Flaking Out: Student Absences and Snow Days as Disruptions of Instructional Time*

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Abstract

Despite the fact that the average American student is absent more than two weeks out of every school year, most research on the effect of instructional time has focused not on attendance but on the length of the school day or year. Student and school fixed effects models using Massachusetts data show a strong relationship between student absences and achievement but no impact of lost instructional time due to school closures. I confirm those findings in instrumental variables models exploiting the fact that moderate snowfall induces student absences while extreme snowfall induces school closures. Prior work ignoring this non-linearity may have mis-attributed the effect of absences to such snow days. Each absence induced by bad weather reduces math achievement by 0.05 standard deviations, suggesting that attendance can account for up to one-fourth of the achievement gap by income. That absences matter but closures do not is consistent with a model of instruction in which coordination of students is the central challenge, as in Lazear (2001). Teachers appear to deal well with coordinated disruptions of instructional time like snow days but deal poorly with disruptions like absences that affect different students at different times.

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1 Introduction

Concerns about the academic performance of American students perennially prompt calls to increase the amount of instructional time by lengthening the school day or year. Early in his first term, for example, President Obama argued in a widely publicized speech that

> We can no longer afford an academic calendar... [that] puts us at a competitive disadvantage. Our children... spend over a month less in school than children in South Korea - every year. That's no way to prepare them for a 21st century economy. That's why I'm calling for us... to rethink the school day to incorporate more time - whether during the summer or through expanded-day programs for children who need it.[1]

Proponents of increased instructional time point not only to international comparisons but also to suggestive domestic evidence. Highly successful charter schools tend to have long school days and years, and within the charter sector, larger amounts of instructional time are correlated with higher school effectiveness (Hoxby and Murarka, 2009; Dobbie and Fryer, 2011; Angrist et al., 2013). In some settings, low-income children's achievement declines over the summer at a faster rate than the achievement of high-income children, a phenomenon known as summer learning loss (Alexander et al., 2001), though such loss is not observed in all settings (Fryer and Levitt, 2004).

Perhaps because of the frequent focus on achievement losses from long summers or short school days, the discussion of instructional time has rarely touched on another major determinant of instructional time, namely attendance rates. This omission from the literature is surprising, given that the average American student is absent more than two weeks out of every school year.[2] What makes this omission particularly odd is that attendance is one of the variables most commonly contained in the local and state administrative data sets underlying much of modern education research.

[1]See President Obama's March 10, 2009 speech to the Hispanic Chamber of Commerce, accessed at `http://www.whitehouse.gov/briefing-room/speeches-and-remarks` on June 2, 2014.

[2]See Table 203.90 in Snyder and Dillow (2014), which lists the average daily attendance rate as 93.9% and the average school year length as 179 days. This implies that the average student misses nearly 11 school days, or more than two weeks, each year. Secondary school students miss three weeks a year on average.

This paper provides some of the first well-identified evidence on the impact of instructional time lost due to absences, as well as to school closures. Using statewide, longitudinal, student-level data from Massachusetts, I run both student and school fixed effects regression models that show a strong relationship between student absences and achievement but no relationship between school closures and achievement. I confirm those findings in instrumental variables models exploiting the fact that moderate snowfall induces student absences while extreme snowfall induces school closures. Each absence induced by bad weather reduces math achievement by 0.05 standard deviations, suggesting that attendance can account for up to one-fourth of the achievement gap by income.

This paper makes three contributions to the literature. First, it provides well-identified evidence that attendance is an important determinant of student achievement. Nearly all of the well-identified literature on instructional time focuses on the amount of time built into the school schedule, generally finding that such time has a substantial impact on student learning.[3] Examples include Lavy (2010) and Rivkin and Schiman (2013), which exploit within-student and within-school variation in instructional time by subject; Pischke (2007) and Lavy (2012), which exploit policy interventions that respectively shorten the West German school year and increase Israeli schools' instructional time budget; and Fitzpatrick et al. (2011) and Carlsson et al. (2012), which exploit random variation in the timing of standardized tests. What little prior research addresses unexpected losses of instructional time due to absences generally depends on identification strategies that leave open the possibility of substantial omitted variable bias, such as simply controlling for observable characteristics of students or instrumenting absences with students' distance from school (Gottfried, 2009, 2010). This paper provides the first credible strategy for identifying the impact of one type of student absences, namely those induced by bad weather.

The paper's second contribution is to show that prior work estimating the impact of unexpected school closures due on student achievement may have mis-identified those effects. Marcotte (2007), Marcotte and Hemelt (2008) and Hansen (2013) provide the first clear evidence that

[3] One recent exception to this is the finding in Abt Associates Inc. (2012) that Massachusetts' Expanded Learning Time Initiative, which added 300 hours of instructional time a year to a subset of schools, had no impact on student achievement.

bad weather disrupts student learning. My results are consistent with such reduced form estimates. Those papers argue that bad weather can serve as an instrument for the number of snow days experienced by a given school or student, allowing identification of the impact of snow days. I show that bad weather violates the exclusion restriction in this context because weather affects not only school closures but also student absences. When I use multiple weather instruments to credibly identify the impact of those two endogenous regressors, I find that all of the impact of weather runs through student absences and none through school closures. This result highlights the importance of non-linearities in instrumental variables estimation, an issue discussed in Loken et al. (2012).

The paper's third contribution is to provide further empirical support for the congestion model of classroom learning presented in Lazear (2001). That absences matter but closures do not is consistent with that model of instruction in which coordination of students is the central challenge. In Massachusetts, teachers and schools deal well with coordinated disruptions of instructional time like snow days but deal poorly with disruptions like absences that affect different students at different times. Student absences can impede the public aspects of the learning process as teachers must split their time between students who have and have not missed the previous day's lessons. Though Lazear (2001) emphasizes behavioral disruptions as the main source of congestion, they are not the only such source. All of the predictions of that model regarding optimal class size and the effects of changing class size hold true if "student behavior" is replaced by "student attendance."

The structure of the paper is as follows. Section 2 describes the data, documents broad patterns in student attendance and achievement, and discusses the relation between weather and school closures. Section 3 estimates the impact of student absences and school closures on achievement, first with fixed effects estimates comparing students and schools to themselves over time and then with instrumental variables estimates that use snowfall as an exogenous source of variation for both types of lost instructional time. In section 4, I argue that these estimates are consistent with a model in which the central challenge of teaching is coordination of students. Section 5 concludes with thoughts for future research.

2 The Data and Sample

2.1 Student Attendance and Achievement

Student-level data on attendance and achievement in the 2003-2010 school years come from the Massachusetts Department of Elementary and Secondary Education (DESE). Students and schools are assigned unique identifiers allowing them to be linked across years and across data sets within years. DESE's Student Information Management System (SIMS) contains basic demographic information on each student, including gender, race/ethnicity, free or reduced price lunch receipt, special education status and current grade. The end-of-year SIMS files include information on each school a student was enrolled in at any point in the year, the number of days the student was enrolled in each school, and the number of days the student actually attended each school. For students enrolled in multiple schools in a given year, I generate the total across all such schools of days enrolled and days in attendance. The modal value of days enrolled is 180, given that most students attend only one school during a given year and that most school years are 180 days long.

I generate for each student the total number of absences in the past academic year, defined as the difference between total days enrolled and total days attended. That these variables are measured annually at the school year's end creates two small disadvantages. First, I have no information on specific dates of student absences, so that I can not link daily weather patterns to daily attendance. As a result, all analysis here is done at the annual level. Second, because standardized tests are given before the end of the school year, this measure of absences includes post-test absences and thus somewhat overstates the number of absences that could affect test performance. I exclude the 1% of student-year observations with more than 60 absences both to diminish the influence of outliers and because such students are functionally barely enrolled, missing at least one of every three school days. This choice has little effect on the estimated impacts of absences and school closures discussed below. Limiting the sample to students with 30 or fewer absences leaves those estimates nearly unchanged, as does removing this threshold entirely.

Data from DESE's Massachusetts Comprehensive Assessment System (MCAS) contain test scores in mathematics and English language arts (ELA). These exams are given annually to Massachusetts students in grades 3-8 and 10.[4] For ease of comparison, I standardize raw test scores by subject, school year and grade. I include in the main analysis only students with valid math or ELA scores in a given year. Most of the tests are administered during a two-week window in late March to early April, in the case of ELA, or in mid to late May, in the case of math. The state does grant waivers to schools or districts allowing them to postpone testing due to extreme circumstances, such as flooding or other potential hazards, but such exceptions are extremely rare.

Schools may choose testing dates within this window, so that endogenous re-scheduling of test dates in reaction to winter weather could confound interpretation of my estimates.[5] Such endogenous re-scheduling is, however, unlikely to be important, for three reasons. First, for planning purposes, most schools announce their testing schedules at the beginning of the year, before any winter weather has occurred. Second, changing such schedules is quite costly for schools given other scheduling constraints, and extensive web searches reveal no evidence of schools changing previously announced testing dates. Third, a subset of tests are scheduled by the state on fixed days and not in windows. These include 10th grade math and ELA tests, as well as ELA composition tests given in grades 4, 7 and 10. I show below that estimates based on those tests look quite similar to estimates based on the broader set of tests.

2.2 Closures and Weather

School closures, almost always due to bad weather, are decided by each school district's superintendent.[6] Superintendents generally consult the weather forecast, neighboring superintendents and other local government officials to determine when impending weather sufficiently threatens the ability of students and teachers to safely travel to school. Superintendents are generally reluctant to call snow days for two reasons. First, parents often become frustrated by the need to find backup childcare arrangements that may interfere with their own work lives. Second, and more important for this study, Massachusetts law requires school years to contain 180 days of instruc-

[4] In 2003-05, not all tests were taken by all students in grades 3-8. ELA tests were taken only by students in grades 3, 4 and 7, while math tests were taken only by students in grades 4, 6 and 8. From 2006 onward, both subjects were taken by all students in grades 3-8.

[5] DESE does not track test administration dates by school, preventing a more rigorous estimate of the extent of endogenous re-scheduling.

[6] Other rare causes of school closures include broken heating systems, bomb threats or shootings, and flooding.

tion. As a result, any closures must be made up later in the year. In practice, the overwhelming majority of such days are tacked onto the end of the school year in June, as districts generally set aside an additional week in June for just such a scenario.[7] This means that, in practice, school closures result in less instructional time prior to the MCAS tests.

DESE does not collect data on school closures. I therefore e-mailed representatives of all of the roughly 350 school districts in Massachusetts, requesting that they send historical data on the number of closures each year dating back to 2003. I then followed up the non-responsive districts with phone calls, focusing efforts on the largest districts in the state. Ultimately, the districts that reported their number of closures in each year from 2003-2010 represented slightly more than half of the students in the state. Students from districts that reported part or none of this history are excluded from the subsequent analysis. I show below that the resulting sample looks very similar to the state as a whole.

