ROCKWOOL Foundation Berlin
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DISCUSSION PAPER SERIES 145/25

Hotter Days, Wider Gap: The Distributional Impact of Heat on Student Achievement

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www.rfberlin.com DECEMBER 2025

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Reference

JEL Codes: I21, I24, Q54

Keywords: Heat, Distributional impact, Student achievement, Adaptation, Air conditioning, Children, Climate change

Recommended Citation: Mika Akesaka, Hitoshi Shigeoka (2025): Hotter Days, Wider Gap: The Distributional Impact of Heat on Student Achievement. RFBerlin Discussion Paper No. 145/25

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Hotter Days, Wider Gap:
The Distributional Impact of Heat on Student Achievement[*]

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First Draft: September 2025
This Draft: October 2025

Abstract

This study demonstrates that heat disproportionately impairs human capital accumulation among low-performing students compared with their high-performing peers, using nationwide examination data from 22 million students in Japan. Given the strong correlation between academic performance and socioeconomic background, this suggests that heat exposure exacerbates pre-existing socioeconomic disparities among children. However, access to air conditioning in schools significantly mitigates these adverse effects across all achievement levels, with particularly pronounced benefits for lower-performing students. These findings suggest that public investment in school infrastructure can help reduce the unevenly distributed damage caused by heat to student learning, thereby promoting both efficiency and equity.

Keywords: Heat, Distributional impact, Student achievement, Adaptation, Air conditioning, Children, Climate change
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[*] The authors thank Rajeev Dehejia, Taiyo Fukai, Joshua Graff Zivin, Koichiro Ito, Daiji Kawaguchi, Ayako Kondo, Teresa Molina, David Molitor, Soodeh Saberian, Takahiro Toriyabe, Bruce Weinberg, Corey White, Chin-Wen Yang, and the seminar participants at 6th World Labor Conference, 13th World Congress of the Econometric Society, 15th TPLS, AAERE 2024, AASLE 2024, ASHEcon 2024, IZA Workshop on Climate and Environmental Economics 2025, Kansai Labor Workshop, Kyoto Summer Workshop on Applied Economics 2025, Osaka University (OSIPP), Recent Advances in Microeconomics (Korea University), and the Research Institute of Economy, Trade and Industry for their comments and suggestions. We also thank Takahiro Miura for shaping AMeDAS data. Akesaka acknowledges financial support from JSPS KAKENHI (23K12492, 22K01534, 21H04397, 20K13511). Shigeoka acknowledges financial support from JSPS KAKENHI (23H00828, 22H00057, 22H00847, 22H05009), JST ERATO (JPMJER2301), Murata Science Foundation, and Japan Center for Economic Research. Any errors are our own.

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1. Introduction

Climate change affects numerous societal outcomes, including health, agriculture, labor productivity, income, cognition, and conflict, among many others (Carleton and Hsiang 2016). However, most studies measure only the *average* impact of heat, and thus its *distributional* impacts; identifying the individuals that disproportionately bear the burden of heat-related damage and the implications for inequality remain largely unexplored.

This study examines how cumulative exposure to extreme heat affects student achievement differently based on their socioeconomic statuses (SES). Cognitive ability constitutes an essential component of human capital and is closely linked to future labor market performance and economic inequality (Cunha and Heckman 2007). Due to their physiological and neurocognitive immaturity, children's cognition may be particularly vulnerable to environmental stressors (Rowland 2008). Prolonged heat exposure can disrupt their learning through distractions and reduced concentration, leading to a lasting impact on their accumulation of human capital. Therefore, the warming climate underscores the importance of improving children's learning environments.

There are two main challenges in studying the distributional consequences of heat exposure. First, assessing distributional impacts requires a representative sample. However, prior studies could not assess these impacts due to *specific* samples or lack of individual-level data. For example, Cho (2017) and Park et al. (2020) examined the effects of cumulative heat exposure on test scores but focused on high school students taking college entrance exams in Korea and the Preliminary Scholastic Aptitude Test (PSAT) in the United States (US). These students likely come from higher socioeconomic backgrounds than the general population, making them unsuitable for distributional analysis. Despite their representativeness, Park et al. (2021a) used aggregated achievement data at the school district level in the US, which did not allow distributional analysis.

Second, even if heat damage on test scores is greater for disadvantaged than advantaged students, two mechanisms (not necessarily mutually exclusive) explain the finding: students from disadvantaged households live in warmer regions and experience extreme heat ("exposure"), or their limited resources make them more susceptible to the same heat exposure ("vulnerability"). This distinction is crucial because different policy responses are required to improve heat resilience among the poor (Hsiang et al. 2019).

To overcome these challenges, we analyze individual-level test scores from nationwide exams in Japan between 2007 and 2019 for all public-school students in grades six and nine during compulsory education, encompassing an extensive sample of approximately 22.8 million students. Importantly, combining individual-level data with the exams' national representativeness provides an ideal setting for examining, for the first time, the distributional impact of temperature on test scores.

Specifically, we analyze test scores at percentile ranks (10th, 25th, 50th, 75th, and 90th percentiles) *within* schools over time, comparing students who experienced hotter summer (colder winter) school days with those who experienced milder ones. Since a student's rank correlates with SES, such as household income and parental education, it serves as a reasonable proxy for socioeconomic background, allowing us to assess whether cumulative exposure to extreme temperatures differentially impacts student performance by SES. Importantly, by holding the "exposure" constant for all students in the school, we can isolate the role of vulnerability—if low-SES students experience greater score declines than high-SES peers under the same heat exposure, the disparity likely reflects differences in "vulnerability" by socioeconomic backgrounds (e.g., differential access to private tutoring).

This study has two major findings. Our first finding is that the negative effects of heat are *regressive*; that is, they are far greater for low-performing than for high-achieving students. Each additional day with maximum temperature exceeding 34°C lowers scores by 0.09% SD for students in the top 10th percentile, but by 0.30% SD for those in the bottom 10th percentile, an impact approximately three times larger. This disproportionate effect of heat by student rank widens academic inequality, highlighting how average effects mask substantial disparities in heat-related damage between low- and high-performing students.

Importantly, by comparing temperature effects within schools, we hold school-level "exposure" constant, eliminating influences by school-level resources such as staffing ratio, teacher quality, or access to air conditioning (AC). Instead, the results likely reflect differences in "vulnerability"—how advantaged and disadvantaged students differentially adapt to the same school heat exposure. Indeed, advantaged students tend to study longer after school, spend more on education, and are more likely to attend cram school. Given the strong link between academic performance and SES, this finding suggests that *without* further intervention, climate change will widen pre-existing socioeconomic disparities among children.

This finding speaks to the emerging literature linking global warming and economic inequalities (Burke et al. 2015; Diffenbaugh and Burke 2019; Gilli et al. 2024). As educational attainment and earnings are positively correlated (Chetty et al. 2011), our findings suggest that differential vulnerabilities, which exacerbate inequality in academic performance, may be a pathway through which a warming climate accelerates economic inequality. Specifically, our sample (grades six and nine) comprises younger students compared with samples from other studies that focus on students nearing high school graduation (Cho 2017; Park et al. 2020). Dynamic complementarities, in which human capital investment in early childhood complement later investments (Cunha and Heckman 2007; Johnson and Jackson 2019), indicate that earlier heat shocks could have a more lasting impact on future economic outcomes. Furthermore, the greater impact of heat on children from disadvantaged families indicates that it reduces their upward intergenerational mobility.

Our second finding is that school AC can largely offset heat's negative effects on learning—and importantly, in a *progressive* manner, benefiting low-performing students more than high-performing ones. In schools without AC, the adverse impact of extreme heat is significantly greater for low-performing students, who are more likely to come from low-SES backgrounds. In contrast, in schools with AC, heat has little effect on test scores across the performance distribution, resulting in greater relative gains for low achievers. Specifically, without AC, one additional day above 34°C increases the 90th–10th percentile test score gap by 0.71 SD%, while AC reduces this widening by 0.55 SD%. These results suggest that public investment in school infrastructure, like AC, can mitigate unequal heat-related learning losses. This is especially encouraging given that both primary and secondary education are compulsory in Japan, as in many countries, reinforcing the importance of equitable learning environments.

This second finding speaks to the literature on temperature adaptation, addressing whether environmental hazards are unavoidable or can be mitigated using current technology (see Carleton et al. 2024 for a review). While evidence supports adaptation for heat-related mortality (Barreca et al. 2016; Cohen and Dechezleprêtre 2022) and violence (Colmer and Doleac 2023), findings on workplace injuries are mixed (Dillender 2021; Park et al. 2021b). Regarding education, a seminal study by Park et al. (2020) demonstrated that school AC reduces the cumulative impact of heat on learning. Moving beyond averages, we examine distributional effects, revealing how adaptation unequally benefits students.

Furthermore, this finding contributes to the debate on the effectiveness of resource-based education policies in fostering human capital accumulation (Baron 2022; Cellini et al. 2010; Jackson et al. 2016; Hyman 2017; Lafortune et al. 2018), especially investments in school facilities (Lafortune and Schönholzer 2022; Martorell et al. 2016; Neilson and Zimmerman 2014). Our findings align with Biasi et al. (2025), who suggest that the impact of capital investments on test scores varies across project types and districts in the US. They found larger returns from school facility investments in socioeconomically disadvantaged districts. Such heterogeneous treatment effects may reflect either differential exposure or other unobserved characteristics across districts. By comparing students within schools, we demonstrate that school air conditioning (AC) disproportionately benefits lower-achieving students and reduces heat-related learning disparities, promoting both *efficiency* and *equity*.

2. Conceptual framework

This section outlines a conceptual framework for the distributional impact of extreme temperatures, based on Hsiang et al. (2019) and Behrer et al. (2021). We discuss how an empirical observation (i.e., climate impacts are often greater for poor individuals) can mask two explanations: differing *exposure* and/or *vulnerabilities*. Exposure refers to the degree individuals are subjected to environmental stressors (e.g., heat, cold, and pollution), while vulnerability denotes their susceptibility to these stressors.

Damage from environmental stressors is defined as a function of two factors: exposure and vulnerability. Here, we estimate the marginal damage, which is the slope of the damage function. Importantly, it can vary by SES (e.g., income, education, and occupation) for two reasons, as shown in Figure 1. We assume that exposure is higher for low-SES than for high-SES individuals because the poor indeed tend to live in hotter places, both within and across countries (Park et al. 2018).

First, as shown in panel A of Figure 1, a convex damage function with respect to exposure can lead to greater marginal damage for low-SES individuals who experience more exposure than high-SES counterparts (i.e., differential exposure). Alternatively (or additionally), as illustrated in panel B of Figure 1, the damage function itself may differ by SES due to factors such as baseline health or defensive investments correlating with SES (i.e., differential vulnerability).

Distinguishing whether SES-based disparities in heat impact stem from a single nonlinear damage function with differential exposure or differing vulnerabilities is crucial for policy design. The former requires reducing direct contact with extreme heat (e.g., urban cooling, housing, and warning systems). Conversely, the latter requires targeted support to enhance adaptive capacity (e.g., subsidizing AC and expanding medical programs to heat-related illnesses) or promoting broader poverty reduction to strengthen the heat resilience of low-SES individuals.

However, distinguishing between exposure and vulnerability is challenging because the poor tend to live in hotter locations. Thus, even if heat damage is greater among the poor by simply comparing damages of the rich and the poor, this may just result from differential exposure (panel A) rather than differential vulnerability (panel B) by SES.

This study is the first to rigorously isolate the impact of vulnerability from exposure. Using individual-level data from nationally representative exams, we analyze the distributional impact of temperature *within* schools, while holding exposure constant, at least in the school environment where most learning occurs. If test score reductions are greater for low-SES students than for their high-SES counterparts in the same school with identical heat exposure, the difference in marginal damages likely arises from varying vulnerabilities between these groups.

3. Data

We combine temperature data with nationwide test data of nearly 22.8 million students in Japan. Appendix B provides details of the data sources. We discuss school AC penetration in Section 6.

3.1. Test scores

We use data on nationwide exams, called the National Assessment of Academic Ability (hereinafter "NAAA"), conducted by the Ministry of Education, Culture, Sports, Science and Technology (MEXT). The NAAA aims to monitor the academic performance and progress of students nationwide and contribute to improving educational policies (MEXT 2024a). The NAAA has been conducted annually since 2007, except in 2011, when it was canceled due to the Great East Japan Earthquake, and in 2010 and 2012, when the NAAA was administered to a random subset of schools.[1]

The NAAA is administered to students in their final years of primary (grade six) and secondary school (grade nine). Both levels are compulsory in Japan. Nearly all public primary and secondary schools participate in the NAAA (National Institute for Educational Policy Research [NIER] 2024).[2] Although the subjects assessed vary slightly over time, we focus on reading and mathematics, consistently tested throughout our sample period.

The NAAA is held on the 3rd or 4th Tuesday of April[3], the month when the academic year begins in Japan. Consequently, the NAAA is designed to assess students' understanding of the material covered until the previous academic year (NIER 2021). This timing aligns with our research design on learning disruptions from the past summer and winter. Since the exam date is predetermined and the NAAA is centrally administered and graded, no room exists for endogenous choice in test timing or score manipulation by schools and students.

The NAAA is not a high-stakes exam for students or schools. Students' scores do not affect promotion to higher grades or better schools. Furthermore, school performance has no direct consequences, such as reduced federal funding, unlike test-based accountability systems like the No Child Left Behind Act in the US. The only potential stakes are reputation concerns for schools (Morozumi and Tanaka 2023); however, publication of school-level scores is not allowed for years before 2014, and very few school councils do so in our sample period.

We use 2007–2019 NAAA data with MEXT's permission for secondary use of confidential information. Table A.1 details the number of participating schools and students each year. From

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[1] This is entirely due to political reasons. In 2009, a change of government occurred, and the new administration cut the NAAA's budget.

[2] In 2022, 1.3% of primary and 7.7% of secondary students attended private schools (MEXT 2022).

[3] From 2019, it was held on Thursday instead of Tuesday.

2007 to 2019, approximately 22.8 million students took the exams, with approximately 30,000 schools participating annually (excluding 2010 and 2012). See Figure A.1 for the school locations nationwide. For statistical power, we combine both grades in the main analysis unless stated otherwise. Since the exams are administered to both grades on the same day, all students experience identical conditions, including cumulative heat exposure and test-day weather.

Our primary outcome is the combined reading and math scores, although we also separately analyze each subject. Since exam difficulty varies by year, we calculate z-scores for each year and grade, multiplying them by 100 for interpretation as percentage changes. Student-level data include limited demographics, such as gender.[4] The NAAA also conducts student surveys every round and parental surveys in 2013 and 2017. Student surveys capture behaviors (e.g., after-school study and study habits), while parental surveys (administered to about 4.8% of randomly selected schools)[5] collect household information such as household income, father's occupation, and parental education. Table A.2 (panel A) provides descriptive statistics of individual characteristics.

3.2. Temperature

We use daily temperature data for 2006–2018 from the Japan Automated Meteorological Data Acquisition System (AMeDAS) operated by the Japan Meteorological Agency. We utilize AMeDAS data from 899 weather stations with daily temperature available for at least 99% of days during 2006–2018. To create a balanced panel, missing daily observations were imputed using the nearest station with complete data. Each school was then assigned to its nearest weather station to ensure estimates remain unaffected by changes in the number or location of stations.

Figure A.2 displays the locations of all 899 weather stations in 2018 and the cumulative distribution of distance from the nearest station to each school. The density of stations is high given the country's size, and consequently, the mean (median) distance is 6.95 (6.48) km, compared with 15.6 km in US (Park et al. 2020).

Our primary measure of cumulative exposure to extreme temperatures is the number of hot and cold school days a student experienced in the year leading up to the test in April (i.e., from April of the previous year to March of the test year). We utilize the daily maximum temperature as a measure because schooling occurs during daytime hours when peak temperatures are typically observed. Following Park et al. (2020), we focus on temperatures during terms as school days and separately include school break days in robustness checks later.[6]

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[4] Student IDs are updated annually, so we cannot track G6 students in the G9 data three years later.

[5] In 2013 and 2017, parental surveys covered 2,821 of 59,734 schools (4.72%) and 203,023 of 4,255,669 students (4.77%), with an 84.9% response rate.

We use weather station data to construct both cumulative and test-date measures for rainfall, wind speed, and relative humidity. We also include pollution and pollen data from the nearest monitoring station, known to impact short-term cognition (e.g., Ebenstein et al. 2016; Marcotte 2015). Table A.2 (panel B) presents the descriptive statistics of weather conditions.

4. Econometric model

4.1. Estimation of the average of marginal damages

We exploit year-to-year variations in the number of hot and cold school days to identify the causal impact of exposure to extreme temperatures on human capital accumulation. Specifically, we compare test scores of students in the same school who experienced hotter summers or cooler winters with those exposed to milder conditions.

