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## Abstract

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

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**Abstract**

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

**JEL code:** I21, I24, Q54

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## 1. Introduction

The impact of global warming on economic inequality is a growing concern (Diffenbaugh and Burke 2019). Previous studies suggest that poor countries and individuals are disproportionately affected by climate change (Dell et al. 2012; Burke et al. 2015). However, these studies have not fully isolated whether this is because they live in warmer regions and experience higher temperatures ("exposure"), or because they have limited resources and poorer health, thereby making them more susceptible to the same heat exposure ("vulnerability"). This distinction is crucial because they require different policy responses: exposure-focused policies to reduce direct contact with extreme heat (e.g., urban cooling and housing interventions), or vulnerability-focused policies that enhance adaptive capacity (e.g., subsidies for air conditioning, healthcare access) to improve the heat resilience among the poor (Hsiang et al. 2019).

Cognitive skills, a key aspect of human capital, play a key role in shaping labor market outcomes and widening the economic gap between the rich and poor (Cunha and Heckman 2007). Children's cognitive functions may be particularly vulnerable to environmental stressors owing to their physiological and neurocognitive immaturity (Rowland 2008). Therefore, prolonged exposure to extreme temperatures can disrupt students' learning owing to distractions and loss of concentration, ultimately leading to a lasting impact on the accumulation of students' human capital. Therefore, the warming climate underscores the importance of improving children's learning environments.

This study examines how cumulative exposure to extreme heat affects student achievement differently based on their socioeconomic background. Historically, educational investment has played a critical role in strengthening economies and improving the social distribution of income and wealth (Hanushek et al. 2003; Blandena et al. 2023). Although progress has been made in understanding the *average* impact of heat on educational outcomes and the effectiveness of mitigation measures (e.g., Park et al. 2020), the *distributional* impacts remain largely unexplored.

Assessing distributional impacts, particularly identifying which individuals bear the burden of heat-related damage disproportionately, requires a representative sample. However, prior studies have been unable to assess the distributional impacts owing to their *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 PSAT in the United States. These students are likely to come from a higher socioeconomic background than the general population, making them unsuitable for a distributional analysis. Park et al. (2021) used school district-level achievement data from the US, precluding an analysis by socioeconomic status (SES) within districts.

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, covering approximately 22.8 million students. Importantly, the combination of individual-level data and the nationally representative nature of the exams provides an ideal setting for examining, for the first time, the distributional impact of temperature on test scores *within* schools. By holding the "exposure" constant for all the 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 is likely to reflect differences in "vulnerability" by socioeconomic backgrounds (e.g., differential access to private tutoring).

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 summer (milder winter) school days. Since a student's rank correlates with socioeconomic factors, 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 based on SES.

This study has four main findings. First, we demonstrate that cumulative exposure to both hot and cold school days negatively affects student learning, *on average*. While prior studies have examined the cumulative impact of heat (Cho 2017; Park et al. 2020, 2021) and cold (Johnston et al. 2021) exposure separately, we show that both extremely hot and cold school days in the previous academic year impair the learning environment. Specifically, each additional summer school day above 34°C, compared with the normal temperature range of 18–22°C, reduces test scores by 0.19% of a standard deviation (SD). Similarly, replacing a day of normal temperature at 18–22°C with a winter school day below 6°C also reduces test scores by 0.13% of SD.

Second, and most importantly, we document that the negative impact of extreme temperatures significantly varies among students across different score distributions. Specifically, we find that the adverse effects of heat are far greater for low-performing students than for top performers. Each additional day above 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 highlights how the average effects mask the substantial heterogeneity of heat damage between low-performing students and their high-performing peers, overlooking a source of academic inequality.

Importantly, by comparing temperature effects within schools (i.e., with the school fixed effect), we hold school-level "exposure" constant, eliminating influences by school-level resources such as staffing ratio, teacher quality, or access to air conditioning. Instead, the results likely reflect differences in "vulnerability"—how advantaged and disadvantaged students differentially adapt to the same school heat exposure after school or at home. Indeed, advantaged students tend to study longer after school, spend more money 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 public investment in school infrastructure, climate change will widen pre-existing socioeconomic disparities among children.

Third, we examine whether adaptation through school air conditioning (AC) can mitigate the impact of heat on learning. Strikingly, all the negative effects of heat occur in schools without AC. Conversely, if considered causal, school AC largely offset the adverse effects of heat. On average, without school AC, test scores decline by 0.56% SD by one additional day above 34°C, but access to school AC lessens this by 0.41% SD, indicating that AC alleviates approximately 73% of the negative effects of heat on learning. However, since school AC may correlate with other adaptive technologies in the school or with additional resources available to students that could independently enhance learning, the results should be interpreted with caution.

