Flaking Out: Snowfall, Disruptions of Instructional Time, and Student Achievement

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April 30, 2012
Georgetown


Framingham Public
School Canceled
(due to snow)
Friday
January 21, 2011

Introduction

- This project began when the MA Dept. of Ed. asked me to crunch numbers on the achievement costs of snow days. (Thanks to Carrie Conaway for getting this started.)

- I started thinking more broadly about instructional time, and disruptions to that time.

- Education researchers have underutilized one important set of variables contained in most state administrative data sets, namely attendance data.

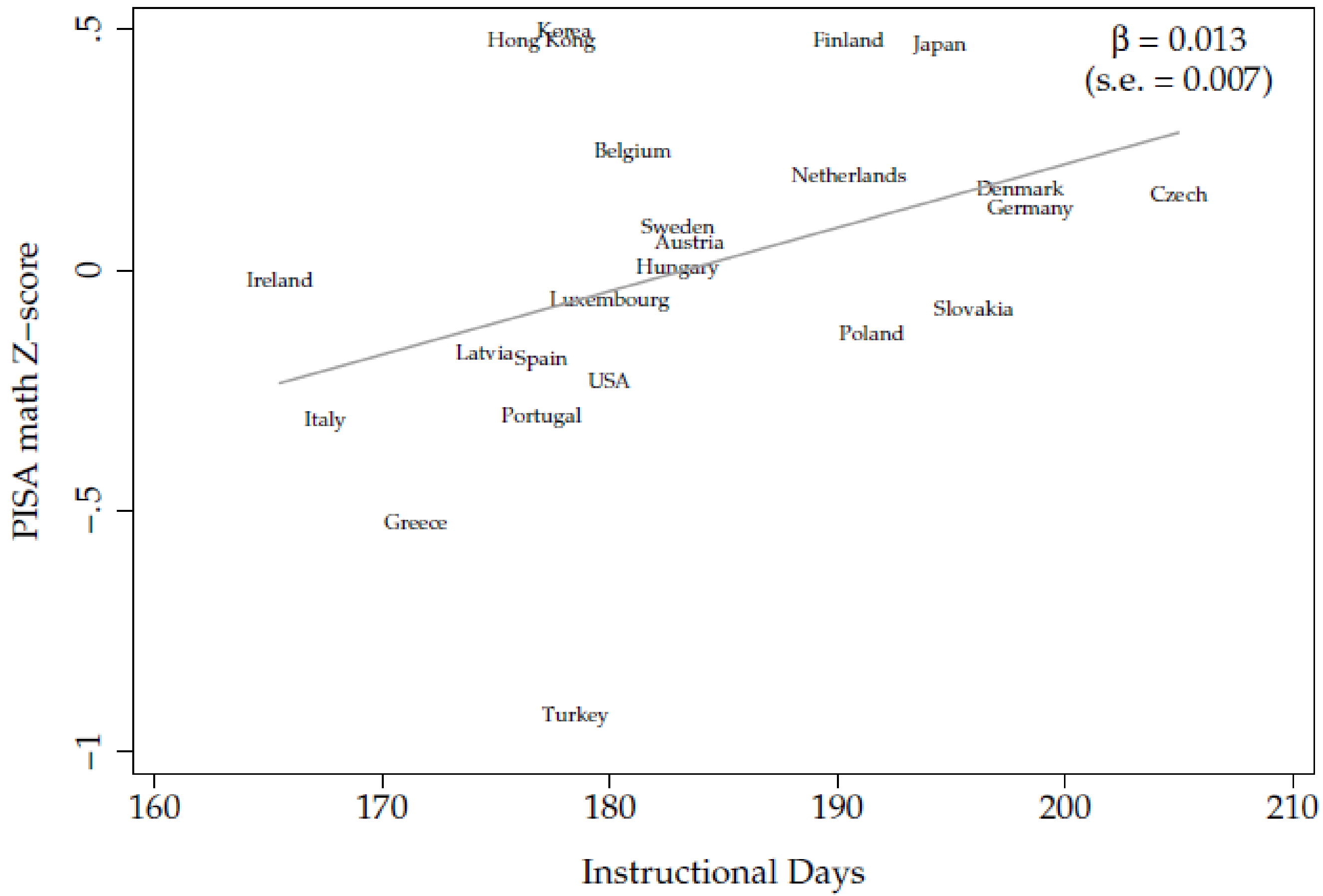
Previous literature

- Instructional time matters
  - Summer learning loss is larger for low-income children (Cooper et al., 1996).
  - Successful schools feature longer school days (Fryer and Dobbie, 2009; Abdulkadiroglu et al., 2009; Hoxby et al., 2009).
  - Within-student variation by in instructional time by subject is correlated with within-student variation in performance by subject (Lavy, 2010).
  - Snowfall in Maryland is related to student achievement (Marcotte, 2006; Marcotte and Hemelt, 2007).

- Instructional time does not matter
  - Summer learning loss doesn't show up in all data (Fryer and Leavitt, 2009).
  - Massachusetts Expanded Learning Time initiative found little impact on test scores of 300 added hours per year (Abt, 2010).

International evidence

Figure 1: Achievement vs. Days in School



Source: PISA 2003 dataset.