Figure A.4 shows both the spatial and temporal variations in the daily maximum temperature that students experienced from last April to March of the test year, highlighting significant climate differences across the region and considerable year-to-year variations in both cold and hot school days.

To reduce the computational burden, we collapse the data into school-year cells and weight estimates by the number of students in each cell. Specifically, we estimate the following specifications:

$$Average\_Z\text{-}score_{st} = \sum_k \beta^k T_{st}^k + \rho_s + \theta_t + \delta X'_{st} + \varepsilon_{st}, [1]$$

where the dependent variable is the average z-score for school *s* in year *t*. T_{st}^k represents the number of school days in the prior year where the maximum temperature falls into one of nine bins *k*: below 6°C, 6–10°C, 10–14°C, 14–18°C, 22–26°C, 26–30°C, 30–34°C, and above 34°C, with 18–22°C as the reference, the optimal range for test performance.

This specification enabled us to flexibly capture nonlinear temperature effects. The coefficients of interest are β^k. ρ_s and θ_t are school FE and year FE, respectively. X'_{st} includes other time-varying school-level controls, such as precipitation, humidity, and pollution. Standard errors are clustered at the weather station level (N=889) to account for potential serial correlations reflecting the underlying variations in our treatment variable (Abadie et al. 2023). The underlying assumption for β^k to reflect the causal impact of temperature is that the temporal and geographic variations in prior-year temperature are uncorrelated with unobserved determinants of student learning.[7]

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[6] School days, school break days, and weekends during the terms are mutually exclusive, averaging 212.6, 85.1, and 67.6 days, respectively. Lacking a comprehensive school calendar dataset, we assign each school a probable start and end date using the 2018 calendar of its prefectural capital (Figure A.3). Colder regions have shorter summer and longer winter breaks, while warmer regions exhibit a reverse pattern.

To visualize identifying variations underlying the baseline specification, we plot residuals from a regression of the number of school days <6°C and >34°C against school fixed effects. Figure A.5 illustrates the interquartile and interdecile ranges of the residuals by prefecture and year. These distributions confirm ample variations in the number of extreme-temperature school days within each prefecture and each year, ensuring that our estimates are not driven by variations in a specific region or year.

4.2. Estimating heterogeneous marginal damages

This study's main contribution is moving beyond the effect of temperature on average test scores (Equation [1]) and examines distributional impacts. Using individual test scores linked to school IDs, we assess the effect of the temperature by score rank within schools. Specifically, for each school, we compute z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles *within* schools (Chetverikov et al. 2016).[8] We use each value separately as the outcome:

$$Z\text{-}score\ at\ X\ percentile\ (X\ = 10, 25, 50, 75, and\ 90)_{st}$$
$$= \sum_k \beta^k T_{st}^k + \rho_s + \theta_t + \delta X_{st}' + \ \varepsilon_{st}. \ [2]$$

We occasionally use the test score gap at different percentiles (e.g., the 90th-10th gap) as the outcome.

What does the student's within-school rank capture? Using the 2013 and 2017 NAAA parental surveys in a subset of schools, Figure 2 illustrates a strong positive correlation between student's rank and socioeconomic background, namely household income (panel A), and father's education (panel B). The income gap between the 90th and 10th percentiles is 1.79 million yen (≈17.9K USD), while the gap in fathers' university education is 30.4 percentage points. Overall, we posit that a student's within-school rank largely indicates their socioeconomic status.

Finally, we demonstrate that the within-school score variation explains most of the variation in scores at the national level. Figure 3 shows the within-school score distribution by school rank. Specifically, we group schools into ventiles based on their average scores each year and plot the average interquartile and interdecile ranges of the within-school score distribution for every ventile. While higher-ranked schools have more compressed score distributions, considerable within-school variations exist across all ranks. This addresses the concern that within-school test score variations are small and potentially missing larger national-level variations. The decomposition of the variation in test scores shows that as much as 91–93% occurs *within* schools rather than *between* schools over the years, likely due to the relatively uniform quality of public schools compared with private ones. Furthermore, the school curriculum is centrally standardized by the MEXT's Course of Study.

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[7] A potential threat to identification is that cumulative heat and cold exposure drive selection into the NAAA, but Table A.3 shows little evidence of endogenous selection into test-taking.

[8] As discussed in Section 2 ("Conceptual framework"), the alternative approach, unconditional quantile regression with individual-level data, cannot differentiate exposure and vulnerability, as shown in Figure 1. For reference, the results of the unconditional quantile regression are available in Appendix Table A.6.

5. Baseline results

5.1. Average impacts

First, we present graphical evidence of the average impacts of cumulative exposure to heat and cold on test scores. Panel A of Figure 4 shows β^k from equation [1] with 95% confidence intervals. Test scores are measured in 0.01σ. Highlighting the nonlinear effect of temperature on learning, the figure shows that scores decline as hot or cold school days increases, especially for extremely hot days at the right end of the figure (>34°C) and extremely cold days at the left end (<6°C).

This aligns with the well-documented "U-shaped" mortality-temperature relationship (or "inverse-U" here, as damage is negative), where both hot and cold days increase mortality globally (e.g., Barreca et al. 2016; Carleton et al. 2022; Cohen and Dechezleprêtre 2022; Heutel et al. 2021). While some studies have examined the cumulative effects of heat (Cho 2017; Park et al. 2020, 2021a) and cold (Johnston et al. 2021) on test scores separately, we are the first to show that both extremes in one country impair students' learning environments and hinder teachers' abilities to teach by causing distractions and concentration loss.

In terms of magnitude, one additional school day <6°C or >34°C in the previous year (compared with 18–22°C) reduces test scores by 0.13% SD and 0.19% SD, respectively ($p < 0.01$). These estimates align with prior research on the effects of cumulative exposure to heat or cold, as shown in Table A.4.

5.2. Distributional impacts

Next, we examine whether the negative impacts of extreme temperatures significantly vary across score distributions. Panel B of Figure 4 presents β^k from Equation [2], which shows these negative effects are significantly greater for lower-performing students (see Table A.5 for corresponding estimates).

One additional hot day >34°C lowers scores by 0.09% SD for students in the top 10th percentile, while the impact on the bottom 10th percentile is 0.30% SD, about three times larger. Adverse effects consistently increase as the rank decreases. Similarly, an extra cold day <6°C leads to a negligible 0.03% SD reduction for students in the top 10th percentile (not statistically significant), while the bottom 10th percentile declines 0.26% SD. Consequently, extreme hot and cold conditions widen the 90th–10th score gap by 0.22% and 0.23% SD, respectively. Given the strong link between academic performance and SES (Figure 2), these results suggest that exposure to extreme temperatures exacerbates pre-existing academic inequality by SES among children.

Source of varying vulnerability—. Importantly, since we compare temperature effects within schools, keeping "exposure" at school constant, our results are not driven by school resources (e.g., class size, teacher quality, or AC). Instead, they align with panel B of Figure 1, likely reflecting "vulnerability"—individual or household adaptations outside school (e.g., private tutoring). This study's main goal is to uncover the *presence* of socioeconomic disparities in vulnerability to extreme temperatures. Consequently, it is beyond the scope of this study to fully explore *sources* of such heterogeneity in vulnerability owing to limited data on detailed student and household behaviors during hot and cold days of the previous summer and winter.

Nevertheless, Figure A.6 shows that higher-SES students tend to study longer after school, spend more money on education, and are more likely to attend cram school. Additionally, Table A.7 suggests that longer after-school study may mitigate negative effects of heat exposure.[9] However, other factors such as better baseline health among higher-SES students (Case et al. 2002), may also contribute to the observed heterogeneity. Understanding specific sources of these unequal vulnerabilities is an avenue for future research.

6. The impact of AC

6.1. AC penetration

AC is the main technology for adapting to heat (Barreca et al. 2016), but its widespread adoption in Japan's public schools is recent. During the sample period from 2006 to 2018, AC coverage in public primary and secondary schools increased from approximately 10% to 50%, reaching nearly 100% by 2022.[10]

Unfortunately, the government began reporting the school AC penetration at the municipal level only in 2017 (MEXT 2024b). Each municipal school council determines AC installation in public schools.[11] Using this data in 2018, the last year of the sample period, we categorize schools into municipalities with 0% ("schools without AC"), 100% ("schools with AC"), or intermediate. Thus, schools without AC had no AC throughout the *entire* period of 2006–2018 without any measurement error. Conversely, schools with AC only indicate full availability *at some point* during the sample period, likely leading to an underestimation of the positive impact of AC on test scores.

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[9] Educational spending and cram school attendance data are limited to parental surveys from 2014 and 2017, covering only 4.7% of students. Thus, unlike after-school hours from student surveys available for all years, they cannot be included as mediators.

[10] Source: https://www.mext.go.jp/content/20240930-mxt_sisetujo01-000013462_02.pdf

[11] A total of 1,724 municipalities exist as of April 1, 2019.

Figure 5 maps municipalities with 100% (“schools with AC”), 0% (“schools without AC”), and partial (>0% and <100%) AC penetration. Clearly, schools without AC are more common in the cooler northern region, while both types are widely distributed in central Honshu, Japan’s main and largest island.

One concern is that school AC penetration may correlate with factors at the school or municipal levels that could directly impact test scores. However, Figure A.7 shows that after controlling the average temperature, the AC penetration rate in 2018 is not strongly linked to taxable income per capita (panel A) or the student-to-teacher ratio (panel B), a measure of per-pupil educational expenditure. Additionally, Figure A.7 shows that the AC penetration rate in 2018 was not associated with average school test scores in 2007, the first year of our sample, when the AC penetration at the national level was only 10.2% (panel C). This suggests that a higher AC rate does not necessarily indicate superior schools. Furthermore, Figure A.8 shows that the distributions of test scores in 2007 were nearly identical between schools with and without AC. Therefore, the observed differential patterns are unlikely due to systematic test score differences between the two groups.

6.2. Average impacts

We examine the average impact of school AC on test scores. Figure 6 illustrates β^k from Equation [1] separately for schools with and without AC. Strikingly, most of the negative heat effects occur in schools that lack AC throughout the sample period. Conversely, AC largely mitigates the adverse impact on learning if taken causally.

To assess how effectively school AC mitigates the impact of heat on learning, we conduct a regression analysis. Specifically, we interact the cross-sectional measure of AC penetration in 2018 (“school AC” dummy; AC_s) with the number of school days in each temperature bin and include them in baseline specification [1]. To highlight the effect of AC availability, we focus on schools in municipalities with either 0% or 100% AC (56.9% of school-year observations). However, as Figure A.9 shows, results remain robust when including schools from municipalities with partial AC (>0% & <100%) in the “with AC” category. Specifically, we estimate

$$Average\_Z\text{-}score_{st} = \sum_k \beta^k T_{st}^k + \sum_k \gamma^k T_{st}^k * AC_s + \rho_s + \theta_t + \tau_t * AC_s + \delta X_{st}' + \varepsilon_{st}, \quad [3]$$

where β^k measures the impact of heat on schools without AC, while γ^k represents the difference in that impact compared to fully air-conditioned schools. Column (1) of Table 1 shows that school AC largely offsets negative effects of extreme heat (>34°C). Without AC, test scores drop by 0.56% SD, but the interaction with the AC dummy reduces this by 0.41% SD, suggesting that AC mitigates approximately 73% of the adverse impact of heat.

The offsetting effect of school AC may reflect other factors that correlate with AC availability. To address this concern, columns (2) and (3) of Table 1 further control for the number of school days in each temperature bin, interacted with municipality-level taxable income per capita, student-teacher ratio, and home AC share, but the results remain robust.

Other robustness—. Table A.8 presents additional robustness checks. The estimates for days with maximum temperature >34°C and their interaction with the school AC dummy are reported due to their greatest relevance to global warming. The estimates remain largely unaffected by controlling test-day weather (temperature, precipitation, wind speed, and relative humidity), test-day air pollution, test-day pollen, the cumulative weather other than maximum temperature, and cumulative minimum temperatures. Notably, Figure A.10—using minimum instead of maximum temperatures—shows no discernible effect on test scores, suggesting that nighttime heat and associated sleep disruption (Mullins and White 2019) is not the channel through which cumulative heat exposure impairs academic performance. Table A.9 also confirms robustness to clustering standard errors at the municipality level, as AC availability varies at this level or at broader geographic units (prefectures) rather than monitoring station.

School breaks—. Table A.10 compares our baseline specification to one that additionally controls for heat during school breaks and their interaction with school AC. Three key findings emerge: (i) the estimated impact of school-day heat is robust after controlling for heat during summer breaks; (ii) heat during breaks negatively affects test scores and is statistically significant, but the effect is much smaller than in-school heat (-0.178 vs. -0.493), highlighting the importance of time in school for learning; and (iii) the interaction between school AC and heat during breaks is small and statistically insignificant (0.054 with a standard error of 0.202). This supports the validity of our school AC variable, as its effects should be confined to the school environment.

Heterogeneity—. Table A.11 explores heterogeneous effects of heat >34°C and the mitigating role of school AC across grades (6th vs. 9th), subjects (math vs. reading), gender (girls vs. boys), question difficulty (basic vs. advanced),[12] and climate (cool vs. warm regions). Overall, the impact of temperature >34°C and AC's offsetting effect are consistent across contexts, with exceptions: extreme heat affects 6th graders and boys more than 9th graders and girls by approximately 50%, suggesting their greater vulnerability. Notably, school AC offsets the effect on basic but not advanced questions, aligning with a stronger benefit for lower-achieving students, as shown next.

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[12] Both math and reading included basic and advanced questions (until 2018), with basic skills practically applied to advanced ones. For example, in 6th grade math, a basic question asks for simple multiplication, while an advanced one requires using it to find a square's area (Figure A.11). The two scores are highly correlated, with correlations of 0.90 (average), 0.83 (math), and 0.85 (reading) for 6th graders.

6.3. Distributional impact

Finally, we analyze how school AC availability affects students across score distributions. Figure 7 presents β^k from Equation [2] for schools without AC (panel A) and with AC (panel B), separately. In schools without AC, heat disproportionately harms lower-ranked students, whereas in schools with AC, nearly all the negative effects disappear across ranks, yielding larger benefits for low-achieving students. As expected, extremely cold conditions (<6°C) do not differentially affect performance as school AC is meant for heat protection. However, as shown in panel A, without school AC, heat is more likely than cold to exacerbate pre-existing academic inequalities.

To assess how school AC mitigates heat-driven inequality in learning, we estimate a variant of Equation [3], where the outcomes are z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools. The estimates from other percentiles appear in Table A.12.

Column (1) shows that high temperatures (>34°C) without AC reduce 10th-percentile scores by 0.93% SD. Since these schools lack AC, the estimates reflect the "pure" negative impact of heat without offsetting effects.[13] However, the interaction term is positive and as large as 0.69% SD ($p<0.01$), indicating school AC significantly offsets heat damage. Conversely, column (2) shows that high temperatures (>34°C) reduce 90th-percentile scores only by 0.22% SD ($p<0.01$), while the offsetting effect of AC is 0.14% SD, albeit not statistically significant. Consequently, column (3) indicates that without AC, extreme heat widens the 90th–10th score gap by 0.71% SD, whereas school AC reduces this widening gap by 0.55% SD, suggesting that the benefit of school AC is *progressive*.[14]

Table A.14 confirms that the impact of school AC on the 90th–10th score gap remains robust when controlling for interactions with municipality-level taxable income per capita, the student-teacher ratio, and prefecture-level home AC share. Furthermore, Tables A.8, A.9, and A.10 confirm robustness to additional checks, alternative clustering, and controls for heat during school breaks and their interaction with school AC.[15]

We demonstrate that school facilities help reduce the widening test score gap between advantaged and disadvantaged students caused by heat. This suggests that the widening gap without school AC is not primarily caused by differences in *outside-of-school* heat exposure (e.g., longer commutes for disadvantaged students); if so, we would not expect school AC to counteract the widening gap. Simultaneously, school AC did not fully offset the growing gap, likely because of measurement errors in AC penetration and/or remaining outside-of-school adaptations by socioeconomic background (e.g., access to cram school).

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[13] Conversely, the distributional impact of a cold day (temperature <6°C) is similar for schools with and without school AC.

[14] Table A.13 replicates the main results from Table 2 but classifies schools from municipalities with partial air conditioning coverage (>0% and <100%) as "with AC." The estimated effects are slightly attenuated but remain qualitatively similar.

[15] Panel B of Table A.11 presents the heterogeneous effects.

This finding suggests that public investment in school AC, rather than household-level adaptation, can largely reduce heat's inequality-enhancing effects. Thus, investment in school infrastructure can mitigate unevenly distributed damage caused by heat to learning, thereby promoting both efficiency and equity. This is encouraging because both primary and secondary education are mandatory in Japan, as in many other countries, where public investment plays a vital role. Moreover, Dechezleprêtre et al. (2025) demonstrate that climate policies that are both environmentally effective and distributionally progressive are more likely to garner public support. However, it should be emphasized that while school AC largely offsets the widening of socioeconomic inequalities, pre-existing socioeconomic disparities *persist*.

