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ABSTRACT

Upside-Down Down-Under: Cold Temperatures Reduce Learning in Australia*

Understanding how variation in weather and climate conditions impact productivity, performance and learning is of crucial economic importance. Recently, studies have established that high temperatures negatively impact cognition and educational outcomes in several countries around the world. We add to this literature by analysing test scores from a national assessment of Australian children aged between 8 and 15 years. Using comparable methods to previous studies, we find that high temperatures in the year prior to the test do not worsen performance. In fact, we find the opposite: additional cold days significantly reduces test scores. Moreover, the effect appears cumulative, with cold school days 1-2 years prior also having a negative effect. This seemingly contradictory finding is consistent with a literature which finds that people living in warm regions tend to inadequately protect themselves from cold temperatures, meaning they are susceptible to cold weather shocks. More generally, we demonstrate that effects of weather conditions are likely to be context specific.

JEL Classification: I20, J24, J54
Keywords: learning, climate, Australia

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1. Introduction

Increased average temperatures and extreme weather due to Global Warming has focussed attention on how environmental factors impact human capital accumulation and performance in cognitively demanding tasks. The preponderance of evidence from economics suggests that high temperatures (hot days) have a negative effect on a range of cognitive outcomes. Cho (2017), Graff Zivin et al. (2018), Roach and Whitney (2019), Park (2020), Park et al. (2020a, 2020b), and Graff Zivin et al. (2020) all demonstrate that high temperatures on the test day and/or in previous days reduce student test scores.[2] Similarly, high temperatures have been found to reduce trade performance by stock market investors (Huang et al. 2020), affect decisions by US immigration judges (Heyes and Saberian, 2019), and weaken performance in cognitively intensive sport (Qui and Zhao, 2019).

But are the strong negative temperature effects universal? Older literatures studying the relationship between temperature and health find substantial heterogeneity across geographical regions, demonstrating that environmental context is crucial. For example, Curriero et al. (2002) conclude that "populations in warmer regions tend to be most vulnerable to cold, and those residing in cold climates are most sensitive to heat" (p.85). Vardoulakis et al. (2013) compared temperature-related mortality patterns in the UK and Australia, countries with similar socioeconomic characteristics but very different climates, and support this conclusion: heat-related mortality risks in Sydney were lower than in London, while the reverse was true for cold-related mortality.

A likely explanation for this counter-intuitive pattern is that people living in warm climates inadequately protect themselves from cold temperatures. Buildings in warmer climates tend to have inferior thermal efficiency (e.g. insulation) than buildings in cooler climates (Healy, 2003; Moore et al., 2019).[3] Similarly, residents of warmer climates are less likely to wear appropriate clothing in winter.[4] The large empirical Eurowinter study (1997) concludes that "protective

[2] Cook and Heyes (2020) explore the cognitive effects of very cold temperatures (e.g. <15°C) relative to cold temperatures (2.5°C). They find that university exam performance in Ottawa worsens as the outdoor temperature declines. Mean temperature in the sample is around -5°C.
[3] Friedman (1987) argued it is rational for houses in warm climates to be colder than houses in cold climates. The article begins with the statement "A native of Chicago who spends a winter in Los Angeles or Canberra [Australia] is likely to find the houses uncomfortably cold and to express surprise that the natives are too stingy to heat their houses properly even though it would cost very little to do so" (p.1089).
[4] The Eurowinter study (1997) found that at the same cold-weather temperature (7°C), residents of Finland were much more likely to wear a hat than residents of Greece (72 percent versus 13 percent). Hats are important because the head has low internal insulation in the cold.

measures against a given degree of cold were fewer in regions with mild winters", implying that residents of warmer climates are particularly susceptible to cold weather shocks.

