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Technology Attenuates the Impact of Heat on Learning

Evidence from Colombia

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Technology Attenuates the Impact of Heat on Learning. Evidence from Colombia [1]

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Abstract

High temperatures hinder learning. An e ective solution is to control the environment. However, technologies such as air conditioning are seldom adopted in developing countries. Information and Communication Technologies (ICTs) are more widely available and could o er an alternative solution by increasing the amount of instruction, allowing the re-allocation of activities, boosting productivity, or improving the quality of instruction. Using data from Colombia, we con rm that heat a ects test scores, and we show that ICTs compensate up to 15 percent of this e ect when used by teachers to teach and for pedagogic purposes.

Keywords: Weather and learning, Adaptation, Climate Change, Economics of Education, Information and Communication Technologies (ICT), Developing Country, Computer Programs

JEL Codes: H54, I2, J24, O15, Q54, Q56

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Technology Attenuates the Impact of Heat on Learning. Evidence from Colombia *

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Abstract

High temperatures hinder learning. An effective solution is to control the environment. However, technologies such as air conditioning are seldom adopted in developing countries. Information and Communication Technologies (ICTs) are more widely available and could offer an alternative solution by increasing the amount of instruction, allowing the re-allocation of activities, boosting productivity, or improving the quality of instruction. Using data from Colombia, we confirm that heat affects test scores, and we show that ICTs compensate up to 15 percent of this effect when used by teachers to teach and for pedagogic purposes.

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1 Introduction

High temperatures make learning more difficult (Villalobos, 2017; Cho, 2017; Park et al., 2018, 2020, 2021; Park, 2022; Garg et al., 2020; Zivin et al., 2020; Heal and Park, 2020). One explanation is that when exposed to high temperatures, pupils experience discomfort, fatigue, and cognitive impairment, due to the biological response of the body to temperatures above or below the thermal comfort zone of 64–72°F (18–22°C) (Heal and Park, 2020; Park, 2022). In addition, high temperatures might affect the quality and quantity of instruction by decreasing school attendance (Villalobos, 2017), by affecting teachers' productivity, or by reducing class and self-study time (Alberto et al., 2021).

Controlling the environment at which students take lessons and tests is an effective solution (Park et al., 2020). However, technologies such as air conditioning (AC) or climate-smart infrastructure are seldom adopted in developing countries. For example, while over 80 percent of households have AC the United States, Korea, and Japan, this share is less than 20 percent for emerging economies like Mexico or Brazil (IEA, 2018). Furthermore, AC is unequally distributed and it is an energy-intensive technology that, unless sourced from clean energy, exacerbates the climate emergency.

In this paper, we study whether school-level access to information and communication technologies (ICTs)—computers, laptops, and tablets—enables adaptation responses to the effects of heat on test scores. There are several mechanisms through which ICTs can directly increase schooling outcomes. For example, (i) by increasing the overall amount of instruction students receive, (ii) by boosting productivity as they could offer the advantage of self-paced instruction and individualization of the content, facilitate the acquisition of information, and boost student motivation and engagement, (iii) by enabling the re-allocation of activities, and (iv) by improving quality of instruction and pedagogical practices (Cristia et al., 2017; Bulman and Fairlie, 2016).

We stress that these mechanisms could be particularly advantageous in facilitating individual adaptation to heat. Our hypothesis is that ICTs allow students to substitute a missed or a poor-quality lecture scheduled during extreme heat for instruction under better conditions. In addition, if used for pedagogical purposes, ICTs could compensate for lower productivity caused by high heat. Although some of the direct effects of ICTs on learning have been documented, their moderating role in dissociating weather conditions from learning time has not been explored.

Our context is students in Colombia, a middle-income country with annual average temperatures of 25°C (77°F), where closing the technological gap has been a central policy objective in recent years. With historically low rates of ICTs per-capita, access to ICTs in schools has substantially improved since 2012, partially due to a government program—*Computadores para Educar (CPE)*—that has delivered more than two million desktops, laptops, and tables to public schools in the entire country (Luxon, 2020). Situated in pre-pandemic times of in-person instruction, we study the moderating effect of improving school-level access to ICTs on the heat-learning phenomenon.

Our data include the universe of third, fifth, and ninth grade test scores from a standardized test (*Pruebas Saber*) during 2012–2016 at the school-grade-subject-year level. We exploit the exogenous variation in weather conditions to explain differences in test scores over time using a two-way fixed-effects model. Then, we test whether ICTs mute the heat effect using time varying information on ICTs penetration and devices' use for each school.

We find that, in line with previous literature, both heat during the year prior to the test and high temperatures during the day of the test decrease test scores. On average, one additional Celsius degree during the year prior to the test lowers scores by 0.14 standard deviations. One additional day above 21°C decreases scores by a magnitude of 0.001–0.004 standard deviations with respect to an additional day at 17–21°C. The effects are statistically significant for math and reading scores, students in urban and rural areas, and public and private schools.

Next, we show that ICTs are a partially effective adaptation solution to the effects of heat. Increasing the number of ICTs per-capita from zero to one decreases the heat effect by 9 percent on average, but up to 15 percent for rural areas. This compensatory effect of ICTs is observed only for schools where ICTs are used for pedagogic purposes, and in schools where ICTs are used by teachers to teach. These ICTs uses are consistent with the idea that ICTs improve the quality of instruction during times of extreme heat. In contrast, we do not find a moderating effect of ICTs through the amount of instruction, re-allocation of activities, or productivity mechanisms.

These findings are a contribution to the literature on the short-term effects of heat on human capital formation in the context of a warm developing country (Park et al., 2021; Garg et al., 2020; Villalobos, 2017). We show that, consistently with previous findings, heat is a factor contributing to the gaps in human capital formation in Colombia. In addition, to the best of our knowledge, this is the first study to document adaptation capacity through virtual technology. We show that in-school ICTs provide incomplete, but non-negligible, adaptation. Still, complementary policies are required to fully adapt to the effect of heat on school performance. For example, home access to ICTs could enhance further adaptation.

