, and 9 percent were of Asian background.

<Table 1 about here>

Finally, we constructed additional student-level covariates to document important facets of the students' academic participation. Using information on each student's date of enrollment in OSD, we constructed dichotomous indicators of whether students entered their fourth grade classes after particular points in the school year. Students who entered classes late in the academic year may have differed from other students in the extent to which their fourth grade instruction was provided by the teachers in our dataset. Additionally, these students may not have experienced some portion of the teacher absences that are our primary question predictor. We also constructed indicators of whether students had repeated third grade, and whether they were repeating fourth grade in the current year.

Teacher-Year Data

Our analytic sample contains 231 unique teachers, 80 of whom are in our sample for both *SY03* and *SY04*.[7] As indicated in Table 1, more than 80 percent of the teachers are female. Twenty-nine percent are African-American and ten percent are Hispanic. On average, teachers possessed 13 years of teaching experience. Eight percent of teachers were in their first year of teaching, and seven percent were in their second year. Their average length of the home-to-school commute was slightly less than seven miles, with seven percent commuting more than 20 miles.

On average, teachers in our sample were absent from their classrooms slightly less than eight days each during the entire instructional year, prior to the administration of the late spring achievement test. However, the sample variation in the number of days of absence among teachers is large. Nineteen percent of the teachers had no absences during the school year, 24 percent were absent for more than 10 days, and six percent were absent for more than 20 days. Absences were most common on Fridays, and second most common on Mondays,[8] a pattern suggesting some personal discretion in absences and potential for future policy influence.

Figure 1 displays the average number of teacher absences in each school in SY03 and SY04, partialling out the effects of teachers' gender, race, and experience The figure illustrates two points. First, there is substantial variation across schools in total days of teacher absence, net of teachers' personal characteristics. Second, the average total days of teacher absence in in some schools differed substantially from one academic year to the next while this was not the case in other schools.

<Figure 1 about here>

School-Level Data

We obtained school-level data from the public, electronic archives of the State Department of Education. As indicated in Table 1, student enrollment for the schools in our sample ranged from 118 to 897 students, with an average of 366. Seven of the 73 schools in the sample had a K-8 grade range, whereas the others were K-5 schools. The demographic composition of the student body varied markedly across schools. However, in all of the schools, at least 45 percent of the student body was students of color, and 50 of the 73 schools had a student body that was made up of more than 80 percent students of color.

Weather Conditions

We drew information on daily weather conditions experienced by the teachers from the *National Climatic Data Center*. We matched teachers to their local home weather stations by identifying the station closest to the centroid of their home ZIP-Code. This matching scheme led us to identify 20 unique weather stations: 17 in SY03 and 19 in SY04. Each line in Figure 2 represents a straight-line commute from the centroid of a teacher's home zip-Code to her school. The line segments illustrate the reasonable success of our strategy for matching teachers to weather stations. For the most peripheral circles, lines tend to start nearby. Note that the straight-line commute can vary among teachers matched to the same weather station because they are employed at different schools.[9] The area of each circle in Figure 2 is proportional to the number of teachers matched to that weather station. The figure illustrates both that there is considerable variation in the location of teachers' homes, but that the majority of teachers live close to one of two weather stations.

<Figure 2 about here>

[8] For each day of the week from Monday to Friday, we computed the percentage of days when school was in session that teachers were absent. The figures are as follows: Monday, 5.2; Tuesday, 4.8; Wednesday, 5.0, Thursday, 4.9; Friday 6.1.

[9] Three teachers appearing in our dataset changed schools between academic years, and six teachers changed home ZIP-Codes.

As instruments in our analyses, we employ several measures of daily weather conditions, including: maximum daily temperature, minimum daily temperature, daily precipitation, daily snow accumulation, and daily snow-depth.[10] Figure 3 displays the minimum daily temperatures over the SY03 and SY04 school years. The length of each daily bar indicates the differences in minimum daily temperatures among the weather stations, variation that is central to the identification strategy that we employ in our instrumental variables estimation.

<Figure 3 about here>

We aggregated the values of the daily weather variables over the days before the spring achievement tests in each school year on which teachers would have offered instruction.[11] Table 2 presents descriptive statistics on the aggregate weather variables used as instruments in our analyses. Notice that there is considerable variation in the weather indicators, from station to station, and that this variation is present in both SY03 to SY04. However, 80 percent of the teachers were matched to 20 percent of the weather stations.

<Table 2 about here>

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[10] A 2005 paper by Jacob, Lefgren, and Moretti on the incidence of crime provided ideas on how to make use of exogenous shocks due to weather. Missing values on the daily weather indicators were not numerous. We replaced them with the respective daily means across the remaining weather stations with non-missing values. The percentage of observations with missing values for daily weather-related variables was 4.5 percent for maximum temperature, 3.4 percent for minimum temperature, 1.8 percent for snowfall, and less than 0.1 percent for precipitation.

[11] For some daily weather variables, we take the total over the days of interest (Total snowfall, for example); for others, we take a count of days (Days of Snow, for example).

VI. STATISTICAL ANALYSIS

Our investigation of the causal impact of teacher absence on student achievement was conducted in a *student-teacher-year* dataset, in which there was a single record ("row") of information for each student, *i*, with each teacher, *j*, in each year, *t*. In our principal regression model, we hypothesized that student mathematics achievement depended on teacher absence, as follows:

$$Y_{ijt} = \beta_0 + \beta_1 ABS_{jt} + \beta_2 T_{jt} + \beta_3 S_{ijt} + \delta_t + \nu_{ijt} \tag{1}$$

where Y_{ijt} is the mathematics achievement of student i, taught by teacher *j* in year *t*. ABS_{jt} is the key question predictor, and represents the square root of the number of days that the j^{th} teacher was absent from her class in year *t*.[12] T_{jt} is a vector of teacher and school characteristics. S_{ijt} is a vector of student characteristics including measures of prior achievement, and δ_t is the fixed-effect of year *t*, which we include in all models to control for secular trends in student achievement. ν_{ijt} is an error term. In estimating standard errors associated with the regression coefficients in our models, we accounted for the nesting of students within classrooms either by using the Huber-White estimator or by bootstrapping. We document these choices in the forthcoming tables of fitted models.

Estimation of β_1 using OLS methods may be biased because teacher absences may be correlated with unobserved teacher skill. We adopt three

[12] There are two reasons for transforming total days of teacher absence. First, the between-teacher distribution of the untransformed variable had a positively-skewed distribution. Second, sample plots of student mathematics achievement versus total days of teacher absence revealed

strategies for resolving this problem. Our first strategy adds the fixed effects of teachers to Equation 1, replacing explicit predictors T_{jt}. This accounts for the impact, on student achievement, of all observed and unobserved time-invariant differences in teacher skill levels, removing them as a potential source of bias from the estimation. However, it does not deal with potential bias that may be introduced by time-varying differences in unobserved teacher or effort skill levels that may be correlated with teacher absences. For example, a teacher with an ill family member during the SY04 school year may be absent from school many more days during that year than during the SY03 school year. However, weaker performance by her students during the SY04 school year than during the SY03 school year may reflect not only her absences from school, but possibly her low energy level and high stress level when she was in class.