The short story

- I’m going to see how annual fluctuations in absence rates and closure days are related to student achievement.
- I’ll use variation in snowfall across time and space as an exogenous source of variation in absences and closures, in order to identify the impact of one particular subset of absences and closures.
- Closures have no impact. Absences do.
- This is consistent with a model in which the central challenge of teaching is coordination of students. With slack time in the schedule, the time lost to closure can be regained. Student absences, however, force teachers to expend time getting students on the same page as their classmates.

Data

- From Massachusetts' Department of Education
  - All students grades 3-10 from 2003-2010
  - Unique student and school identifiers allows linkage over time
  - Basic demographics (gender, race, poverty, special ed status)
  - Math and English Language Arts test scores (MCAS)
    - Exams taken in mid May at fixed point in year (with rare exceptions)
    - I normalize these by grade and year
  - Enrollment information
    - Schools report each student's membership and attendance days
    - I construct absences = membership – attendance
    - I exclude students with > 30 absences (> 1/6 of the 180 day school year)
    - This is measured annually at year's end (i.e. no specific absence dates)
    - This includes some post-test absences (overcounts by ~15%)

Data

- School closures are determined by school district superintendents.
  - MA law says students must have 180 school days
  - Closures are usually made up at year's end, after MCAS exams

- The state does not collect snow day information from districts
  - I e-mailed/phoned every district in MA.
  - For half the students in the overall sample, I know school closures for all years 2003-2010.
  - That's the analysis sample.

Data

- Weather sensors
    - Downloaded date from NOAA from weather sensors scattered across MA, which measure daily snowfall (and other variables).
    - Keep the ~30 sensors missing fewer than 5% of November-April days from 2003-2010.
    - Get each school's latitude/longitude from NCES' Common Core of Data and assign each school to its nearest sensor.
    - Generate annual weather measures for each school.
    - For example: number of school days with 4+ inches of snow.