We also contribute to the literature on the benefits of providing schools with ICTs. While the effects of ICTs on schooling outcomes have been widely studied finding mixed results (McEwan, 2015; Bulman and Fairlie, 2016; Cristia et al., 2014; Yanguas, 2020; Comi et al., 2017; Barrera-Osorio and Linden, 2009; Rodríguez et al., 2011), we look at a new mechanism through which ICTs could improve schooling outcomes. If heat hinders learning but ICTs compensate some of this effect, observed test scores will be higher compared to the counterfactual of high temperatures and no access to ICTs.

This paper is organized as follows: Section 2 describes the data, Section 3 presents the empirical framework, Section 4 reports the results, and Section 5 provides concluding remarks.

2 Data

We rely on three sources of data: *Pruebas Saber* test scores from ICFES (Instituto Colombiano para el Fomento de la Educación Superior), ICTs penetration from DANE (Departamento Administrativo Nacional de Estadística), and high resolution weather information from the CHC (Climate Hazards Center). We detail each source in the next subsections.

2.1 Test scores

Pruebas Saber are standardized tests administered every year to evaluate the quality of primary and secondary education (ICFES, 2020). The annual test is taken on the same day nationally, roughly between September and October. We obtained the precise date on which each test was taken from public on-line records. The test is mandatory (census) for all students of third, fifth, and ninth grades (typically ages 9, 11, and 15).

Third grade students are randomly selected to take one test (math or reading), while students in fifth and ninth grades are randomly selected to take two out of four subjects: math, reading, science or civic education. We focus on math and reading as they are consistently available for all grades. During 2012–2016, between 50 and 60 percent of fifth and ninth graders took either math or reading. Importantly, because the tests are mandatory and students are not allowed to choose subjects, there is no self-selection on who takes what exams.

The dependent variable is the average score by school-grade-subject-year, standardized to have zero mean and variance equal to one at the grade-subject-year level. The sample includes the universe of scores in every school of the country (15,220 institutions) between 2012 and 2016[1]. Therefore, this is a representative sample of test scores at the national level.

[1]We focus on the 2012–2016 period because rules changed in 2017, making subsequent rounds of tests incomparable with previous years. In particular, science and civics exams were removed for fifth and ninth graders, and both math and reading became mandatory for third graders.

2.2 ICT penetration and use

We obtain official and public data on ICT penetration from DANE (2014). Those data are collected annually through a questionnaire completed by every school in the country. We define the variable *ICTs per-capita* as the number of ICT devices (laptops, desktops, tablets) that are available in school s in year t, divided by the number of students in school s and year t. Importantly, this survey started to collect information on ICTs only after year 2014. Therefore, this part of our analysis restricts the sample to years 2014–2016.

This survey contains detailed information on the use of ICTs. We obtain school-level time-varying data on (i) whether students use the ICTs, (ii) whether ICTs are used daily *vs* less frequently, (iii) whether students can access the ICTs during class-time only; (iv) whether there is internet available, (v) whether the ICTs have pedagogic software; (vi) whether ICTs are used for pedagogic purposes, and (vii) whether ICTs are used by teachers to teach. We group these characteristics into four categories that broadly correspond to the mechanisms mentioned in Section 1: *Amount of instruction* (i and ii), *Re-allocation of activities* (iii), *Productivity effects* (iv and v), and Quality of instruction (vi and vii).

2.3 Weather Data

We obtained municipality-day level weather data from the Climate Hazards Center (CHC). For temperature, we use the Climate Hazards InfraRed Temperature with Station data (CHIRTS) (CHC, 2000b). Similarly, precipitation data come from the Climate Hazards InfraRed Precipitation with Station product (CHIRPS) (CHC, 2000a). This is a quasi-global data set that combines satellite imagery and in-situ station data to create a gridded temperature and rainfall time series at the 0.05 resolution (approximately 5 Km2) (Funk et al., 2015).

From this daily data we compute the maximum average temperature and total precipitation during the year prior to the test, and the maximum temperature and precipitation on the test-day. To test for non-linear effects, we also compute the number of days that fall into each of the 4°C temperature bins, using the maximum daily temperature.

2.4 Sample and descriptive statistics

Our unit of observation is the school-grade-subject-year. For example, we observe the average test score that 3rd-graders in school s obtained for math in year t. We have information for almost 76,000 mean test scores in over 15,000 schools in 1,115 municipalities (99.5 percent of all municipalities in Colombia).

On average, the temperature was 25°C during the year prior to the test, and 26°C on the day of the test (Table 1). On average, temperatures were higher than 29°C during 116 days per year. There is no difference between weather conditions at which math and reading tests were taken. Instead, rural areas tend to be warmer and score lower on tests.

On average, there are 0.16 ICTs per-capita, with rural areas having a higher ratio of 0.21. This is not surprising given that the program *Computadores para Educar* has channeled substantial resources to equip these schools with ICTs. From the variables that classify the different uses given to ICTs, we observe that virtually all schools allow students to use the technology, although there is substantial variation in the frequency with which they do. For about three quarters of the observations students have access to ICTs during class time only. About 80% of the observations are in schools where internet is available. In less than half of the observations there is pedagogic software available. Almost every observation is in a school that uses ICTs for pedagogic purposes, and in most cases ICTs are used by teachers to teach. The within-school variation in these variables is what allows us to identify the mechanism through which ICTs moderate the effect of heat on learning.

Figure 1 depicts the relationship between test scores and cumulative temperature using all school-grade-subject-year observations. Each dot represents the average score for each temperature value rounded by tenths of a degree. The fitted values curve suggests a negative relationship between heat exposure and test scores.

3 Empirical Strategy

We exploit the exogenous variation in weather conditions to explain differences in school-grade-subject test scores over time, using a fixed-effects model. We begin by estimating the average effect of heat on test scores using Model 1.

$$\begin{aligned} Score_{jgsmt} = \beta_0 + \beta_1 Tyear_{mt} + \beta_2 Tday_{mt} + \beta_3 Pyear_{mt} + \beta_4 Pday_{mt} + \\ \mu_{jgs} + \theta_t + \epsilon_{jgsmt} \end{aligned} \tag{1}$$

The dependent variable is the standardized test score for subject j (math or reading), grade g (3rd, 5th, 9th) in school s, located in municipality m, in year t. We define cumulative heat exposure, $Tyear$, as the average maximum temperature in municipality m during the year prior to the test. As control variables, we include the maximum temperature on the day of the test $Tday$, the total precipitation during the year prior to the test $Pyear$, and precipitation on the test day $Pday$. μ_{jgs} are school-grade-subject fixed-effects that control for non-observable time-invariant characteristics, and θ_t are year fixed-effects that control for annual shocks that may affect test scores in all schools.