Our second identification strategy deals with the potential endogeneity of teacher absence using an instrumental variables estimation (*IVE*) approach. Under the IVE strategy, we specify a new "first stage" model that represents teacher absence as a function of instruments and covariates, as follows:

$$ABS_{jt} = \alpha_0 + \alpha_1 D_{jt} + \alpha_2 W_{jt} + \alpha_3 \left(D_{jt} \times W_{jt}\right) + \alpha_4 T_{jt} + \alpha_5 S_{ijt} + \delta_t + \varepsilon_{jt} \qquad (2)$$

This model includes all covariates present in Equation 1 (which now becomes the "second-stage" model under the *IVE* strategy) and adds the impacts of the hypothesized instruments, including: (a) D_{jt}, a polynomial function of the teacher's home-to-school commuting distance, (b) W_{jt}, indicators of the annual aggregate weather conditions and two-way interactions among them, and (c)

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a non-linear relationship in which the marginal impact of absence on achievement diminished with two-way interactions among predictors D_{jt} and W_{jt}. Parameter β_1 in what has now become the second-stage model of the IVE strategy (Equation 1) is then identified under the assumption that at least one of the instruments is not correlated with residual v_{ijt}.

One potential problem with this identification strategy is that the distances that teachers commute to work may also be correlated with unobserved indicators of their skill or commitment. If this is the case, then the distance and two-way distance-weather interaction variables may not be legitimate instruments. We attempt to deal with this potential problem by adopting a third identification strategy that is a synthesis of the first two strategies. We include the same instruments in the first-stage model in Equation 2, but add the fixed effects of teachers to the second-stage model in Equation 1 in order to control for all time-invariant differences in unobserved teacher skills and effort. In implementing this third strategy, we did not include fixed effects for teachers in the first stage model in Equation 2 because there is insufficient variation in the instruments within teachers over the two school years.

Quality of the Instruments

The instrumental variables in the first stage model of the IVE strategy in Equation 2 must predict a substantial portion of the variation in teacher absence, for our strategy to be successful. Concerns that IV estimates are biased in the direction of the flawed OLS estimates escalate when the instruments are weakly correlated with the endogenous predictor (see, for example, Bound, Jaeger, &

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the number of absences.

Baker, 1995; Staiger & Stock, 1997). To assess the impact of the instruments in the first-stage model in Equation 2, we conducted generalized linear hypothesis tests of the null-hypothesis that the parameters associated with the IVs were simultaneously zero. We rejected the null hypothesis that these parameters were simultaneously zero (df=41, $p<.0001$) . Similarly, the inclusion of the instruments in the first stage model in Equation 2 led to a 255% increase in the overall R^2 statistic, from .028 to .096.

VII. RESULTS

Table 3 presents parameter estimates, standard errors and approximate p-values from the fitting of the model in Equation 1 using our several analytic strategies.[13] The columns of this table are labeled 1(a) through 1(f). Columns 1(a) through 1(c) contain estimates that were obtained using OLS-methods. Column 1(a) contains *OLS*-estimates of the parameters in Equation 1 based on information on all 231 teachers who taught fourth grade in *either* the *SY03 or SY04* school year. Column 1(b) presents OLS-estimates of the parameters in the same model, but using only the sample of 80 teachers who taught fourth grade in *both* the *SY03* and *SY04* school years. We provide this column of estimates for comparison with the results of fitting subsequent models that include a specific strategy for identifying the causal effect of teacher absences on student achievement. Column 1(c) contains OLS-estimates of the parameters in

[13] We do not display stage-one results for the models fitted with an IVE strategy, but such results are available from the authors. Two- and three-way interaction terms make these results difficult to interpret.

Equation 1 after the inclusion of teacher fixed effects in this model. The sample of teachers and students used in the fitting of this model is identical to the sample that was used to fit the model reported in column 1(b). Columns 1(d) through 1(f) of Table 3 contain estimates of the parameters in Equation 1 using instrumental variables estimation, with weather, length of commute, and their interactions as instruments for total number of days of teacher absence. Column 1(d) presents IV-estimates based on the same sample that was used to fit the model reported in column 1(a). Column 1(e) presents IV-estimates, using the sample of 80 teachers who taught fourth grade in both SY03 and SY04 and that were used to obtain the *OLS*-estimates in column 1(b). Column 1(f) presents IV-estimates for this same sample but from a version of Equation 1 that includes the fixed effects of teachers.

<Table 3 about here>

As indicated in column 1(a) of Table 3, the *OLS* estimate of the impact of (the square root of) total days of teacher absence on students' mathematics achievement is negative and different from zero (at the 0.10 level). When this model is refitted using only data on the sample of 80 teachers who taught fourth grade in both the *SY03* and *SY04* school years, the estimated absence parameter has almost the same magnitude, but it lacks statistical significance. In column 1(c), the fixed effect estimate is again negative and larger than the estimate obtained in the model without fixed effects in column 1(b), but it is again not statistically significantly different from zero.

As mentioned above, even though the fixed effects estimate controls for potential time-invariant differences among teachers in unobserved skill and effort levels, it does not control for any time-varying differences. For that reason we fit models in which we instrumented for teacher absences. Column 1(d) presents results from a model in which the instruments are functions of weather, length of commute, and their interactions. Here, the coefficient on teacher absence is again negative (-0.713) and now statistically significantly different from zero at the 0.01 level. The magnitude of the coefficient implies that the first ten days of teacher absences in an academic year causes students' mathematics achievement to be reduced by 2.25 points.[14] Since the standard deviation of students' mathematics scores in the analytic sample is 14.60, this means that the impact of the first ten days of a teachers absence reduces student mathematics achievement by approximately 0.15 of a standard deviation.