Given this context, it is important to explore whether the negative temperature-cognition relationship can be replicated in different environments around the world. This is the aim of our study. We estimate the effects of temperature on maths and literacy test scores in Australia using individual-level data on over 2.2 million national standardised tests taken by almost 400,000 students in over 1,500 schools between 2009 and 2018 in New South Wales.[5] The tests are taken each year in May by nearly all students in grade 3 (age 8-9), grade 5 (age 10-11), grade 7 (age 12-13) and grade 9 (age 14-15). The wide range of ages allows us to explore the effects of temperature at younger ages than most previous studies. With matched government administrative data, we can also explore the moderating effects of family and school socioeconomic status.

Comparing the within school-grade performance of students exposed to different temperatures across time, and controlling for test-day and non-school-day temperatures, we do not find a negative effect of heat on test scores. In fact, we find the opposite relationship: cold days significantly reduce test performance. Importantly, the effect sizes are large. Ten additional cold school days (<60°F) in the year prior to the test, instead of ten warm school days (70-75°F), are estimated to reduce scores by 1.5% of a standard deviation. This is around twice the effect size of ten additional hot school days (>100°F) in the United States, as reported by Park et al. (2020b). Moreover, the negative effects appear cumulative, with cold school days 1-2 years prior to the test also having a negative effect on scores.

These findings for Australia suggest that the negative temperature-cognition relationship does not hold worldwide. In hotter areas, warmer winters caused by global warming may actually improve human capital accumulation.

[5] New South Wales is Australia's most populated state at approximately 8 million people. The state's capital city is Sydney.

2. Data and Methods

We use individual-level test score data from the National Assessment Program—Literacy and Numeracy (NAPLAN) for all New South Wales (NSW) Government Schools.[6] NAPLAN is an annual assessment of students in grades 3, 5, 7 and 9, designed to measure grade-specific knowledge. The tests cover knowledge in the areas of reading, writing, language conventions (spelling; grammar and punctuation) and numeracy. They are undertaken every year in the second week of May, and all students across Australia sit the tests on the same days.

Students with significant intellectual disability and students who arrived in Australia less than one year before the tests may be exempted from testing (Miller and Voon, 2012). Parents also have the possibility to withdraw their children from the tests, for reasons such as religious beliefs and philosophical objections to testing. Overall, NAPLAN participation rates are over 90% in all subjects and grades (ACARA, 2019, AIHW, 2018).

In addition to test results, the data contain information on the date of birth and gender of each student, their quartile of socio-educational advantaged - derived from parental occupation and education, and the school in which they were enrolled when they completed the test. School-level data is also provided including geographic coordinates and index of community socio-educational advantage, which represents relative socioeconomic status of students in a particular school (ACARA, 2015).

Data from the Australian Bureau of Meteorology were used to construct various temperature variables. Specifically, we matched each school to its five closest weather stations, and calculated the weighted average daily maximum temperature, with weights equalling the inverse squared Euclidian distance from schools to stations. Some schools are far from weather stations, introducing measurement error in the predicted temperatures for those schools. To reduce the associated estimation bias we restrict our main analysis to all students attending schools within 20km of at least one weather station (90 percent of all students). With this

[6] We obtained data on NAPLAN test scores from the NSW Department of Education. Anonymised data were provided for all students who attended a NSW Government school in any calendar year between 2010 and 2018 inclusive, and who completed at least three assessments (NAPLAN or HSC) assessments during these years. 2009 NAPLAN data were also provided for students who met these criteria. In the main analysis we drop observations in year-grade cells that are significantly smaller than in other years. In Appendix A we show that the main results are not sensitive to alternate sample selection decisions.

restriction, mean distance to the closest weather station is 7.85km. In a robustness analysis reported below, we test the sensitivity of our results by relaxing the 20km distance restriction.

To estimate the effects of exposure to hot and cold days on student performance, we exploit year-to-year variation in temperature within a grade in a given school. Specifically, we estimate a baseline specification of the form:

$$y_{igst} = \sum_{j=1}^{J} \beta_j Temp_{j,st} + \alpha_{sg} + \theta_{gt} + \gamma X_{it} + \lambda T_{st} + \varepsilon_{igst} \quad (1)$$

where y_{igst} is the standardized numeracy or literacy score for student i in grade g at school s in year t.[7] $Temp_{j,st}$ represents the number of school days in the prior twelve months in which the temperature was in bin j. Potential confounding factors are controlled for with the inclusion of school-grade fixed effects (α_{sg}), year-grade fixed effects (θ_{gt}), and temperatures on non-school days and test days (T_{st}). Finally, student age and gender are also included (X_{it}).