Next, we test for non-linear effects by including the number of days that fall in various temperature ranges (bins) as defined in Model 2. We include the same set of control variables as in Model 1.

$$\begin{aligned} Score_{jgsmt} = \beta_0 + \beta_1 DaysBelow17°\text{C}_{mt} + \beta_2 DaysIn[21 - 25°\text{C})_{mt} + \\ \beta_3 DaysIn[25 - 29°\text{C})_{mt} + \beta_4 DaysAbove29°\text{C}_{mt} + \\ \beta_5 Pyear_{mt} + \beta_6 Pday_{mt} + \mu_{jgs} + \theta_t + \epsilon_{jgsmt} \end{aligned} \tag{2}$$

The coefficients β_1 to β_4 can be interpreted as the impact of experiencing one additional day with temperatures in the corresponding range, relative to an additional day with temperatures between 17–21°C. This model allows us to study non-linear effects of accumulated heat on test scores.

Next, we test whether ICTs moderate the effect of cumulative temperature on test scores by including an interaction term $Tyear \times ICT$ (Model 3). We focus on the moderating effect of ICTs on the cumulative temperature, because there is little that ICTs can do to mend the effect of same test-day heat on scores.

$$\begin{aligned} Score_{jgsmt} = \beta_0 + \beta_1 Tyear_{mt} + \beta_2 ICT_{st} + \beta_3 Tyear_{mt} \times ICT_{st} + \\ \beta_4 Tday_{mt} + \beta_5 Pyear_{mt} + \beta_6 Pday_{mt} + \\ \mu_{jgs} + \theta_t + \epsilon_{jgsmt} \end{aligned} \tag{3}$$

Observing *ICTs per-capita* at the school-year level rules out cross-sectional factors that correlate with ICTs, such as quality of management, or school remoteness. Hence, our identification comes from marginal changes in within-institution ICTs per-capita over time. Still, a first order concern with Model 3 is that *ICTs per-capita* is not exogenous, potentially introducing omitted variable bias. For example, if schools with poor infrastructure tend to under-perform *and* invest less in ICTs, the coefficients of Model 3 could be biased.

To address this concern, we test whether the heat effects differ between schools with low *vs* high levels of *ICTs per-capita*, defined with respect to the median value of *ICTs per-capita*. The advantage of this approach is that *ICTs per-capita* is not directly introduced in the model, avoiding the omitted variable bias. If there are no differences in the heat effects between these two sub-samples, we could conclude that ICTs are not a moderating factor. However, even if we do observe differences, we would still be unsure whether they can be attributed to higher penetration of ICTs because this variable could be picking up effects of other factors, such as changes in infrastructure investments.

To strengthen the case, we conduct a placebo test where we repeat this analysis for other key inputs of education, including the number of teachers per-capita. We do not expect to see any difference in the effect of heat on test scores by levels of teachers per-capita. Although this placebo test is not conclusive, it might provide additional evidence in favor of ICTs being the moderating factor of the effect of heat on learning.

For this test of differences in the heat effect by levels of input, we create a dummy variable indicating whether a school is within the lower 50-th percentile of the corresponding variable distribution (*ICTs per-capita* or *teachers per-capita*). Then, we fully interact Model 2 with this variable, and plot the coefficients of the interactions with the temperature bins[2]. These coefficients measure whether the heat effect is different between types of schools for each temperature bin.

In all specifications, we cluster the standard errors by municipality-year because this is the level of variation in the weather data. In addition, since there could be correlation in weather for nearby municipalities, in Table A2 we show that the results hold if we correct the standard errors for spatial correlation between nearby municipalities within the same year (Conley, 1999; Colella et al., 2019). We use a threshold of 100 Kilometers, which means that the error of each municipality is assumed to be correlated with all municipalities located within a radius of 100 Kilometers from its geometrical centroid.

4 Results

Table 2 presents our main results. In this table, we only present the coefficients for cumulative heat and hot days, whereas the coefficients for the control variables are presented in Table A1.

Panel A of Table 2 shows the linear average effect of an additional Celsius degree during the year prior to the test on scores (Model 1). On average, a one degree hotter year decreases scores by 0.14 standard deviations (SD). One additional degree decreases math scores by 0.17, and reading by 0.11 SD. Interestingly, the point estimates for urban schools is larger than for rural, and the effect for private is larger compared to public schools. Without being a formal test, these results suggest that there are non-linearities in the heat effects according to levels of ICTs: the lower the level of (*ICTs per-capita*, the stronger the effect of heat on

[2]This is equivalent to running to separate regressions, one for the sample of schools with low levels of the input and the second for the ones with high levels, and plotting the differences in the coefficients. The advantage of a fully interacted model is that it calculates the standard errors for these differences

learning. In fact, private schools have almost half the number of (*ICTs per-capita* of public schools (0.11 *vs* 0.19) and their heat effect is more than twice the one for public schools (-0.22 vs -0.11 SD).

To put these magnitudes in context, we compare them with the effects of school-based interventions on learning in developing countries. Avoiding annual exposure to one additional temperature degree from the mean value of 25.45 Celsius degrees is comparable to the largest mean effects of the interventions reported in the literature, which include treatments with computers or instructional technology (0.15 SD); teacher training (0.12); and smaller classes, smaller learning groups within classes, or ability grouping (0.12) (McEwan, 2015). Furthermore, the benefits of avoiding heat surpass those of monetary grants, nutritional interventions, and school management treatments (McEwan, 2015).

Panel B of Table 2 tests for non-linear effects (Model 3). We find that test scores decrease with more days at temperatures above 21°C. An additional day with temperature within 21–25°C decreases scores by 0.002 SD, compared to an additional day within 17-21°C. Additional days at higher temperatures also decrease test scores by a similar magnitude (0.002–0.003 SD). One additional day at temperatures higher than 29°C decreases math and reading scores by 0.003 and 0.002 SD, respectively. These effects are identical to the ones found by Garg et al. (2020) in India, although their comparison bin is 15–17°C. Figure 2 presents these results visually. The coefficients across the sub-samples are consistently in range of 0.001–0.004 SD.