One could argue that a teacher's skill or effort level is correlated with the length of a teacher's commute and consequently that commute length is not a credible instrument. To deal with that possibility, we fit the model in column 1(f) of Table 3, including the fixed effects of teachers in the second-stage model. Now, the coefficient on teacher absence is -0.750 and is again statistically significantly different from zero at the 0.01 level. Note that the magnitude of the coefficient on teacher absences is larger in the IV-estimated model that includes the teacher fixed effects (column 1(f): -0.75) than in the IV-estimated model fitted to the data on the same sample but not including the teacher fixed effects (column 1(e): -0.59). One explanation is that, on average, teachers with longer commutes are more skilled or exhibit larger effort levels while in school than teachers with shorter commutes. Not accounting for these differences among teachers results in a downward bias in the estimate of the impact of teachers absences on student achievement. In summary, our results provide strong evidence that teacher absence negatively impacts student mathematics achievement.[15]

We also fitted models in which the outcome was replaced by students' scores on the state fourth grade *English Language Arts* examination, using the same set of analytic strategies, but we do not report those findings explicitly here. The estimated coefficient on teacher absences in these fitted models was also consistently negative, but its magnitude was smaller and not always statistically significantly different from zero. This raises the question of why teacher absence would influence students' mathematics skills more than their ELA skills. To gain some insight into the answer to this question, we conducted interviews with four elementary school principals in the OSD. They told us that OSD had adopted a new elementary school mathematics curriculum in 2000 that placed great emphasis on developing children's mathematical problem-solving skills, their ability to make use of alternative computational algorithms, and their ability to explain their reasoning processes in writing. Teaching the new mathematics

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[14] $\sqrt{10}\times^{-} 0.713 = 2.2547$

[15] We also fit models in which only functions of weather were used as instruments. While the coefficient on teacher absences was also negative in these models, it was very small and the standard error was very large. The problem is that the variation in weather conditions over a school year for teachers in the sample is quite modest.

curriculum successfully required the development of new teaching skills for most OSD elementary school teachers. The district invested heavily in mathematics coaches and in summer training institutes to provide OSD's elementary with the requisite skills. The net effect of the new mathematics curriculum and the retraining of OSD's elementary school teachers – training that was not received by OSD substitute teachers – is that the gap in instructional quality, when a fourth grade teacher was replaced by a substitute teacher was particularly large.

VIII. THREATS TO VALIDITY

Correlation between Teacher Absence and Unobserved Skill or Effort

The primary objection to using *OLS*-methods to fit the hypothesized regression model in Equation 1 is that teacher absences may be correlated with unobserved teacher skill or effort level, both potentially impacting student achievement. If this were the case, and if teachers who were absent during the months leading up to the early May student test date were also the teachers most likely to be absent after the test date, then post-test-date teacher absences would also have a negative relationship with students' mathematics scores. To examine this possibility, we added the square root of the total number of post-test-date teacher absences as a predictor to Equation 1 and refitted the model using analytic strategies that matched those in columns 1(a) through 1(c) of Table 3.

We present the results of this sensitivity analysis in Table 4, where we list *OLS*-estimates of the parameters associated with the (square root) of total days of teacher absence before and after the May testing date. The coefficients associated with the square root of *pre*-test-date teacher absences are very similar in value to those reported in Table 3. The coefficients associated with the square root of *post*-test-date teacher absences are much smaller than those on *pre*-test-date absences and their standard errors are much larger. While not definitive, this pattern lends credence to the proposition that the pre-test-date teacher absences are not *primarily* providing information about unobserved teacher skills or effort levels for, if they were, we would anticipate that the effects of absence would differ little, regardless of whether they occurred pre- or post-the anticipated May student testing date.

<Table 4 about here>

Imputation of Missing Values for Student Prior Achievement

It is possible that the students in our dataset with missing values on the measures of prior achievement in mathematics and reading differed systematically from other students on observed or unobserved characteristics that are correlated with the outcome variable, measured student achievement. If so, values that we imputed for these important control predictors for these students could bias our estimates, in one direction or the other. To assess this threat to validity, we refit all our regression models on a restricted dataset excluding students for whom we imputed values on either measure of prior achievement. Table 5 presents the critical coefficients associated with teacher absence under each of the analytic strategies we employed. Comparison of the estimated coefficients with the analogous coefficients in Table 3 reveals that they are strikingly similar, under all analytic conditions. This leads us to conclude that our imputation of student scores on measures of prior achievement did not influence the principal findings.

<Table 5 about here>

Extreme Values of Teacher Absence

In our dataset, the distribution of the annual total days of teacher absence is highly skewed by the values contributed by a few teachers who exhibit extraordinary numbers of absences. To assess whether the presence of these teachers in our analytic sample has exerted undue influence on our results, we refit all of our hypothesized regression models excluding students and teachers where the teachers have values of absence, above selected threshold levels, defined by percentiles. The results are presented in Table 6. They suggest that the regression coefficients associated with teacher absence in models 1(a) through 1(c) fitted using *OLS*-methods typically become smaller when the sample is re-defined to exclude students taught by teachers with high levels of absence. However, this is not the case for regression coefficients obtained by instrumental variables estimation in models 1(d) through 1(e). Indeed, the coefficient on the square root of teacher absence becomes larger when the IV models are fitted in samples that exclude teachers with especially high levels of absences.

<Table 6 about here>

Students Who Enter A Class Late in the Academic Year

Approximately 8 percent of students in our analytic sample entered their fourth grade teachers' classes at some point *after* the beginning of the academic year. These students pose a threat to the validity of our inferences for two reasons. First, their teachers may then have fewer opportunities to affect the achievement of these late-entering students, who may also miss crucial early lessons designed to facilitate cooperative experiences, build interpersonal trust, or otherwise lay groundwork for later academic instruction. By this reasoning, late-entering students may accentuate the estimated impact of teacher absence. Second, late-entering students may not be exposed to some of the teacher absences whose impact we seek to estimate.

We test the robustness of our results to this threat by refitting our statistical models in successively-restricted datasets, omitting those students who entered fourth grade after selected dates. The results, which are summarized in Table 7, indicate that the impact of teacher absence is not very sensitive to the removal of students who enter fourth grade after the beginning of the school year.

<Table 7 about here>

VIII. DISCUSSION

On average, teachers in OSD are absent from their classrooms on 5% of the days when they are expected to teach.[16] This rate of absence exceeds that of executives and managers, who have similar levels of education (Rhodes & Steers, 1990). However, the difference is not surprising given that teachers work with large numbers of students every day, some of whom carry infectious diseases. However, variation in total days of absence is large. Twenty-four percent of teachers were absent more than 10 days in the school year and six per percent were absent more than 20 days. On average, teachers are more likely to be absent from school on Mondays and Fridays than on other days of the week. This pattern suggests that some of their absences reflect personal convenience rather than illness, a situation that is important because school district policies regarding teacher absence can affect those absences.

Whether it is prudent policy to negotiate policies that would reduce teacher absence depends in part on the impact that teacher absences have on student achievement. Obtaining an unbiased estimate of that causal impact is the primary objective of this study. We found that the first ten days of teacher absence reduced student mathematics achievement in fourth grade by approximately 0.15 of a standard deviation. This pattern suggests that school districts struggling to improve student achievement in the face of strong external

[16]Teachers in our sample missed a total of 8.9 days, on average, during an academic year comprising 180 days.

accountability provisions may find it cost-effective to negotiate policies with their teachers that would reduce absences.

Table 1. Summary statistics on selected variables describing students, teachers, and schools in the analytic sample.