Under the plausible assumption that temperature varies randomly across years within a given school, estimates of β_j can be interpreted as the causal effect of exposure to hot and cold days on student performance. Below we present estimates from regression specifications that include control variables representing other weather conditions, atmospheric pollution, and local economic conditions. The results from these regressions support the identification assumption.

3. Results

3.1. Main Effect Estimates

The main results are shown in Figure 1. Panel A shows estimated effects of cold and warm school days, relative to 70-75 degree days. Panel B shows estimated effects of cold or warm years, relative to years in the 5th decile. Visually, there is a similar pattern, with both panels illustrating a positive relationship between temperature and test scores: lower test scores coincide with cooler temperatures.

[7] We standardize test scores by subject (literacy and numeracy), grade level and calendar year.

Specifically, Panel A indicates that one additional cold school day (<60°F) reduces test scores by 0.15 hundredths of a standard deviation (HSD), one additional 60-65°F day reduces scores by 0.10 HSDs, and one additional 65-70°F day reduces scores by 0.09 HSDs. These magnitudes are comparable to, indeed larger than, Park et al.'s (2020) estimated effects of hot days. Though, the relatively large standard errors should be taken into account.

Importantly, these estimated relationships are clearly very different to those presented in previous research, such as in Park et al. (2020). In particular, there is no evidence that hot days or hot years have any impact relative to moderate days or years. In Panel A the estimated coefficients of the highest four temperature categories are all small, similar and statistically insignificant. The results are similar for relatively high deciles in Panel B.

Table 1 shows corresponding regression estimates. Column (1) Panel A shows estimates from the main specification, but with mean annual temperature instead of temperature categories. This estimate is not statistically significant, so there is no evidence of a monotonic relationship between temperature and test performance. Panel B of Column (1) shows the results which correspond to Figure 1 Panel A. The other columns in Table 1 test the sensitivity of the results to the inclusion of various control variables. Columns (2) and (3) include controls for school day and test day rainfall and for atmospheric pollution[8], which are likely to be correlated with temperature and may also affect student outcomes. Column (4) includes controls for local economic conditions, because temperature-driven shocks to the economy might affect child wellbeing. The inclusion of these different controls has little impact on most of the results. The only exception is Panel A Column (3), where the inclusion of the pollution control results in a statistically significant effect of mean temperature.

3.2 Lagged and Cumulative Effects

We now consider whether these effects are temporary or have lasting effects on student performance. Table 2 shows results from models based on the main specification, with two modifications. For parsimony, these models include just one variable measuring the number of cold days (<70°F). Except for column (1), the models also include variables representing lagged number of cold days. Column (2) includes one lag, which captures the effect of cold

[8] The pollution controls are constructed from the Air Quality Index. This is based on atmospheric concentrations of ozone, nitrogen dioxide, carbon monoxide, sulphur dioxide, particular matter (PM)-2.5 and PM-10, and visibility, collected from monitoring stations around the state. See https://www.environment.nsw.gov.au/topics/air/understanding-air-quality-data/air-quality-index

school days between 24 and 12 months prior to the test date. Column (3) includes two lags. Each column also includes an estimated ‘cumulative’ effect, which is the sum of the lagged and unlagged coefficients. The results are largely consistent with those of Park et al. (2020). To the extent that temperature effects grades, the effect is not completely transitory. It lasts at least until the following year, and the cumulative effect is 2-3 times greater than the immediate effect.

3.3 Heterogeneity

Whilst constrained by statistical power, we present heterogeneity of the estimates along some key dimensions. Each estimate in Figure 2 is from models based on the main specification, with cold days defined as days where the maximum temperature was <70°F, with the sample restricted to the subpopulation of interest. The results suggest that the effects are larger for boys than girls, for English than Math test scores, larger in High Schools than Primary Schools, and similar for high and low SES schools.