We note that higher temperatures on the test-day also decrease scores (Table A1). On average, one additional degree during the test decreases scores by 0.008 SD. Cumulative precipitation increases test scores, whereas test-day precipitation has a positive effect.

Next, we focus the attention to ICTs as a moderating factor of the heat effect. Panel A in Table 3 shows the coefficients for the variables of interest (Model 2), whereas Panel B shows the marginal effects evaluated at the mean values of the explanatory variables. These models are estimated using the sub-sample of years 2014–2016, when information on ICTs is available.

We first note that the marginal effect of the cumulative temperature for this sample is consistently negative and statistically significant, and slightly higher in magnitude compared to the estimates using the full sample. ICTs increase test scores, but this effect is not statistically significant. The coefficient for the interaction between temperature and ICTs is positive and significant in all sub-samples. On average, one ICT per-capita compensates the effect of temperature on test scores by 0.02 SD, compared to zero ICTs per-capita. This is equivalent to 9 percent of the average effect of temperature on test scores. This compensatory effect is 11 percent for math, 15 percent for rural areas, and 11 percent for public schools.

Table 4 shows the marginal effect of temperature evaluated at different values of *ICT per-capita*. The effect of temperature on test scores at zero *ICT per-capita* is 0.003 SD higher compared to the effect at the mean value of *ICT per-capita*. This difference is statistically significant at the conventional levels, and it is equivalent to 1.5 percent of the average effect of temperature on test scores. This suggests that a school that invested in increasing ICTs from zero units per student to the sample average of 0.16, already avoided lower test scores due to high temperatures.

4.1 Placebo test

Figure 3 plots the difference in the heat effects between schools with low *vs* high levels of ICTs (Panel A), and teachers (Panel B) per-capita. Whereas temperatures higher than 21° decrease test scores both for school with low and high levels of *ICT per-capita* (results not shown), the effect is stronger (more negative) for schools with low levels of *ICT per-capita*. These differences are statistically significant only for high temperatures, whereas there is no difference at temperatures lower than 17°. As expected, we do not find such a difference in the heat effect between schools with low *vs* high levels of teachers per-capita. This placebo test is reassuring evidence suggesting that ICTs—and not other important education inputs—moderate the effect of heat on test scores.

4.2 Mechanisms

To better understand the attenuation effect of ICTs, we run Model 3 but instead of the variable *ICT per-capita*, we run separate models interacting each of the variables that indicate the use given to ICTs (see Table 1, Panel D). We plot the interaction coefficient for each of these models in Figure 4. The main message of this analysis is that quality of instruction seems to be the mechanism through which ICTs moderate the effect of heat on test scores. All other mechanisms, including the amount of instruction, the re-allocation of activities, and the productivity effects do not seem to moderate the effect of heat on learning.

5 Discussion and Conclusions

In this paper we investigate the effect of exposure to high temperatures during a school year on test scores, and the role of ICTs in adapting to these effects. We found that both higher cumulative temperature and more days under high temperatures decrease scores, a result that is consistent with previous findings in United States, South Korea, and India. The benefit of avoiding heat is comparable to the most successful school-level interventions in developing countries.

In addition, we detected an effect both for math and reading, urban and rural schools, and public and private institutions. These results add evidence to the literature on the impacts of environmental factors on schooling outcomes in the short run.

A key question is how to adapt to the negative effects of heat on learning. Notably, air conditioning has lessened the negative effects of thermal stress in the United States (Park et al., 2020). However, this technology is available only to a very limited extent in developing countries (IEA, 2018), and a wider adoption of this energy intensive technology might exacerbate emissions. In addition, AC tends to be unevenly distributed across income levels, making evident the existence of a disparity in access to cooling devices (Pavanello et al., 2021).

We found that increasing ICTs from zero to one unit per-capita compensates the effects of temperature by 0.02 SD for math, rural areas, and public institutions. Adaptation starts to occur even at relatively low values of ICTs per-capita. Schools that increased ICTs from zero to the sample mean of 0.16 units per-capita avoided a 1.5 percent decrease in test scores that would have occurred due to heat. We conclude that, similarly to other countries, heat hurts learning in Colombia, and ICTs provide incomplete, but non-negligible, capacity to adapt.

This paper contributes to a relatively large literature on the factors that affect test performance in developing countries. Other papers have found that factors such as infrastructure, violence, and incentives for teachers are determinants of educational attainment and learning outcomes. We find that heat is yet another factor contributing to the gaps in human capital formation, and that in-school access to technological capital has the potential to mend part of this effect, specifically when used to improve the quality of instruction.

Table 1: Summary Statistics. Means and Standard Deviations (SD)