Variable	Mean	Std. Dev.
Students (N=6166[a])		
Mathematics achievement	229.19	14.60
ELA achievement[b]	232.54	13.68
Prior mathematics achievement	56.62	3.08
Prior reading achievement	57.96	3.38
Repeated 3rd grade	0.08	-
Repeating 4th grade	0.03	-
Receiving special education services	0.13	-
First language is English	0.68	-
Eligible for free/reduced lunch	0.84	-
Female student	0.50	-
Asian student	0.09	-
Black student	0.47	-
Hispanic student	0.31	-
White student	0.13	-
Teachers (N=231 distinct teachers)		
Absences (before May student test date)	7.77	9.58
Absences (after May student test date)	1.10	1.73
One-way commuting distance	6.89	8.21
Years of experience	13.25	12.27
Female teacher	0.86	0.35
Asian teacher	0.03	-
Black teacher	0.29	-
Hispanic teacher	0.10	-
White teacher	0.59	-
Schools (N=73 distinct schools)		
Total Enrollment	366.94	187.07
% of students free/reduced lunch eligible	0.81	0.10
% of students female	0.48	0.03
% of students Asian	0.07	0.11
% of students Black	0.47	0.25
% of students Hispanic	0.31	0.21
% of students White	0.00	0.01
Grades K-8	0.15	-

Notes:

a. *An observation is a student-year. Our 6166 observations include 190 students who appear in both SY03 and SY04. Eighty of the 231 unique teachers appear in both SY03 and SY04. Sixty-five of the 73 unique schools are present in both SY03 and SY04.*

b. Sixty of the 6166 student-year observations have missing values on English Language Arts achievement.

Table 2. Summary statistics on selected variables describing aggregated weather conditions across weather-stations to which we matched teachers.[a] Observations in the dataset represent a single year for a unique weather-station.[b]

	Mean	Std.Dev.	Min	Max
SY03: 17 Stations				
Total snowfall (in.)	37.27	11.83	19.71	64.55
Total precipitation (in.)	17.28	2.43	13.23	21.24
Days with snowfall	27.94	9.38	13	42
Days with snow on ground	52.77	14.68	24	69
Days of bitter cold[c]	7.88	2.67	4	14
Days of precipitation	67.65	10.09	51	84
Days of extreme heat[d]	3.75	1.15	1	7
SY04: 19 Stations				
Total snowfall (in.)	21.73	7.15	11.68	39.18
Total precipitation (in.)	25.06	2.72	20.17	29.94
Days with snowfall	21.53	7.88	11	39
Days with snow on ground	34.63	9.86	13	48
Days of bitter cold	8.79	1.78	6	13
Days of precipitation	73.68	9.64	51	90
Days of extreme heat	0.79	1.03	0	3

Notes:

a. *We aggregated daily weather variables over "instructional days" – those days falling before the spring administration of the student achievement tests on which we believe a teacher who was not absent from school would have had opportunity to instruct students. Thus, we exclude holidays, weekend-days, professional development days, and days on which OSD officials closed schools because of snow. There were 152 such instructional days in SY03 and 157 in SY04.*

b. *Approximately 80 percent of teachers are matched to 20 percent of stations, so variation between stations does not translate into much variation between teachers.*

c. *A day is "bitter cold" if the maximum temperature is less than 25º F.*

d. *A day is of "extreme heat" if the maximum temperature exceeds 85º F.*

Table 3. Parameter estimates (standard errors) for a sequence of fitted regression models in which the outcome is the mathematics achievement of fourth grade students in SY03 or SY04. Fitted models are arrayed by analytic strategy.

	Model/Estimation Strategy					
	1(a) *OLS*	*1(b)* *OLS*	*1(c)* *OLS*	*1(d)* *IV*	*1(e)* *IV*	*1(f)* *2SLS*[d]
Fixed Effects of Teachers	no	no	yes	no	no	yes
Square-Root of Absence	-0.279~	-0.223	-0.317	-0.713**	-0.592~	-0.750**
	(0.169)	(0.204)	(0.229)	(0.225)	(0.319)	(0.247)
Prior Math Achievement	-1.277	-2.546	-2.465	-1.285	-2.581~	-2.484
	(1.521)	(1.854)	(2.009)	(1.436)	(1.422)	(1.525)
Square of Prior Math.	0.029*	0.040*	0.039*	0.029*	0.040**	0.039**
	(0.014)	(0.016)	(0.018)	(0.013)	(0.012)	(0.013)
Prior Reading Achievement	-5.712**	-8.044**	-7.674**	-5.744**	-8.064**	-7.691**
	(0.989)	(1.852)	(1.908)	(1.025)	(1.777)	(1.425)
Square of Prior Reading	0.058**	0.079**	0.076**	0.058**	0.079**	0.076**
	(0.008)	(0.016)	(0.016)	(0.009)	(0.015)	(0.012)
Receiving Special Education	0.102	0.228	0.295	0.095	0.216	0.282
	(0.425)	(0.588)	(0.593)	(0.387)	(0.585)	(0.492)
First Language English	-1.129**	-1.090*	-1.167*	-1.111**	-1.061**	-1.129**
	(0.307)	(0.430)	(0.445)	(0.269)	(0.401)	(0.421)
Free/Reduced Lunch Eligible	-1.014**	-1.420**	-1.331**	-1.012**	-1.417**	-1.331**
	(0.356)	(0.468)	(0.457)	(0.328)	(0.418)	(0.443)
Female Student	0.071	-0.203	-0.200	0.080	-0.193	-0.189
	(0.227)	(0.312)	(0.313)	(0.207)	(0.286)	(0.303)
White Student	2.916**	2.752**	1.668**	2.906**	2.732**	1.682**
	(0.496)	(0.670)	(0.631)	(0.480)	(0.675)	(0.525)
Hispanic Student	0.841**	1.106**	1.103**	0.862*	1.123**	1.123*
	(0.309)	(0.374)	(0.390)	(0.343)	(0.416)	(0.438)
Asian Student	2.828**	2.621**	2.502**	2.858**	2.650**	2.537**