Weather data come from the National Oceanic and Atmospheric Administration's (NOAA) Climate Data Online.[8] NOAA reports historical weather data measured daily by sensors scattered across the state of Massachusetts. Data collected include daily snowfall, rainfall, and minimum and maximum temperatures. To ensure accurate snowfall estimates, I keep data from the 33 sensors missing fewer than 5% of the daily observations between November and April of 2003-2010. Figure A.1 shows a map of these sensors, which are concentrated in areas of higher population density. I use the National Center for Education Statistics' Common Core of Data to assign each Massachusetts school a latitude and longitude. I then assign each school to its closest sensor and construct annual measures of snowfall for each school and its students. For example, I can generate for each school the number of school days in a given year with four or more inches of snow. To more accurately measure weather relevant to the school closure decision, I generate such measures excluding clear non-school days, such as weekends and common holidays. I do not, however, exclude non-school days that vary by school district, such as the February vacation week.[9]

[7] Districts can be excused from the 180 day requirement only when the number of school closures exceeds five, at which point they apply to the state for a waiver. Such waivers are quite rare.

[8] The data can be accessed at `http://www.ncdc.noaa.gov/cdo-web/`.

[9] Finding a complete history of district calendars from this time period proved impossible.

2.3 Descriptive Statistics

To summarize, the main analysis sample is defined as students in Massachusetts public schools from 2003-2010, in grades 3-8 and 10, with valid math or ELA test scores, with 60 or fewer measured absences and from districts who reported their complete annual history of school closures. Table 1 reports descriptive statistics. Column 1 includes all Massachusetts students, column 2 includes all students with valid MCAS scores, and column 3 includes only students in districts that reported the full history of school closures, the analysis sample. As column 1 shows, the average Massachusetts student misses 8.7 days of school a year. Column 2 shows that the average MCAS-taker misses a 8.0 days of school a year, somewhat less than column 1 because 9th, 11th and 12th graders have high absence rates but do not take the MCAS. Comparing columns 2 and 3 shows that the analysis sample appears largely representative of the MCAS-taking population. It is, however, slightly poorer, likely because of the over-representation of larger, urban districts that I was more likely to follow up with phone calls.

Although school closures garner more attention, they constitute less than one-fourth of missed instructional time, as seen in column 3. Students absences are nearly four times as prevalent but are less dramatic events than closures. I also construct for each student the average number of peers' absences in the same grade and school.[10] The average student's peers are absent 8.1 days a year. The average student experiences 2.3 school days a year on which four or more inches of snow falls, with only 0.3 days of 10 or more inches of snow. A little over one-third of the students are poor, as measured by receipt of free or reduced price lunch. Over two-thirds of the students are white, while 11% are black, 14% are Hispanic and 6% are Asian. The average test score in the analysis sample is slightly below the statewide mean, again because of the slight over-representation of low-scoring urban school districts.

Columns 4 and 5 of Table 1 separate the sample by poverty status. Poor students miss an average of 12.6 days of school a year, nearly four days more than the 9.0 missed by non-poor students. Most of this difference is driven by absences, with poor students absent 10.1 days and non-poor students absent 6.9 days a year. Figure 1 shows that this gap is relatively constant from

[10] I used grade and school to define peers because classroom identifiers are not available in this data.

first grade through fifth grade but widens in sixth grade and throughout middle and high school, particularly in ninth grade. Figure 2 emphasizes that the right tail of the absence distribution is substantially fatter for poor students, more than 6% of whom are absent between 30 and 60 days a year. Fewer than 2% of non-poor students are so frequently absent. These differences would be even more pronounced if I had not excluded students with more than 60 absences from the analysis. Poor students are also exposed to peers who, on average, are absent for 1.6 days more a year than the peers of non-poor students. There is little difference in the weather to which poor and non-poor students are exposed.

Columns 5-8 reveal striking differences in absence rates by race/ethnicity. White students miss 9.8 days of school a year, 7.7 of which are due to absences. Asian students, conversely, miss only 7.3 days because they are absent only 5.0 days a year, less than two-thirds the absence rate of white students. Black and Hispanic students respectively miss 11.3 and 13.0 days of school a year, 9.1 and 10.3 of which are due to absences. Figure 3 shows that these racial gaps are relatively constant in early grades but widen in middle school and then very dramatically at the start of high school. Even more striking is the distribution of absences by race shown in Figure 4, which reveals that 17 percent of Asian students have perfect attendance, compared to six percent of other students. Perhaps surprisingly, there are no substantial differences by gender in absence rates.[11]

3 Estimating the Effects of Disruptions to Instructional Time

3.1 Fixed Effects Estimates

The major challenge of estimating the effect of disruptions to instructional time on student achievement is that students and schools with high absence and closure rates differ in both observable and unobservable ways from those with low absence and closure rates. Some dimensions along which absence rates vary, such as socioeconomic status, are at least crudely observable in the data. Other dimensions are not. The data do not contain, for example, any measure of students' physical or mental health problems, which likely increase absence rates and decrease student achievement.

[11] See Figure A.2 for mean absence rates by gender and grade and Figure A.3 for the full distribution of absences by gender.

Ordinary least squares regressions measuring the association between missed instructional time and student achievement are thus likely to yield overestimates because of such unobserved factors.

As a first attempt at eliminating some of these sources of omitted variable bias, I run two types of fixed effects regression models. In the first, I collapse the data into school-grade-year cells, then run the following specifications using school-by-grade fixed effects:

$$Score_{sgt} = \beta_0 + \beta_1 DaysMissed_{sgt} + \gamma X_{sgt} + \mu_{sg} + \lambda_t + \epsilon_{sgt} \quad (1)$$

$$Score_{sgt} = \beta_0 + \beta_1 Absences_{sgt} + \beta_2 Closures_{sgt} + \gamma X_{sgt} + \mu_{sg} + \lambda_t + \epsilon_{sgt} \quad (2)$$

The outcome of interest, *Score*, represents the mean standardized math or ELA score for a school s and grade g in year t. I measure lost instructional time as the total number of days missed due to absences and school closures (*DaysMissed*) averaged by school-grade-year, so that the coefficient of interest (β_1) measures the impact of an entire school-grade missing an additional day. I also explore the separate impact of each of those types of missed days.

These regressions include school-grade fixed effects so that identification is driven by within school-grade changes over time in the average amount of days missed. In other words, a given school and grade is compared to itself across years when it has higher and lower rates of missed school days. These fixed effects therefore eliminate sources of omitted variable bias generated by across school-grade differences that are constant over time and may be associated with different attendance rates, such as socioeconomic or racial composition, and different school closure rates, such as geography. Because the composition of the student body is not entirely constant over time in a given school-grade, I also include a vector of controls (X_{sgt}) for school-grade-year averaged measures of gender, race, poverty, special education and grade size. Finally, year fixed effects control for annual shocks that affect students statewide.

The longitudinal nature of the data also allows me to run such regression of the following form using student fixed effects:

$$Score_{igt} = \beta_0 + \beta_1 DaysMissed_{igt} + \gamma X_{igt} + \mu_i + \lambda_{gt} + \epsilon_{igt} \quad (3)$$

$$Score_{igt} = \beta_0 + \beta_1 Absences_{igt} + \beta_2 Closures_{igt} + \beta_3 PeerAbs_{igt} + \gamma X_{igt} + \mu_i + \lambda_{gt} + \epsilon_{igt} \quad (4)$$

Here the outcome of interest, *Score*, represents the standardized test score for an individual student i in grade g and year t, while lost instructional time is the total number of days missed by an individual student in a given year.

The inclusion of student fixed effects means that identification is driven by within-student changes over time in the number of days missed. A given student is therefore compared to himself across years when he has higher and lower numbers of missed school days. These fixed effects therefore eliminate sources of omitted variable bias generated by across student differences that are constant over time and may be associated with different attendance rates, such as socioeconomic status, race or engagement with school. Because some of these factors may actually vary over time for a given student, I also include a vector of controls (X_{igt}) for students' poverty status, special education status, and grade size. Finally, grade-by-year fixed effects control for annual grade-specific shocks that affect students statewide. I also include a measure ($PeerAbs$) of the average number of absences recorded that year for each student's peers, defined as those in his same school and grade.[12] These student fixed effects regressions thus parallel the school-grade fixed effects regressions, with the absences of an individual student and his peers adding up to the total number of absences in his school and grade.

Table 2 shows the results of these fixed effects regressions. Panel A estimates the impact of total days missed due to school closures and absences, while panel B estimates separately the impacts of closures, own absences and peer absences. The school-grade fixed effects results in column 1 of panel A imply that one additional day missed by a given school-grade is associated with a 0.010 standard deviation decrease in math scores. The student fixed effects results in column 2 are similar, implying that one additional day missed by a given student is associated with a 0.008 standard deviation decrease in math scores. In columns 3 and 4, the relationship between lost in-

[12] The data lack more detailed information on which classrooms students are assigned to.

structional time and ELA achievement is quite similar, though slightly smaller in the school-grade fixed effects model, with each additional day missed associated with a 0.008 standard deviation decrease.

These estimates mask, however, substantial variation between the impact of school closures and the impact of student absences. In column 1 of panel B, which separates those types of missed days, the estimates imply that a one-day increase in a given school-grade's overall absence rate is associated with a 0.020 standard deviation decrease in math scores, whereas school closures show no relationship with achievement. The student fixed effects regression in column 2 shows similarly little relation between closures and achievement. That regression also suggests that the impact of school-grade level absence rates observed in column 1 is actually the combination of two separate channels. A student's own additional absence has a 0.008 standard deviation impact on his math score and an overall increase of one additional absence among his peers has a separate 0.008 standard deviation impact. Results for ELA scores are again similar, though slightly smaller in the school-grade fixed effects model.

In Table 3, I explore heterogeneous impacts in the school-grade fixed effects estimates.[13] In columns 1 and 2, I test heterogeneity by income by dividing schools into those with poverty rates below and above 50%, as measured by the fraction of students over this entire time period who receive free or reduced price lunch. The estimates for both math and ELA suggest that the relationship between absence rates and achievement is large and statistically significant for both types of schools, but is somewhat stronger for poor schools than for non-poor schools. There is also statistically significant evidence of a small relationship between school closures and math achievement for poor schools, though none for non-poor schools and none in ELA for either school type. There is no evidence of heterogeneity in the estimated impact of absences by student age, as seen in columns 3-5, which divide school-grades into grades 3-5, 6-8 and 10. There is small but statistically significant evidence that closures affect math achievement in younger grades. Both columns 5 and 6, which use as outcomes tests given on fixed dates and not in testing windows, show little relationship between closures and achievement. This suggests that the lack of such relationship in

[13] I focus here on heterogeneity by school-grade rather than student characteristics because my subsequent instrumental variables estimates exploit variation at the level of the school and not the individual.

the other regressions is not due to endogenous re-scheduling within the testing window.