7. Conclusion

Many studies have investigated the average impact of extreme temperatures, but their distributional impact across SES remains poorly understood. Even less explored is how different socioeconomic groups adapt to environmental stressors such as heat. Using nationwide exam data from Japan for 2007–2019, we find that extreme temperatures disproportionately hinder human capital accumulation among low-achieving students, deepening academic and social inequalities. However, school AC largely offsets these effects, highlighting the potential for public infrastructure investments to reduce heat-related learning disparities.

This study offers several avenues for future research. First, it is essential to determine whether the inequality-enhancing effects of heat exposure on learning persist across contexts and environments. Second, although we focus on heat damage because of its relevance to global warming, understanding how to mitigate the adverse effects of cold exposure, although smaller, may be important in specific situations. Third, while we highlight the presence of social disparities in vulnerabilities, understanding the sources of these differentials, supported by more comprehensive data on individual and household behaviors, is essential for addressing them. Finally, it is important to examine whether the inequality-enhancing effects of heat exposure on learning translate into long-term economic disparities, such as wages and income.

References

Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Wooldridge. 2023. “When Should You Adjust Standard Errors for Clustering?” *The Quarterly Journal of Economics,* 138(1): 1–35.

Baron, E. Jason. 2022. “School Spending and Student Outcomes: Evidence from Revenue Limit Elections in Wisconsin.” *American Economic Journal: Economic Policy*, 14(1): 1–39.

Barreca, Alan, Karen Clay, Olivier Deschênes, Michael Greenstone, and Joseph S. Shapiro. 2016. “Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century.” *Journal of Political Economy*, 124(1): 105–159.

Behrer, A. Patrick, Jisung Park, Gernot Wagner, Colleen Golja, and David Keith. 2021. “Heat has Larger Impacts on Labor in Poorer Areas.” *Environmental Research Communications*, 3(9): 095001.

Biasi, Barbara, Julien Lafortune, and David Schönholzer. 2025. “What Works and for Whom? Effectiveness and Efficiency of School Capital Investments Across the U.S.” *The Quarterly Journal of Economics*, 140(3): 2329–2379.

Burke, Marshall, Mustafa Zahid, Mariana C. M. Martins, Christopher W. Callahan,

Burke, Marshall, Solomon M. Hsiang, and Edward Miguel. 2015. “Global Non-Linear Effect of Temperature on Economic Production.” *Nature*, 527(7577): 235.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E. McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiacan Yuan, and Alice Tianbo Zhang. 2022. “Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits.” *The Quarterly Journal of Economics*, 137(4): 2037–2105.

Carleton, Tamma, and Solomon Hsiang. 2016 “Social and Economic Impacts of Climate.” *Science*, 353, aad9837.

Carleton, Tamma, Esther Duflo, Kelsey Jack, and Guglielmo Zappalà. 2024. “Adaptation to Climate Change.” In *Handbook of the Economics of Climate Change*, edited by Lint Barrage and Solomon Hsiang. Elsevier, Chapter 4: 143-248.

Case, Anne, Darren Lubotsky, and Christina Paxson. 2002. “Economic Status and Health in Childhood: The Origins of the Gradient.” *American Economic Review*, 92(5): 1308–1334.

Cellini, Stephanie Riegg, Fernando Ferreira, and Jesse Rothstein. 2010. “The Value of School Facility Investments: Evidence from a Dynamic Regression Discontinuity Design.” *The Quarterly Journal of Economics*, 125(1): 215–261.

Chetty, Raj, John N. Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan. 2011. “How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project STAR.” *The Quarterly Journal of Economics*, 126(4): 1593–1660.

Chetverikov, Denis, Bradley Larsen, and Christopher Palmer. 2016. “IV Quantile Regression for Group-Level Treatments, with an Application to the Distributional Effects of Trade.” *Econometrica*, 84(2): 809–833.

Cho, Hyunkuk. 2017. “Effect of Summer Heat on Test Scores: A Cohort Analysis.” *Journal of Environmental Economics and Management*, 83: 185–196.

Cohen, François, and Antoine Dechezleprêtre. 2022. "Mortality, Temperature, and Public Health Provision: Evidence from Mexico." *American Economic Journal: Economic Policy*, 14(2): 161–192.

Colmer, Jonathan, and Jennifer L Doleac. 2023. "Access to Guns in the Heat of the Moment: More Restrictive Gun Laws Mitigate the Effect of Temperature on Violence." *The Review of Economics and Statistics*, 1–40.

Cunha, Flavio, and James Heckman. 2007. "The Technology of Skill Formation." *American Economic Review*, 97(2): 31–47.

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S. and Stantcheva, S. 2025. "Fighting Climate Change: International Attitudes toward Climate Policies." *American Economic Review*, 115(4): 1258–1300.

Diffenbaugh, Noah S., and Marshall Burke. 2019. "Global Warming has Increased Global Economic Inequality." *PNAS*, 116(20): 9808–9813.

Dillender, Marcus. 2021. "Climate Change and Occupational Health: Are There Limits to Our Ability to Adapt?" *Journal of Human Resources*, 56(1): 184–224.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth. 2016. "The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution." *American Economic Journal: Applied Economics*, 8(4): 36–65.

Gilli, Martino, Matteo Calcaterra, Johannes Emmerling, and Francesco Granella. 2024. "Climate Change Impacts on the Within-Country Income Distributions." *Journal of Environmental Economics and Management*, 127: 103012.

Heutel, Garth, Nolan H. Miller, David Molitor. 2021. "Adaptation and the Mortality Effects of Temperature across U.S. Climate Regions." *The Review of Economics and Statistics*, 103(4): 740–753.

Hsiang, Solomon, Paulina Oliva, and Reed Walker. 2019. "The Distribution of Environmental Damages." *Review of Environmental Economics and Policy*, 13(1): 83–103.

Hyman, Joshua. 2017. "Does Money Matter in the Long Run? Effects of School Spending on Educational Attainment." *American Economic Journal: Economic Policy*, 9(4): 256–280.

Jackson, C. Kirabo, Rucker C. Johnson, and Claudia Persico. 2016. "The Effects of School Spending on Educational and Economic Outcomes: Evidence from School Finance Reforms." *The Quarterly Journal of Economics*, 131(1): 157–218.

Johnson, Rucker C., and C. Kirabo Jackson. 2019. "Reducing Inequality through Dynamic Complementarity: Evidence from Head Start and Public School Spending." *American Economic Journal: Economic Policy*, 11(4): 310–349.

Johnston, David W., Rachel Knott, Silvia Mendolia, and Peter Siminski. 2021. "Upside-Down Down-Under: Cold Temperatures Reduce Learning in Australia." *Economics of Education Review*, 85: 102172.

Lafortune, Julien, and David Schönholzer. 2022. "The Impact of School Facility Investments on Students and Homeowners: Evidence from Los Angeles." *American Economic Journal: Applied Economics*, 14(3): 254–289.

Lafortune, Julien, Jesse Rothstein, and Diane Whitmore Schanzenbach. 2018. "School Finance Reform and the Distribution of Student Achievement." *American Economic Journal: Applied Economics*, 10 (2): 1–26.

Marcotte, Dave E. 2015. "Allergy Test: Seasonal Allergens and Performance in School." *Journal of Health Economics*, 40: 132–140.

Martorell, Paco, Kevin Stange, and Isaac McFarlin, Jr. 2016. "Investing in Schools: Capital Spending, Facility Conditions, and Student Achievement." *Journal of Public Economics*, 140: 13–29.

Ministry of Education, Culture, Sports, Science, and Technology (MEXT). 2022. "Basic Data on Private Schools and School Organization." (in Japanese) https://www.mext.go.jp/a_menu/koutou/shinkou/main5_a3_00003.htm#topic3 (accessed May 16, 2024).

Ministry of Education, Culture, Sports, Science, and Technology (MEXT). 2024a. "Overview of the National Assessment of Academic Ability." (in Japanese) https://www.mext.go.jp/a_menu/shotou/gakuryoku-chousa/zenkoku/1344101.htm (accessed May 16, 2024).

Ministry of Education, Culture, Sports, Science, and Technology (MEXT). 2024b. "Installation of Air Conditioning Equipment in Public School Facilities." (in Japanese) https://www.mext.go.jp/a_menu/shotou/zyosei/mext_01278.html (accessed May 16, 2024).

Morozumi, Atsuyoshi, and Ryuichi Tanaka. 2023. "School Accountability and Student Achievement: Neighboring Schools Matter." *RIETI Discussion Paper Series 23-E-004.*

Mullins, Jamie T., and Corey White. 2019. "Temperature and Mental Health: Evidence from the Spectrum of Mental Health Outcomes" *Journal of Health Economics*, 68: 102240.

National Institute for Educational Policy Research (NIER). 2021. "Survey Questions, Sample Correct Answers, and Explanatory Materials for the 2021 National Survey of Academic Performance and Learning." (in Japanese) https://www.nier.go.jp/21chousa/21chousa.htm (accessed May 16, 2024).

National Institute for Educational Policy Research (NIER). 2024. "NAAA Aggregate Results." (in Japanese) https://www.nier.go.jp/tyousakekka/04shou_shuukeikekka_zenkoku.htm (accessed May 16, 2024).

Neilson, Christopher A., and Seth D. Zimmerman. 2014. "The Effect of School Construction on Test Scores, School Enrollment, and Home Prices." *Journal of Public Economics*, 120: 18–31.

Park, Jisung, Mook Bangalore, Stephane Hallegatte, and Evan Sandhoefner. 2018. "Households and Heat Stress: Estimating the Distributional Consequences of Climate Change." *Environment and Development Economics*, 23(3): 349–368.

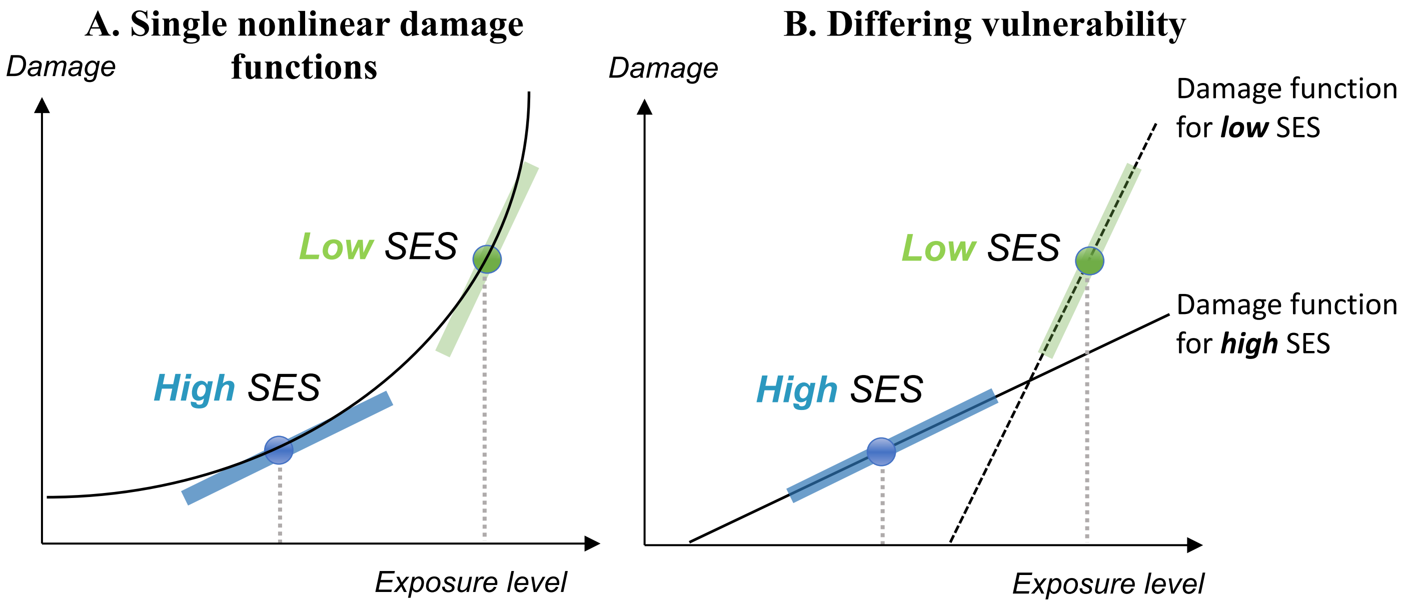
Park, R. Jisung, A. Patrick Behrer, and Joshua Goodman. 2021a. "Learning is Inhibited by Heat Exposure, both Internationally and within the United States." *Nature Human Behaviour*, 5: 19–27.

Park, R. Jisung, Joshua Goodman, Michael Hurwitz, and Jonathan Smith. 2020. "Heat and Learning." *American Economic Journal: Economic Policy*, 12(2): 306–339.

Park, R. Jisung, Nora Pankratz, and A. Patrick Behrer. 2021b. "Temperature, Workplace Safety, and Labor Market Inequality." *IZA DP No. 14560.*

Rowland, Thomas. 2008. "Thermoregulation during Exercise in the Heat in Children: Old Concepts Revisited." *Journal of Applied Physiology*, 105: 718–724.

Figure 1—Heterogeneity in marginal damages from two explanations

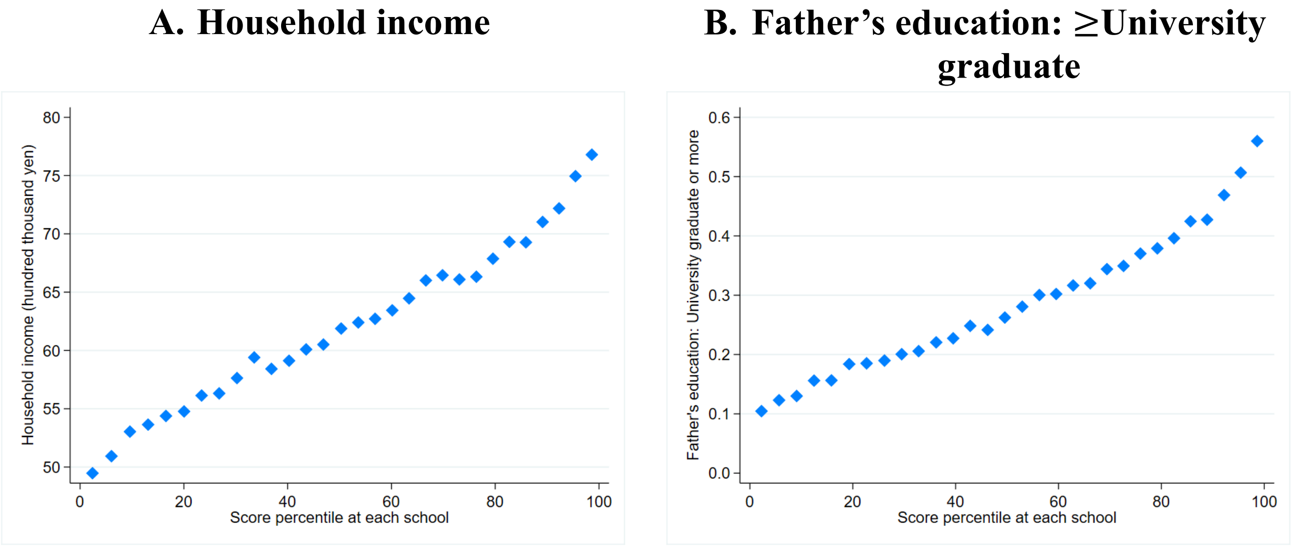


A. Single nonlinear damage functions

B. Differing vulnerability

Notes: Adapted from Hsiang et al. (2019, Figure 1), this figure presents two explanations for the empirically observed heterogeneity in marginal damages between high and low socioeconomic status (SES): a single nonlinear damage function, illustrated in panel A, or different damage functions (i.e., differential vulnerability) related to SES that correlate with exposure levels, as shown in panel B.