	(0.555)	(0.722)	(0.731)	(0.548)	(0.526)	(0.737)
Repeated 3rd Grade	-3.160**	-2.525**	-2.637**	-3.168**	-2.545**	-2.656**
	(0.388)	(0.565)	(0.575)	(0.365)	(0.588)	(0.572)
Repeated 4th Grade	4.086**	4.317**	4.221**	4.069**	4.297**	4.211**
	(0.640)	(0.887)	(0.882)	(0.623)	(0.816)	(0.816)
Female Teacher	0.692	0.248		1.006	0.339	
	(1.018)	(1.183)		(0.879)	(1.516)	
Asian Teacher	0.115	-5.287**		0.032	-5.163*	
	(1.818)	(1.368)		(2.260)	(2.327)	
Black Teacher	-2.193**	-1.663		-1.853*	-1.254	
	(0.798)	(1.127)		(0.739)	(1.150)	
Hispanic Teacher	-0.512	0.928		-0.021	1.158	
	(1.336)	(1.648)		(1.567)	(2.403)	
1 or 2 Years of Experience	-2.042*	-4.242*	-2.901	-2.087*	-3.952	-1.654
	(0.973)	(1.886)	(4.974)	(1.032)	(2.628)	(2.832)
3 or 4 Years of Experience	-0.141	-1.371	-0.300	0.061	-0.977	0.815
	(1.145)	(1.628)	(4.098)	(1.190)	(2.405)	(2.276)
5 to 10 Years of Experience	1.052	0.160	1.011	1.211	0.465	-1.654
	(0.988)	(1.288)	(3.229)	(0.802)	(2.205)	(2.832)
S/White×T/Black	-2.479*	-4.178**		-2.420*	-4.082**	
	(0.966)	(1.123)		(0.944)	(1.235)	
S/White×T/Hisp	7.502*	-1.453		7.556~	-1.431	
	(3.019)	(1.157)		(4.208)	(1.278)	
S/White×T/Asian	6.016	-8.034**		6.011	-7.891**	
	(4.695)	(0.826)		(6.634)	(0.834)	
Grades K-8	-44.549~	-98.303**		-42.177~	-95.440*	
	(24.625)	(26.741)		(22.607)	(41.549)	
Log of Enrollment	-1.619*	-1.985~		-1.718*	-2.241	
	(0.772)	(1.082)		(0.843)	(1.764)	
K-8×Log of Enrollment	7.539*	16.636**		7.131*	16.149*	

	(3.818)	(4.112)		(3.502)	(6.455)	
2002-03 School-Year	-3.656**	-3.699**	-3.723**	-3.652**	-3.677**	-3.747**
	(0.446)	(0.482)	(0.531)	(0.518)	(0.445)	(0.323)
Intercept	357.806**	461.906**	437.176**	360.084**	465.488**	438.800**
	(50.863)	(78.649)	(83.404)	(43.624)	(71.982)	(47.438)
N Students	6166	3191	3191	6166	3191	3191
N Teachers	231	80	80	231	80	80
Variance Components						
σ_u^2	26.37	20.89	31.17	25.70	20.27	34.35
σ_e^2	69.52	67.44	67.63	69.62	67.60	67.50
ρ	0.28	0.24	0.32	0.27	0.23	0.34
Goodness-of-Fit						
overall r^2	0.565	0.533	0.474	0.563	0.53	0.457
between r^2	0.738	0.645	0.459	0.734	0.638	0.404
within r^2	0.445	0.473	0.471	0.445	0.473	0.472

*~ p<.1, * p<.05; ** p<.01*

Notes:

a. *For models fit using an IV strategy, the instruments for teacher absence include the main effects of linear and cubic transformations of the teacher's commuting distance, the main effects of the weather descriptors, a subset of two-way interactions among the weather descriptors, and the interaction of the main effects of weather and the two-way interactions among the weather descriptors with the distance main effects.*

b. *We include both measures of prior achievement and their squares as controls for students' earlier academic experience. We experimented with different polynomial forms of commuting distance. We settled on a cubic polynomial without a quadratic term. In our range of values of distance, the linear and quadratic terms are highly collinear. We suppress the first stage output of the models fit with an IV strategy.*

c. *Other student controls include indicators of grade-repetition, special education and free/reduced-price lunch eligibility, gender, race; teacher controls include indicators of race, experience, and gender; school controls include log of enrollment, grade-span, and their interaction. We also include two-way interactions between one indicator of student race (White) and indicators of teacher race.*

d. *We fit models representing an IV strategy in two different ways. For models that included the random-effects for teachers, we used Stata's XTIVREG command; for models that included the fixed-effects of teachers, we used a 2SLS approach in order to include the fixed-effects explicitly in the second-stage only. For the latter 2SLS approach, we corrected the standard errors using methods described in the Stata Technical Database.*

Table 4. Selected parameter estimates (standard errors) for a sequence of fitted regression models where the outcome is measured mathematics achievement in fourth grade students in SY03 or SY04. Model specifications are identical to those presented for the models representing IV strategies in Table 3 except that we add an additional predictor: the square root of absences occurring after the May administration date of the mathematics achievement test.

	Model/Estimation Strategy					
	1(a) OLS	*1(b) OLS*	*1(c) OLS*	*1(d) IV*	*1(e) IV*	*1(f) 2SLS*
Fixed Effects of Teachers	no	no	yes	no	no	yes
Square-Root of Absence Before May Test Date	-0.279	-0.225	-0.319	-0.690**	-0.545*	-0.732**
	(0.172)	(0.204)	(0.232)	(0.237)	(0.242)	(0.248)
Square-Root of Absence After May Test Date	-0.028	-0.134	-0.124	0.862	0.880	0.512
	(0.548)	(0.617)	(0.669)	(0.653)	(0.567)	(0.549)
N Students	6166	3191	3191	6166	3191	3191
N Teachers	231	80	80	231	80	80
Variance Components						
σ_u^2	26.430	21.151	31.114	27.217	21.492	34.258
σ_e^2	69.539	67.453	67.667	69.672	67.700	67.503
ρ	0.275	0.239	0.315	0.281	0.241	0.337
Goodness-of-Fit						
overall r^2	0.565	0.533	0.474	0.562	0.527	0.458
between r^2	0.738	0.646	0.46	0.735	0.628	0.405
within r^2	0.445	0.473	0.471	0.444	0.471	0.472

*~ p<.1, * p<.05; ** p<.01*

Notes: In Columns 1(d) -1(f), we instrument only for the square root of pre-test absences. The reason is that the aggregation of the daily weather variables applies to the period of time before the May administration of the mathematics achievement test.

Table 5. Parameter estimates (robust standard errors) for sequence of regression models in which the outcome is student mathematics achievement of fourth grade students in SY03 or SY04, fitted to a restricted dataset, by analytic strategy. For these analyses, we omitted from the dataset any student whose prior achievement score, either math or reading, was imputed.

	Model/Estimation Strategy					
	1(a) OLS	*1(b) OLS*	*1(c) OLS*	*1(d) IV*	*1(e) IV*	*1(f) 2SLS*
Fixed Effects of Teachers	no	no	yes	no	no	yes
Square-Root of Absence	-0.337~	-0.250	-0.339	-0.734**	-0.628	-0.788**
	(0.204)	(0.254)	(0.280)	(0.270)	(0.428)	(0.275)
N Students	4768	2483	2483	4768	2483	2483
N Teachers	229	80	80	229	80	80
Variance Components						
σ_u^2	27.91	20.62	34.63	29.03	21.67	37.88
σ_e^2	73.32	70.16	70.48	73.44	70.38	70.32
ρ	0.28	0.23	0.33	0.28	0.24	0.35
Goodness-of-Fit						
overall r^2	0.546	0.517	0.451	0.543	0.513	0.435
between r^2	0.704	0.604	0.403	0.7	0.596	0.359
within r^2	0.432	0.46	0.456	0.432	0.459	0.458

*~ p<.1, * p<.05; ** p<.01*

Notes: For the models in Columns 1(d) and 1(e), we use the default standard errors produced by Stata's XTIVREG command because the restriction on the dataset is fairly severe, resulting in problems for bootstrap methods. For Column 1(d), for example, we analyzed only 4768 students, a 23 percent reduction in cases compared to this specification in Table 3. We suppress the parameter estimates for control predictors, and we suppress the first stage results for the models fit with the IV estimator. These models have the same specifications, by strategy, as portrayed in Table 3. See the notes following Table 3 for a description of the instruments.