Overall, these results highlight three important patterns. First, variation in school closures across time are unrelated to variations in overall student achievement, suggesting that instructional time lost to such school-level disruptions does not impact student learning. The exceptions to this are low income and primary schools, where there is evidence of a small impact of closures on math achievement. Second, changes in school absence rates are strongly associated with changes in student achievement, suggesting that instructional time lost to such student-level disruptions does impact student learning. Third, an individual student's achievement appears to be separately related to both his own absences and those of his peers, suggesting that student learning is affected both by one's own lost instructional time and the time lost by one's peers.

All of these patterns are suggestive but not conclusive, given that these fixed effects regressions do not eliminate all potential sources of omitted variable bias. Increases in school-grade level absence rates may, for example, be driven by changes in the composition of the student body, so that absences are serving as a proxy for families less invested in their children's education. Increases in individual students' absence rates may be driven by underlying health or family problems that are the true cause of observed achievement drops. Increases in school closures may be driven partly by newly hired school district superintendents who change other practices as well. I now turn to an instrumental variables approach that, I argue, can purge these estimates of any such remaining bias.

3.2 Instrumental Variables Estimates

Prior research has convincingly argued that temporal and geographic variation in snowfall may provide a plausibly exogenous source of variation in instructional time because school closures are driven almost entirely by concerns about weather (Marcotte, 2007; Marcotte and Hemelt, 2008; Hansen, 2013). Use of snowfall as an instrument for school closures is, however, complicated by facts this paper is the first to document. To identify the impact of weather on instructional time, I first run school-grade fixed effects regressions of the form

$$Y_{sgt} = \alpha_0 + \alpha_1 SnowyDays_{sgt} + \gamma X_{sgt} + \mu_{sg} + \lambda_t + \epsilon_{sgt} \tag{5}$$

where $SnowyDays$ is the number of school days with four or more inches of snow for a given school in a given year, and Y represents various measures of lost instructional time. I choose the four inch threshold purely for expositional purposes, as will become clearer below. Because of the school-grade fixed effects, the impact of snowy days on lost instructional time and achievement is identified off of within-school-grade variation in snowfall over time. The marginal snowy day here is an excess snowy day, in that it is unusual both relative to the school's own mean over time and relative to the statewide mean that year.

Massachusetts winters provide ample identifying variation for this empirical strategy. Figure 5 shows variation over time in the mean number of school days with four or more inches of snow experience by students in the analysis sample. This varies from a low of less than one day in 2007 to a high of nearly five days in 2005, and is strongly correlated with the number of school closures in a given year. I include absences in the figure simply to emphasize how much more prevalent they are than closures. Figure 6 shows that snowfall varies in Massachusetts not only over time but also by geography, with the Berkshire Mountains in the west receiving much more snow than areas such as Cape Cod in the east.

Estimates from equation 5 are shown in Table 4.[14] Panel A shows how strongly snowfall is related to school closures, with column 1 suggesting that each excess day with four or more inches of snow leads to a highly statistically significant 0.09 additional school closures. The remaining columns show that these estimates vary very little by student characteristics, an unsurprising result given that superintendents often feel obligated to close schools for safety reasons regardless of the composition of their student body.

Closures are, however, not the only source of instructional time lost due to weather. Panel B shows that student attendance is also affected by snowfall, with each excess snowy day inducing a

[14]Here the sample is defined as students with valid math scores. Using students with valid ELA scores makes little difference to these first stage estimates.

highly statistically significant 0.08 additional absences. Unlike the closure estimates in panel A, the absence estimates do vary substantially by student characteristics. The impact of snowfall on poor students' absences is more than twice the size of the impact on non-poor students' absences. A similar pattern holds when comparing white and Asian students to black and Hispanic students. There is little difference by gender. The fact that disadvantaged students' attendance rates are more strongly affected by weather may be due to their dependence on forms of transportation more likely to fail during snowstorms, such as public transit or low quality cars. Poor parents and children may also place less value on school attendance so that a given amount of snow discourages a higher fraction from attending school, relative to their higher income peers.

Snowy days thus affect instructional time through two channels. Some snowy days result in school closures, in which case all students miss school. On other, presumably less, snowy days, schools remain open but some subset of students remain home perhaps because of transportation or health problems. The fact that snowfall affects both closures and absences violates the exclusion restriction required to estimate the impact of closures alone on achievement. To see how this may have confounded the estimates in previous papers, Table 5 runs the specification in equation 5 using different measures of snowfall, as well as test scores as outcomes. In the top row of panel A, the first two columns replicate the prior results that snowy days induce both closures and absences. As shown in column 3, each excess snowy day thus leads to 0.17 days missed of school, roughly half of which are due to closures and half of which are due to absences. Column 4 shows that each excess snowy day reduces math scores by a marginally significant 0.004 standard deviations. If this measure of snowfall is used an instrument for total days missed, as in column 5, the resulting estimate suggests that each day missed due to bad weather reduces math scores by a marginally significant 0.023 standard deviations. Because the instrument fails the exclusion restriction, that simple measure of snowfall can not identify whether the negative impacts on math achievement are driven by school closures, by student absences, or by both forms of lost instructional time.

The bottom half of panel A further highlights the challenge of using snowfall as an instrument in this setting. Defining the instrument with a more extreme measure of snowfall, namely the number of days with 10 or more inches of snow, substantially changes the instrumental variables estimates of the impact of lost instructional time. Each additional extremely snowy day leads to a huge rise in the number of school closures but no additional absences, likely because nearly all schools shut down in such weather conditions and no students can therefore be absent.[15] Columns 4 and 5 reveal, however, that, unlike moderately snowy days, extremely snowy days have no relationship with student achievement. In panel B, first stage results using ELA scores look quite similar to those in panel A, though neither form of the instrument suggests a relationship between weather and ELA scores.

Prior research using weather as an instrument for lost instructional time has thus failed to note two important facts. First, bad weather affects both school closures and student absences, so that no single instrument can successfully distinguish the effects of those two types of lost instructional time. The results documented here suggest that prior work may have mistakenly attributed the impact of absences to the impact of closures. Second, and relatedly, estimates of the impact of weather on student achievement can be quite sensitive to the chosen definition of the instrument. I observe non-linearities in the impact of weather, with moderately snowy days appearing to have much more of an impact on student achievement than extremely snowy days. This non-linearity turns out to be quite helpful for dealing with the exclusion restriction violation documented here.

To exploit this non-linearity, I re-estimate the school-grade fixed effects model from equation 2, this time recognizing that both school-grade absences rates and closures are potentially endogenous.[16] I therefore instrument both of those endogenous variables with the same vector of snowfall measures. Because two endogenous regressors require at least two instruments, the simplest form of the first stages I use have the following specifications:

$$Absences_{sgt} = \alpha_0 + \alpha_1 ModerateSnow_{sgt} + \alpha_2 ExtremeSnow_{sgt} + \gamma X_{sgt} + \mu_{sg} + \lambda_t + \epsilon_{sgt} \quad (6)$$

$$Closures_{sgt} = \delta_0 + \delta_1 ModerateSnow_{sgt} + \delta_2 ExtremeSnow_{sgt} + \gamma X_{sgt} + \mu_{sg} + \lambda_t + \epsilon_{sgt} \quad (7)$$

[15] That each extremely snowy day does not yield a 100% closure rate is likely due to measurement error. I do not, for example, have each district's February vacation schedule and therefore may be including snowstorms in this total that did not actually fall on school days. Also, because most schools would also shut down on days with nine inches of snow, the counterfactual here is not zero closures.

[16] I use the school-grade fixed effects model because the exogenous weather shocks occur at the school level. The student fixed effects model would be unable to separately identify the impact of own absences and peer absences because both would be similarly affected by the weather.

Here, again purely for expositional purposes, I define $ModerateSnow$ as the number of school days with 4-10 inches of snow and $ExtremeSnow$ as the number of school days with 10 or more inches of snow.

The first two columns of table 6 show the estimates from those first stages. In column 1 of panel A, extremely snowy days are strongly related to school closures whereas moderately snowy days are not, conditional on the number of extremely snowy days. In column 2, conversely, moderately snowy days are strongly related to student absences whereas extremely snowy days are not.[17] This nonlinear impact of snowfall therefore allows me to separately identify the impact of school closures and student absences. The reduced form estimates in column 3 imply that each additional moderately snowy day lowers math scores by a statistically significant 0.004 standard deviations, while extremely snowy days have no detectable impact on achievement. Given that moderate snowfall affects absences but not closures, this suggests that absences and not closures are responsible for the achievement impacts of bad weather.

The instrumental variables estimates in column 4, in which absences and closures are instrumented using the first stages shown in columns 1 and 2, confirm this. Each additional absence induced by snowfall decreases math achievement by a large and statistically significant 0.05 standard deviations. The point estimate on the effect of school closures is almost identical to zero and the standard error allows me to rule out negative effects greater than 0.01 standard deviations per closure day. To show that these estimates are not sensitive to this particular choice of two instruments, column 5 replicates column 4 but uses a vector of ten instruments measuring the number of school days with 1-2 inches of snow, 2-3 inches of snow, and so on through 10+ inches of snow. This specification has little effect on the estimates, with absences now estimated to decrease math scores by a more precisely estimated 0.05 standard deviations and closures still showing no detectable impact. The parallel estimates in panel B also rule out impacts of closures on ELA scores larger than 0.01 standard deviations. Absences decrease ELA scores by an imprecisely estimated 0.01 standard deviations.

Table 7, like Table 3, explores heterogeneity in the impacts of lost instructional time, this time

[17] The magnitude of this coefficient on moderately snowy days (0.08) implies that, for a classroom of 25 students, each additional moderately snowy day would result in about two students being absent.

generating estimates through the instrumental variables specification that uses the vector of ten snowfall instruments. Dividing the sample reduces the precision of the resulting estimates but a few patterns can nonetheless be discerned. First, estimated impacts of absences on math achievement are large and negative for both poor and non-poor schools and for younger and older grades. Second, the estimated impacts of absences on ELA achievement, though mostly negative, are generally indistinguishable from zero. Third, closures generally have little effect on achievement except in poor schools, where each closure is associated with a 0.01-0.02 decrease in math and ELA scores. Finally, both columns 5 and 6, which use as outcomes tests given on fixed dates and not in testing windows, show no relationship between closures and achievement. Consistent with the non-instrumented estimates, this again suggests endogenous re-scheduling within the testing window can not explain the non-impact of closures.