	All	Reading	Math	Urban	Rural	Public	Private
(A) Outcome							
Test score (standardized)	-0.00	-0.00	-0.00	0.26	-0.41	-0.38	0.76
SD	1.00	1.00	1.00	0.99	0.88	0.76	0.99
(B) Cumulative heat							
Temperature(C)	25.45	25.46	25.45	24.94	26.28	26.09	24.18
SD	4.91	4.91	4.91	5.22	4.31	4.55	5.34
(C) Temperature bins							
Days below 17C	18.6	18.6	18.6	26.3	6.8	11.3	33.1
SD	45.2	45.2	45.2	51.2	30.2	37.2	55.2
Days within 17-21C	66.2	66.2	66.2	77.5	49.8	51.9	94.8
SD	103.7	103.7	103.7	109.2	93.1	94.0	115.6
Days within 21-25C	83.3	83.2	83.4	79.1	88.2	86.7	76.6
SD	110.2	110.2	110.3	109.2	111.1	112.4	105.6
Days within 25-29C	80.9	80.9	81.0	73.1	91.6	89.0	64.8
SD	93.9	93.9	93.9	92.1	94.6	95.5	88.2
Days above 29C	116.0	116.1	115.8	109.1	128.6	126.1	95.7
SD	146.2	146.2	146.2	147.8	143.6	146.0	144.6
(D) ICT penetration and use							
ICTs per-capita	0.16	0.16	0.16	0.13	0.21	0.19	0.11
SD	0.20	0.20	0.20	0.17	0.23	0.22	0.11
Students use ICTs	1.00	0.99	1.00	0.99	1.00	1.00	0.99
SD	0.07	0.07	0.07	0.08	0.05	0.05	0.10
ICTs used daily	0.38	0.38	0.38	0.37	0.39	0.44	0.25
SD	0.48	0.48	0.48	0.48	0.49	0.50	0.43
Class-time ICTs access only	0.78	0.78	0.78	0.80	0.76	0.79	0.77
SD	0.41	0.41	0.41	0.40	0.42	0.41	0.42
Internet available	0.82	0.82	0.82	0.95	0.62	0.74	0.98
SD	0.39	0.39	0.39	0.22	0.49	0.44	0.15
ICTs have pedagogic software	0.41	0.41	0.41	0.44	0.36	0.40	0.42
SD	0.49	0.49	0.49	0.50	0.48	0.49	0.49
ICTs used for pedagogic purposes	1.00	1.00	1.00	1.00	1.00	1.00	0.99
SD	0.06	0.06	0.06	0.06	0.05	0.05	0.07
ICTs used by teachers to teach	0.99	0.99	0.99	0.99	0.99	0.99	0.99
SD	0.11	0.11	0.11	0.11	0.11	0.11	0.10
(E) Control variables							
Temperature on test day (C)	25.88	25.88	25.88	25.39	26.66	26.49	24.65
SD	5.02	5.03	5.02	5.29	4.51	4.72	5.37
Cumulative precipitation	6.06	6.06	6.05	5.81	6.38	6.34	5.49
SD	8.67	8.67	8.67	8.08	9.52	9.17	7.54
Precipitation on test day	1716.05	1716.37	1715.73	1539.32	1972.46	1867.38	1413.57
SD	979.38	979.60	979.16	896.01	1040.18	1030.50	785.20
Obs(municipios)	1,115	1,115	1,114	867	1,045	1,115	432
Obs(school-grade-subject)	75,983	38,002	37,981	45,436	27,727	48,176	27,807
Obs(school-grade-subject-year)	307,295	153,826	153,469	187,043	114,740	204,825	102,470

Table 2: Effects of cumulative temperature on test scores

	All sample	Math	Reading	Urban	Rural	Public	Private
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Cumulative Heat							
Temperature (C)	-0.1395***	-0.1691***	-0.1099***	-0.1621***	-0.0966***	-0.1055***	-0.2219***
	(0.0240)	(0.0268)	(0.0226)	(0.0310)	(0.0226)	(0.0223)	(0.0525)
(B) Hot days							
Days below 17C	0.0020**	0.0026**	0.0014	0.0020**	0.0027***	0.0023**	0.0022***
	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0005)	(0.0010)	(0.0008)
Days within 21-25C	-0.0016***	-0.0019***	-0.0013***	-0.0020***	-0.0011***	-0.0012***	-0.0025***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0006)
Days within 25-29C	-0.0028***	-0.0034***	-0.0022***	-0.0030***	-0.0026***	-0.0027***	-0.0033***
	(0.0005)	(0.0005)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.0008)
Days above 29C	-0.0024***	-0.0030***	-0.0019***	-0.0031***	-0.0016***	-0.0021***	-0.0036***
	(0.0007)	(0.0008)	(0.0006)	(0.0010)	(0.0006)	(0.0007)	(0.0012)
Municipios	5,514	5,512	5,512	4,173	5,108	5,507	1,735
N	300,109	149,864	150,245	183,226	112,783	201,451	98,658

Notes: The dependent variable is test scores standardized by school-grade-subject. Standard errors clustered by municipio and year are in parenthesis. The omitted category in Panel B is Days within 17-21C. All regressions control for precipitation during one year before the test, and day of the test maximum temperature and total precipitation. In addition, all models include fixed effects for school-grade-subject, and year. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table 3: Information and Communication Technologies (ICTs) as an adaptation response to the effects of heat on test scores

	ICT subsample	Math	Reading	Urban	Rural	Public	Private
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Coefficients							
Temperature (C)	-0.1998***	-0.2399***	-0.1598***	-0.2239***	-0.1531***	-0.1575***	-0.3023***
	(0.0290)	(0.0334)	(0.0273)	(0.0390)	(0.0316)	(0.0275)	(0.0786)
ICTs per-capita	-0.4527***	-0.6573***	-0.2458**	-0.3338**	-0.5523***	-0.4245***	-0.6977*
	(0.1010)	(0.1241)	(0.0959)	(0.1649)	(0.1366)	(0.0985)	(0.4164)
ICTs per-capita × Temperature (C)	0.0180***	0.0259***	0.0100***	0.0138**	0.0219***	0.0170***	0.0319**
	(0.0037)	(0.0045)	(0.0035)	(0.0057)	(0.0052)	(0.0036)	(0.0158)
N	174,061	86,843	87,218	107,425	65,459	116,275	57,786
(B) Marginal effects at means							
ICTs per-capita	0.0044	0.0010	0.0081	0.0097	0.0240	0.0204	0.0730
	(0.0190)	(0.0220)	(0.0185)	(0.0308)	(0.0228)	(0.0162)	(0.0927)
Temperature (C)	-0.1969***	-0.2356***	-0.1582***	-0.2220***	-0.1484***	-0.1542***	-0.2989***
	(0.0291)	(0.0335)	(0.0273)	(0.0391)	(0.0317)	(0.0275)	(0.0788)

Notes: The dependent variable is test scores standardized by school-grade-subject. This subsample is restricted to years 2014-2016 when information on ICTs is available. Standard errors clustered by municipality are in parenthesis. All models include fixed effects for school–grade–subject, and year. * p<0.10 ** p<0.05 *** p<0.01.