Table 6. Selected parameter estimates (standard errors) and estimated p-values for sequence of regression models in which the outcome is measured mathematics achievement of fourth grade students in SY03 or SY04, fitted to restricted datasets, by analytic strategy.

Estimation sample restricted to teachers with total absences that are less than the ...		Model/Estimation Strategy 1(a) OLS	1(b) OLS	1(c) OLS	1(d) IV	1(e) IV	1(f) 2SLS
	Fixed-Effects for Teachers	no	no	yes	no	no	yes
99th percentile (54)	Square-Root of Absence	-0.173	-0.095	-0.245	-0.776*	-0.531~	-0.869**
		(0.195)	(0.228)	(0.286)	(0.309)	(0.306)	(0.314)
	N Students	6110	3173	3173	6110	3173	3173
	N Teachers	229	80	80	229	80	80
95th percentile (23)	Square-Root of Absence	-0.108	0.042	-0.113	-0.965*	-0.646	-1.072**
		(0.264)	(0.327)	(0.398)	(0.407)	(0.414)	(0.400)
	N Students	5876	3072	3072	5876	3072	3072
	N Teachers	222	80	80	222	80	80
90th percentile (16)	Square-Root of Absence	0.023	0.175	-0.301	-2.053**	-1.818**	-2.406**
		(0.395)	(0.589)	(0.822)	(0.616)	(0.632)	(0.664)
	N Students	5474	2803	2803	5474	2803	3072
	N Teachers	??	??	??	??	??	??
50th percentile (6)	Square-Root of Absence	0.261	-0.326	-2.068	-0.551	-2.596*	-[a]
		(0.567)	(0.800)	(1.334)	(1.029)	(1.168)	-
	N Students	3093	1411	1411	3093	1411	
	N Teachers	133	50	50	133	50	

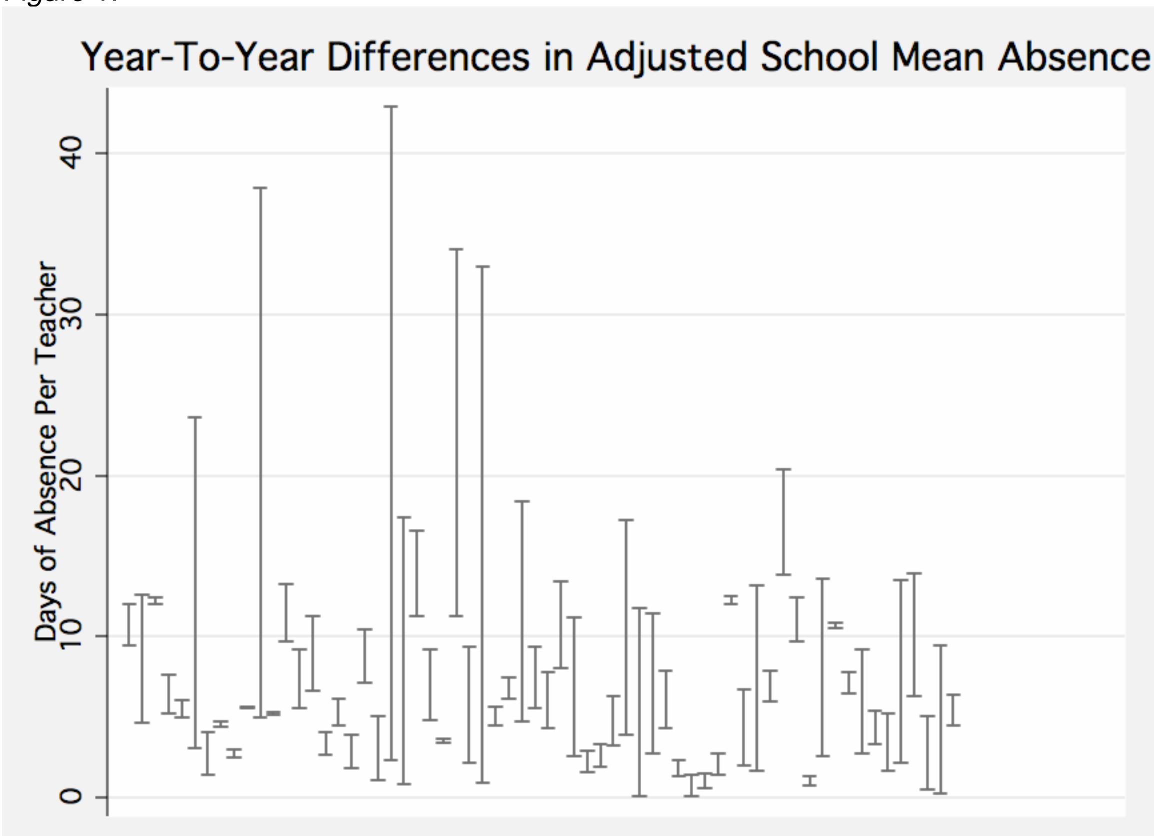
*~ p<.1, * p<.05; ** p<.01*
Notes:
a. We were unable to fit this model due to data limitations.

Table 7. Selected parameter estimates (standard errors) for sequence of regression models in which the outcome is measured mathematics achievement of fourth grade students in SY03 or SY04, fitted to restricted datasets, by analytic strategy. Horizontal lines separate results corresponding to models fitted to datasets from which students who entered class after January 15, November 15, and September 15 have been omitted.

Estimation sample restricted to those students entering class before...		Model/Estimation Strategy					
		1(a) OLS	*1(b) OLS*	*1(c) OLS*	*1(d) IV*	*1(e) IV*	*1(f) 2SLS*
	Fixed Effects of Teachers	no	No	yes	no	no	yes
	Square-Root of Absence	-0.233	-0.156	-0.234	-0.612*	-0.485*	-0.623*
Jan 15		(0.170)	(0.208)	(0.236)	(0.240)	(0.243)	(0.252)
	N Students	6015	3104	3104	6015	3104	3104
	Square-Root of Absence	-0.236	-0.161	-0.241	-0.622*	-0.484*	-0.639*
Nov 15		(0.175)	(0.216)	(0.242)	(0.242)	(0.245)	(0.254)
	N Students	5919	3044	3044	5919	3044	3044
	Square-Root of Absence	-0.238	-0.167	-0.250	-0.642*	-0.523*	-0.663*
Dec 15		(0.179)	(0.224)	(0.249)	(0.252)	(0.256)	(0.266)
	N Students	5705	2958	2958	5705	2958	2958
	N Teachers	231	80	80	231	80	80

*~ p<.1, * p<.05; ** p<.01*

Figure 1.