4 Discussion

The evidence presented here shows that the impact of lost instructional time depends on the particular form of the time lost. Student absences are strongly related to achievement, particularly in math, in both fixed effects and instrumental variables specifications. School closures show little relationship to achievement. The contrast between the effects of absences and of closures is consistent with a model of instruction in which coordination of students is the central challenge for teachers.

Such a model can be thought of as a re-interpretation of the optimal class size model in Lazear (2001). In that model, student achievement occurs only at times when the classroom is not being disrupted by a single student. Achievement is thus proportional to p^n, where p is the probability of any given student behaving well and n is the class size. Though the discussion in that paper focuses on behavioral disruptions, it notes that p more generally refers to the proportion of time that a given student is not interfering with the public aspects of knowledge production in the classroom.

Absences are one such form of disruption. An absent student presents a teacher with one of two choices upon his return to the classroom. The teacher may take time out of the classroom schedule to catch the absent student up on missed material, in which case his classmates lose instructional time from the teacher. Or the teacher may not set aside such time, in which case the student himself has lost instructional time and may disrupt his classmates' future lessons because he has fallen behind. The fixed effects estimates are consistent with this model of disruption, suggesting both a direct effect of absences on a student's own achievement and a spillover effect of peer absences.

School closures present no such challenge of coordinating students to be on the same page. When students return to school after a snow day, they have all missed exactly the same lesson. Teachers can thus compensate by pushing all of the their lesson plans back a day for the rest of the school year.[18] This will have no effect on student achievement as measured by standardized tests so long as the teacher's planned schedule had included at least some instructional time devoted to subjects not on the tests. Such lessons on non-tested material can be compressed, eliminated or postponed until after the test, so that school closures do not effectively reduce the amount of instructional time relevant to the available measures of student achievement.

Two further pieces of evidence presented here are consistent with this coordination challenge explaining why absences are so much more detrimental than closures to student achievement. First, in both the fixed effects models and particularly in the instrumental variables models, absences have a substantially larger impact on math achievement than on ELA achievement. More so than ELA, math is a subject where understanding the current topic depends on having understood prior topics. As a result, absences in math thus have longer-run effects in which students lose mastery of both the material for which they were absent and the subsequent material that depends on such knowledge. Teachers may therefore feel more obligated during math instructional time to catch up absent students, thus depriving the rest of the class of instructional time. Missing an ELA lesson, conversely, may not have as deep an impact on a student's ability to learn from subsequent lessons.

Second, the magnitude of the instrumental variables estimate of the impact of absences on math achievement is two and half times larger than that of the fixed effects estimate. One potential

[18] In informal conversations with me, numerous current and former teachers have concurred that snow days are much simpler to deal with than student absences, for precisely the reasons highlighted here.

explanation for this is that snowfall-induced changes in absence rates involve unusually high numbers of students. If on a typical day two students are absent in a given classroom, that number may jump to four on a moderately snowy day. The congestion effects model in Lazear (2001) would imply that the disruptive effect of absences increases more than linearly in the number of absent students. This would explain why absences induced by snowfall hurt student achievement more than the more typical absences driving variation in the fixed effects models.

There are other reasons instrumental variables estimates of absences may exceed fixed effects estimates in this context. Fixed effects estimates may be biased slightly downward by the fact that the absence measure covers the entire year and thus includes post-exam absences. It may thus overstate annual fluctuations in pre-exam absences by about 10% in math and 30% in ELA, if absences are uniformly distributed throughout the school year. The instrumental variables estimates do not suffer from this problem because all snowfall and thus all snowfall-induced absences contributing to identification occur pre-exam. The fact the ELA-relevant absences are more mismeasured than math-relevant absences may partly explain why the non-instrumented estimates of absences are larger in math than in ELA.

Alternatively, because snowfall increases absence rates more for disadvantaged students, the marginal students whose absences are estimated by the instrumental variables specification are disproportionately disadvantaged. Instrumental variables estimates should therefore exceed fixed effects estimates if such students' learning is more disrupted by absences than the average absent student's learning, perhaps because such families are less able to compensate for their children's lost instructional time.

Finally, instrumental variables estimates would overstate the impact of student absences if moderate snowfall affects other channels such as student tardiness or teacher absences, neither of which are observable in my data. That tardiness is unobservable implies my absence measure may understate the true amount of instructional time lost. Unobservable teacher absences may cause me to mistakenly attribute the impact of teacher absences to student absences. Though teacher absences harm student achievement (Clotfelter et al., 2009), this is not a major concern here because weather does not often affect teacher absences (Herrmann and Rockoff, 2012) and because when it does the resulting impact on student achievement is too small to explain my estimated effects (Miller et al., 2008).[19]

5 Conclusion

This paper provides some of the clearest evidence to date on the substantial role that school attendance plays in student achievement, a role that has been understudied in the literature. Fixed effects and instrumental variables estimates are consistent with a Lazear-type congestion model of learning, where congestion comes not from behavioral disruptions but from student absences. The results highlight the fact that increasing instructional time does not necessarily require lengthening the school day or year as some gains may be made by increasing the fraction of already scheduled time that students are in school.

The magnitude of the estimated impact of absences on math achievement is a substantial 0.05 standard deviations. Relative to non-poor students, poor students are absent three more days per year and have peers who are absent one and a half more days per year. Assuming, as the fixed effects estimates suggest, that own and peer absences have similar effects, then exposure to four additional absences every year would reduce math scores by 0.20 standard deviations. This represent roughly one-fourth the math achievement gap between poor and non-poor students. The ELA estimates, though imprecise, suggest that absences explain roughly one-twentieth of the reading achievement gap by income.

That school closures have little impact on student achievement might imply that lost instructional time does not matter, though the bulk of the empirical evidence suggests otherwise. A more likely explanation is that schools and teachers are well-prepared to deal with the coordinated disruptions of such snow days, perhaps by postponing or canceling lesson plans on untested topics. That absences have such a substantial effect suggests, however, that schools and teachers are not well-prepared with the less dramatic but much more frequent disruptions caused by poor student attendance. Schools and teacher may be under-investing in strategies to cope with such disrup-

[19] The central estimate presented in Miller et al. (2008) is that 10 days of weather-induced teacher absences reduces student achievement by 0.033 standard deviations. My central estimate of a 0.055 standard deviation impact of a single student absence would thus be equivalent to nearly 17 teacher absences.

tions. It is conceivable that the increasing use of self-paced learning technologies may reduce the impact of absences by shifting the classroom model to one in which not all students must learn the same lesson at the same time.

One limitation of this research is that the marginal absence providing identification is one induced by bad weather. Weather is likely not the main driver of student absences, as illness and, for older students, engagement with school are probably much more common determinants of attendance. Future research should focus on identifying the impacts of more typical absences, though finding exogenous sources of variation in such circumstances may be hard. Currie et al. (2009) provide evidence, for example, that ambient pollution that aggravates asthma can increase absenteeism, though they do not connect such absences to student achievement results. A number of school districts are beginning to experiment with interventions to directly address chronic absenteeism, known as truancy.[20] It remains to be seen whether such interventions reduce absenteeism and, if so, whether such improved attendance translates into better student outcomes, either for the truants themselves or their peers.

[20]For a description of New York City's recent efforts, see `http://www.nyc.gov/html/truancy/html/home/home.shtml`.