The larger effect for boys is consistent with earlier work. In particular Cook & Heyes (2020) find larger effects of cold weather on test scores for boys, also citing earlier work which suggests female students wear more layers of clothing in cold weather (Donaldson et al., 2001). Cho (2017) also finds slightly larger effects of heat on test performance for boys. Ebenstein et al. (2016) found male test performance to be more vulnerable to pollution, while a broader literature finds male mortality more vulnerable to heat (e.g. Deschênes & Greenstone, 2011).

The larger effect for English vs Math is consistent with Cho (2017), although Cho also found no significant effect for reading. Others have found similar effects of temperature across English and Maths tests (Park et al. 2020b; Roach & Whitney, 2019).

The larger effect for high school versus primary school children seems surprising at first glance. We are not aware of previous studies which have examined heterogeneity by age of children. A potential explanation is that younger children are more closely monitored and guided on their clothing and environment, with older children more likely to make their own choices and hence more vulnerable to weather fluctuations.

Park et al. (2020b) found much larger immediate effects of heat for low income and minority students, partly due to differential access to air-conditioning access in schools and homes. We do not find such heterogeneity. This may reflect NSW's centrally funded public school system, in which SES-related discrepancies in air-conditioning, insulation or heating are unlikely.

3.4. Sensitivity Tests

As indicated in the text, the original data provided by the custodian were restricted to students who completed at least three assessments (NAPLAN or HSC) assessments between 2010 and 2018. This leads to some unusual sample characteristics- for example, Year 7 results for 2010 and 2011 were only provided for the subset of students who completed the Year 12 exam (HSC), but for later years, students did not need to complete the HSC to meet the selection criteria. In the main analysis, we exclude observations in such clearly anomalous cells. Table A.1 show key results from the baseline specification (column 1), compared to corresponding results without excluding those observations (column 2). Column (3) shows results from another sample selection criterion, which ensures that student-year observations are included strictly consistently across calendar years for each grade.[9] The key estimates are similar in all three columns, suggesting that the results are not sensitive to the chosen sample selection strategy.

The main analysis excludes schools that are not within 20km of a weather station. Table A.2 presents results that use alternate restrictions. Results are generally robust, however, increasing the allowable distance seems to introduce attenuation bias. For example, estimated effects for the most extreme temperature bin (days below 60°F) are 31 percent larger for our main sample (within 20km) than for the sample using all schools within 50km of a weather station.

3.5. Testing a Potential Mechanism – Sickness and Attendance

A potential mechanism for the cold-day effect is through greater rates of student illness and/or school absenteeism. We explored this mechanism using regression models based on the model in the main analysis, but with student attendance rates as the dependent variable. Our main database does not include school attendance. However, we accessed a published school-year level data set with student attendance rates for the first half of each school year from 2011 to 2018. The results (shown in Figure 3) do not provide evidence for this mechanism. The estimates have the wrong sign to explain our main results. The estimates are also small and mostly statistically insignificant. For example, the point estimates suggest that a week of

[9] There is more than one way to construct such a sample. We show results from the version that yields the largest sample size. Further details available from the authors.

weather in the coldest category (relative to the omitted category) would increase attendance by less than 0.1 percentage points.

4. Conclusion

Unlike several previous studies for other countries, we have found that cold, not heat, inhibits learning in Australia. The estimated effects are meaningful. Experiencing 10 additional school days of moderately cold weather (<70F) is estimated to decrease test scores in the same year by 0.92% of a standard deviation, and by 0.79% of a standard deviation in the following year. These effect sizes are larger than the heat effects presented in most previous studies. The heterogeneity analysis is statistically under-powered, but suggests that boys and high-school students suffer most in cold weather, and that literacy learning is more negatively affected than mathematics learning. We find little heterogeneity in effect magnitude by family SES or by school SES.