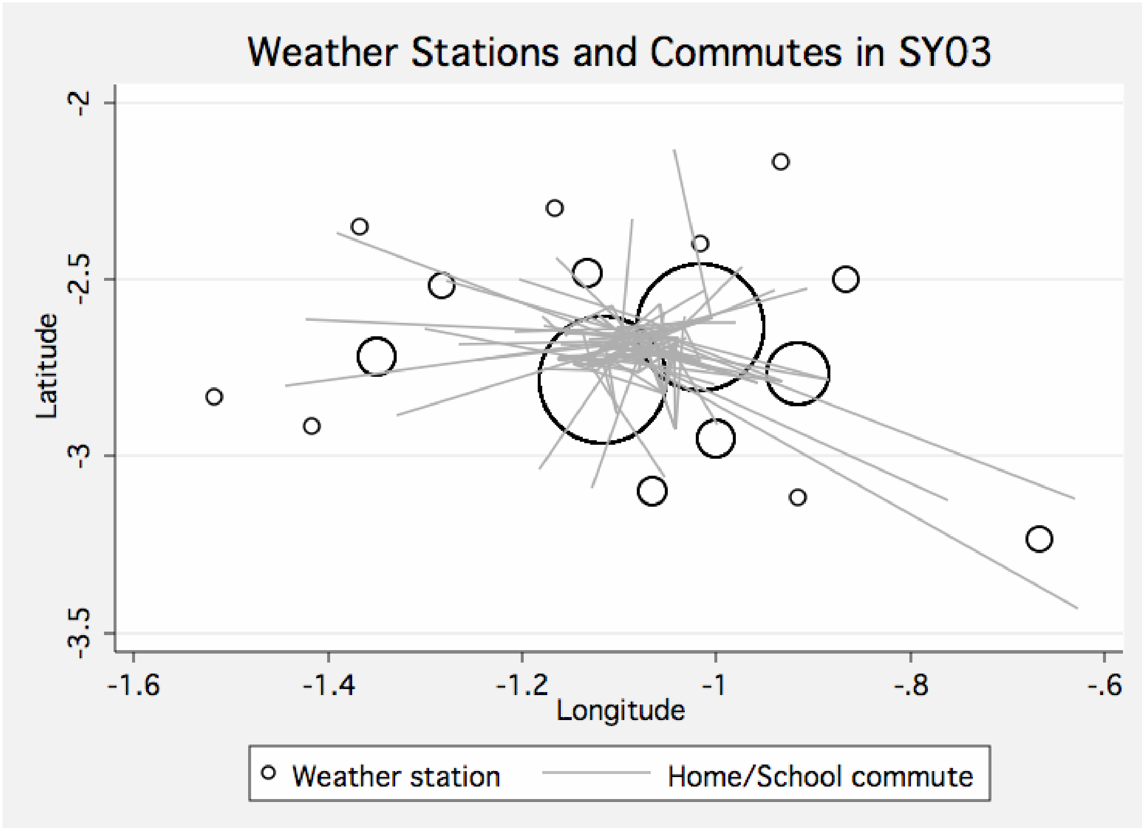
Notes:

a. *Separately for SY03 and SY04, we estimated the adjusted school mean values of the square root of absence in two steps. First, we regressed this variable on the indicators of teacher gender, teacher race, teacher experience, and fixed effects of schools. Second, we calculated school means of predicted values with the teacher variables set to their average levels across the dataset. We square the adjusted means to present them on the most natural scale, days of absence.*

b. *For each of the models, we conducted a GLH test of whether the fixed effects of schools were simultaneously zero. For SY03, we rejected the null hypothesis with $F(7,65)=26.05$ ($p<.0001$); for SY04, $F(8,70)=20.37$ ($p<.0001$).*

c. *Sixty-five schools were featured in both years. The correlation coefficient for the unadjusted school means of square root of absence between years is -0.020; for the adjusted school means, 0.024*

Figure 2. Weather stations (circles) and straight-line commuting routes (lines). The area of a circle is proportional to the number of teachers matched to that weather station for SY03.



Notes:

a. *We transform the longitudes and latitudes to ensure the anonymity of our research site, which is not, as portrayed above, in the Gulf of Guinea. One degree of longitude represents 69.0 statute miles.*
b. *The analogous graph for SY04 has an appearance similar to the one above.*

Figure 3. The length of each bar represents the range of minimum temperatures, by day, across 20 weather stations. The black squares within each bar represent the minimum temperature in the weather-station to which the greatest number of teachers was matched.