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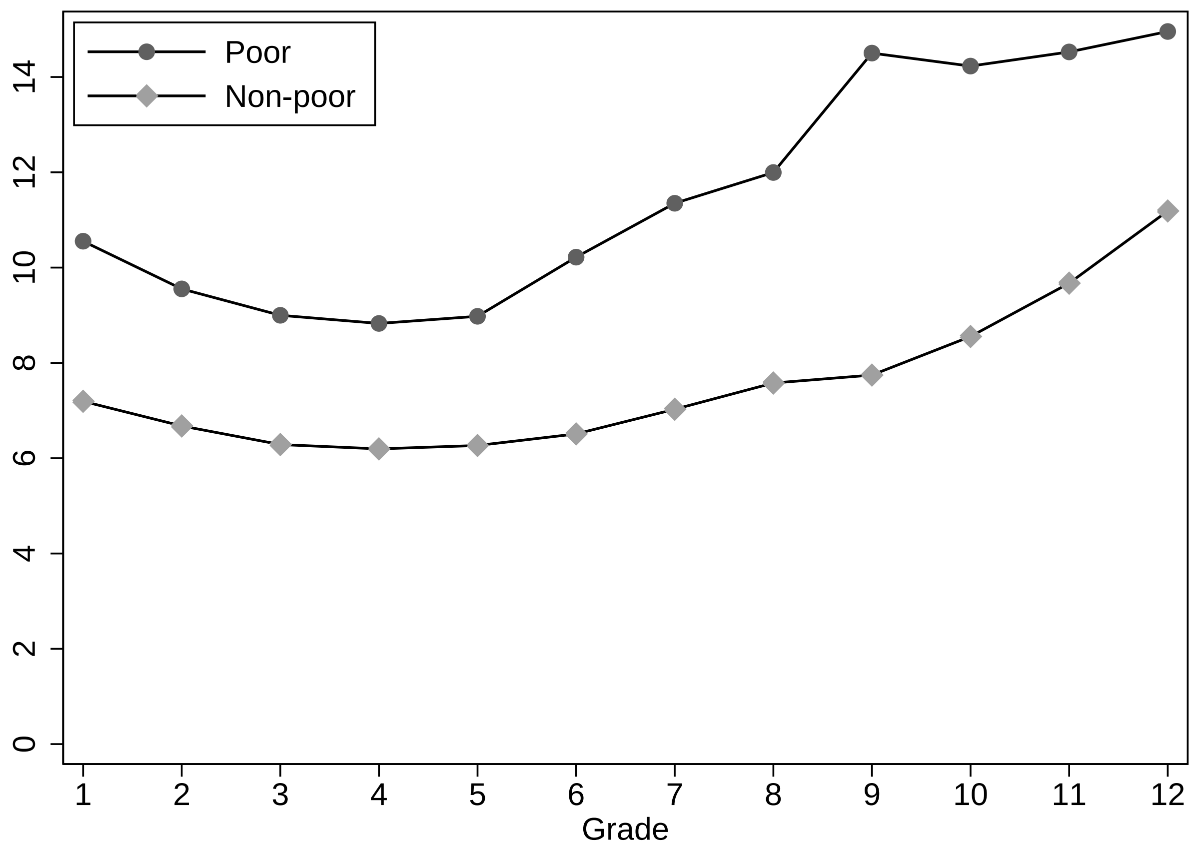
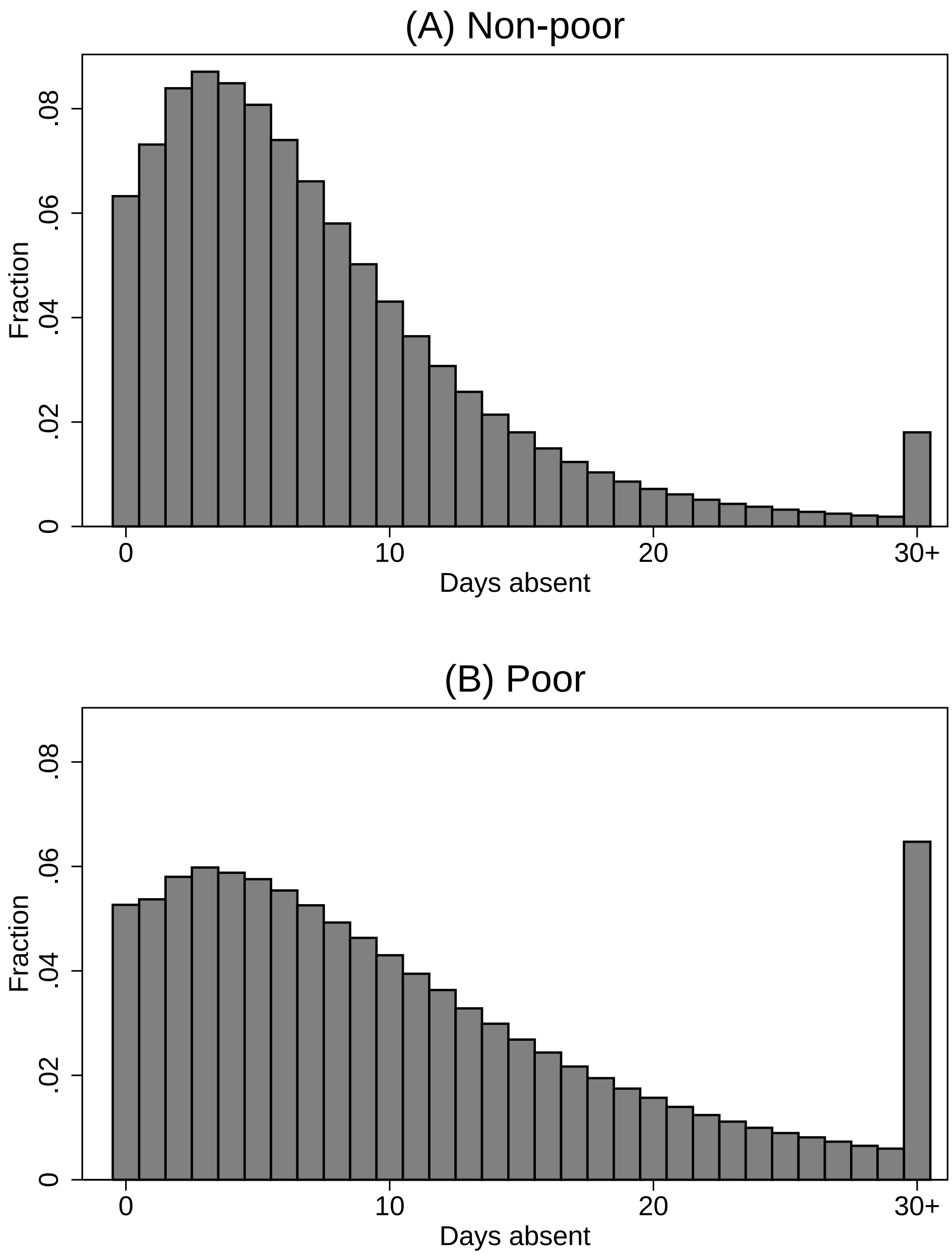
Figure 1: Mean Absences by Grade and Poverty Status



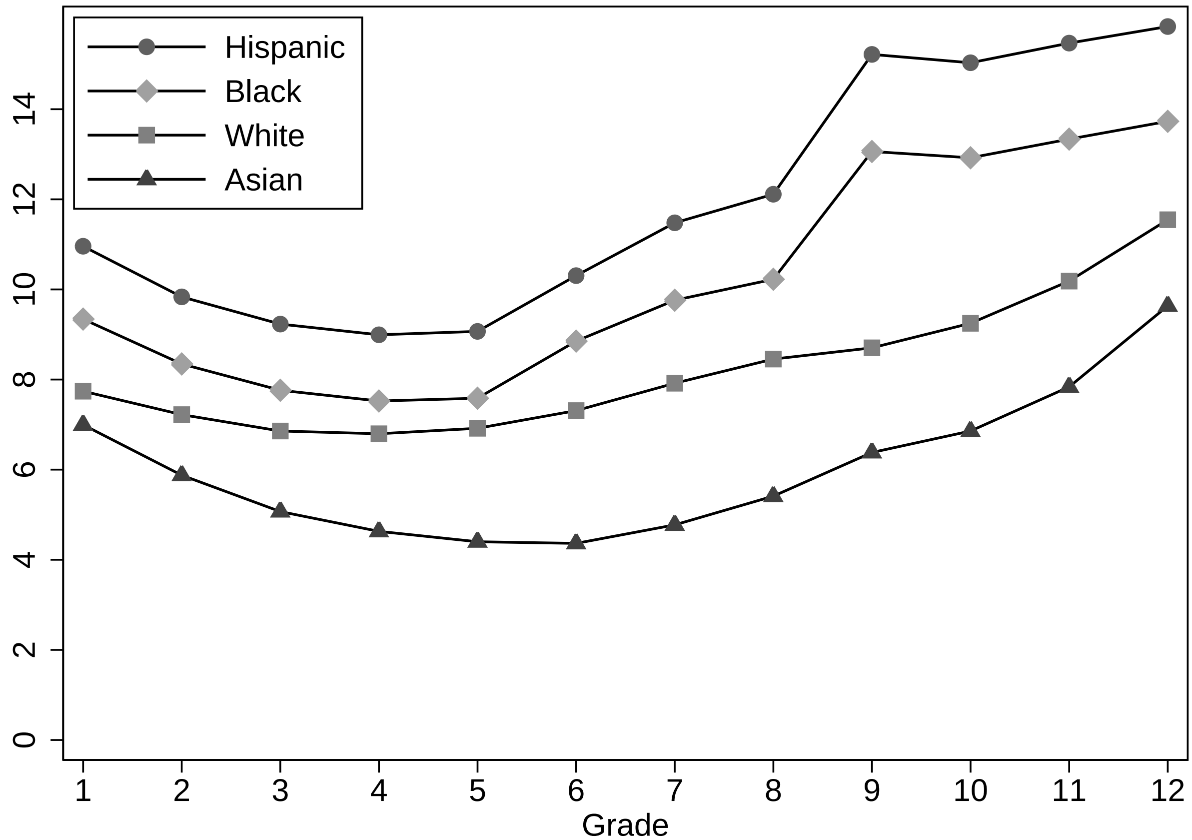
Notes: Mean numbers of days absent are shown by grade and poverty status, as determined by federally subsidized lunch receipt. The sample consists of all Massachusetts public school students from the 2003-2010 school years with no more than 60 absences. Data come from the Massachusetts Department of Elementary and Secondary Education's Student Information Management System.

Figure 2: Absence Distribution by Poverty Status



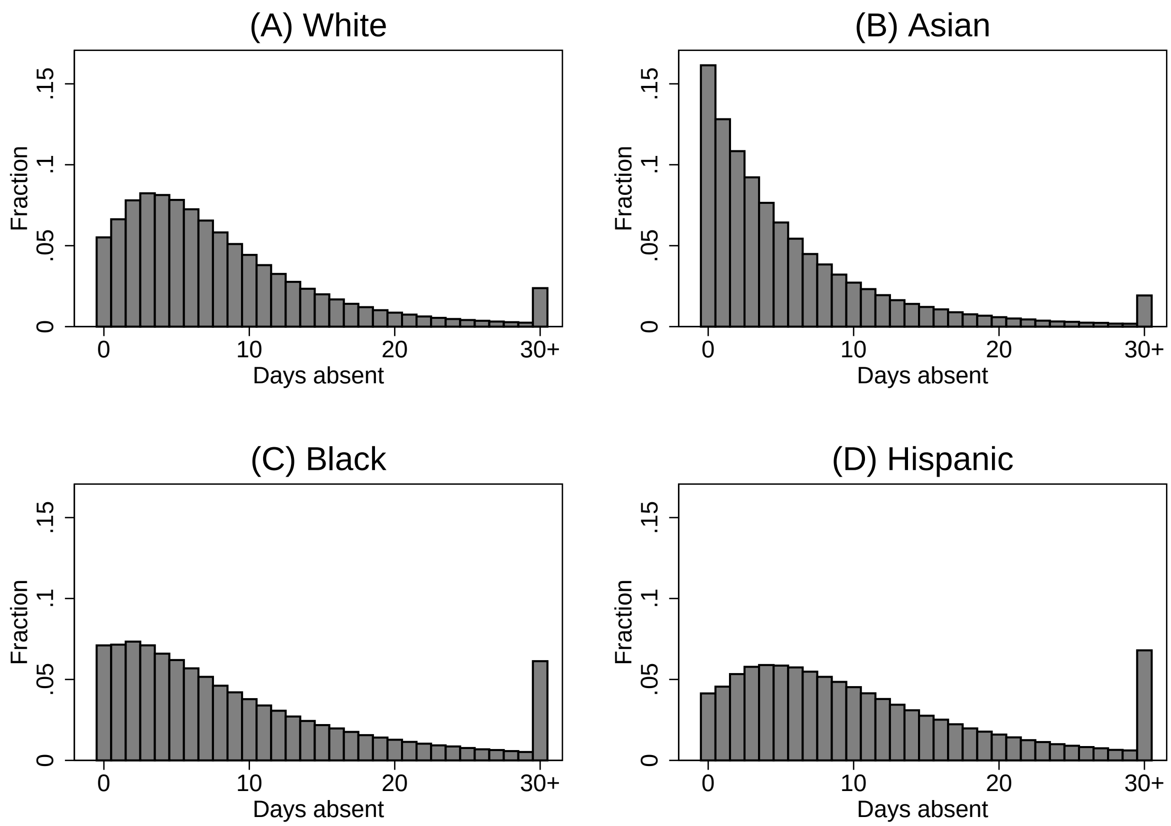
Notes: The distributions of number of days absent are shown by poverty status, as determined by federally subsidized lunch receipt. The sample consists of all Massachusetts public school students from the 2003-2010 school years with no more than 60 absences. Data come from the Massachusetts Department of Elementary and Secondary Education's Student Information Management System.