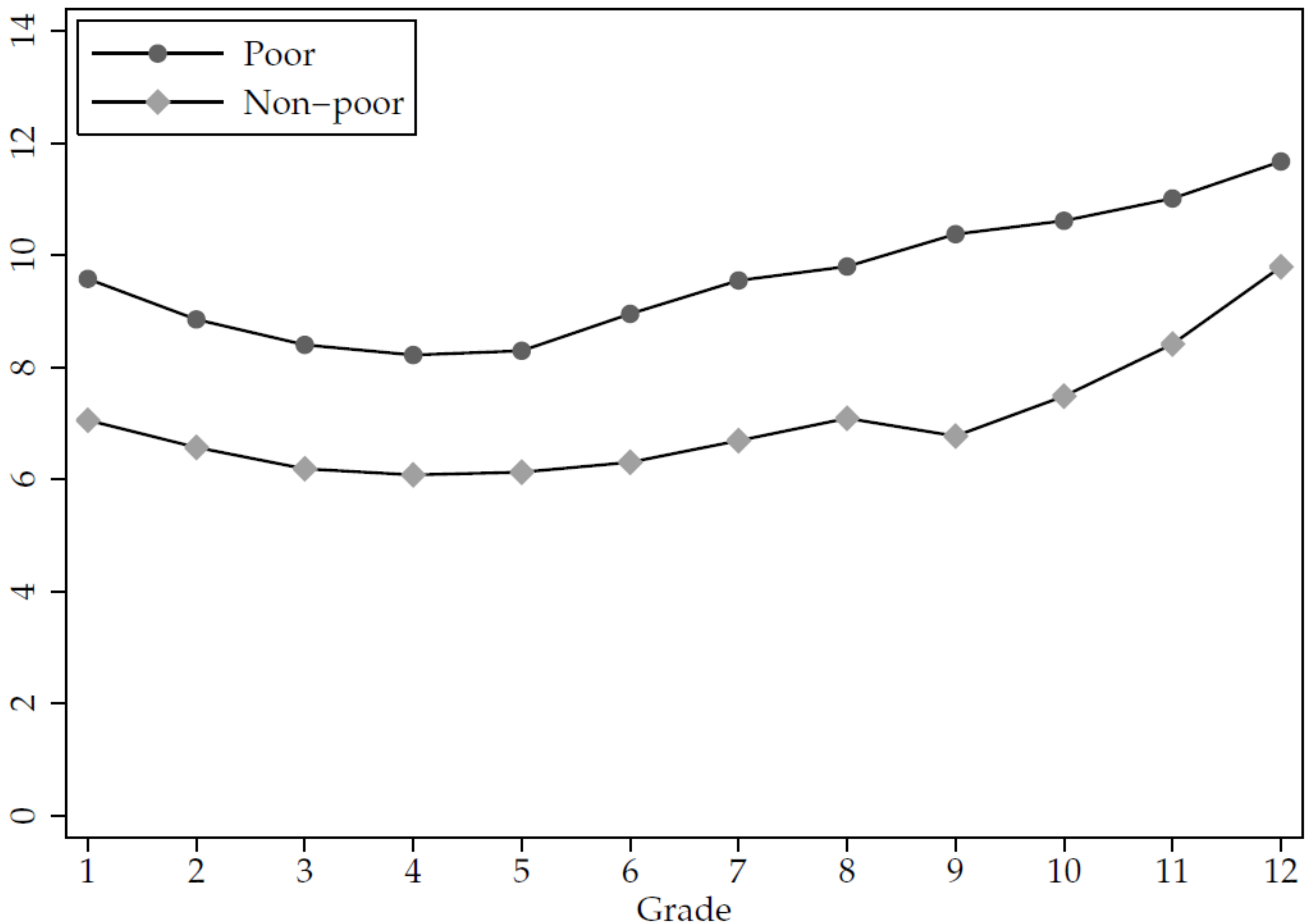
Summary statistics

Table 1: Summary Statistics

	(1) Full sample	(2) Closings sample	(3) Nonpoor	(4) Poor	(5) White	(6) Asian	(7) Black	(8) Hispanic
(A) Days in school								
Days missed	.	9.52	8.59	11.25	9.25	6.86	9.92	11.71
Days closed	.	2.20	2.04	2.51	2.10	2.27	2.14	2.75
Days absent	7.31	7.32	6.56	8.75	7.15	4.59	7.78	8.96
Days attended	172.74	172.63	173.47	171.08	172.87	175.41	172.02	170.77
Days in membership	180.04	179.95	180.02	179.82	180.02	180.00	179.80	179.72
Peer days absent	7.33	7.34	6.99	8.02	7.08	7.13	8.18	8.13
(B) Weather								
4+ inch snow days	2.63	2.64	2.59	2.72	2.59	2.66	2.81	2.78
10+ inch snow days	0.34	0.34	0.35	0.33	0.35	0.34	0.33	0.33
(C) Controls								
Poor	0.30	0.35	.	.	0.17	0.52	0.75	0.84
Black	0.08	0.11	0.04	0.23	.	.	.	.
Hispanic	0.11	0.13	0.03	0.32	.	.	.	.
Asian	0.05	0.06	0.04	0.08	.	.	.	.
Special education	0.17	0.17	0.14	0.22	0.16	0.08	0.22	0.21
Grade size	174.85	176.37	187.48	155.58	185.48	175.91	155.75	148.73
(D) Outcomes								
Math Z	0.00	-0.06	0.22	-0.57	0.13	0.31	-0.65	-0.70
ELA Z	-0.00	-0.07	0.23	-0.62	0.15	0.02	-0.62	-0.75
Math scaled	240.91	239.82	244.48	230.92	242.80	247.47	229.65	229.11
ELA scaled	244.33	243.39	247.51	235.59	246.18	245.30	235.73	234.20
N	3,644,329	1,914,023	1,247,079	666,944	1,314,113	107,470	202,617	254,387