Figure 2—Within-school student rank and socioeconomic status

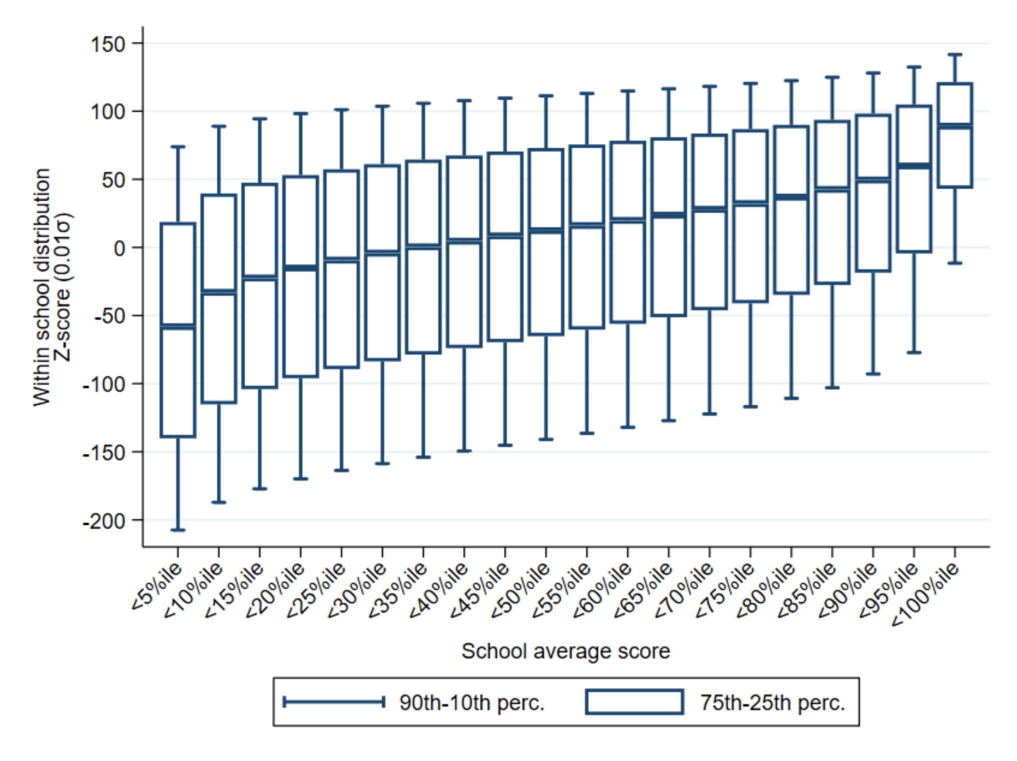


A. Household income

B. Father's education: ≥University graduate

Notes: The data are obtained from parent surveys in 2013 and 2017 NAAA. The bin scatter plot illustrates the relationship between within-school student rank and various measures of students' socioeconomic status, net of school fixed effects, specifically household income (panel A), and the proportion of fathers with education at or above a 4-year university/college degree (panel B). Household income (panel A) is reported in hundreds of thousands of yen, with US$1 equal to approximately 100 yen. We transform the median of each household income bin into a continuous variable.

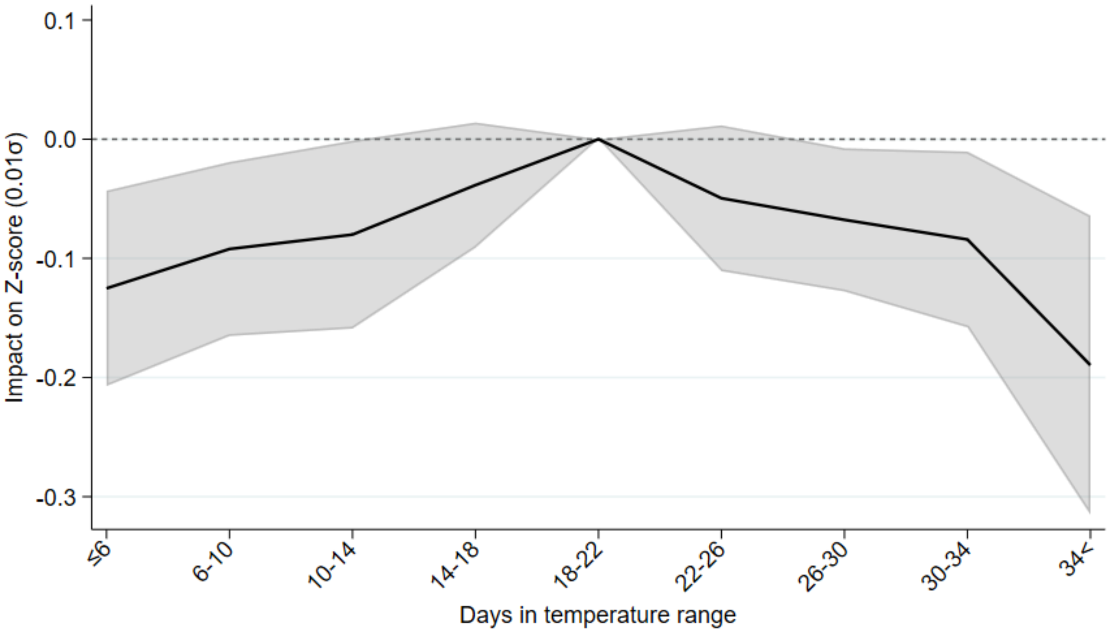
Figure 3—Within-school score distribution across school ranks



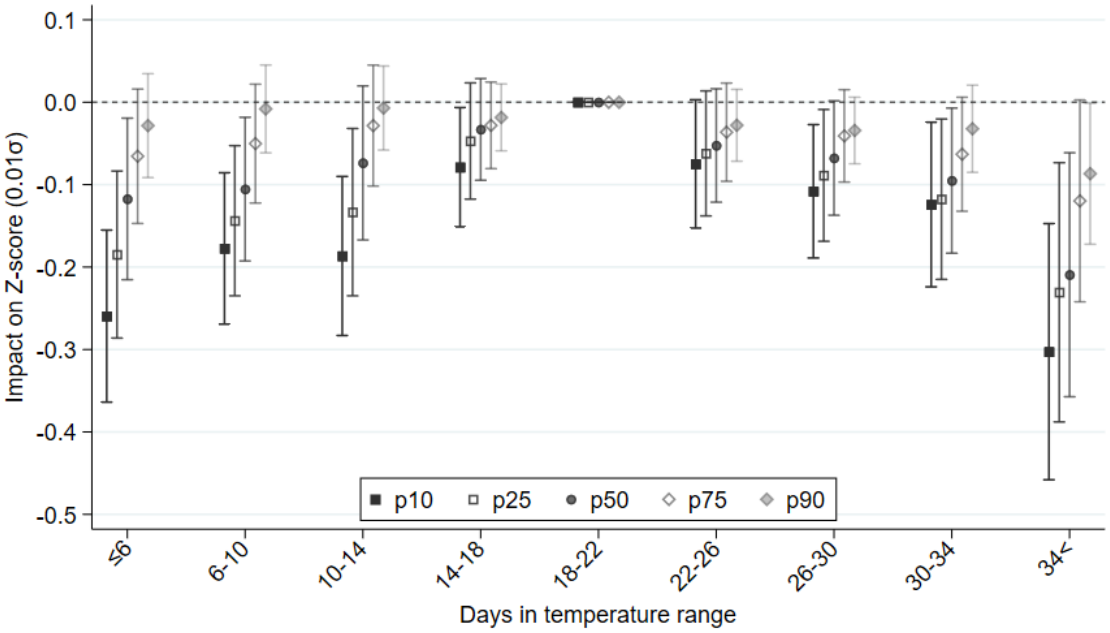
Notes: This figure illustrates the variations in *within*-school score distribution across school ranks based on the average school scores. Specifically, we group schools into ventiles based on their average scores each year and plot the average interquartile and interdecile ranges of the within-school score distribution for every ventile.

Figure 4—Cumulative heat/cold exposure and test performance

A. Average impacts

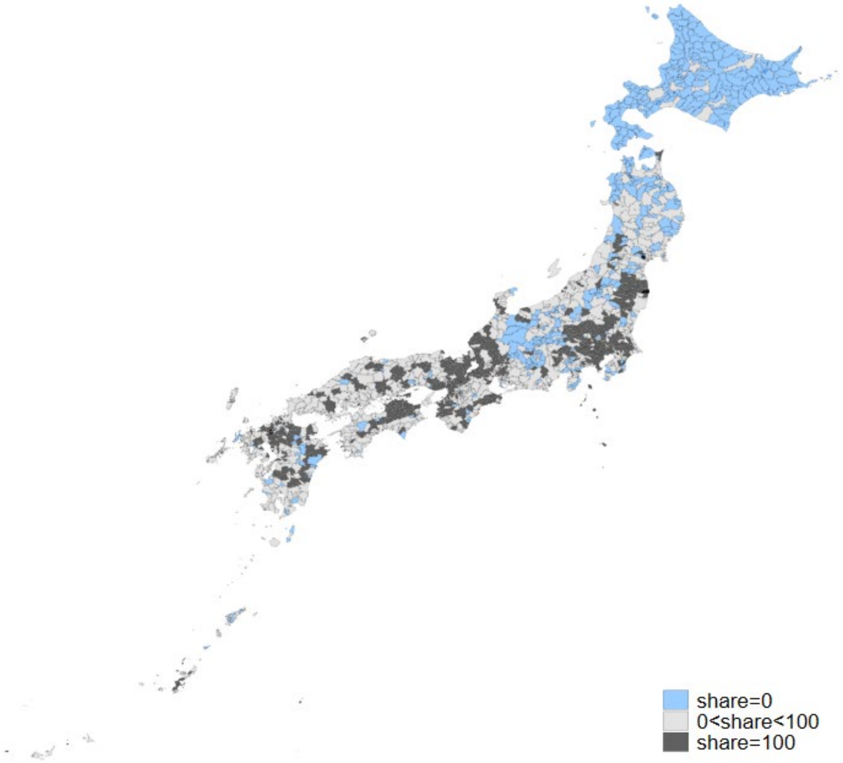


B. Distributional impacts



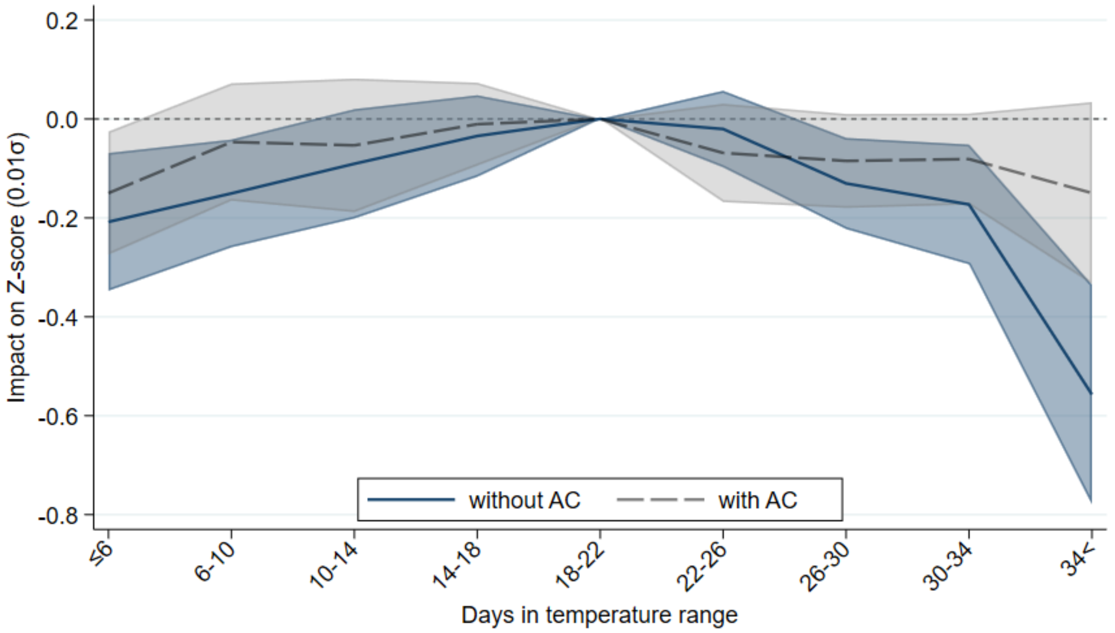
Notes: Panel A plots β^k from an estimating Equation [1], where the average z-score (measured in 0.01σ) is regressed on the number of school days within a given maximum temperature bin in the year prior to the test date, along with the 95% confidence intervals. Panel B plots β^k from an estimating Equation [2], where z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools (measured in 0.01σ) are regressed separately on the number of school days within a given maximum temperature bin from the year prior to the test date, along with the 95% confidence intervals. The omitted category is the temperature range between 18–22°C.

Figure 5—Map of the school AC penetration



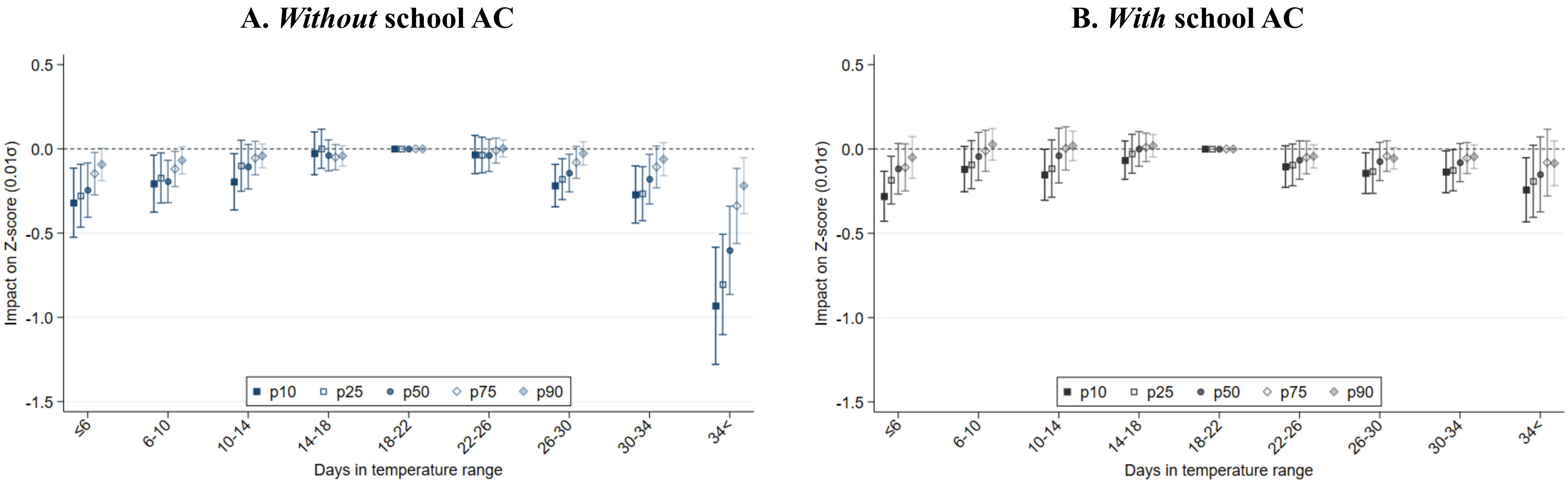
Notes: The figure displays the locations of municipalities according to the degree of school AC penetration rate. Using school AC penetration rates for public primary and secondary schools at the municipal level in 2018 (the last year of the sample period), schools are categorized into municipalities with a 0% share (in blue), a 100% share (in dark gray), and the remaining (in light gray) of school AC penetration as of 2018.

Figure 6—Average impact of cumulative heat/cold exposure and test performance (with and without school AC)



Notes: The figure plots β^k from an estimating Equation [1], where the average z-score (measured in 0.01σ) is regressed on the number of school days within a given maximum temperature bin in the year prior to the test date, , separately for schools without AC and with AC in 2018, respectively, along with the 95% confidence intervals. The omitted category is the temperature range between 18–22°C.

Figure 7—Distributional impact of cumulative heat/cold exposure (with and without school AC)



Notes: The figures plot β^k from an estimating Equation [2], where z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools (measured in 0.01σ) are regressed separately on the number of school days within a given maximum temperature bin from the year prior to the test date, separately for schools without AC (panel A) and with AC (panel B) in 2018, respectively, along with the 95% confidence intervals. The omitted category is the temperature range between 18–22°C.