Figure 3: Mean Absences by Grade and Race



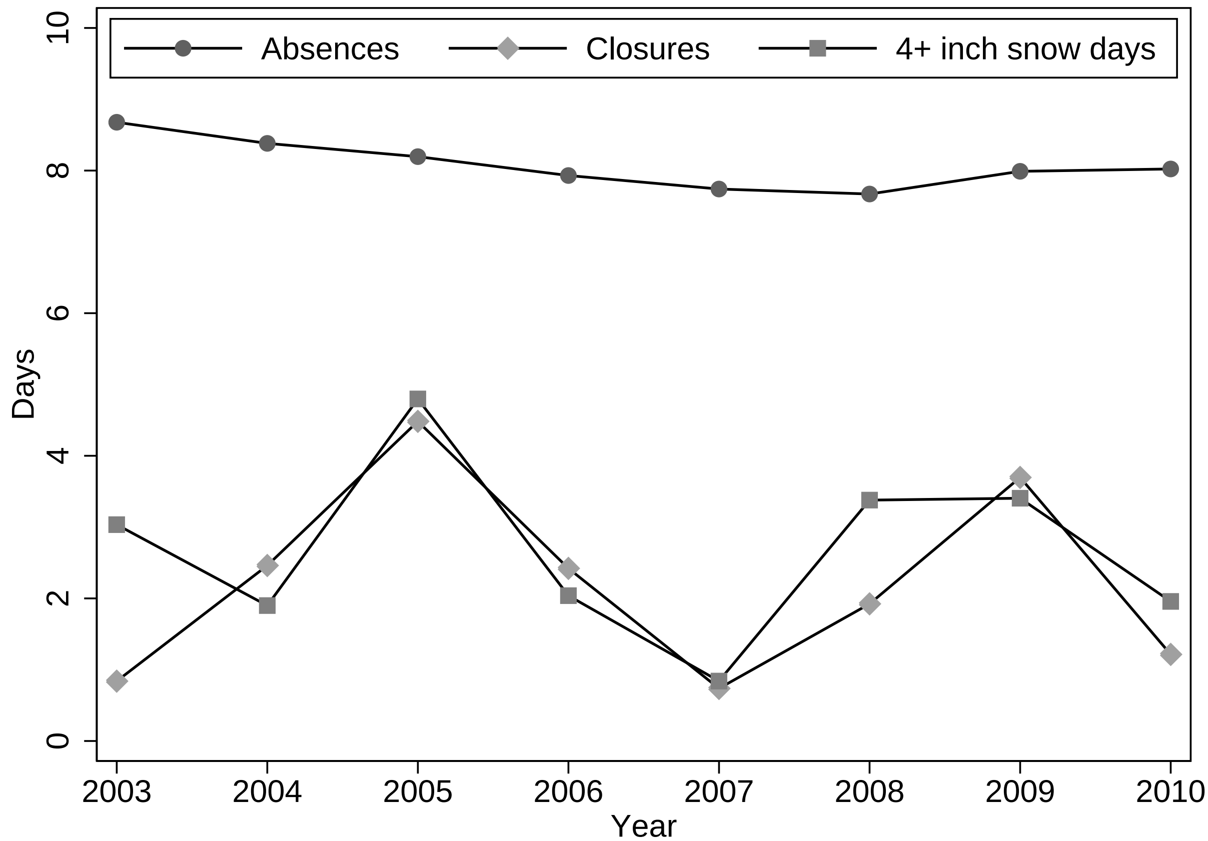
Notes: Mean numbers of days absent are shown by grade and race, as determined by federally subsidized lunch receipt. The sample consists of all Massachusetts public school students from the 2003-2010 school years with no more than 60 absences. Data come from the Massachusetts Department of Elementary and Secondary Education's Student Information Management System.

Figure 4: Absence Distribution by Race



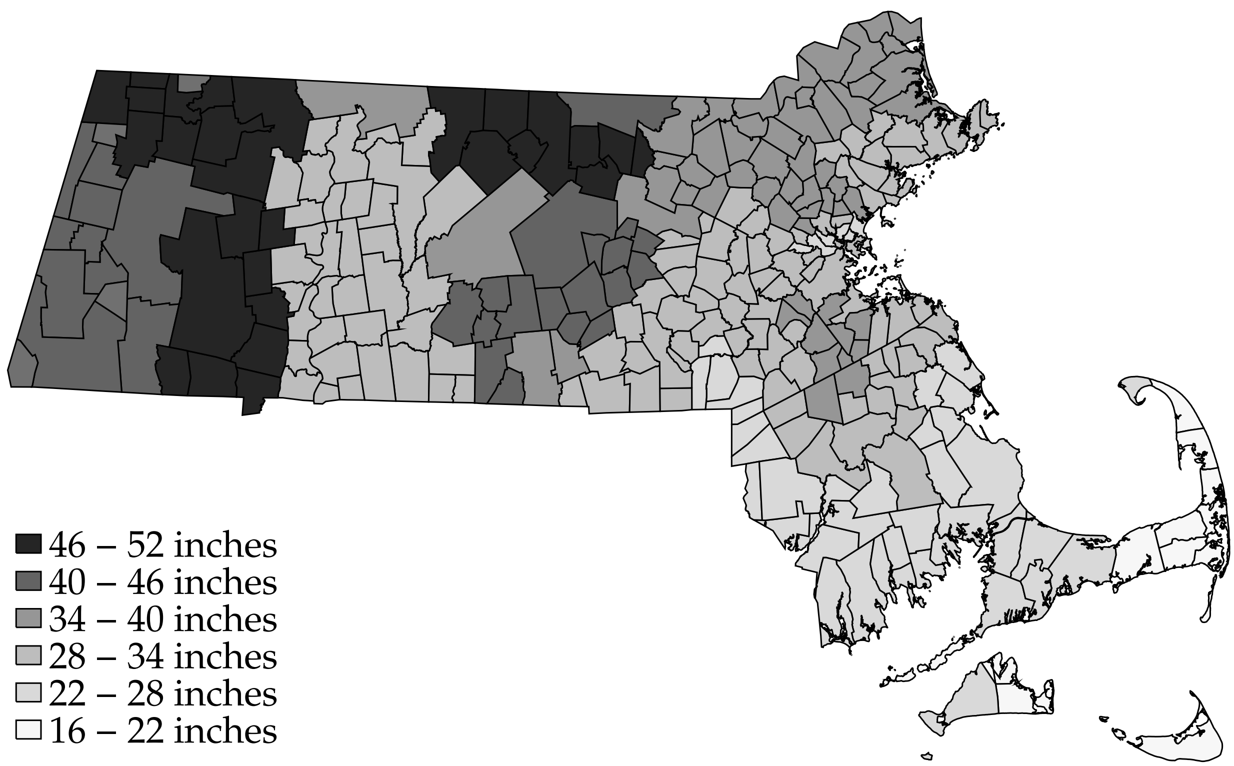
Notes: The distributions of number of days absent are shown by race, as determined by federally subsidized lunch receipt. The sample consists of all Massachusetts public school students from the 2003-2010 school years with no more than 60 absences. Data come from the Massachusetts Department of Elementary and Secondary Education's Student Information Management System.

Figure 5: Absences, Closures and Snowfall Over Time



Notes: The mean number of days absent, school closures and days with four or more inches of snow experienced by Massachusetts students are shown by school year. The sample consists of Massachusetts public school students from the 2003-2010 school years with no more than 60 absences, whose schools reported annual school closure numbers for this entire time period. Data on absences come from the Massachusetts Department of Elementary and Secondary Education's Student Information Management System. Data on school closures come from school districts directly. Data on snowfall come from the National Oceanic and Atmospheric Administration's Climate Data Online.

Figure 6: Mean Annual Snowfall by School District



Notes: The mean annual snowfall on school days is shown by school district for the 2003-2010 school years. Non-school days such as weekends and common holidays are excluded from the calculations. Data on snowfall come from the National Oceanic and Atmospheric Administration's Climate Data Online.

Table 1: Summary Statistics

	(1) Full sample	(2) MCAS sample	(3) Closures sample	(4) Nonpoor	(5) Poor	(6) White	(7) Asian	(8) Black	(9) Hispanic
(A) Days in school									
Days missed	.	.	10.27	8.95	12.63	9.79	7.28	11.28	13.02
Days closed	.	.	2.20	2.03	2.50	2.10	2.27	2.14	2.75
Days absent	8.71	8.01	8.06	6.92	10.13	7.69	5.01	9.14	10.27
Days attended	170.98	171.97	171.80	173.09	169.49	172.29	174.88	170.48	169.21
Days in membership	179.69	179.98	179.87	180.01	179.61	179.98	179.88	179.62	179.48
Peer days absent	8.71	8.00	8.06	7.49	9.09	7.62	7.84	9.57	9.20
(B) Weather									
4-10 inch snow days	2.32	2.29	2.30	2.25	2.40	2.24	2.32	2.48	2.46
10+ inch snow days	0.34	0.34	0.34	0.35	0.33	0.35	0.34	0.33	0.33
(C) Controls									
Poor	0.30	0.31	0.36	.	.	0.18	0.52	0.76	0.84
Black	0.08	0.08	0.11	0.04	0.23	.	.	.	.
Hispanic	0.12	0.12	0.14	0.03	0.32	.	.	.	.
Asian	0.05	0.05	0.06	0.04	0.08	.	.	.	.
Special education	0.17	0.17	0.17	0.14	0.22	0.16	0.08	0.22	0.21
Grade size	178.50	178.50	180.34	190.36	162.28	188.60	180.43	163.07	155.40
(D) Outcomes									
Math Z	-0.00	-0.00	-0.06	0.23	-0.57	0.14	0.32	-0.65	-0.70
ELA Z	-0.00	-0.00	-0.07	0.24	-0.62	0.15	0.03	-0.62	-0.75
Student-years	6,761,496	3,737,241	1,965,306	1,263,748	701,558	1,339,526	109,172	212,890	267,197
Students	1,513,103	49,844	25,912	23,932	25,374	4,318	7,963	11,120	

Notes: Mean values of each variable are shown by sample. Column 1 includes all Massachusetts students from 2003-2010. Column 2 includes all students with valid MCAS scores. Column 3 includes all students with valid MCAS scores and whose school districts reported school closures for all years from 2003-2010. Columns 4-9 divide the sample in column 3 by poverty status (as indicated by subsidized lunch receipt) and race/ethnicity.