Table 4: Marginal effects of temperature evaluated at different values of ICT per-capita

	ICT subsample (1)	Math (2)	Reading (3)	Urban (4)	Rural (5)	Public (6)	Private (7)
Temperature (C) at ICTs per-capita = 0	-0.1998***	-0.2399***	-0.1598***	-0.2239***	-0.1531***	-0.1575***	-0.3023***
	(0.0290)	(0.0334)	(0.0273)	(0.0390)	(0.0316)	(0.0275)	(0.0786)
Temperature (C) at ICTs per-capita = mean	-0.1969***	-0.2356***	-0.1582***	-0.2220***	-0.1484***	-0.1542***	-0.2989***
	(0.0291)	(0.0335)	(0.0273)	(0.0391)	(0.0317)	(0.0275)	(0.0788)
Temperature (C) at ICTs per-capita = mean+1SD	-0.1963***	-0.2348***	-0.1579***	-0.2216***	-0.1480***	-0.1536***	-0.2989***
	(0.0291)	(0.0335)	(0.0274)	(0.0392)	(0.0317)	(0.0275)	(0.0788)
Temperature (C) at ICTs per-capita = 1	-0.1819***	-0.2141***	-0.1499***	-0.2101***	-0.1311***	-0.1404***	-0.2703***
	(0.0296)	(0.0343)	(0.0277)	(0.0402)	(0.0322)	(0.0277)	(0.0820)
Change	0.0030	0.0043	0.0017	0.0019	0.0047	0.0033	0.0034
Pvalue	0.0000	0.0000	0.0044	0.0159	0.0000	0.0000	0.0429

Notes: *Change* is the difference between the marginal effect of temperature at ICTs per-capita = 0 and the marginal effect of temperature at ICTs per-capita = mean. The dependent variable is test scores standardized by school-grade-subject. This subsample is restricted to years 2014-2016 when information on ICTs is available. Standard errors clustered by municipality are in parenthesis. All models include fixed effects for school–grade–subject, and year. * p<0.10 ** p<0.05 *** p<0.01.

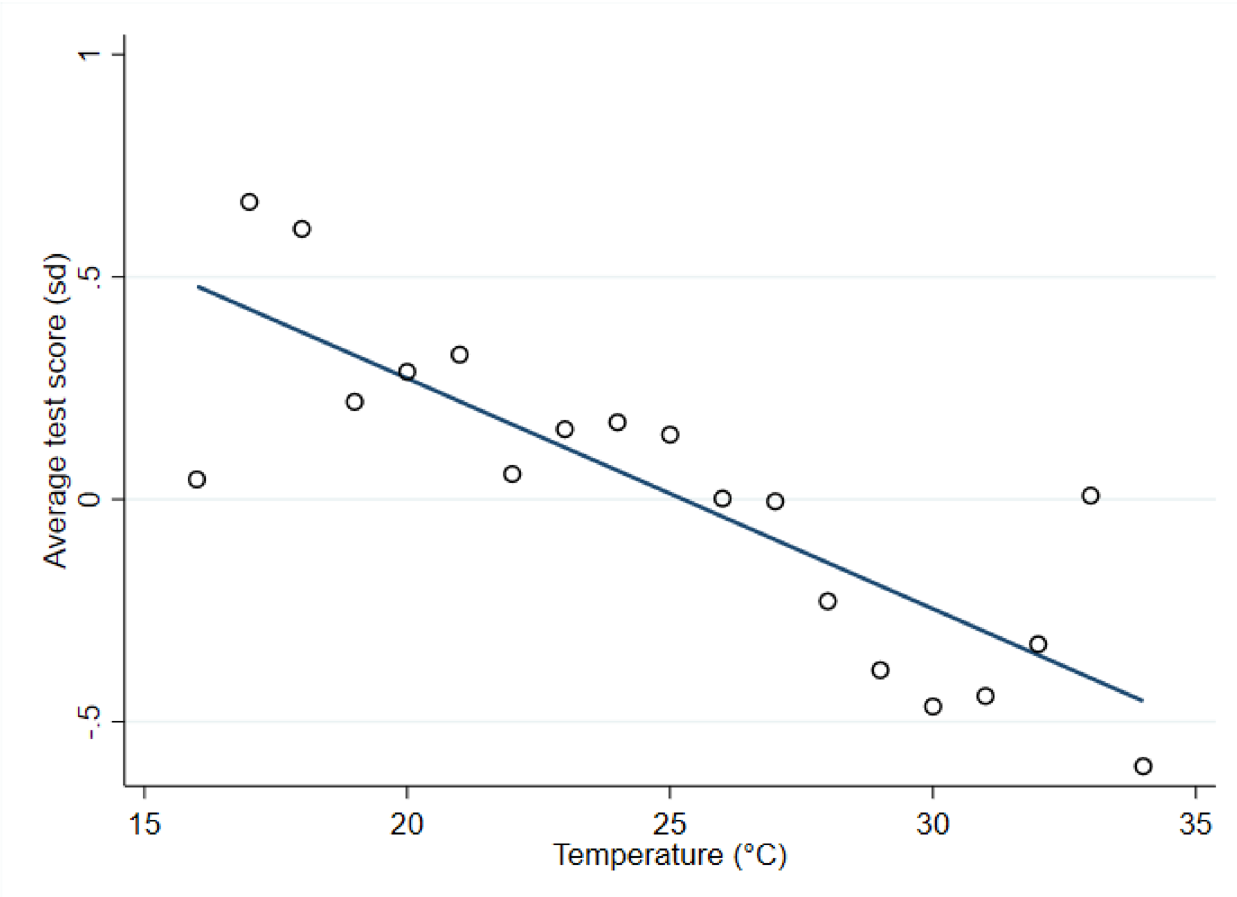

Figure 1: Temperature and test scores

Notes: Scatter plot of test scores at the school-grade-subject-year level. Each dot represents the average score for each temperature value (rounded by tenths of a degree). The line shows the predicted values from a linear regression of test scores on temperature