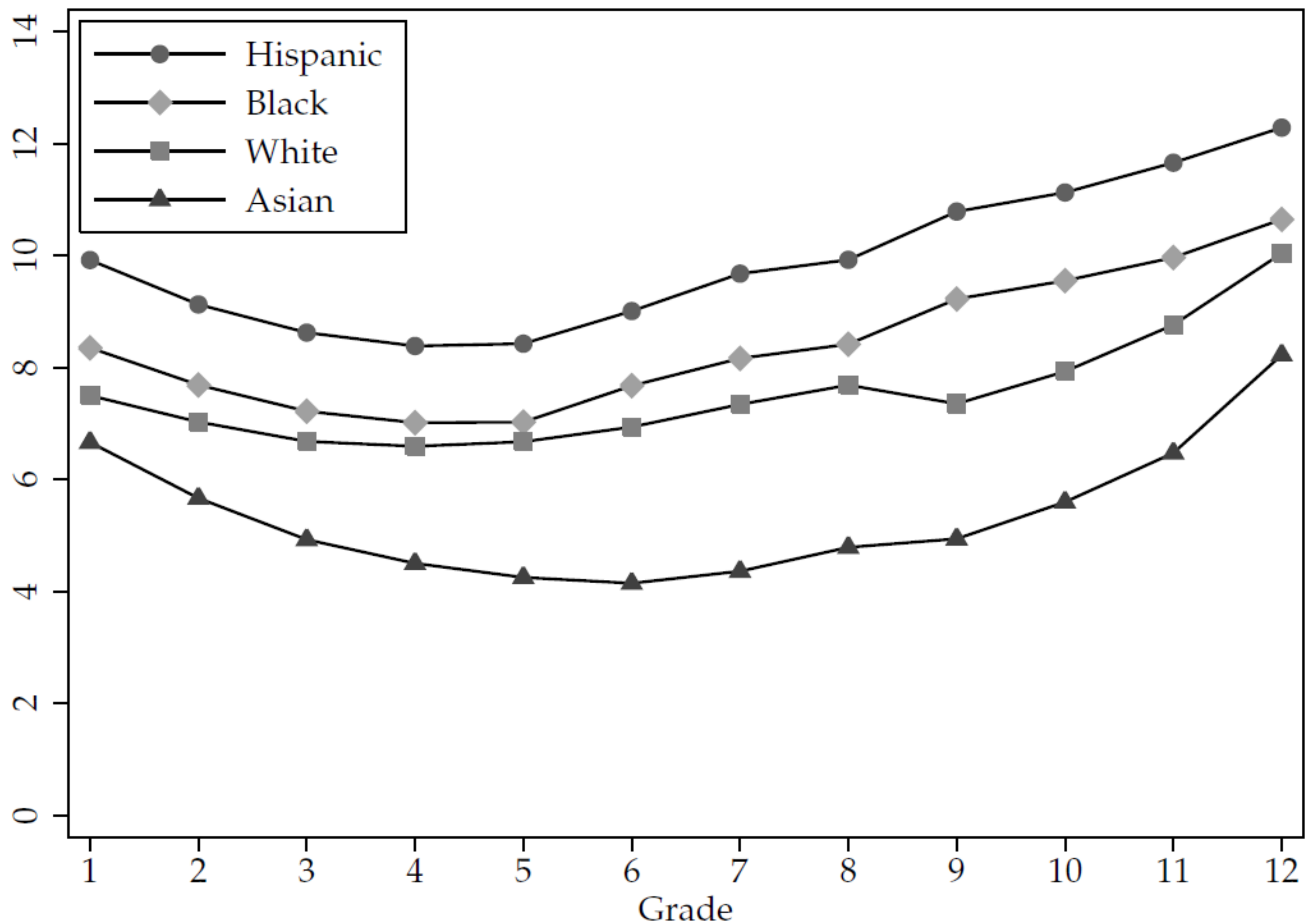
Basic facts

Figure 2: Mean Absences by Grade and Poverty Status



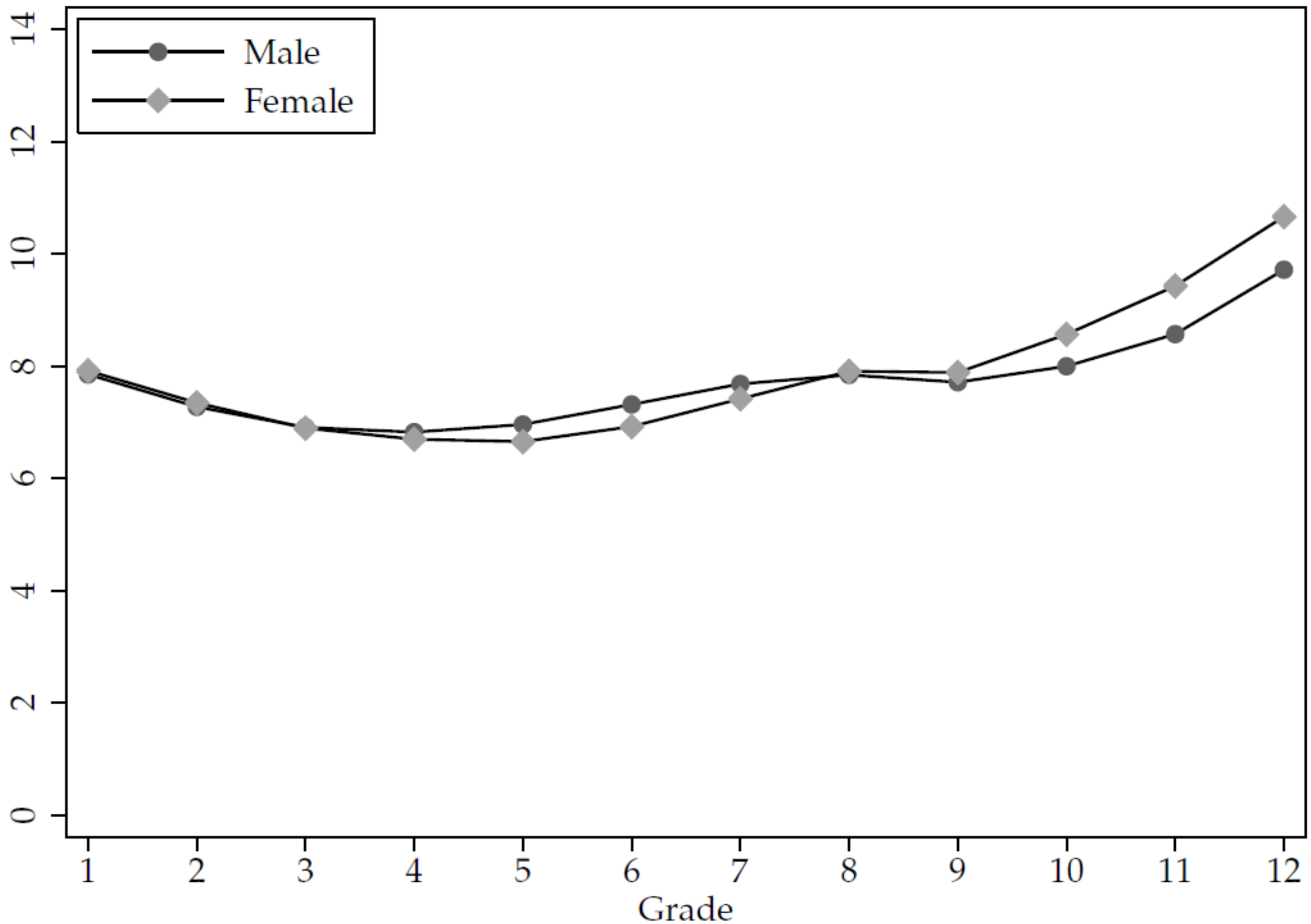
Basic facts

Figure 3: Mean Absences by Grade and Race



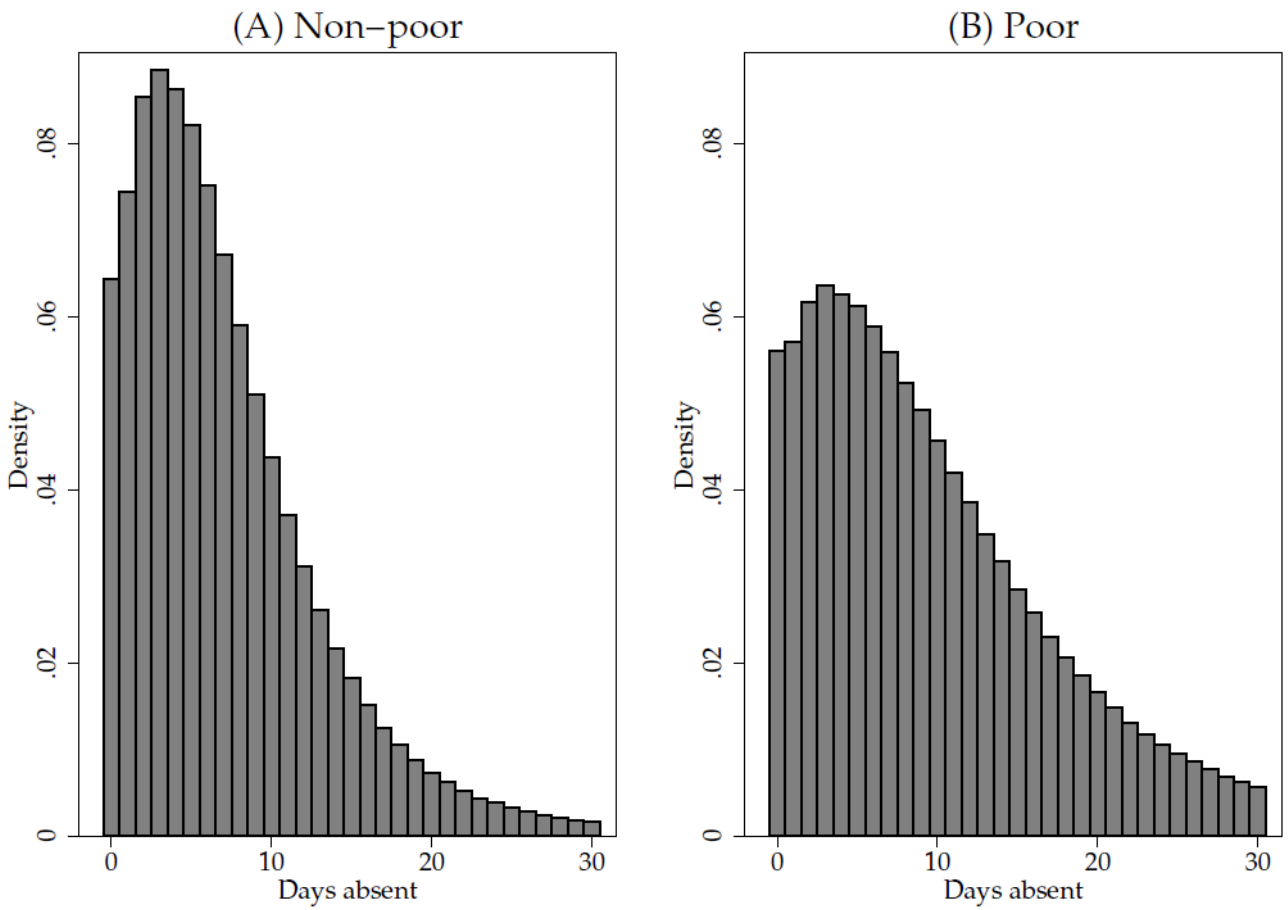
Basic facts

Figure 4: Mean Absences by Grade and Gender



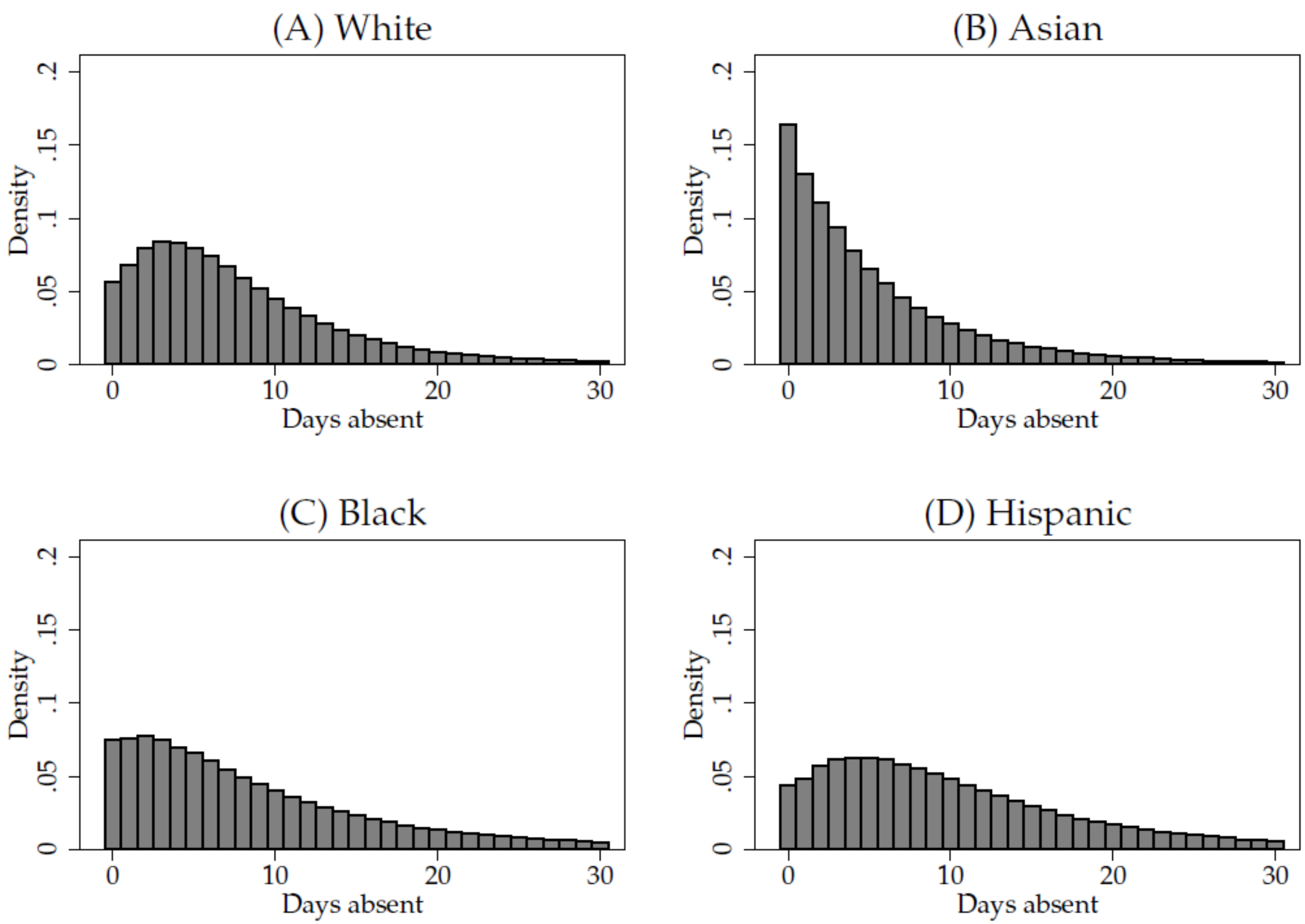
Basic facts

Figure 5: Absence Distribution by Poverty Status