The relationship we have identified here is in-line with studies on morbidity and mortality that demonstrate cold temperatures are particularly damaging in hot regions with mild winters, and conversely, that hot temperatures are particularly damaging in cold regions with mild summers. International research suggests that this difference is due to populations in hot regions inadequately protecting themselves from cold temperatures. Australia has an ingrained identity of a sunburnt country, and has a long history of focusing on adaption and resilience to hot temperatures, rather than cold (Daniel et al., 2019).

Further research is needed to determine whether the positive temperature gradients that have been robustly identified in the U.S., China, Korea and other countries, have broad external validity, especially in regions with mild winters and hot summers.

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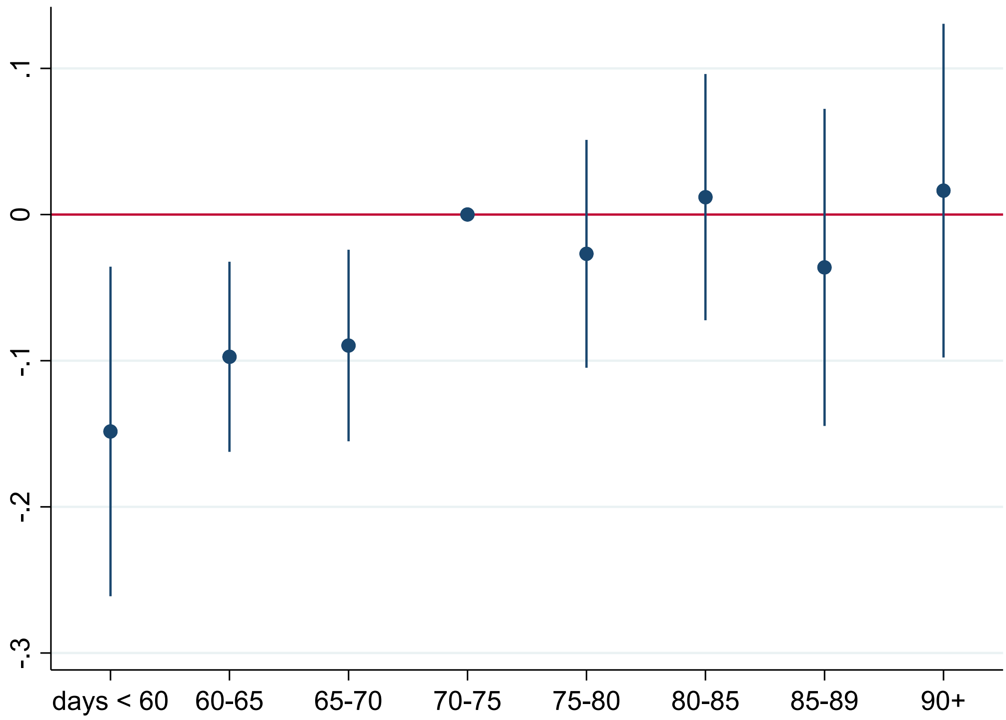
Figures

Figure 1: Main Results

A: Estimated test score effects of number of school days at various temperatures



B Estimated test score effects of average school temperature during school days in past year by temperature decile