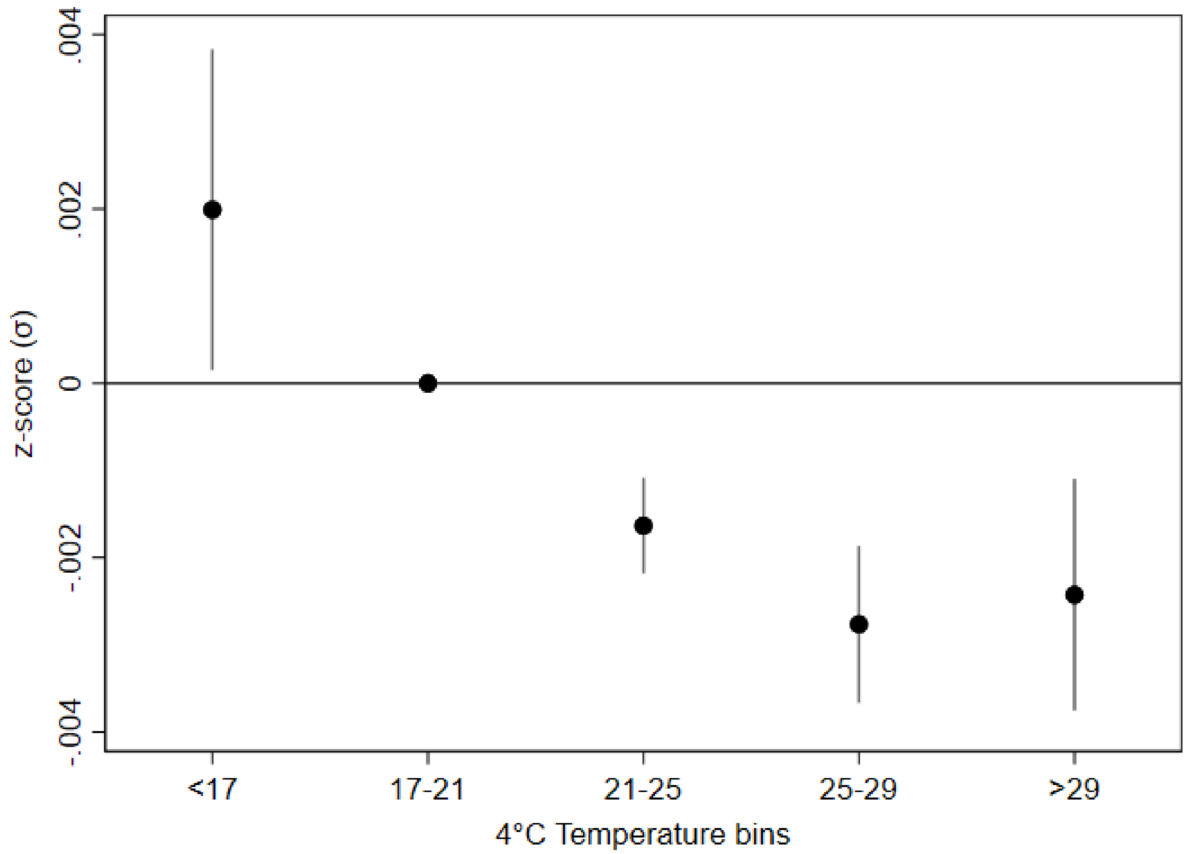

Figure 2: Effect of cumulative temperature on test scores
Notes: Coefficients and 95 percent confidence intervals from a regression of test scores on the number of days during the year prior to the test that fall in each temperature range. The model includes fixed-effects for the unit of observation (school-grade-subject) and year, and as control variables it includes: temperature and precipitation on the test-day, and total precipitation during the year prior to the test. Standard errors to construct the confidence intervals are clustered by municipality.

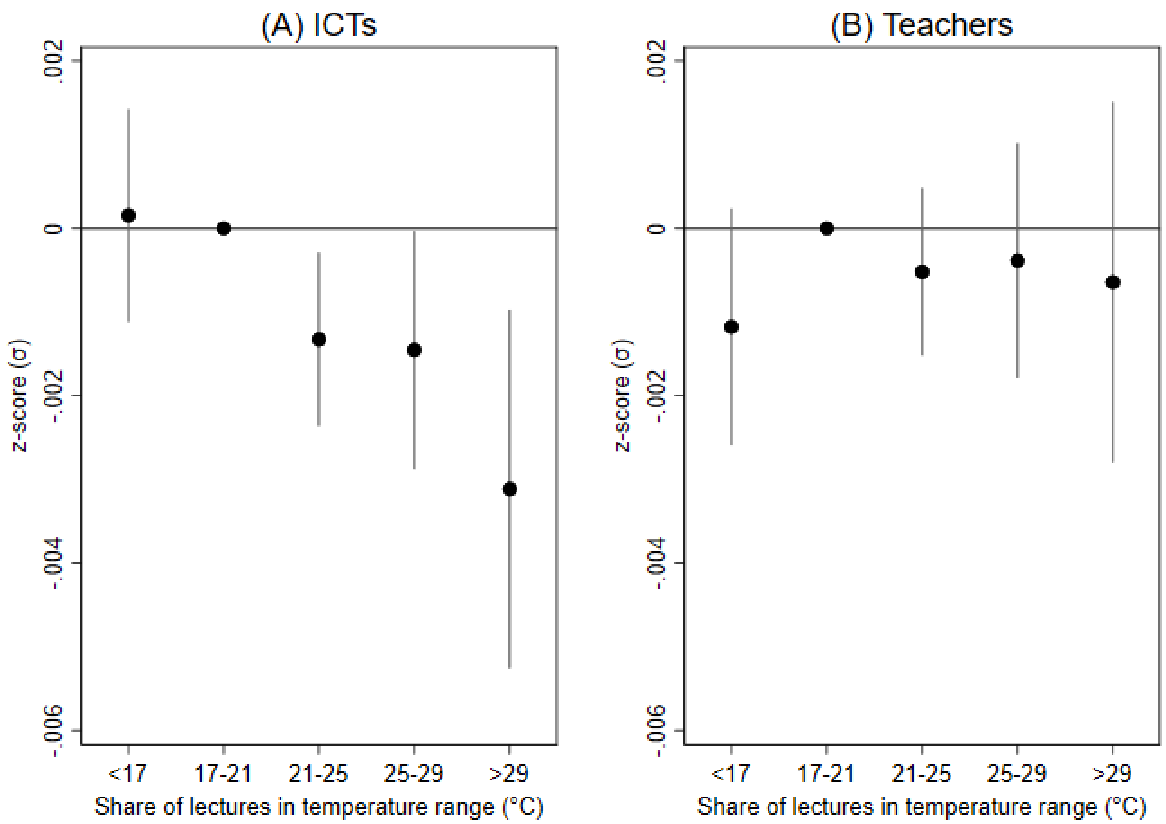

Figure 3: Difference in heat effects between schools with low vs high level of various inputs per-capita