Table 1—The average impact of school AC

	(1)		(2)		(3)	
Outcomes:	**Average Z-score**		**Average Z-score**		**Average Z-score**	
		× school AC		× school AC		× school AC
Days 6℃≤	-0.216***	0.068	-0.235***	0.061	-0.080	-0.109
	(0.069)	(0.090)	(0.077)	(0.097)	(0.061)	(0.082)
Days 6-10℃	-0.158***	0.114	-0.111**	-0.007	-0.063	0.010
	(0.053)	(0.076)	(0.056)	(0.074)	(0.052)	(0.074)
Days 10-14℃	-0.098*	0.046	-0.082	-0.059	-0.041	-0.044
	(0.054)	(0.084)	(0.059)	(0.073)	(0.047)	(0.082)
Days 14-18℃	-0.040	0.031	-0.020	-0.040	0.043	-0.080
	(0.041)	(0.057)	(0.050)	(0.064)	(0.043)	(0.053)
Days 22-26℃	-0.024	-0.043	-0.042	0.019	-0.115***	0.069
	(0.039)	(0.063)	(0.043)	(0.057)	(0.042)	(0.081)
Days 26-30℃	-0.134***	0.050	-0.140***	0.125*	-0.243***	0.187***
	(0.046)	(0.066)	(0.050)	(0.067)	(0.048)	(0.069)
Days 30-34℃	-0.177***	0.097	-0.209***	0.202*	-0.298***	0.310***
	(0.061)	(0.073)	(0.071)	(0.113)	(0.065)	(0.084)
Days 34℃>	-0.562***	0.413***	-0.565***	0.476***	-0.623***	0.501***
	(0.112)	(0.145)	(0.121)	(0.141)	(0.107)	(0.153)
Interaction with						
taxable income			X			
student-teacher ratio			X			
home AC share					X	
R-squared	0.751		0.752		0.751	
Observations	190,210		188,911		190,210	

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. The outcome is the average test score at the school-year level, measured in 0.01σ. Column (1) presents the estimates from Equation [3], along with standard errors clustered at the weather station level in parentheses. School AC is a dummy variable that equals one if an air conditioner was available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. Column (2) adds to column (1) the interaction of municipality-level taxable income per capita and the student-teacher ratio in 2018 with the number of school days within a given maximum temperature bin in the year prior to the test date. Column (3) adds to column (1) the interaction of prefecture-level home AC shares in 2014 with the number of school days within a given maximum temperature bin in the year before the test date. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range (18–22℃). Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 2—The distributional impact of school AC

	(1)		(2)		(3)	
Outcomes:	**10th percentile score**		**90th percentile score**		**90th-10th score gap**	
		× school AC		× school AC		× school AC
Days 6℃≤	-0.320***	0.040	-0.099**	0.050	0.222**	0.011
	(0.101)	(0.124)	(0.047)	(0.076)	(0.086)	(0.110)
Days 6-10℃	-0.207**	0.088	-0.075*	0.104*	0.132*	0.016
	(0.083)	(0.103)	(0.040)	(0.059)	(0.078)	(0.089)
Days 10-14℃	-0.196**	0.043	-0.047	0.067	0.149**	0.025
	(0.082)	(0.108)	(0.035)	(0.053)	(0.074)	(0.088)
Days 14-18℃	-0.027	-0.039	-0.046	0.067	-0.019	0.106
	(0.062)	(0.083)	(0.030)	(0.042)	(0.052)	(0.078)
Days 22-26℃	-0.034	-0.070	-0.000	-0.042	0.034	0.028
	(0.057)	(0.083)	(0.026)	(0.043)	(0.050)	(0.068)
Days 26-30℃	-0.218***	0.075	-0.030	-0.024	0.188***	-0.099
	(0.063)	(0.087)	(0.035)	(0.046)	(0.053)	(0.075)
Days 30-34℃	-0.271***	0.136	-0.065	0.020	0.207***	-0.116
	(0.085)	(0.102)	(0.049)	(0.058)	(0.076)	(0.094)
Days 34℃>	-0.932***	0.690***	-0.223***	0.139	0.709***	-0.551***
	(0.176)	(0.201)	(0.085)	(0.108)	(0.170)	(0.184)
R-squared	0.669		0.603		0.552	
Observations	190,210		190,210		190,210	

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. Columns (1) and (2) present the estimates from the variant of Equation [3], where the outcomes are z-scores at the 10th and 90th percentiles within schools (measured in 0.01σ). School AC is a dummy variable that equals one if an air conditioner was available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. The complete table showing the results for the other percentiles is presented in Table A.12. Column (3) presents the estimate of the score gap between the 90th and 10th percentiles within the school (measured in 0.01σ). Standard errors are clustered at the weather station level in parentheses. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range between 18 and 22℃. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Online Appendix
(Not for Publication)

Hotter Days, Wider Gap:
The Distributional Impact of Heat on Student Achievement

By Mika Akesaka and Hitoshi Shigeoka

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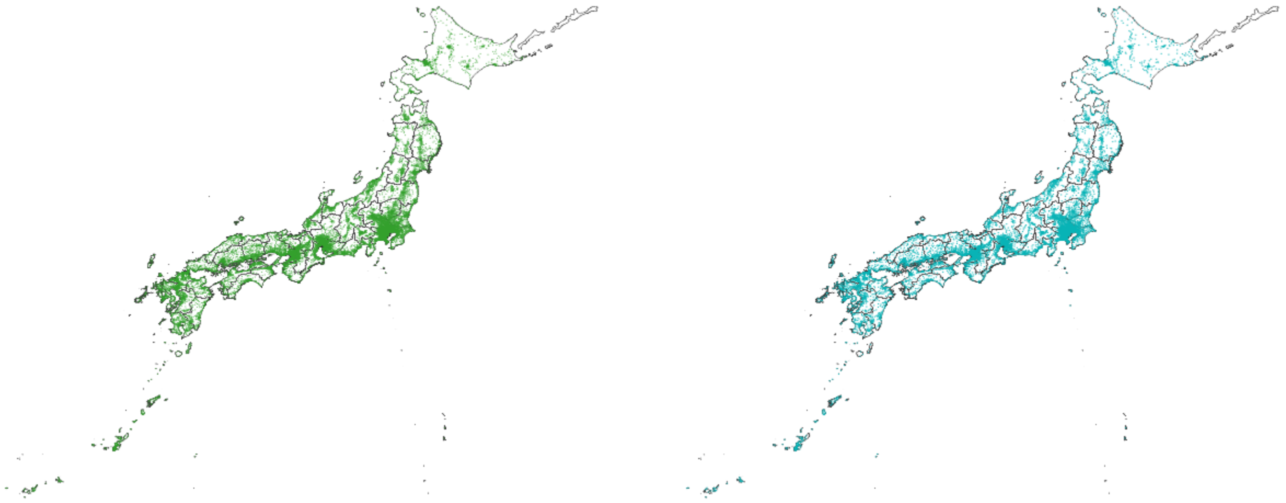
Section A Additional Figures and Tables
Section B Data Appendix

Appendix A: Additional figures and tables

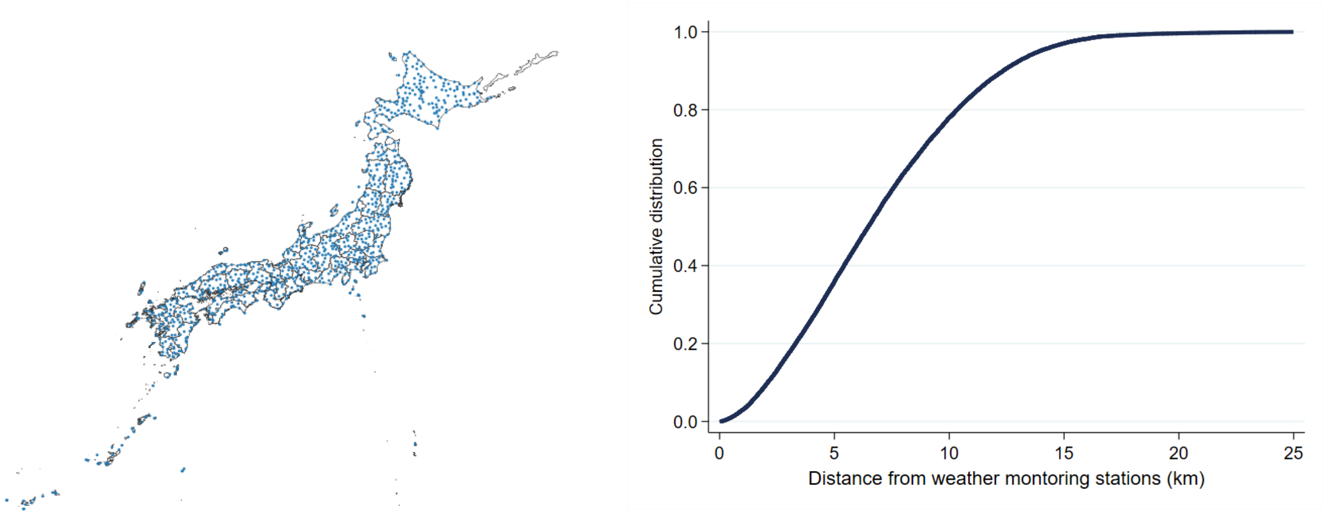
Figure A.1—Location of schools



A. Primary schools (grade 6) **B. Secondary schools (grade 9)**

Notes: Panels A and B illustrate the locations of primary (grade 6) and secondary (grade 9) schools as of April 2019. There are 19,304 primary schools and 9,776 secondary schools.

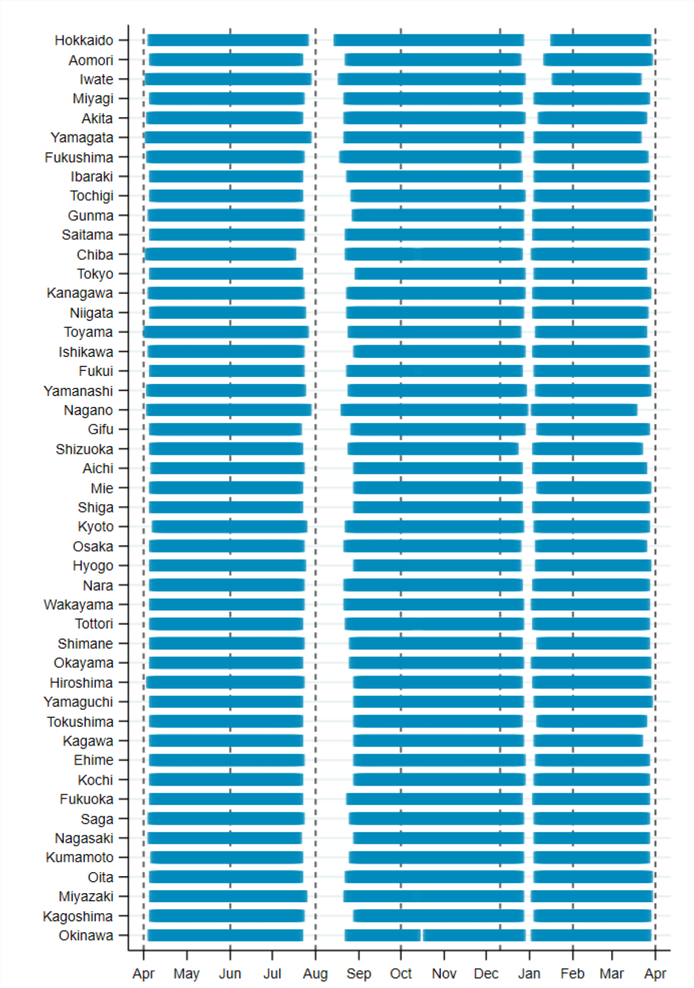
Figure A.2—Weather stations



A. Location of weather stations **B. Distance to the weather stations**

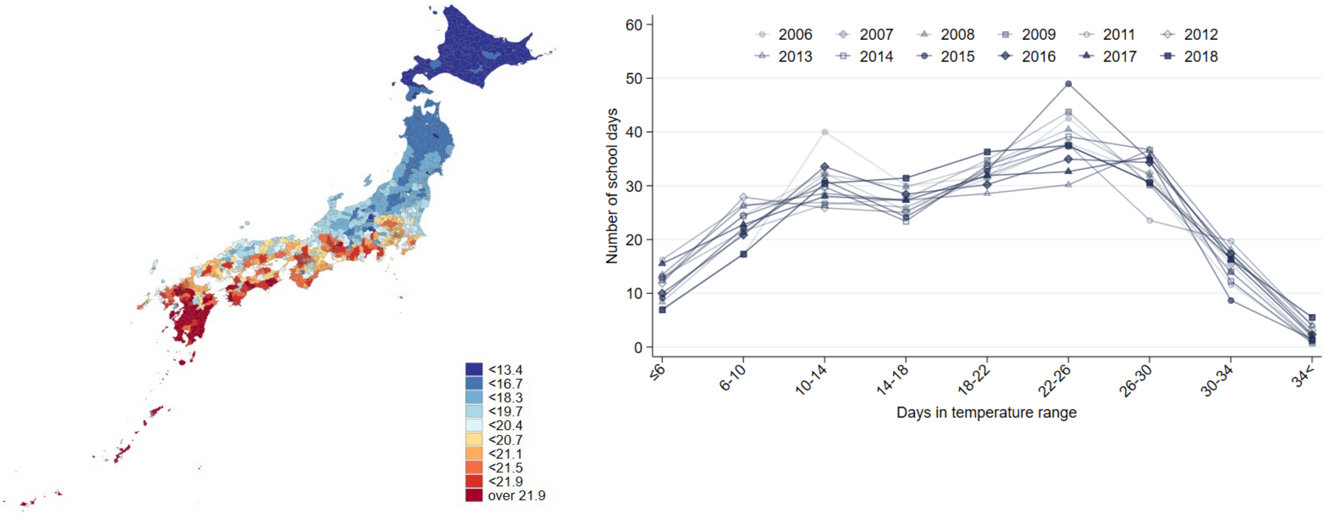
Notes: Panel A displays the locations of all 899 weather stations as of 2019. Panel B shows the cumulative distribution of the distances from schools to the nearest weather stations. The mean (median) distance from the weather stations is 6.95 (6.48) km.

Figure A.3—School days by region



Notes: The figure displays the academic calendar of the prefectural capital in the school's prefecture for 2018. Japan is divided into 47 prefectures. The academic calendar mostly comprises three terms: spring, fall, and winter.

Figure A.4—Spatial and temporal variations in prior year temperature


A. Average temperature **B. Number of school days**

Notes: The figures illustrate the spatial variations in the mean daily maximum temperature in the year preceding the test year (panel A) and temporal variations in the number of school days within a given maximum temperature bin from last April to March of the test year, as experienced by students on school days (panel B).

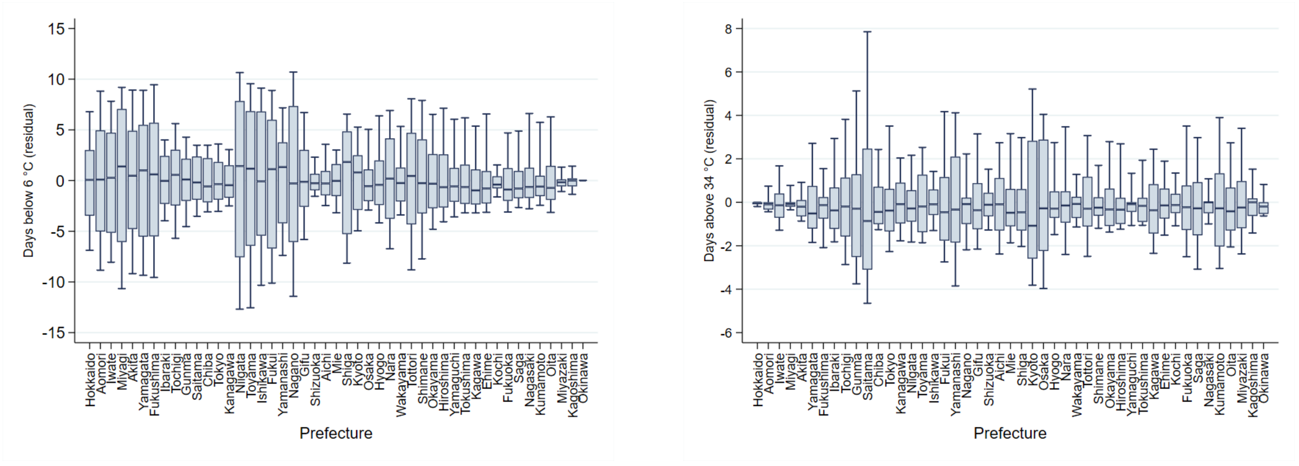
Figure A.5—Identifying variations in prior year temperature