Table 2: Fixed Effects Estimates of the Impact of Days Missed on Achievement

	(1)	(2)	(3)	(4)
	Math		ELA	
(A) Days missed overall				
Days missed	-0.010***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.000)	(0.001)	(0.000)
N	19,194	1,723,606	19,845	1,717,509
(B) Days missed by type				
Days absent	-0.020***	-0.008***	-0.016***	-0.008***
	(0.002)	(0.000)	(0.001)	(0.000)
Days closed	-0.001	0.002	-0.000	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Peer days absent		-0.008***		-0.008***
		(0.001)		(0.001)
N	19,194	1,723,606	19,845	1,717,509
School-grade fixed effects	X		X	
Student fixed effects		X		X

Notes: Heteroskedasticity robust standard errors are in parentheses (* p<.10 ** p<.05 *** p<.01).Panel A regresses standardized test scores on total days missed annually, while panel B separates days missed into absences and closures. Columns 1 and 3 collapse the data to school-grade-year cells, weight each cell by the number of test-takers, and include school-grade and year fixed effects. Columns 2 and 4 use student-level data and include individual student and grade-year fixed effects. Columns 2 and 4 also include the average number of days absent for the other students in a given student's school-grade-year. Columns 1 and 3 control for school-grade-year averaged measures of gender, race/ethnicity, poverty, special education and grade size. Columns 2 and 4 control for such measures both at the individual student level and averaged across each student's school-grade-year peers.

Table 3: Heterogeneity by School Type, Fixed Effects Estimates

	(1) Nonpoor schools	(2) Poor schools	(3) Grades 3-5	(4) Grades 6-8	(5) Grade 10	(6) ELA composition
(A) Math						
Days absent	-0.018***	-0.022***	-0.021***	-0.021***	-0.018***	
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	
Days closed	0.000	-0.006**	-0.005**	0.002	-0.003	
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	
N	11,486	7,709	10,435	7,068	1,692	
(B) ELA						
Days absent	-0.014***	-0.019***	-0.015***	-0.018***	-0.014***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Days closed	-0.001	-0.003	-0.001	-0.000	0.001	0.000
	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
N	11,888	7,958	12,284	5,876	1,686	8,967

Notes: Heteroskedasticity robust standard errors clustered by school are in parentheses (* $p<.10$ ** $p<.05$ *** $p<.01$). Each column regresses standardized test scores on annual absences and closures, collapsing the data to school-grade-year cells, weighting each cell by the number of test-takers, and including school-grade and year fixed effects. All regressions include school-grade-year averaged measures of gender, race/ethnicity, poverty, special education and grade size. Panels A and B limit the sample to school-grade-year cells with valid math and ELA scores respectively. Columns 1 and 2 limit the collapsed sample to schools above and below a 50% poverty rate over this time period. Columns 3-5 limit the collapsed sample to grades 3-5, 6-8 and 10, respectively. Column 6 uses as an outcome the ELA composition sub-test, given in grades 4, 7 and 10 on fixed dates each year.

Table 4: Impacts of Snow on Absences and Closures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Non-poor	Poor	White/ Asian	Black/ Hispanic	Male	Female
(A) Closures							
4+ inch snow days	0.094***	0.077***	0.094***	0.077***	0.070*	0.095***	0.092***
	(0.022)	(0.022)	(0.032)	(0.021)	(0.040)	(0.022)	(0.022)
N	19,195	17,063	18,137	17,780	16,656	17,930	17,693
(B) Absences							
4+ inch snow days	0.076***	0.050**	0.114***	0.059***	0.115***	0.071***	0.082***
	(0.019)	(0.020)	(0.030)	(0.019)	(0.041)	(0.021)	(0.020)
N	19,195	17,063	18,137	17,780	16,656	17,930	17,693

Notes: Heteroskedasticity robust standard errors clustered by school are in parentheses (* $p<.10$ ** $p<.05$ *** $p<.01$). Each coefficient comes from a regression of annual closures or absences on the number of school days with four or more inches of snow, collapsing the data to school-grade-year cells, weighting each cell by the number of math test-takers, and including school-grade and year fixed effects. All regressions include school-grade-year averaged measures of gender, race/ethnicity, poverty, special education and grade size. Column 1 includes all students. Columns 2-7 limit the sample to the listed subgroup of students prior to collapsing the data to the school-grade-year level.

Table 5: Weather as an Instrument for Lost Instructional Time

	(1) Closures	(2) Absences	(3) Days missed	(4) RF impact	(5) IV impact
(A) Math					
4+ inch snow days	0.094***	0.076***	0.169***	-0.004*	
	(0.022)	(0.019)	(0.032)	(0.002)	
Days missed					-0.023*
					(0.012)
N	19,195	19,195	19,195	19,195	19,195
10+ inch snow days	0.482***	-0.042	0.440***	0.002	
	(0.049)	(0.028)	(0.054)	(0.003)	
Days missed					0.005
					(0.007)
N	19,195	19,195	19,195	19,195	19,195
(B) ELA					
4+ inch snow days	0.095***	0.070***	0.166***	-0.001	
	(0.021)	(0.018)	(0.030)	(0.002)	
Days missed					-0.004
					(0.010)
N	19,846	19,846	19,846	19,846	19,846
10+ inch snow days	0.483***	-0.050*	0.432***	0.002	
	(0.046)	(0.028)	(0.051)	(0.003)	
Days missed					0.006
					(0.007)
N	19,846	19,846	19,846	19,846	19,846

Notes: Heteroskedasticity robust standard errors clustered by school are in parentheses (* p<.10 ** p<.05 *** p<.01). Columns 1-3 regress various measures of days missed on the number days that school year with four-plus or ten-plus inches of snow. Column 4 estimates the reduced form impact of the given weather measure on standardized test scores. Column 5 estimates the impact of total days missed on standardized test scores, instrumenting days missed with the given weather measure. Each regression collapses the data to school-grade-year cells, weights each cell by the number of test-takers, and includes school-grade and year fixed effects. All regressions include school-grade-year averaged measures of gender, race/ethnicity, poverty, special education and grade size. Panels A and B limit the sample to school-grade-year cells with valid math and ELA scores respectively.

Table 6: The Differential Effects of Different Types of Lost Instructional Time

	(1)	(2)	(3)	(4)	(5)
	First stage:		Reduced	IV	IV
	Closures	Absences	form	(2 Zs)	(10 Zs)
(A) Math					
4-10 inch snow days	0.040*	0.084***	-0.004**		
	(0.023)	(0.020)	(0.002)		
10+ inch snow days	0.508***	0.011	-0.001		
	(0.048)	(0.030)	(0.003)		
Days absent				-0.052**	-0.053**
				(0.025)	(0.021)
Days closed				-0.000	-0.005
				(0.006)	(0.004)
N	19,195	19,195	19,195	19,195	19,195
(B) ELA					
4-10 inch snow days	0.042*	0.080***	-0.001		
	(0.022)	(0.019)	(0.002)		
10+ inch snow days	0.509***	0.000	0.002		
	(0.045)	(0.029)	(0.003)		
Days absent				-0.014	-0.012
				(0.021)	(0.016)
Days closed				0.003	-0.003
				(0.006)	(0.004)
N	19,846	19,846	19,846	19,846	19,846

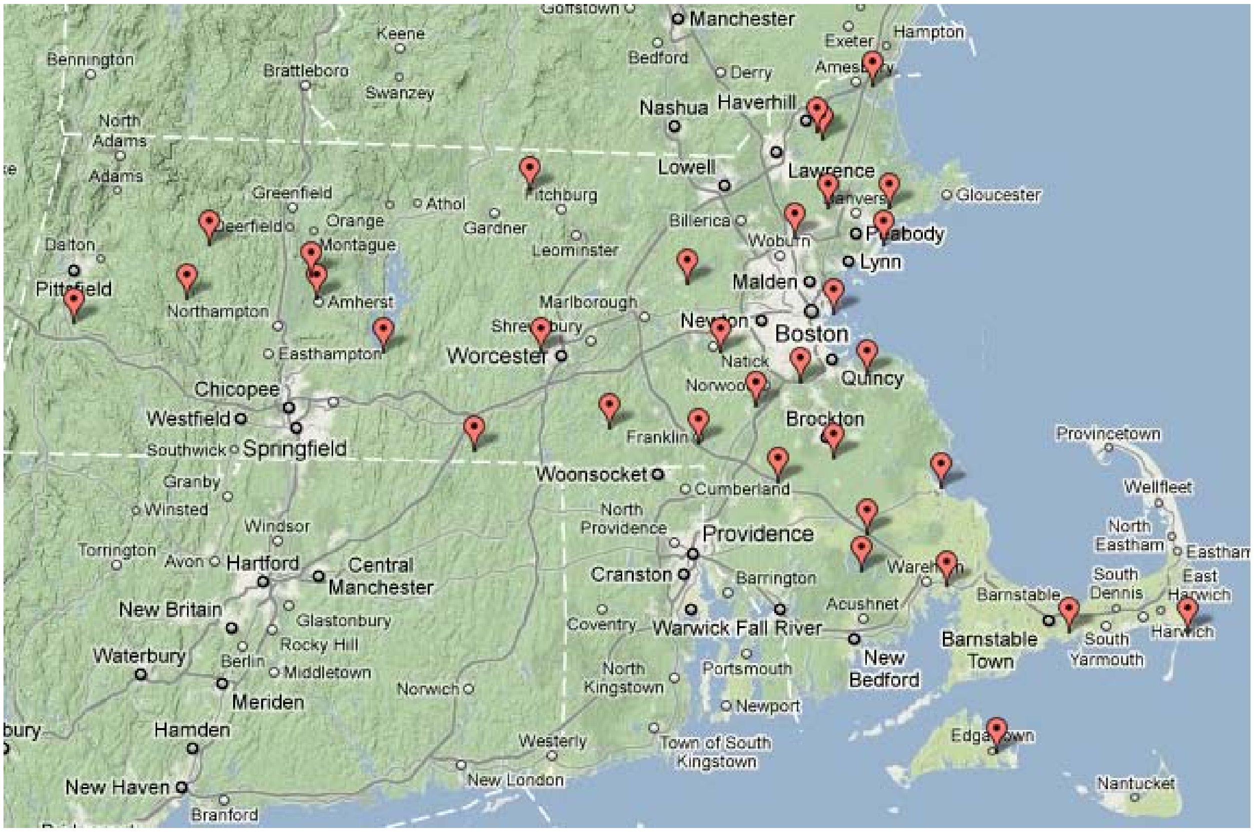
Notes: Heteroskedasticity robust standard errors clustered by school are in parentheses (* p<.10 ** p<.05 *** p<.01). Columns 1 and 2 regress measures of days missed on the number days that school year with 4-10 inches of snow and 10+ inches of snow. Column 3 estimates the reduced form impact of those two weather measure on standardized test scores. Column 4 estimates the impact of absences and closures on standardized test scores, instrumenting those measures of days missed with the two measures of snowy days. Column 5 replicates column 4 but uses a vector of ten instruments measuring the number of school days with 1-2 inches of snow, 2-3 inches of snow, and so on through 10+ inches of snow. Each regression collapses the data to school-grade-year cells, weights each cell by the number of test-takers, and includes school-grade and year fixed effects. All regressions include school-grade-year averaged measures of gender, race/ethnicity, poverty, special education and grade size. Panels A and B limit the sample to school-grade-year cells with valid math and ELA scores respectively.