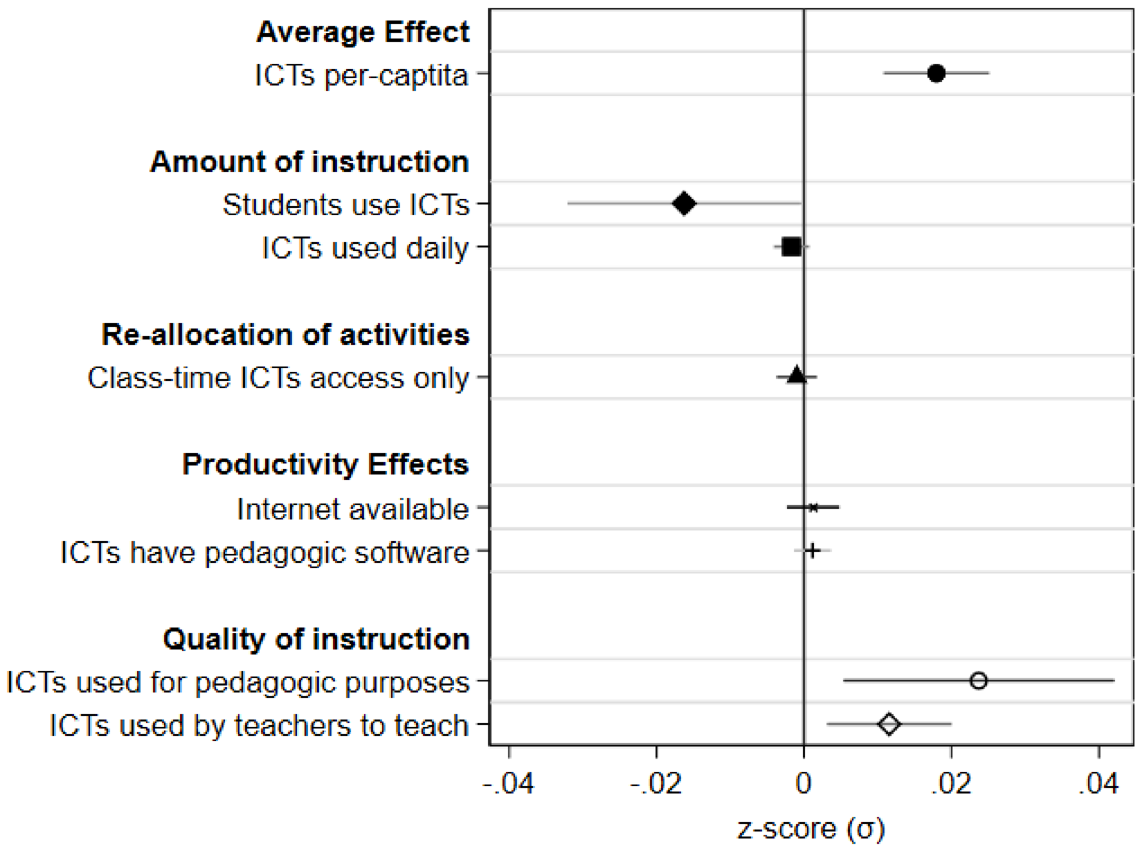

Figure 4: Attenuation effect of heat on learning by mechanism

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Appendix

Table A1: Effects of control variables on test scores

	All sample (1)	Math (2)	Reading (3)	Urban (4)	Rural (5)	Public (6)	Private (7)
(A) Cumulative Heat							
Temperature on test day (C)	-0.0082**	-0.0084**	-0.0079**	-0.0144***	0.0031	-0.0009	-0.0245***
	(0.0034)	(0.0039)	(0.0031)	(0.0048)	(0.0032)	(0.0029)	(0.0093)
Cumulative precipitation	0.0011***	0.0017***	0.0006	0.0011**	0.0011***	0.0011***	0.0015*
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0009)
Precipitation on test day	-0.0000**	-0.0000*	-0.0000*	-0.0000**	-0.0000	-0.0000	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
(B) Hot days							
Temperature on test day (C)	-0.0075**	-0.0078**	-0.0071**	-0.0130***	0.0026	-0.0008	-0.0218***
	(0.0033)	(0.0039)	(0.0030)	(0.0046)	(0.0031)	(0.0029)	(0.0082)
Cumulative precipitation	0.0011***	0.0016***	0.0005	0.0010**	0.0011***	0.0011***	0.0013
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0008)
Precipitation on test day	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Municipios	5,514	5,512	5,512	4,173	5,108	5,507	1,735
N	300,109	149,864	150,245	183,226	112,783	201,451	98,658

Notes: The dependent variable is test scores standardized by school-grade-subject. Standard errors clustered by municipality are in parenthesis. All models include fixed effects for school–grade–subject, and year. * p<0.10 ** p<0.05 *** p<0.01.

Table A2: Robustness test of the effects of cumulative temperature on test scores

	All sample (1)	Math (2)	Reading (3)	Urban (4)	Rural (5)	Public (6)	Private (7)
(A) Cumulative Heat							
Temperature (C)	-0.1395***	-0.1691***	-0.1099***	-0.1621***	-0.0966***	-0.1055***	-0.2219***
	(0.0294)	(0.0337)	(0.0266)	(0.0336)	(0.0353)	(0.0294)	(0.0567)
(B) Hot days							
Days below 17C	0.0020**	0.0026***	0.0014*	0.0020***	0.0027***	0.0023***	0.0022***
	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0009)	(0.0007)
Days within 21-25C	-0.0016***	-0.0019***	-0.0013***	-0.0020***	-0.0011***	-0.0012***	-0.0025***
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0006)
Days within 25-29C	-0.0028***	-0.0034***	-0.0022***	-0.0030***	-0.0026***	-0.0027***	-0.0033***
	(0.0006)	(0.0007)	(0.0005)	(0.0007)	(0.0007)	(0.0006)	(0.0009)
Days above 29C	-0.0024***	-0.0030***	-0.0019***	-0.0031***	-0.0016**	-0.0021***	-0.0036***
	(0.0008)	(0.0009)	(0.0007)	(0.0011)	(0.0008)	(0.0007)	(0.0013)
Municipios							
N	307,295	153,469	153,826	187,043	114,740	204,825	102,470

Notes: The dependent variable is test scores standardized by school-grade-subject. Standard errors corrected for spatial and same-year temporal correlation, using a spatial threshold of 100 Km between municipalities' centroids (Conley, 1999; Collela et al. 2019) The omitted category in Panel B is Days within 17-21C. All regressions control for precipitation during one year before the test, and day of the test maximum temperature and total precipitation. In addition, all models include fixed effects for school-grade-subject, and year. * p<0.10 ** p<0.05 *** p<0.01.