A. Number of days below 6°C

By prefecture

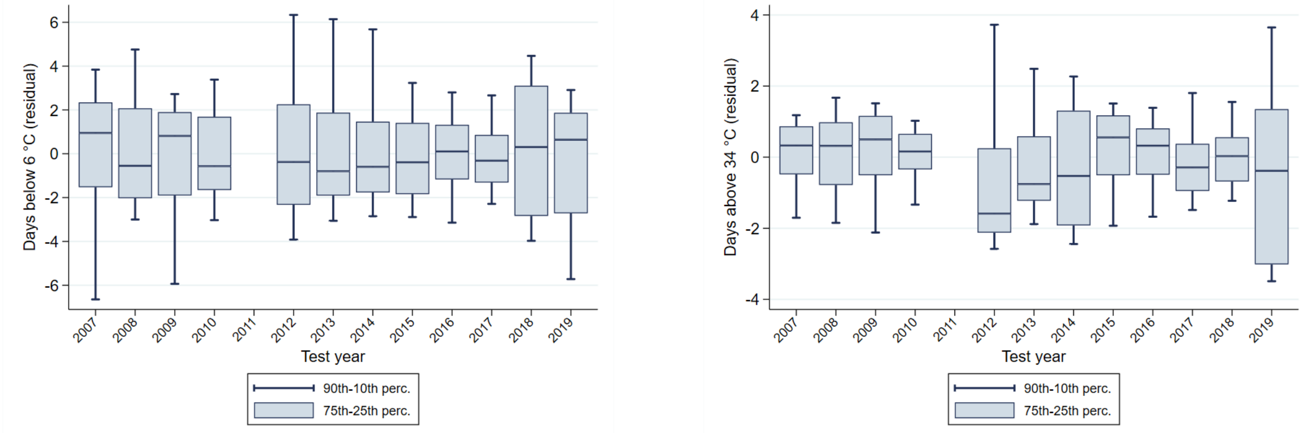
B. Number of days above 34°C

By prefecture



By year

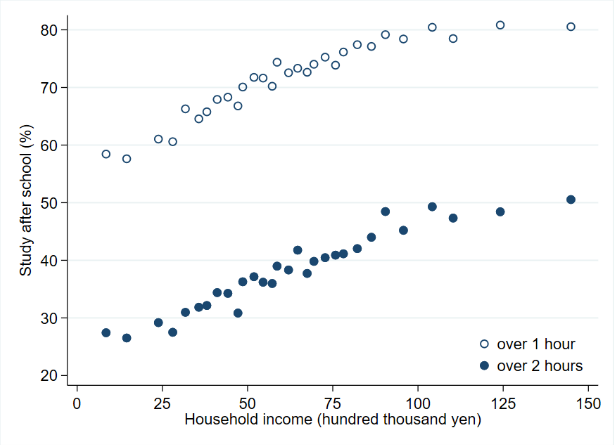
By year



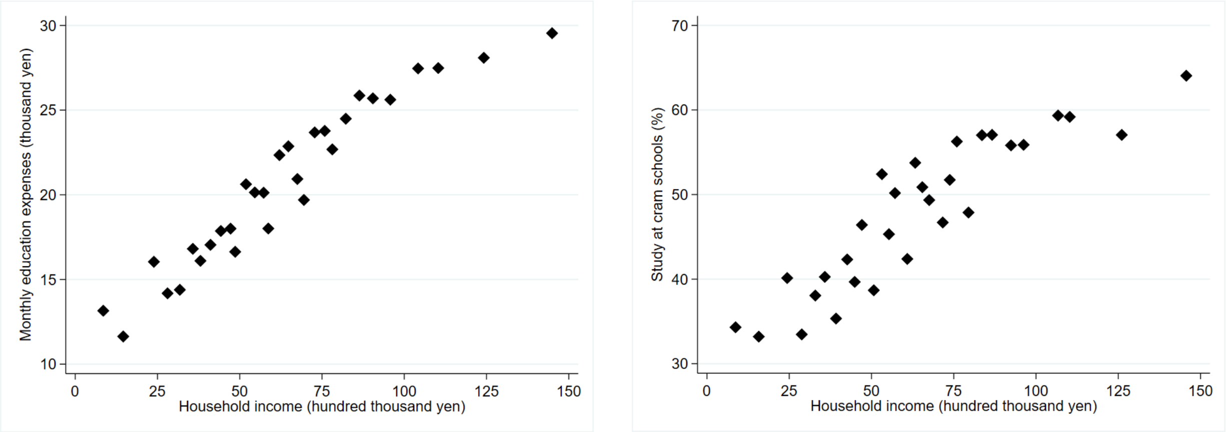
Notes: This figure illustrates the interquartile and interdecile ranges of the residual variation, net of school fixed effects, in the number of school days below 6°C in the year prior to the test date (panel A) and the number of school days above 34°C in the year prior to the test date (panel B), by prefecture and year. Japan has a total of 47 prefectures. The estimates are weighted by the number of students in each school.

Figure A.6—Socioeconomic status and studying after school

A. Household income and studying after school

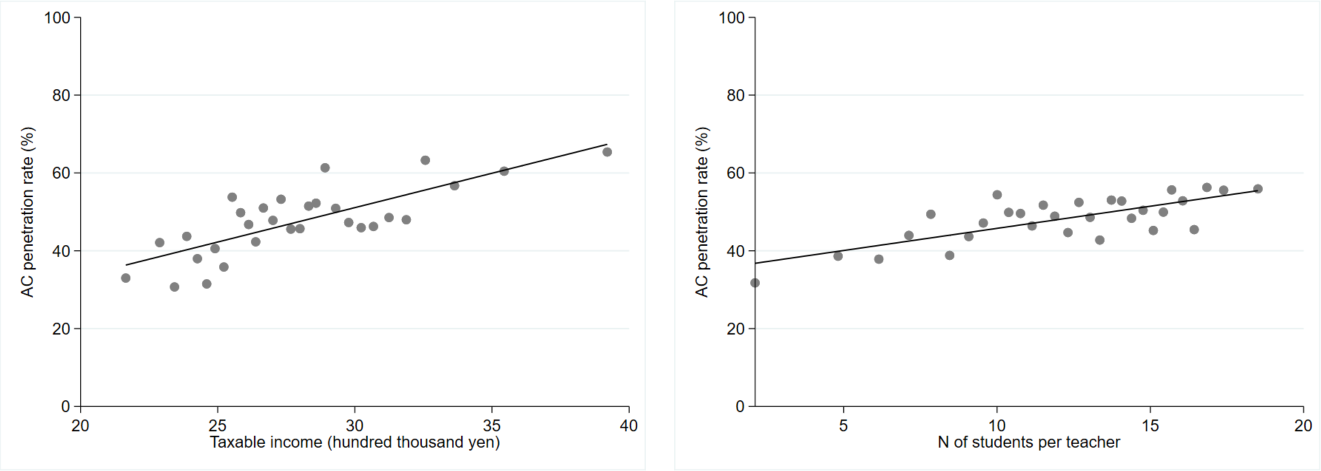


B. Household income and education expenses **C. Household income and cram school**



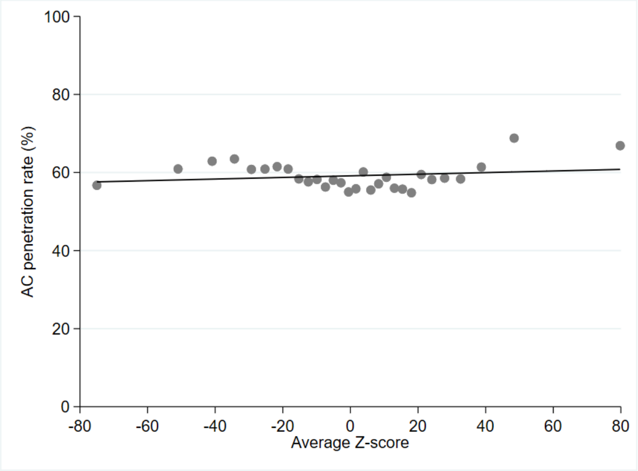
Notes: The data are obtained from parent surveys in the 2013 and 2017 NAAA, except for the fraction of students who study for more than 1 or 2 hours in panel A, which is obtained from student surveys in the 2013 and 2017 NAAA. The binscatter plot illustrates the relationship between students' socioeconomic status, as indicated by household income, and various study-related variables after school, net of school fixed effects. Specifically, it shows the proportion of students studying after school for more than 1 or 2 hours (panel A), monthly education expenses (panel B), and the proportion of students attending cram schools (panel C). Household income (panels A-C) is presented in hundreds of thousands of yen, while monthly education expenses (panel B) are presented in thousands of yen, with US$1 being approximately equal to 100 yen. For both variables, we use the median of each household income/monthly education expense bin to transform them into continuous variables.

Figure A.7—Correlation with school AC penetration rates


A. Taxable income per capita

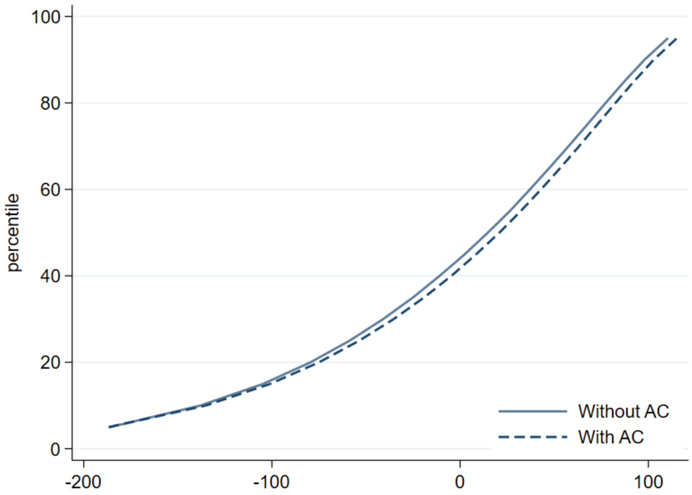
B. Student-teacher ratio

C. Average test scores



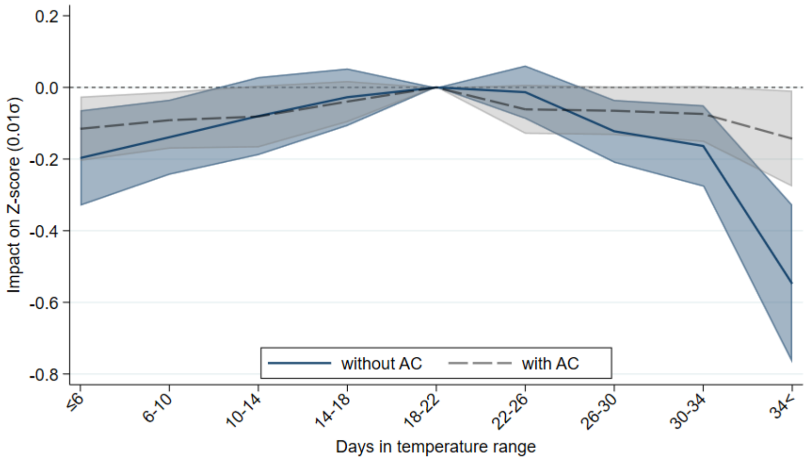
Notes: The binscatter plot illustrates the cross-sectional relationship between school AC penetration rates at the municipality level in 2018 and the average taxable income per capita between 2006 and 2018 (panel A), the average student-teacher ratio between 2006 and 2018 (panel B), and the municipality-average test scores in 2007, the first year of our sample period, when the AC penetration rate was only 10.2% (panel C), after controlling for the average temperature between 2006 and 2018.

Figure A.8—Test score distributions between schools with and without AC in 2007



Notes: This figure plots the average test scores at 5-percentile increments in 2007 (the first year of our sample period), when the AC penetration at the national level was only 10.2%, separately for schools with and without AC. These averages were obtained by first calculating test scores at each 5th percentile within schools, then averaging across schools within each group.

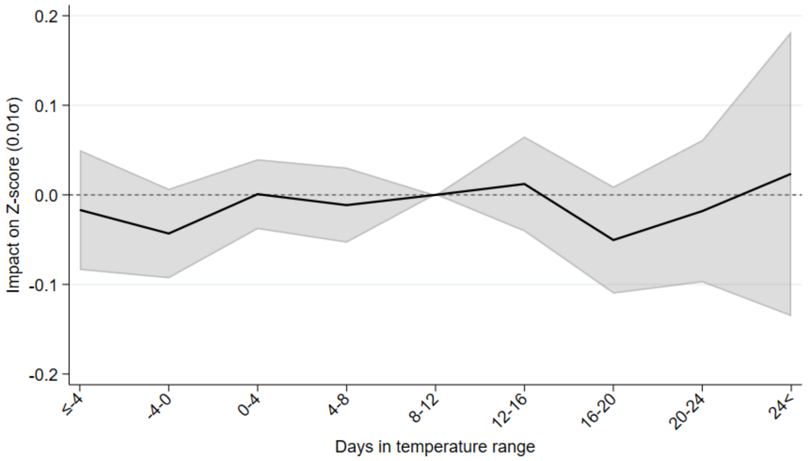
Figure A.9—Cumulative heat/cold exposure and test performance
(school AC 0% vs. AC>0%)



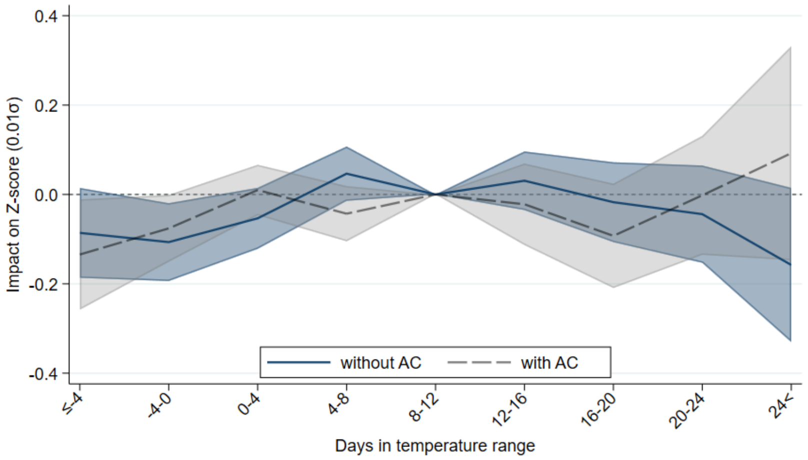
Notes: The figure displays β^k from an estimating Equation [1], separately for schools in municipalities with a positive share of AC and those in municipalities with 0% AC availability in 2018, along with the 95% confidence intervals. The omitted category is the temperature range between 18 and 22°C. Figure 5 shows the locations of schools for each school AC penetration category.

Figure A.10—Minimum temperature and test performance (average impacts)

A. All schools

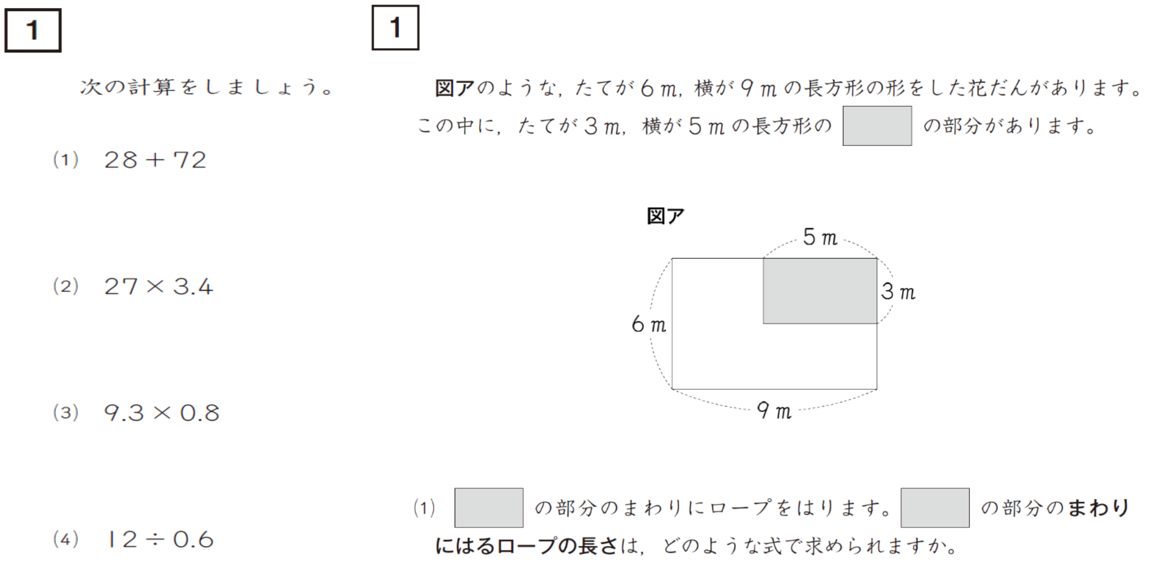


B. Schools with vs. without AC



Notes: Panel A plots β^k from an estimating Equation [1], where the average z-score (measured in 0.01σ) is regressed on the number of school days within a given *minimum* temperature bin in the year prior to the test date, and panel B plots β^k separately for schools with and without AC in 2018, along with the 95% confidence intervals. The omitted category is the temperature range (8–12°C).

Figure A.11—Examples of basic and advanced questions (math for grade 6)



Basic

1

次の計算をしましょう。

(1) 28＋72

(2) 27×3.4

(3) 9.3×0.8

(4) 12÷0.6

Advanced

1

図アのような，たてが６ｍ，横が９ｍの長方形の形をした花だんがあります。この中に，たてが３ｍ，横が５ｍの長方形の ▨ の部分があります。

図ア
5 m
3 m
6 m
9 m

(1) ▨ の部分のまわりにロープをはります。▨ の部分の**まわりにはるロープの長さ**は，どのような式で求められますか。

Notes: The examples are from mathematics for grade 6 in the NAAA.