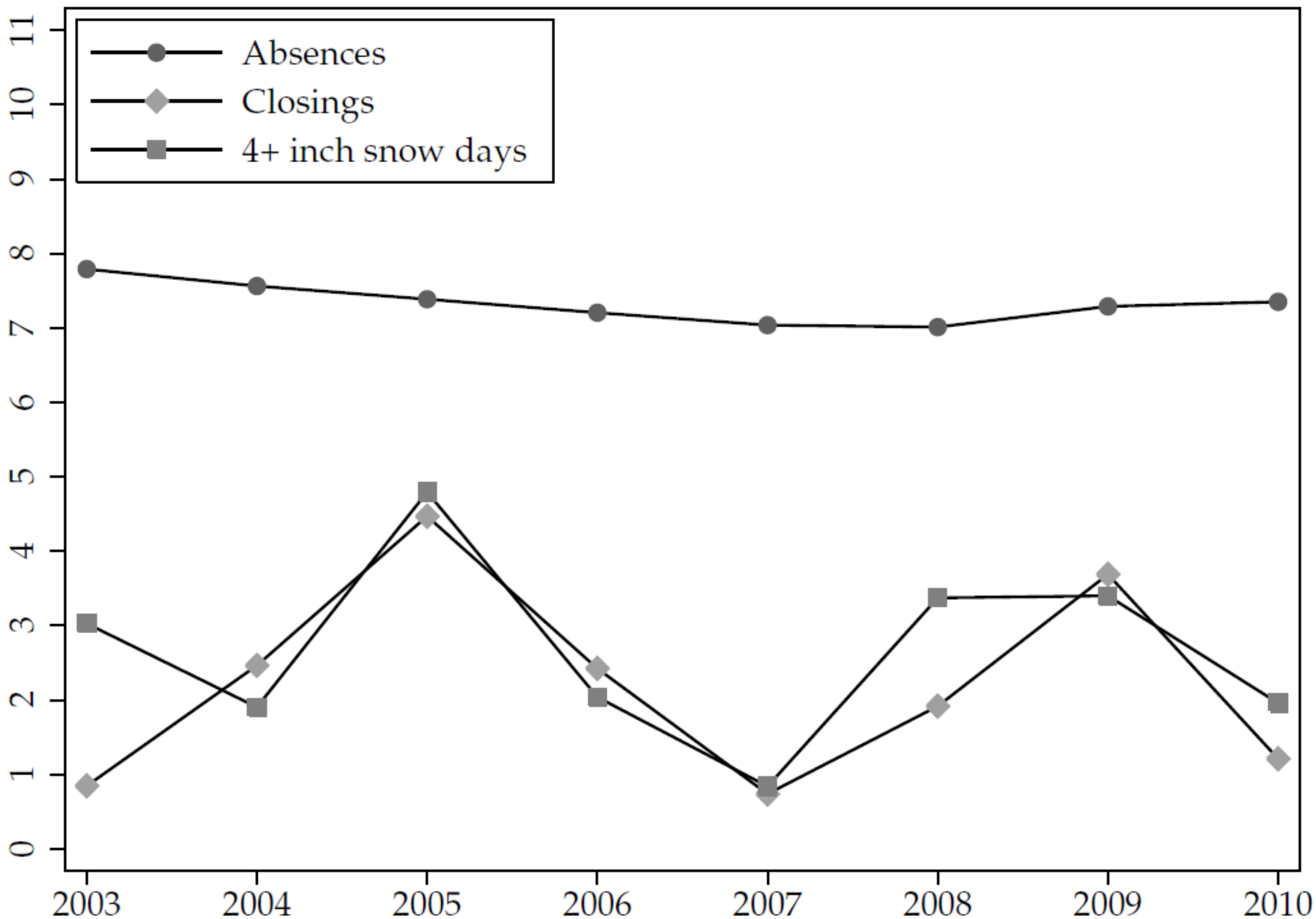
Basic facts

Figure 6: Absence Distribution by Race



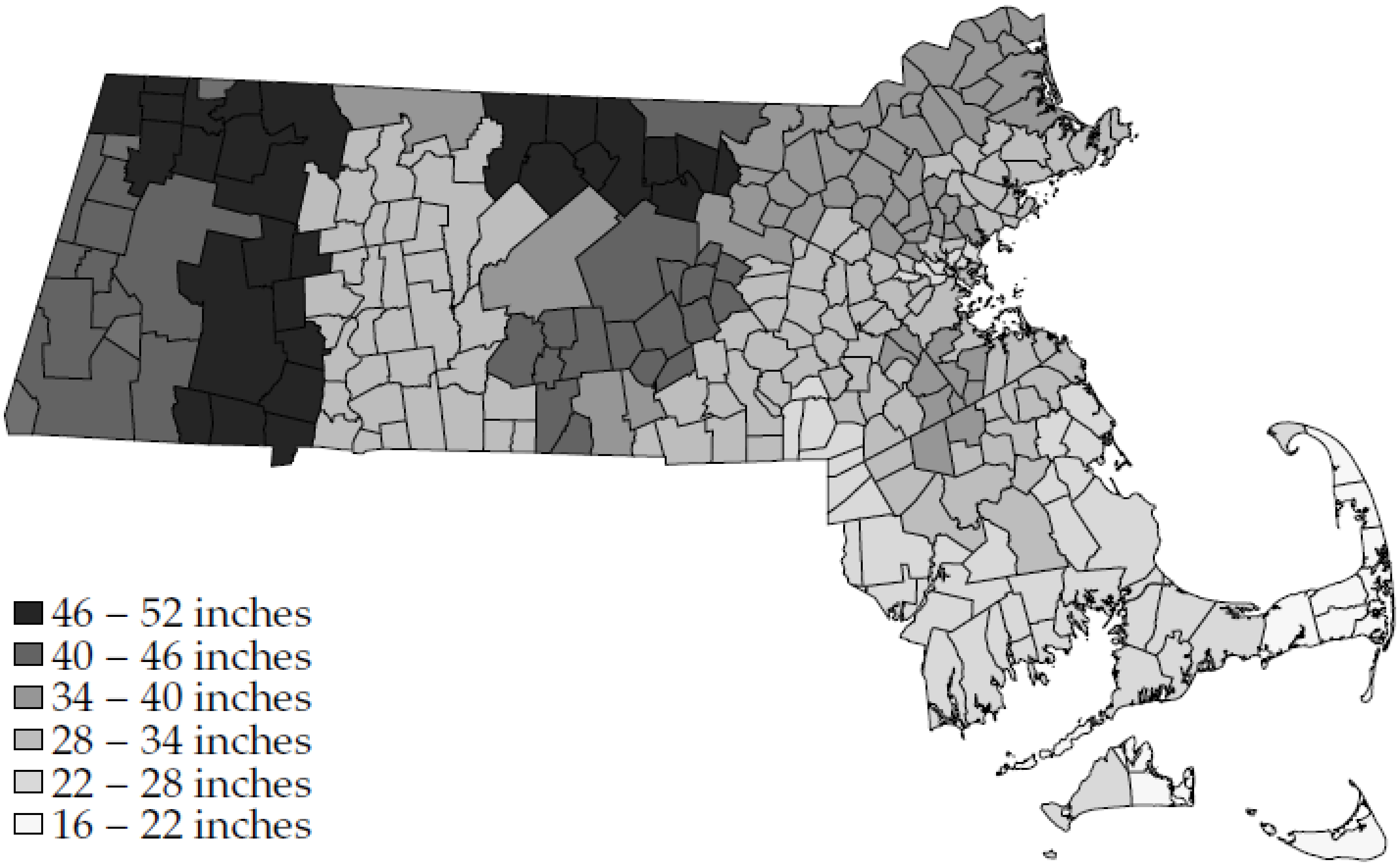
The instrument

Figure 8: Absences, Closings and Snowfall Over Time



The instrument

Figure 9: Mean Annual Snowfall by School District



Empirical strategy

- School-grade fixed effects – identify impact of absences/closures by comparing same school and grade to itself over time

$$Y_{sgt} = B_0 + B_1 Absences_{sgt} + B_2 Closings_{sgt} + B_3 X_{sgt} + \lambda_t + \mu_{sg} + \varepsilon_{sgt}$$

- Student fixed effects – identify impact of absences/closures by comparing same student to him/herself over time

$$Y_{isgt} = B_0 + B_1 Absences_{isgt} + B_2 Closings_{isgt} + B_3 X_{isgt} + \lambda_t + \mu_i + \varepsilon_{isgt}$$

- Instrumental variables – instrument absences/closures with weather in the school-grade FE model (shock is at school/sensor level).

Un-instrumented estimates

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***	-0.007***	-0.007***
	(0.001)	(0.000)	(0.001)	(0.000)
N	19,097	1,718,176	19,758	1,711,979
(B) Days missed by type				
Days absent	-0.020***	-0.008***	-0.015***	-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	19,097	1,718,176	19,758	1,711,979
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).