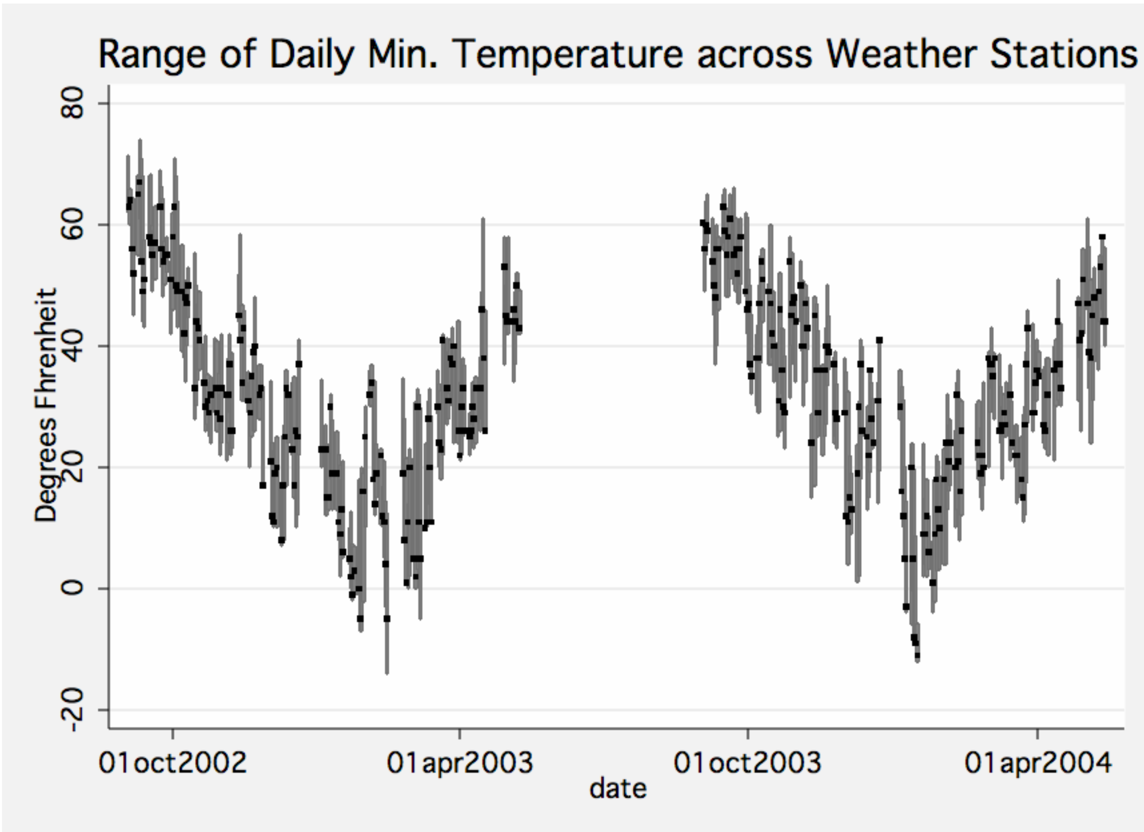
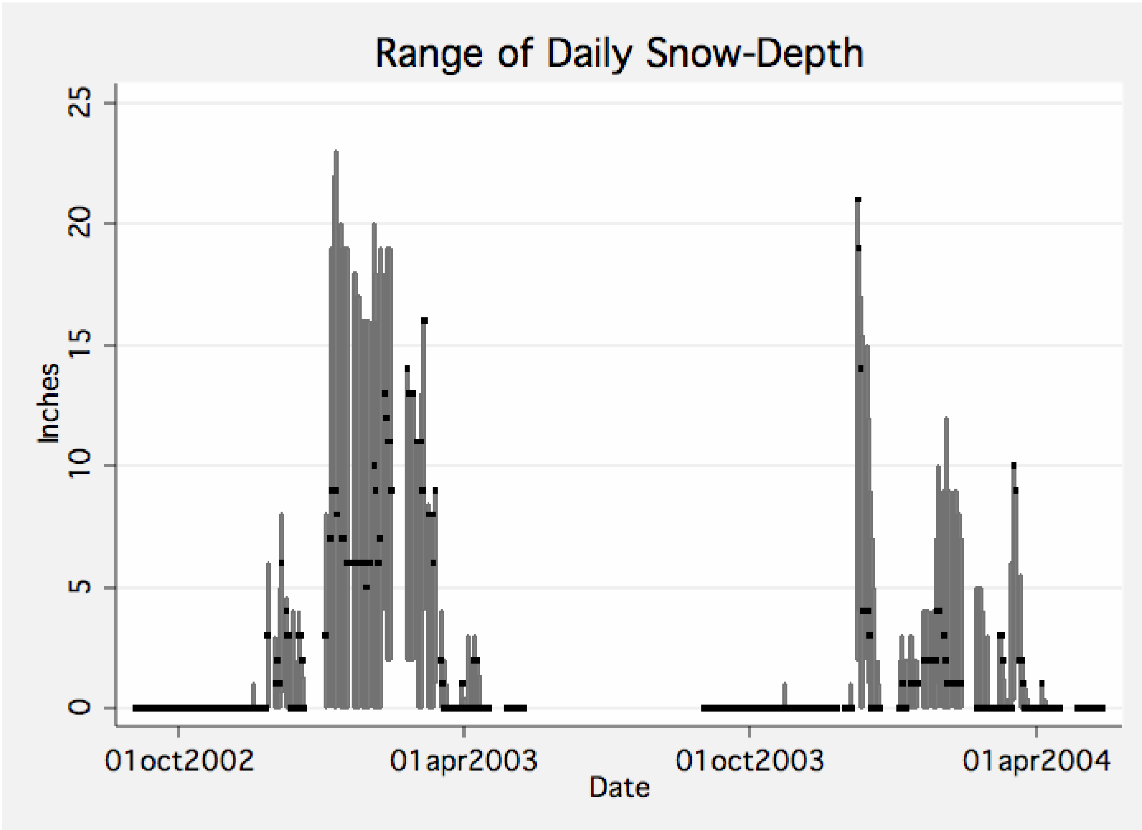


Figure 4. The length of each bar represents the range of snow-depths, by day, across 20 weather stations. The black squares within each bar represent the snow-depth in the weather-station to which the greatest number of teachers was matched.



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APPENDICES

Appendix A: Teachers and Weather Stations

Table A1. Numbers of unique teachers matched to weather stations, by year.

Weather station	Number of teachers SY03	Number of teachers SY04
1	2	1
2	60	53
3	58	49
4	5	6
5	0	1
6	2	2
7	1	1
8	14	15
9	1	1
10	1	1
11	2	3
12	1	1
13	1	3
14	1	1
15	5	5
16	1	0
17	0	1
18	0	2
19	3	2
20	3	2
Total	161	150

Notes: We enumerate the weather stations without betraying the location of our research site. These station numbers are not the original National Climatic Data Center cooperative weather station ID numbers.

Appendix B: Data

We constructed a dummy predictor indicating whether a school engages in team-teaching or specialization in the fourth-grade classrooms, by surveying OSD curriculum coordinators and coaches and by reviewing the school websites. This predictor enables sensitivity analyses that are important because instruction provided to students by teachers other than the ones to whom they are matched in our dataset represents a potential threat to the validity of inference about the effects of the matched teachers' absences.

We deal with missing values in the student-level variables in the following ways. After eliminating students who could not be matched to teachers, we eliminated the 9.2 percent of students who lack values on both the MATH and ELA outcomes. We eliminated 2.7 percent of students who appear to be in classes with fewer than 14 students. In OSD, a contractual agreement stipulated a maximum class-size of 27 in SY02 and 25 in SY03 and SY04, so the 13 students with the same teacher in my data set could actually be part of a class with a heterogeneous mix of students in fourth and other grades, say third or fifth.[17] Eliminating classes of 13 or fewer students composed entirely of fourth-grade students also makes sense because these classes are abnormally small. Finally, we eliminated 0.6 percent of students who appear in classes in which more than 40 percent of the students received special education. A provision in the OSD teachers' bargaining agreement discourages classroom percentages of these students rising higher than 30 percent, and 40 percent appears to be a natural cutoff.

Among the remaining 6,166 students, other variables also contained missing values. For the measures of prior student achievement, and the indicators of English as first language and eligibility for free or reduced-price lunch, we estimated these missing values with student-level regression imputation methods, treating the observed values of all other student-level variables as predictors in the imputation.[18] Students who entered classes late are especially likely to have missing values for the measures of prior achievement.

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[17] We learned of the existence of mixed-grade classes through discussions with an OSD curriculum coordinator. Some school websites confirm current practice of using mixed-grade classroom.

[18] For the measures of prior achievement, we imputed 16 percent of the values for reading and 24 percent of the values for math; for the demographic variables, 2 and 6 percent of the values for free or reduced-price lunch eligibility and English as first language, respectively.