Table A.1—Number of participating schools and students in NAAA

	N of schools			N of students		
Year	Total	Grade 6	Grade 9	Total	Grade 6	Grade 9
2007	31,899	21,523	10,376	2,203,309	1,115,808	1,087,501
2008	32,095	21,670	10,425	2,243,391	1,162,311	1,081,080
2009	31,835	21,498	10,337	2,264,473	1,153,059	1,111,414
2010	9,866	5,421	4,445	708,995	271,004	437,991
2011	-	-	-	-	-	-
2012	9,545	5,177	4,368	703,244	262,114	441,130
2013	30,560	20,468	10,092	2,207,777	1,124,018	1,083,759
2014	30,233	20,221	10,012	2,162,765	1,097,584	1,065,181
2015	29,962	20,030	9,932	2,136,316	1,076,832	1,059,484
2016	29,125	19,397	9,728	2,076,404	1,037,066	1,039,338
2017	29,174	19,375	9,799	2,047,892	1,018,505	1,029,387
2018	29,248	19,431	9,817	2,012,527	1,041,474	971,053
2019	28,989	19,252	9,737	2,025,844	1,046,722	979,122
Total	322,531	213,463	109,068	22,792,937	11,406,497	11,386,440

Notes: This table shows the number of schools and students participating in the National Assessment of Academic Ability (NAAA) each year. We exclude schools that are observed only once during the sample period, along with their corresponding students, and those without math and reading scores (0.24% of schools and 1.59% of students). The NAAA has been conducted annually across the nation by the Ministry of Education, Culture, Sports, Science, and Technology (MEXT) since 2007. Exceptions occurred in 2011, when the NAAA was entirely canceled because of the Great East Japan Earthquake, and in 2010 and 2012, when it was administered to a random subset of schools: approximately 25% of sixth graders and 40% of ninth graders.

Table A.2—Descriptive statistics

Variable:	N of schools	Mean	Std. dev.	Min	Max	N of station	Available period
Panel A. Student information							
Student survey:							
Female	301,821	0.48	0.08	0	1	-	2007-2019
Study time after school: >1 hour	323,144	0.65	0.13	0	1	-	2007-2019
Study time after school: >2 hours	323,144	0.31	0.13	0	1	-	2007-2019
Parent survey:							
Household income	2,624	62.26	31.68	10	150	-	2013, 2017
Father’s educ: ≥University graduate	2,779	0.31	0.46	0	1	-	2013, 2017
Education expenses	2,628	17.03	14.48	0	50	-	2013, 2017
Attending a cram school	1,952	0.33	0.47	0	1	-	2017
Regional information:							
School AC	322,962	0.60	0.46	0	1	-	2018
Taxable income per capita	323,153	32.29	5.86	18.89	126.67	-	2007-2019
Student-teacher ratio	321,263	15.63	3.06	0.09	25.05	-	2007-2019
Home AC	323,153	0.90	0.15	0.27	0.99	-	2014
Panel B. Weather conditions							
Number of school days							
6℃≤	322,531	11.02	16.83	0	194	891	2007-2019
6-10℃	322,531	22.59	8.37	0	53	891	2007-2019
10-14℃	322,531	30.93	8.78	0	60	891	2007-2019
14-18℃	322,531	27.20	5.80	0	58	891	2007-2019
18-22℃	322,531	32.42	6.34	0	71	891	2007-2019
22-26℃	322,531	38.37	8.51	0	88	891	2007-2019
26-30℃	322,531	32.95	9.58	0	97	891	2007-2019
30-34℃	322,531	14.87	8.90	0	79	891	2007-2019
34℃>	322,531	2.25	2.95	0	20	891	2007-2019
Mean precipitation (mm)	322,531	4.53	1.37	0.82	21.48	1,165	2007-2019
Mean wind speed (m/s)	322,531	2.51	0.91	0.26	8.75	887	2007-2019
Mean relative humidity	322,531	68.44	4.92	58.39	82.94	153	2007-2019

Notes: Panel A provides descriptive statistics of student information aggregated at the school level. Gender information for grade 6 was not collected in 2015. Household income is presented in hundreds of thousands of yen, while monthly education expenses are shown in thousands of yen, with US$1 being approximately equal to 100 yen. For both variables, we calculate the median household income and monthly education expense bin to convert them into continuous variables. For school and home AC, data from 2018 and 2014, respectively, are applied to all years. Panel B displays the descriptive statistics of the cumulative weather conditions from last April to March of the test year, as experienced by students on school days.

Table A.3—Cumulative heat/cold exposure and test attendance rates

	(1)	(2)
Outcomes:	**Test attendance rates**	
Days 6℃≤	-0.008	-0.008
	(0.005)	(0.006)
Days 6-10℃	-0.005	-0.006
	(0.005)	(0.005)
Days 10-14℃	-0.005	-0.004
	(0.004)	(0.004)
Days 14-18℃	-0.002	-0.003
	(0.003)	(0.004)
Days 22-26℃	0.004	0.005*
	(0.003)	(0.003)
Days 26-30℃	0.004	0.006
	(0.004)	(0.004)
Days 30-34℃	0.000	0.001
	(0.004)	(0.005)
Days 34℃>	0.007	0.006
	(0.006)	(0.007)
Weight	Number of test takers	Number of students enrolled
Joint Test:		
F-stats	1.401	1.407
p-value	0.192	0.189
Mean (%)	95.194	94.967
R-squared	0.349	0.352
Observations	242,322	242,322

Notes: The data come from the NAAA (2009–2019), Basic School Survey (2009–2019), and AMeDAS (2008–2018), as the Basic School Survey is only available from 2009–2019. The unit of observation is the school-year. The table presents estimates from a variant of equation [1], in which the outcome is replaced with test attendance rates. Test attendance rates are calculated by dividing the number of NAAA test takers by the number of students enrolled as of May 1, as reported in the Basic School Survey. The estimates are weighted by the number of test takers in each school-year in column (1) and by the number of enrolled students in each school-year in column (2). Standard errors are clustered at the weather station level in parentheses. The omitted category is the temperature range between 18 and 22°C. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A.4—Comparison with previous studies of cumulative exposure to heat or cold on test scores

Study	Country (period)	Exam type	Stakes	Grades	Representation	Exam Days	Effect size by one additional day
Our Study	Japan (‘07-’19)	Achievement test	Low	G6 and G9	All students in public schools	3rd or 4th Tuesday in April	Reference: 18–22°C Above 34°C ↓ 0.19% SD Below 6° ↓ 0.13% SD
Cho (2017)	Korea (‘09-’13)	College entrance exam	High	G12	Takers of university entrance exam	2nd Thursday in November	Reference: 28–30°C Above 34°C ↓ 0.42% SD (Math) ↓ 0.64% SD (English)
Park et al. (2020)	US (’01-’14)	PSAT	Intermediate	G10 or G11	Takers of PSAT at least twice	3rd week of October	Reference: 60–69°F (15.6-20.6°C) Above 100°F (37.8°C) ↓ 0.07% SD Above 90°F (32.2°C) ↓ 0.05% SD
Park et al. (2021)	US (’09-’15)	State-specific exams	Intermediate	G3 to G8	12,000 US school districts	Spring (differ by state)	Reference: 60–69°F (15.6-20.6°C) Above 80°F (26.7°C) ↓ 0.10% SD (G3–G5) ↓ 0.03% SD (G6–G8)
Johnston et al. (2021)	Australia (’09-’18)	Achievement test	Low	G3, G5, G7 and G9	All students in public schools in New South Wales	2nd week of May	Reference: 65–75°F (18.3-23.9°C) Below 60°F (15.6°C) ↓ 0.15% SD

References:

Cho, Hyunkuk. 2017. “Effect of Summer Heat on Test Scores: A Cohort Analysis.” *Journal of Environmental Economics and Management*, 83: 185–196.

Park, R. Jisung, Joshua Goodman, Michael Hurwitz, and Jonathan Smith. 2020. “Heat and Learning.” *American Economic Journal: Economic Policy*, 12(2): 306–339.

Park, R. Jisung, A. Patrick Behrer, and Joshua Goodman. 2021. “Learning is Inhibited by Heat Exposure, both internationally and within the United States.” *Nature Human Behaviour*, 5: 19–27.

Johnston, David W., Rachel Knott, Silvia Mendolia, and Peter Siminski. 2021. “Upside-Down Down-Under: Cold Temperatures Reduce Learning in Australia.” *Economics of Education Review*, 85: 102172.

Table A.5—School-level analysis of distributional impact of cumulative heat/cold exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcomes:	**10th percentile**	**25th percentile**	**50th percentile**	**75th percentile**	**90th percentile**	Resulting score gap		
						90th-10th	90th-50th	50th-10th
Days 6℃≤	-0.260***	-0.185***	-0.117**	-0.066	-0.028	0.231***	0.089***	0.142***
	(0.053)	(0.052)	(0.050)	(0.042)	(0.032)	(0.042)	(0.026)	(0.036)
Days 6-10℃	-0.177***	-0.144***	-0.105**	-0.050	-0.008	0.169***	0.097***	0.072**
	(0.047)	(0.046)	(0.044)	(0.037)	(0.027)	(0.037)	(0.023)	(0.032)
Days 10-14℃	-0.187***	-0.133**	-0.074	-0.028	-0.007	0.180***	0.067***	0.113***
	(0.049)	(0.052)	(0.048)	(0.037)	(0.026)	(0.036)	(0.026)	(0.027)
Days 14-18℃	-0.079**	-0.047	-0.033	-0.028	-0.018	0.060*	0.015	0.046*
	(0.037)	(0.036)	(0.031)	(0.027)	(0.021)	(0.036)	(0.019)	(0.027)
Days 22-26℃	-0.075*	-0.062	-0.052	-0.036	-0.028	0.047	0.024	0.022
	(0.040)	(0.039)	(0.035)	(0.030)	(0.022)	(0.031)	(0.019)	(0.023)
Days 26-30℃	-0.108***	-0.089**	-0.068*	-0.041	-0.034*	0.074**	0.033	0.040*
	(0.041)	(0.041)	(0.035)	(0.029)	(0.021)	(0.034)	(0.021)	(0.024)
Days 30-34℃	-0.124**	-0.118**	-0.095**	-0.063*	-0.032	0.092**	0.063**	0.029
	(0.051)	(0.050)	(0.045)	(0.035)	(0.027)	(0.043)	(0.027)	(0.029)
Days 34℃>	-0.303***	-0.231***	-0.209***	-0.120*	-0.087**	0.216***	0.123***	0.093**
	(0.079)	(0.080)	(0.075)	(0.062)	(0.044)	(0.062)	(0.043)	(0.047)
R-squared	0.648	0.687	0.691	0.647	0.573	0.531	0.532	0.359
Observations	322,531	322,531	322,531	322,531	322,531	322,531	322,531	322,531

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. Columns (1)–(5) present the estimates from Equation [2], where the outcome is the z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within school (measured in 0.01σ), along with standard errors clustered at the weather station level in parentheses. Columns (6), (7), and (8) present the estimate of the score gap between the 90th and 10th percentiles, 90th and 50th percentiles, and 50th and 10th percentiles within the school, respectively, measured in 0.01σ. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range (18–22°C). Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table A.6—Student-level analysis of distributional impact of cumulative heat/cold exposure

	(1)	(2)	(3)	(4)	(5)
Outcomes:	**10th percentile**	**25th percentile**	**50th percentile**	**75th percentile**	**90th percentile**
Days 6℃≤	-0.208***	-0.160***	-0.122***	-0.065***	-0.036***
	(0.021)	(0.019)	(0.015)	(0.012)	(0.009)
Days 6-10℃	-0.167***	-0.132***	-0.100***	-0.054***	-0.018**
	(0.019)	(0.015)	(0.011)	(0.009)	(0.007)
Days 10-14℃	-0.170***	-0.126***	-0.065***	-0.018**	-0.019***
	(0.017)	(0.014)	(0.011)	(0.007)	(0.006)
Days 14-18℃	-0.068***	-0.044***	-0.027***	-0.017**	-0.023***
	(0.015)	(0.012)	(0.007)	(0.007)	(0.006)
Days 22-26℃	-0.087***	-0.073***	-0.049***	-0.018***	-0.014***
	(0.014)	(0.010)	(0.008)	(0.006)	(0.004)
Days 26-30℃	-0.112***	-0.093***	-0.076***	-0.035***	-0.016***
	(0.016)	(0.011)	(0.008)	(0.006)	(0.005)
Days 30-34℃	-0.118***	-0.124***	-0.112***	-0.044***	-0.020***
	(0.018)	(0.015)	(0.010)	(0.008)	(0.007)
Days 34℃>	-0.252***	-0.259***	-0.226***	-0.114***	-0.073***
	(0.031)	(0.023)	(0.019)	(0.015)	(0.012)
R-squared	0.022	0.037	0.052	0.059	0.052
Observations	22,792,937	22,792,937	22,792,937	22,792,937	22,792,937

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is each individual. Columns (1)–(5) present the estimates of unconditional quantile regression with school and year FEs, where the outcome is the z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles (measured in 0.01σ), along with the bootstrapped standard errors clustered at the weather station level with 100 repetitions in parentheses. The omitted category is the temperature range (18–22°C). Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A.7—The impact of studying after school

	(1)		(2)	
Outcomes:	**Average Z-score**		**Average Z-score**	
		× study more than 1 hour		× study more than 2 hours
Days 6°C≤	-0.117***	0.151***	-0.126***	-0.042
	(0.041)	(0.038)	(0.041)	(0.049)
Days 6-10°C	-0.064*	0.376***	-0.095**	0.599***
	(0.036)	(0.047)	(0.037)	(0.060)
Days 10-14°C	-0.080**	0.331***	-0.084**	0.316***
	(0.039)	(0.053)	(0.039)	(0.058)
Days 14-18°C	-0.052**	0.415***	-0.047*	0.188**
	(0.026)	(0.063)	(0.025)	(0.080)
Days 22-26°C	-0.053	0.039	-0.047	0.007
	(0.032)	(0.040)	(0.031)	(0.045)
Days 26-30°C	-0.075**	0.288***	-0.077**	0.212***
	(0.030)	(0.042)	(0.030)	(0.051)
Days 30-34°C	-0.094**	0.248***	-0.101***	0.149**
	(0.037)	(0.069)	(0.038)	(0.070)
Days 34°C>	-0.186***	0.403**	-0.206***	0.150
	(0.060)	(0.170)	(0.062)	(0.201)
R-squared	0.748		0.737	
Observations	322,523		322,523	

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. The outcome is the average test score at the school-year level, measured in 0.01σ. Estimates from a variant of Equation [1], which additionally includes the interaction between the fraction of students studying after school for more than 1 hour (column 1) and for 2 hours (column 2), with the number of days in each temperature bin during school days from the previous year, are reported along with standard errors clustered at the weather station level in parentheses. Note that both fractions of students studying after school for more than 1 (column 1) and 2 (column 2) hours are demeaned by the average for the NAAA between 2007 and 2019. The interaction terms in columns (1) and (2) reflect the offsetting effect of studying after school, as the fraction of students studying for more than 1 or 2 hours after school increased from 0% to 100%. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range (18–22°C). Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table A.8—Other robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Average Z-score										
Days above 34°C	-0.562***	-0.568***	-0.557***	-0.297***	-0.278***	-0.409***	-0.381***	-0.503***	-0.552***	-0.551***
	(0.112)	(0.113)	(0.111)	(0.106)	(0.105)	(0.112)	(0.107)	(0.113)	(0.120)	(0.123)
Days above 34°C × school AC	0.413***	0.425***	0.421***	0.400***	0.401***	0.359***	0.335**	0.363**	0.316*	0.440***
	(0.145)	(0.145)	(0.139)	(0.130)	(0.126)	(0.139)	(0.135)	(0.146)	(0.190)	(0.150)
R-squared	0.751	0.751	0.751	0.772	0.772	0.761	0.761	0.751	0.751	0.759
Panel B: 90th-10th score gap										
Days above 34°C	0.709***	0.700***	0.702***	0.586***	0.564***	0.536***	0.544***	0.681***	0.685***	0.729***
	(0.170)	(0.169)	(0.170)	(0.187)	(0.188)	(0.174)	(0.176)	(0.174)	(0.183)	(0.200)
Days above 34°C × school AC	-0.551***	-0.548***	-0.548***	-0.542***	-0.518**	-0.472**	-0.481**	-0.525***	-0.464**	-0.580***
	(0.184)	(0.184)	(0.185)	(0.201)	(0.201)	(0.185)	(0.187)	(0.187)	(0.208)	(0.217)
R-squared	0.552	0.552	0.552	0.573	0.573	0.563	0.563	0.552	0.552	0.568
Observations	190,210	190,210	190,210	145,769	145,769	165,323	165,323	190,210	190,210	141,733
Sample period	Full	Full	Full	2009-2019	2009-2019	2008-2019	2008-2019	Full	Full	Full
Baseline	X			X		X				
Temperature (test day)		X								
Weather (test day)			X							
Pollution (test day)					X					
Pollen (test day)							X			
Weather (cumulative)								X		
Minimum temperature (cumulative)									X	
Sensor within 10 km										X

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. The outcomes in panels A and B are the average test score at the school-year level and the gap between the 90th and 10th percentile scores within the school, measured at 0.01σ, respectively. The estimates for the number of school days above 34°C and their interaction with the school AC dummy are reported along with the standard errors clustered at the weather station level in parentheses, while the estimates for days in other temperature ranges are omitted for expositional purposes. School AC is a dummy variable that takes the value of one if an AC was available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. The estimates are weighted by the number of students in each school year. The omitted category is the temperature range (18–22°C). The full sample period is from 2007 to 2019. Column (1) presents the baseline estimate without any controls other than school and year fixed effects, as reported in column (1) of Table 1 and column (3) of Table 2. Column (2) adds the test-day temperature and column (3) includes additional test-day weather conditions (precipitation, wind speed, and relative humidity). Column (4) replicates the baseline for the 2009-2019 period, as pollution data are only available for this period and column (5) includes test-day air pollution (SO_2, NO, NO_2, CO, OX, and PM_{10}). Column (6) replicates the baseline for the 2008-2019 period, as pollen data are only available for this period and column (7) includes test-day pollen counts. Columns (8) and (9) include other cumulative weather conditions (precipitation, wind speed, and relative humidity) and the number of days within a given minimum temperature bin from the year prior to the test date, respectively. Column (10) restricts the sample to schools located within 10 km of the weather stations. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A.9—Different levels of clustering

	(1)		(2)		Clustering variables	Number of clusters
Outcomes:	**Average Z-score**		**90th-10th score gap**			
Days above 34°C	-0.562		0.709			
	(0.112)	***	(0.170)	***	Station	816
	(0.194)	**	(0.186)	***	Municipality	1,571
	(0.108)	***	(0.267)	**	Prefecture	47
Days above 34°C × school AC	0.413		-0.551			
	(0.145)	***	(0.184)	***	Station	816
	(0.206)	*	(0.198)	***	Municipality	1,571
	(0.124)	***	(0.272)	**	Prefecture	47

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. The outcomes in columns (1) and (2) are the average test score at the school-year level and the gap between the 90th and 10th percentile scores within the school, measured at 0.01σ, respectively. The estimates for the number of school days above 34°C and their interaction with the school AC dummy are reported, while the estimates for days in other temperature ranges are omitted for expositional purposes. School AC is a dummy variable that takes the value of one if an AC was available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. The estimates are weighted by the number of students in each school year. The omitted category is the temperature range (18–22°C). Significance levels: *** *p*<0.01, ** *p*<0.05, * *p*<0.10.