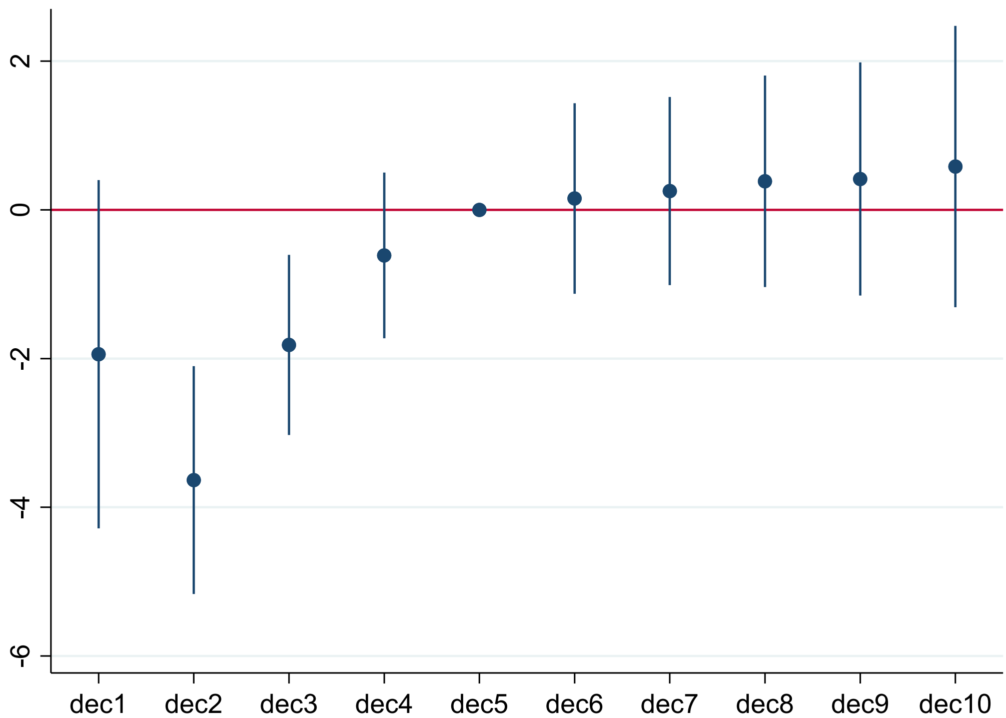


Figure 2 – Heterogeneity Analysis

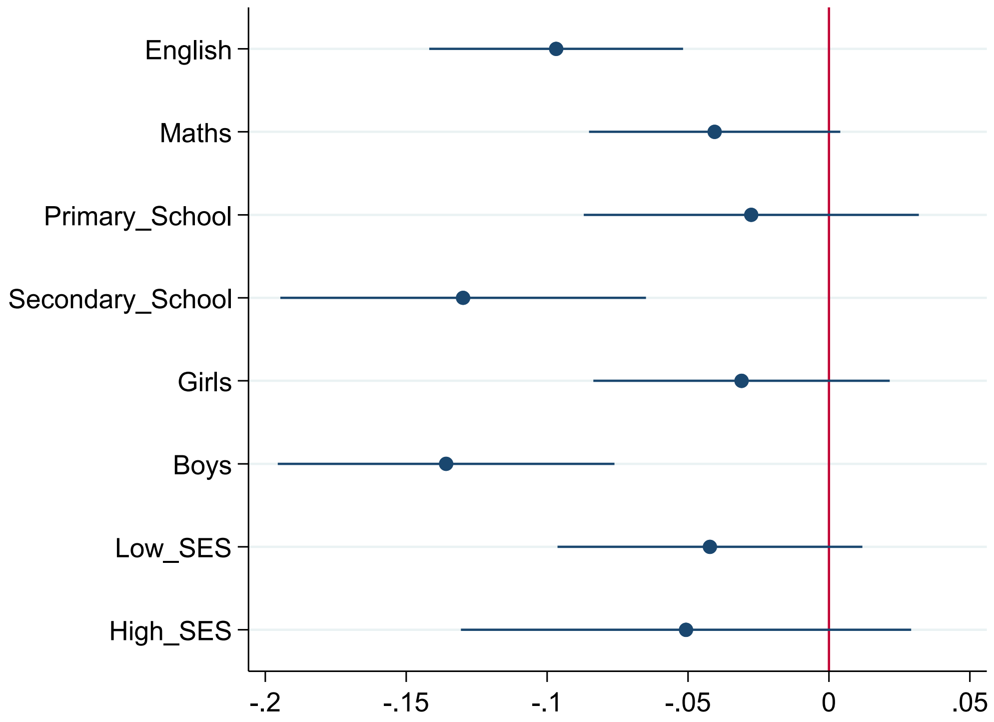
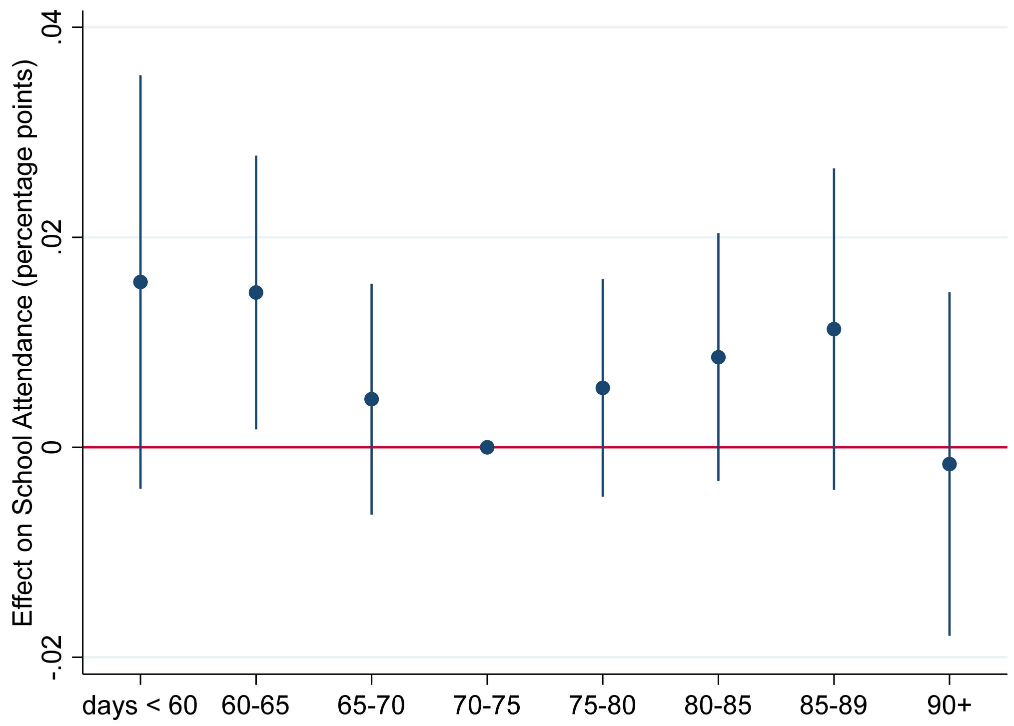