Heterogeneity

Table 3: OLS Impacts of Days Missed by School Type

	(1) All schools	(2) Nonpoor schools	(3) Poor schools	(4) Grades 3-6	(5) Grades 7-10
(A) Math					
Days absent	-0.022***	-0.017***	-0.026***	-0.023***	-0.020***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Days closed	-0.001	0.001	-0.004*	-0.004**	0.002
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
N	18,871	9,733	8,313	13,309	5,561
(B) ELA					
Days absent	-0.017***	-0.014***	-0.022***	-0.017***	-0.017***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Days closed	-0.000	-0.001	-0.002	-0.002	0.001
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
N	19,544	10,134	8,558	13,996	5,554

Notes: Heteroskedasticity robust standard errors clustered by school are in parentheses (* p<.10 ** p<.05 ***

Summary of OLS results

- In fixed effects models, days missed are strongly associated with achievement, but absences differ from closures.
- An increase in a school-grade's average absence rate by one day is associated with a decrease in that school-grade's achievement of 0.02 standard deviations.
- This seems to be a combination of a student's own absences and the absences of his or her peers.
- Closures are not associated with changes in achievement.
- But absences (and closures) may be picking up important omitted variables. Absences in particular may be proxies for student quality, separate from instructional time. Hence the need for an instrument.

Choosing an instrument

Table 4: Snowy Days as an Instrument for Days Missed

	(1) Closings	(2) Absences	(3) Days missed	(4) RF impact	(5) IV impact
(A) Math					
4+ inch snow days	0.093***	0.063***	0.156***	-0.004*	
	(0.022)	(0.015)	(0.029)	(0.002)	
Days missed					-0.026*
					(0.014)
N	18,871	18,871	18,871	18,871	18,871
10+ inch snow days	0.486***	-0.035	0.451***	0.002	
	(0.049)	(0.023)	(0.052)	(0.003)	
Days missed					0.004
					(0.007)
N	18,871	18,871	18,871	18,871	18,871

The instrumented results

Table 5: Distinguishing Types of Days Missed

	(1)	(2)	(3)	(4)	(5)
	First stage:		Reduced	IV	IV
	Closings	Absences	form	(2 Zs)	(10 Zs)
(A) Math					
4-10 inch snow days	0.039*	0.070***	-0.004**		
	(0.023)	(0.016)	(0.002)		
10+ inch snow days	0.511***	0.009	-0.001		
	(0.048)	(0.023)	(0.003)		
Days absent				-0.062**	-0.054**
				(0.031)	(0.023)
Days closed				-0.001	-0.006
				(0.006)	(0.004)
N	18,871	18,871	18,871	18,871	18,871
(B) ELA					
4-10 inch snow days	0.041*	0.074***	-0.001		
	(0.022)	(0.015)	(0.002)		
10+ inch snow days	0.513***	0.011	0.002		
	(0.045)	(0.024)	(0.003)		
Days absent				-0.016	-0.003
				(0.023)	(0.017)
Days closed				0.004	-0.004
				(0.006)	(0.004)
N	19,544	19,544	19,544	19,544	19,544

IV heterogeneity

Table 7: Heterogeneous Impacts of Days Missed on Achievement

	(1) All schools	(2) Nonpoor schools	(3) Poor schools	(4) Grades 3-6	(5) Grades 7-10
(A) Math					
Days absent	-0.054**	-0.073***	-0.048	-0.046*	-0.073**
	(0.023)	(0.026)	(0.031)	(0.026)	(0.033)
Days closed	-0.006	-0.007	-0.013**	-0.006	-0.007
	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)
N	18,871	9,733	8,313	13,309	5,561
(B) ELA					
Days absent	-0.003	-0.021	-0.015	-0.007	-0.029
	(0.017)	(0.020)	(0.026)	(0.020)	(0.025)
Days closed	-0.004	0.002	-0.013**	-0.007	-0.000
	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)
N	19,544	10,134	8,558	13,996	5,554

Summary of IV results

- The precise choice of instrument matters here. Prior work may have mistakenly attributed the impact of absences to the impact of closures.

- Moderately bad weather impacts absences and achievement. Extremely bad weather impacts closures but not achievement.

- The marginal absence induced by bad weather lowers math test scores by 0.05 standard deviations (though there's no evidence of ELA impact).

- Why is the IV estimate for absences double the OLS estimate?
  - OLS estimate is biased downward by including post-exam absences.
  - Weather-induced absences may involve unusually high numbers of students, making coordination costs even higher for teachers.
  - Student absences aren't the only channel affected by moderately bad weather (teacher absences, tardiness).

Conclusions

- The closure results suggest either that instructional time does not matter or, more likely, that schools are prepared to deal with coordinated disruptions like snow days.
- Schools do not, however, seem to deal well with less extreme disruptions in which only some students are absent. The OLS and IV estimates suggest that absences explain 8-20% of the achievement gap between poor and nonpoor students.
- These results are consistent with a model in which the central challenge of teaching is coordination of students. One policy implication is that schools may be under-preparing for such disruptions.
- Of course, schools have little control over the weather. Other sources of variation in absences may be more interesting from a policy perspective: illness, transportation problems, domestic trouble. Constructing instruments from these is, however, tough.