Table A.10—Controlling for school breaks

	(1)	(2)	(3)	(4)
Outcomes:	**Average Z-score**		**90th-10th score gap**	
Days above 34°C	-0.562*** (0.112)	-0.493*** (0.105)	0.709*** (0.170)	0.650*** (0.173)
Days above 34°C × school AC	0.413*** (0.145)	0.386*** (0.130)	-0.551*** (0.184)	-0.545*** (0.190)
Days above 34°C during school break		-0.178** (0.086)		0.244* (0.132)
Days above 34°C during school break × school AC		0.054 (0.202)		-0.002 (0.217)
R-squared	0.751	0.751	0.552	0.553
Observations	190,210	190,210	190,210	190,210

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. The outcomes in columns (1) and (2) are the average test score at the school-year level (measured at 0.01σ) and the outcomes in columns (3) and (4) are the gap between the 90th and 10th percentile scores within the school (measured at 0.01σ). Compared to the odd-numbered columns (baseline), the even-numbered columns additionally include the number of days during the school break within a given maximum temperature bin in the year prior to the test date and their interactions with the school AC dummy. The estimates for the number of days above 34°C and their interaction with the school AC dummy are reported, while the estimates for days in other temperature ranges are omitted for expositional purposes. School AC is a dummy variable that takes the value of one if an AC was available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. The estimates are weighted by the number of students in each school year. The omitted category is the temperature range (18–22°C). Significance levels: *** *p*<0.01, ** *p*<0.05, * *p*<0.10.

Table A.11—Heterogeneous impacts of heat

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	By grade		By subject		By gender		By difficulty		By region	
	6th	9th	Math	Reading	Girls	Boys	Basic	Advanced	Cool	Warm
Panel A: Average Z-score										
Days above 34°C	-0.731***	-0.443***	-0.523***	-0.504***	-0.467***	-0.755***	-0.588***	-0.465***	-0.530***	-0.520***
	(0.180)	(0.109)	(0.111)	(0.118)	(0.123)	(0.145)	(0.123)	(0.108)	(0.128)	(0.178)
Days above 34°C × school AC	0.378*	0.495***	0.309**	0.431***	0.356**	0.581***	0.395***	0.132	0.470***	0.312
	(0.210)	(0.148)	(0.145)	(0.142)	(0.153)	(0.176)	(0.153)	(0.141)	(0.142)	(0.220)
R-squared	0.682	0.807	0.742	0.712	0.676	0.679	0.741	0.753	0.721	0.778
Panel B: 90th-10th score gap										
Days above 34°C	1.110***	0.493***	0.590***	0.654***	0.669***	0.767***	0.819***	0.378**	0.746***	0.462
	(0.234)	(0.190)	(0.147)	(0.228)	(0.206)	(0.195)	(0.258)	(0.176)	(0.198)	(0.317)
Days above 34°C × school AC	-0.776***	-0.505**	-0.407**	-0.626***	-0.575***	-0.588***	-0.584**	-0.297	-0.591**	-0.284
	(0.256)	(0.211)	(0.170)	(0.241)	(0.219)	(0.215)	(0.274)	(0.198)	(0.243)	(0.324)
R-squared	0.377	0.678	0.536	0.518	0.427	0.475	0.557	0.488	0.507	0.594
Observations	115,312	74,898	190,210	190,210	176,297	176,169	173,005	173,005	105,672	84,538

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. The outcomes in panels A and B are the average test score at the school-year level and the gap between the 90th and 10th percentile scores within the school, measured at 0.01σ, respectively. The estimates for the number of school days above 34°C and their interaction with the school AC dummy are reported along with the standard errors clustered at the weather station level in parentheses, while the estimates for days in other temperature ranges are omitted for expositional purposes. School AC is a dummy variable that takes the value of one if an AC was available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range (18–22°C). Columns (1) and (2) present the estimates by grade (grade 6 vs. grade 9). Columns (3) and (4) show estimates by subject area (math vs. reading). Columns (5) and (6) show estimates by student gender (girls vs. boys). Columns (6) and (7) present the estimates based on the difficulty of the test questions (basic vs. advanced). Finally, Columns (9) and (10) divide the sample into cool and warm regions based on the national median of the average temperature from 2006 to 2018. Note that the number of observations is at the school-year level; therefore, we observe the average test score of each school-year for each subject, gender, and question difficulty, while we observe only one test score for each grade and each region, as they are mutually exclusive. Thus, the sum of the observations in columns (1) and (2) and the sum of the observations in columns (9) and (10) is 190,210, which is equal to the number of school-years in columns (3) and (4). The slightly smaller observations for columns (5) and (6), compared with columns (3) and (4), are because gender information was not collected for grade 6 in 2015. Similarly, the slightly smaller observations in columns (7) and (8) compared to those in columns (3) and (4) are due to the absence of such a distinction in 2019. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A.12—Distributional impact of school AC (at the five key percentile scores)

	(1)		(2)		(3)		(4)		(5)	
Outcomes:	**10th percentile score**		**25th percentile score**		**50th percentile score**		**75th percentile score**		**90th percentile score**	
		× school AC		× school AC		× school AC		× school AC		× school AC
Days 6°C≤	-0.320***	0.040	-0.293***	0.112	-0.257***	0.143	-0.152**	0.044	-0.099**	0.050
	(0.101)	(0.124)	(0.092)	(0.113)	(0.080)	(0.107)	(0.062)	(0.090)	(0.047)	(0.076)
Days 6-10°C	-0.207**	0.088	-0.187***	0.098	-0.206***	0.166*	-0.124**	0.115	-0.075*	0.104*
	(0.083)	(0.103)	(0.072)	(0.097)	(0.061)	(0.091)	(0.051)	(0.076)	(0.040)	(0.059)
Days 10-14°C	-0.196**	0.043	-0.113	0.001	-0.117*	0.081	-0.059	0.064	-0.047	0.067
	(0.082)	(0.108)	(0.074)	(0.109)	(0.065)	(0.102)	(0.049)	(0.077)	(0.035)	(0.053)
Days 14-18°C	-0.027	-0.039	-0.009	-0.017	-0.047	0.050	-0.053	0.064	-0.046	0.067
	(0.062)	(0.083)	(0.057)	(0.080)	(0.045)	(0.067)	(0.037)	(0.053)	(0.030)	(0.042)
Days 22-26°C	-0.034	-0.070	-0.044	-0.049	-0.045	-0.019	-0.013	-0.036	-0.000	-0.042
	(0.057)	(0.083)	(0.054)	(0.082)	(0.049)	(0.075)	(0.037)	(0.061)	(0.026)	(0.043)
Days 26-30°C	-0.218***	0.075	-0.187***	0.056	-0.150***	0.077	-0.083*	0.041	-0.030	-0.024
	(0.063)	(0.087)	(0.061)	(0.089)	(0.056)	(0.079)	(0.047)	(0.065)	(0.035)	(0.046)
Days 30-34°C	-0.271***	0.136	-0.274***	0.149	-0.187**	0.108	-0.110*	0.057	-0.065	0.020
	(0.085)	(0.102)	(0.081)	(0.097)	(0.074)	(0.090)	(0.062)	(0.074)	(0.049)	(0.058)
Days 34°C>	-0.932***	0.690***	-0.813***	0.624***	-0.610***	0.461***	-0.341***	0.262*	-0.223***	0.139
	(0.176)	(0.201)	(0.151)	(0.186)	(0.133)	(0.171)	(0.113)	(0.149)	(0.085)	(0.108)
R-squared	0.669		0.708		0.714		0.673		0.603	
Observations	190,210		190,210		190,210		190,210		190,210	

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. Columns (1)–(5) present the estimates from the variant of Equation [3], where the outcomes are z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools (measured in 0.01σ), along with standard errors clustered at the weather station level in parentheses. School AC is a dummy variable that equals one if an air conditioner is available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range (18–22°C). Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table A.13—The impact of school AC (school AC 0% vs. AC>0%)

	(1)		(2)		(3)	
Outcomes:	**10th percentile score**		**90th percentile score**		**90th-10th score gap**	
		× school AC		× school AC		× school AC
Days 6°C≤	-0.201*	-0.060	-0.024	0.003	0.178*	0.062
	(0.104)	(0.116)	(0.049)	(0.057)	(0.092)	(0.105)
Days 6-10°C	-0.178**	-0.013	-0.047	0.020	0.130*	0.033
	(0.084)	(0.091)	(0.041)	(0.045)	(0.078)	(0.083)
Days 10-14°C	-0.213**	0.005	-0.061*	0.042	0.152**	0.037
	(0.086)	(0.092)	(0.034)	(0.037)	(0.075)	(0.079)
Days 14-18°C	-0.027	-0.069	-0.051*	0.029	-0.024	0.098
	(0.064)	(0.071)	(0.030)	(0.033)	(0.053)	(0.061)
Days 22-26°C	0.014	-0.090	0.013	-0.041	-0.001	0.049
	(0.059)	(0.070)	(0.026)	(0.032)	(0.053)	(0.059)
Days 26-30°C	-0.121*	0.064	0.004	-0.021	0.125**	-0.085
	(0.062)	(0.071)	(0.031)	(0.036)	(0.057)	(0.065)
Days 30-34°C	-0.154*	0.083	-0.015	0.003	0.139*	-0.080
	(0.086)	(0.093)	(0.046)	(0.049)	(0.081)	(0.087)
Days 34°C>	-0.803***	0.667***	-0.155**	0.119	0.648***	-0.549***
	(0.182)	(0.196)	(0.079)	(0.089)	(0.178)	(0.191)
R-squared	0.649		0.574		0.532	
Observations	322,341		322,341		322,341	

Notes: This table replicates the main results from Table 2, but classifies schools from municipalities with partial air conditioning coverage (>0% and <100%) as "with AC." The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. Column (1) presents the estimates from Equation [3] where the outcome is the average test score at the school-year level (measured in 0.01σ). Columns (2) and (3) present the estimates from the variant of Equation [3], where the outcomes are z-scores at the 10th and 90th percentiles within schools (measured in 0.01σ). School AC is a dummy variable that equals one if an air conditioner was available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. Column (4) presents the estimate of the score gap between the 90th and 10th percentiles within the school (measured in 0.01σ). Standard errors are clustered at the weather station level in parentheses. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range between 18 and 22°C. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table A.14—Robustness: The impact of school AC on academic inequality

	(1)		(2)		(3)	
Outcomes:	**90th-10th score gap**		**90th-10th score gap**		**90th-10th score gap**	
		× school AC		× school AC		× school AC
Days 6°C≤	0.222**	0.011	0.225***	0.025	0.154	0.107
	(0.086)	(0.110)	(0.086)	(0.110)	(0.094)	(0.123)
Days 6-10°C	0.132*	0.016	0.121	-0.015	0.052	0.122
	(0.078)	(0.089)	(0.077)	(0.089)	(0.086)	(0.102)
Days 10-14°C	0.149**	0.025	0.134*	0.065	0.115	0.081
	(0.074)	(0.088)	(0.074)	(0.088)	(0.079)	(0.099)
Days 14-18°C	-0.019	0.106	-0.054	0.130*	-0.051	0.146
	(0.052)	(0.078)	(0.056)	(0.078)	(0.063)	(0.089)
Days 22-26°C	0.034	0.028	0.029	0.037	0.063	-0.008
	(0.050)	(0.068)	(0.053)	(0.070)	(0.057)	(0.078)
Days 26-30°C	0.188***	-0.099	0.185***	-0.137*	0.233***	-0.154*
	(0.053)	(0.075)	(0.054)	(0.072)	(0.058)	(0.081)
Days 30-34°C	0.207***	-0.116	0.213***	-0.143	0.257***	-0.213**
	(0.076)	(0.094)	(0.078)	(0.098)	(0.082)	(0.107)
Days 34°C>	0.709***	-0.551***	0.629***	-0.402**	0.714***	-0.584***
	(0.170)	(0.184)	(0.172)	(0.191)	(0.169)	(0.199)
Interaction with						
taxable income			X			
student-teacher ratio			X			
home AC share					X	
R-squared	0.552		0.553		0.552	
Observations	190,210		188,911		190,210	

Notes: The data come from the NAAA (2007–2019) and AMeDAS (2006–2018). The unit of observation is the school-year. The outcome is the gap between the 90th and 10th percentile scores within the school, measured at 0.01σ. Columns (1)–(3) present the estimates from the variant of Equation [2], which additionally includes the interaction of the number of school days within a given maximum temperature bin in the year prior to the test date and the school AC dummy, along with standard errors clustered at the weather station level in parentheses. School AC is a dummy variable that equals one if an air conditioner is available at the school in 2018. Figure 5 shows the locations of the schools within each AC penetration category. Column (1) replicates the estimates in column (3) of Table 2. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range (18–22°C). Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Appendix B: Data Appendix

Data	**Source**
National Assessment of Academic Ability (NAAA)	Years: 2007–2019 Data description: Reading and math scores for grades 6 and 9, after-school study participation (student survey), and students' socioeconomic status (parent survey, conducted only in 2013 and 2017) Source: The National Institute for Educational Policy Research https://www.nier.go.jp/kaihatsu/zenkokugakuryoku.html
Weather	Years: 2006–2019 Data description: daily temperature (maximum, average, minimum), precipitation, wind speed, and relative humidity Source: Japan Automated Meteorological Data Acquisition System (AMeDAS) operated by the Japan Meteorological Agency (JMA) https://www.data.jma.go.jp/obd/stats/etrn/
Pollution	Years: 2009 April–2019 March Data description: hourly SO_2, NO, NO_2, CO, OX, PM_{10} Source: National Institute for Environmental Studies https://tenbou.nies.go.jp/download/
Pollen	Years: 2008–2019 Data description: hourly pollen counts from 120 stations (February to May except for Hokkaido, where the pollen season is March to June). Source: Ministry of the Environment (MOE), Pollen Monitoring System "Hanako-san" https://tenki.jp/pollen/
School enrollment	Years: 2009–2019 Data description: the number of students enrolled at each school as of May 1 Source: School Basic Survey https://www.mext.go.jp/b_menu/toukei/chousa01/kihon/1267995.htm
Taxable income	Years: 2006–2018 Data description: taxable income per capita at the municipality level Source: Survey on Municipal Taxation Status (Shichōsonzei kazeijōky tou no shirabe) https://www.soumu.go.jp/main_sosiki/jichi_zeisei/czaisei/czaisei_seido/ichiran09.html
Student-teacher ratio	Years: 2006–2018 Data description: student-teacher ratio at the municipality level Source: School Basic Survey https://www.mext.go.jp/b_menu/toukei/chousa01/kihon/1267995.htm
School AC penetration rate	Year: 2018 Data description: school AC penetration rate for public primary and secondary schools at the municipality level Source: Survey of Air Conditioning Installation Status in Public School Facilities https://www.mext.go.jp/a_menu/shotou/zyosei/mext_01278.html
Home AC share	Year: 2014 Data description: home AC share at the prefecture level National Survey of Family Income and Expenditure https://www.stat.go.jp/data/zensho/2014/index.html