Table 7: Heterogeneous Impacts of Lost Instructional Time, Instrumental Variables Estimates

	(1) Nonpoor schools	(2) Poor schools	(3) Grades 3-5	(4) Grades 6-8	(5) Grade 10	(6) ELA composition
(A) Math						
Days absent	-0.081**	-0.046	-0.056**	-0.036	-0.038**	
	(0.032)	(0.031)	(0.023)	(0.036)	(0.017)	
Days closed	-0.006	-0.014**	-0.010	-0.007	0.007	
	(0.006)	(0.006)	(0.007)	(0.006)	(0.009)	
N	11,486	7,709	10,435	7,068	1,692	
(B) ELA						
Days absent	-0.027	-0.027	-0.021	0.008	0.008	-0.026
	(0.020)	(0.025)	(0.019)	(0.030)	(0.016)	(0.020)
Days closed	-0.000	-0.016***	-0.007	-0.005	0.002	0.003
	(0.004)	(0.006)	(0.005)	(0.007)	(0.008)	(0.006)
N	11,888	7,958	12,284	5,876	1,686	8,967

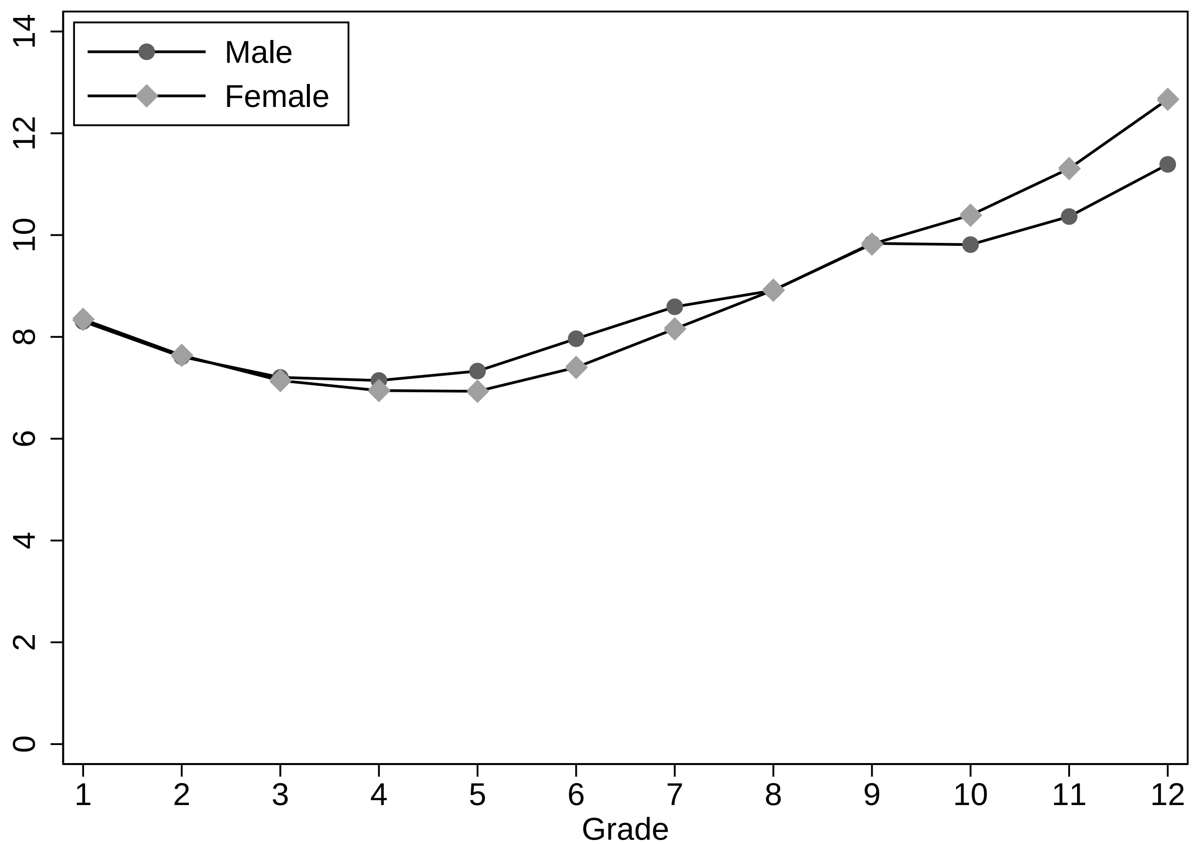
Notes: Heteroskedasticity robust standard errors clustered by school are in parentheses (* $p<.10$ ** $p<.05$ *** $p<.01$). Each column estimates the impact of absences and closures on standardized test scores, instrumenting those measures of days missed with a vector of ten instruments measuring the number of school days with 1-2 inches of snow, 2-3 inches of snow, and so on through 10+ inches of snow. Each regression collapses the data to school-grade-year cells, weights each cell by the number of test-takers, and includes school-grade and year fixed effects. All regressions include school-grade-year averaged measures of gender, race/ethnicity, poverty, special education and grade size. Panels A and B limit the sample to school-grade-year cells with valid math and ELA scores respectively. Columns 1 and 2 limit the collapsed sample to schools above and below a 50% poverty rate over this time period. Columns 3-5 limit the collapsed sample to grades 3-5, 6-8 and 10, respectively. Column 6 uses as an outcome the ELA composition sub-test, given in grades 4, 7 and 10 on fixed dates each year.

Figure A.1: Map of Massachusetts Weather Sensors



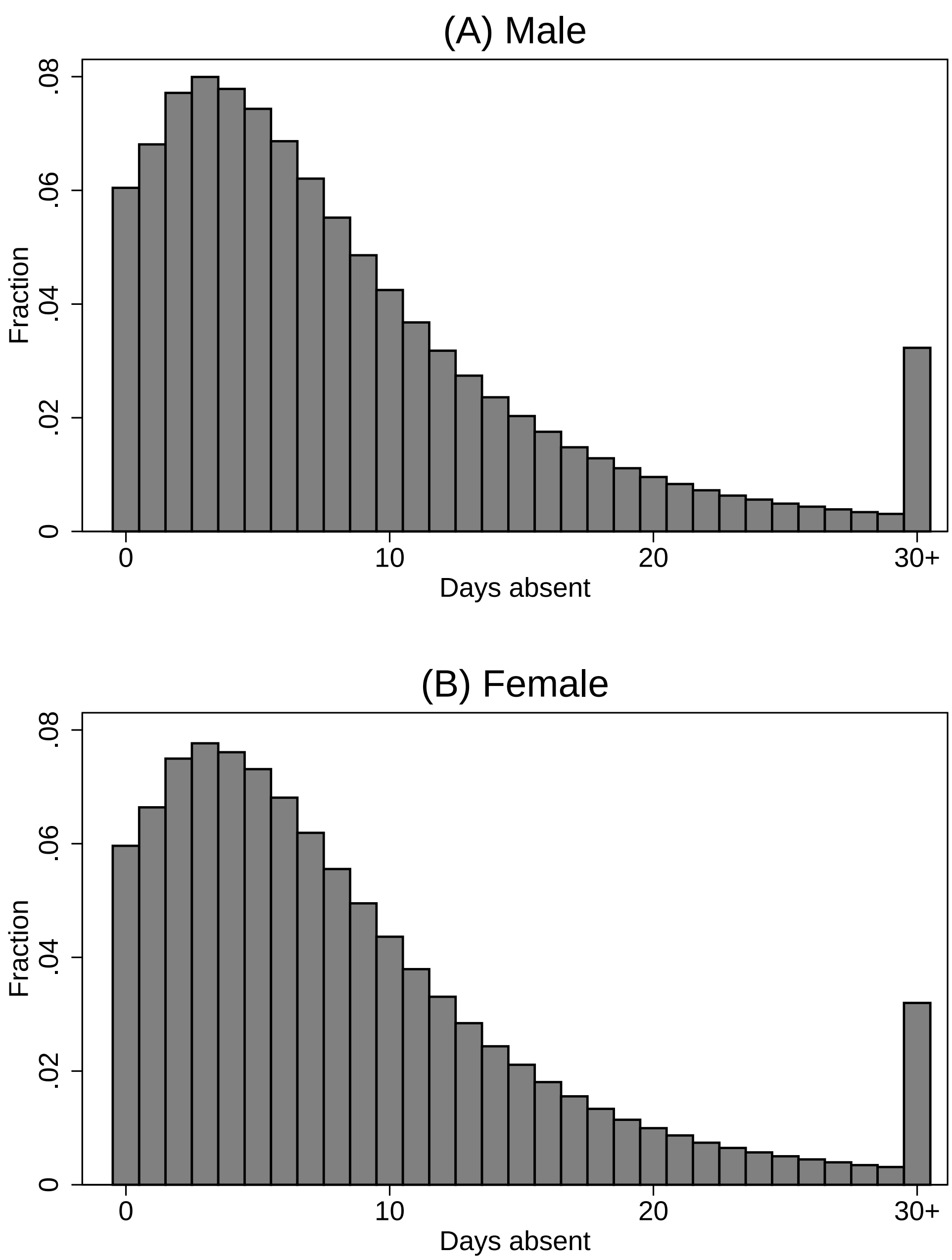
Notes: The map shows the location of the 33 Massachusetts weather sensors used to compute snowfall by school district and year. Locations of the sensors comes from the National Oceanic and Atmospheric Administration's Climate Data Online.

Figure A.2: Mean Absences by Grade and Gender



Notes: Mean numbers of days absent are shown by grade and gender. The sample consists of all Massachusetts public school students from the 2003-2010 school years with no more than 60 absences. Data come from the Massachusetts Department of Elementary and Secondary Education's Student Information Management System.

Figure A.3: Absence Distribution by Gender



Notes: The distributions of number of days absent are shown by gender. The sample consists of all Massachusetts public school students from the 2003-2010 school years with no more than 60 absences. Data come from the Massachusetts Department of Elementary and Secondary Education's Student Information Management System.