Figure 3 – Estimated school attendance effects of school days at various temperatures



Tables

Table 1: Estimated effects of temperature on NAPLAN test scores

	(1)	(2)	(3)	(4)
Panel A – Impact of average daily maximum temperature				
Average temperature	0.436	0.363	0.621**	0.450
	(0.278)	(0.315)	(0.285)	(0.280)
Panel B – Impact of days in various maximum temperature ranges				
Days below 60°F	-0.148***	-0.147**	-0.144**	-0.158***
	(0.058)	(0.061)	(0.058)	(0.058)
Days between 60°F and 64°F	-0.097***	-0.088**	-0.092***	-0.101***
	(0.033)	(0.035)	(0.033)	(0.033)
Days between 65°F and 69°F	-0.090***	-0.071**	-0.085**	-0.088***
	(0.033)	(0.034)	(0.034)	(0.033)
Days between 75°F and 79°F	-0.027	-0.021	-0.007	-0.026
	(0.040)	(0.040)	(0.041)	(0.040)
Days between 80°F and 84°F	0.012	0.004	0.044	0.013
	(0.043)	(0.045)	(0.045)	(0.043)
Days between 85°F and 89°F	-0.036	-0.019	0.008	-0.036
	(0.055)	(0.057)	(0.057)	(0.055)
Days above 90°F	0.016	0.035	0.062	0.016
	(0.058)	(0.060)	(0.061)	(0.058)
Number of observations	2,234,842	2,234,842	2,234,842	2,234,842
Prior year rain	No	Yes	No	No
Prior year pollution	No	No	Yes	No
Economic conditions	No	No	No	Yes

Note: Included covariates: Days with max temperatures in various ranges (as specified above) during the week and weekends in the last 12 months; max temperature on test day; age; gender; year-grade FE; school-grade FE. Standard errors clustered at school level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Estimated effects of lagged and cumulative temperature on NAPLAN test scores

	(1)	(2)	(3)
Days below 70°F in previous year	-0.083***	-0.092***	-0.100***
	(0.021)	(0.022)	(0.026)
Days below 70°F 1 year earlier (t-1)		-0.079***	-0.084***
		(0.023)	(0.025)
Days below 70°F 2 years earlier (t-2)			-0.028
			(0.029)
Total effect (sum of presented coefficients)		-0.170***	-0.211***
		(0.036)	(0.062)
Number of observations	2,234,842	2,234,842	2,234,842

Note: Included covariates: Days below 70°F in the last 12 months; max temperature on test day; age; gender; year-grade FE; school-grade FE. Standard errors clustered at school level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix

Table A.1 – Analysis on different samples (varying samples' restrictions)

	Baseline	Complete Sample	Small Sample
	(1)	(2)	(3)
Days below 60°F	-0.148***	-0.146**	-0.169**
	(0.058)	(0.059)	(0.069)
Days between 60°F and 64°F	-0.097***	-0.115***	-0.133***
	(0.033)	(0.034)	(0.040)
Days between 65°F and 69°F	-0.090***	-0.093***	-0.139***
	(0.033)	(0.033)	(0.040)
Days between 75°F and 79°F	-0.027	0.034	-0.002
	(0.040)	(0.041)	(0.047)
Days between 80°F and 84°F	0.012	0.050	0.019
	(0.043)	(0.043)	(0.052)
Days between 85°F and 89°F	-0.036	0.007	0.028
	(0.055)	(0.055)	(0.066)
Days above 90°F	0.016	0.085	-0.017
	(0.058)	(0.060)	(0.069)
r2	0.234	0.238	0.252
N	2,234,842	2,470,799	1,435,451

Note: Included covariates: Days with max temperatures in various ranges (as specified above) during the week and weekends in the last 12 months; max temperature on test day; age; gender; year-grade FE; school-grade FE. Standard errors clustered at school level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.2 – Analysis varying distance from weather stations

	No km restr	<50km	<40km	<30km	<20km	<10 km
Days below 60°F	-0.104**	-0.102*	-0.113**	-0.118**	-0.148***	-0.131**
	(0.052)	(0.053)	(0.054)	(0.055)	(0.058)	(0.066)
Days between 60°F and 64°F	-0.076**	-0.074**	-0.078**	-0.086***	-0.097***	-0.086**
	(0.031)	(0.031)	(0.031)	(0.032)	(0.033)	(0.038)
Days between 65°F and 69°F	-0.063**	-0.063**	-0.063**	-0.073**	-0.090***	-0.084**
	(0.031)	(0.031)	(0.032)	(0.032)	(0.033)	(0.040)
Days between 75°F and 79°F	-0.015	-0.013	-0.018	-0.024	-0.027	0.018
	(0.037)	(0.037)	(0.038)	(0.038)	(0.040)	(0.046)
Days between 80°F and 84°F	0.021	0.021	0.025	0.018	0.012	0.069
	(0.039)	(0.040)	(0.040)	(0.041)	(0.043)	(0.050)
Days between 85°F and 89°F	-0.026	-0.029	-0.028	-0.026	-0.036	-0.041
	(0.050)	(0.051)	(0.052)	(0.053)	(0.055)	(0.066)
Days above 90°F	0.015	0.016	0.025	0.019	0.016	0.052
	(0.053)	(0.054)	(0.055)	(0.056)	(0.058)	(0.067)
r2	0.224	0.225	0.226	0.227	0.234	0.242
N	2,471,999	2,444,519	2,418,593	2,370,926	2,234,842	1,651,009

Note: Included covariates: Days with max temperatures in various ranges (as specified above) during the week and weekends in the last 12 months; max temperature on test day; age; gender; year-grade FE; school-grade FE. Standard errors clustered at school level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.