Finally, we examine how the impact of school AC availability differs among students across various score distributions. In schools without AC, the negative effects of extreme temperatures are significantly more pronounced for low-performing students, who are more likely to come from low-SES backgrounds. However, in schools with AC, extreme heat has little impact on test scores across all achievement levels. Consequently, the benefits of such public investments are *progressive,* benefiting low-performing students more than high-performing ones. Specifically, without AC, one extra day above 34°C widens the 90th–10th score gap by 0.71% SD, but school AC reduces this widening gap by 0.55% SD. This finding suggests that public investment, such as installing AC in schools (instead of at the household level), can largely mitigate unevenly distributed heat damage. This is particularly encouraging because both primary and secondary education are compulsory in Japan, as in many other countries where public investment plays a critical role.

This study contributes to several strands of literature. First, it contributes to the nascent body of research on the distribution of climate damage (Hsiang et al. 2019) and environmental inequality more broadly (Banzhaf et al. 2019; Cain et al. 2024). We show that heat disproportionately impairs the human capital accumulation of disadvantaged students, suggesting that they face not only greater exposure to climate risks but also greater vulnerability to these risks, both of which may contribute to the widening socioeconomic disparities among students.

Second, this study contributes to the emerging literature linking environmental and economic inequalities (Diffenbaugh and Burke 2019; Gilli et al. 2024). As educational attainment and earnings are positively correlated (Chetty et al. 2011), our findings suggest that environmental inequality, which worsens educational inequality, could be a pathway through which global warming accelerates economic inequality. Specifically, our sample (grades six and nine) comprises younger students compared with samples from other studies that focused more on students nearing high school graduation (Cho 2017; Park et al. 2020). Dynamic complementarities, in which human capital investment in early childhood may 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.

Third, this study contributes to the literature on temperature adaptation (Carleton et al. 2022; Burke et al. 2024), addressing whether environmental hazards are unavoidable or can be mitigated using current technology.[1] 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 educational outcomes, a seminal study by Park et al. (2020) demonstrated that school AC reduces the cumulative impact of heat on learning. Moving beyond the average impact, we examine its distributional effects, revealing how adaptation unequally benefits students.

Finally, this study contributes to the debate on the effectiveness and efficiency of resource-based education policies in relation to the accumulation of human capital (Baron 2022; Cellini et al. 2010; Jackson et al. 2015; Lafortune et al. 2018), particularly focusing on investments in school facilities (Lafortune and Schönholzer 2022; Martorell et al. 2016; Neilson and Zimmerman 2014). With a few exceptions, such as mold remediation and ventilation by Stafford (2015) and school air conditioning by Park et al. (2020), previous studies have not examined the impact of upgrades on specific school facilities. To the extent that policymakers are concerned about equity, the social returns on public investment in school infrastructure, particularly school AC, may be higher than previously recognized.

The remainder of the paper is structured as follows: Section 2 offers a simple conceptual framework; Section 3 details the data; Section 4 outlines the econometric model; Section 5 discusses the baseline findings on the cumulative effects of heat and cold on test scores as well as their distributional implications; Section 6 examines the offsetting impact of school air conditioning on these adverse effects; and finally, Section 7 concludes the study.

## 2. Conceptual framework

This section outlines a simple conceptual framework for the distributional impact of extreme temperatures, based on Hsiang et al. (2019) and Behrer et al. (2021). We discuss below how an empirical observation—that climate impacts are often greater for poor countries/regions/individuals—can mask two different explanations: differing *exposure* and/or

[1] See, for example, Carleton et al. (2024) for a review of this literature.

*vulnerabilities* by socioeconomic conditions.

Damage is defined as a function of two factors: the level of exposure to environmental stressors (e.g., heat, cold, and pollution) and vulnerability, both of which can correlate with SES (e.g., income, education, and occupation). Marginal damage, which is the slope of the damage function, can vary by SES for two reasons. First, as shown in panel A of Figure 1, nonlinearities in the exposure-damage relationship can lead to greater damage for low-SES individuals who experience more heat exposure than their high-SES counterparts.[2] 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.

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. If the issue is differential exposure by SES, reducing direct contact with extreme heat (e.g., urban cooling, housing interventions, and warning systems) could help. Conversely, if vulnerability varies by SES, policies should prioritize targeted support to enhance adaptive capacity (e.g., subsidizing air conditioning and expanding medical programs to address heat-related illnesses) or promote broader poverty reduction to strengthen the heat resilience of low-SES individuals (Hsiang et al. 2019; Burke et al. 2024).

However, distinguishing between exposure and vulnerability is difficult because both exposure and vulnerability are highly correlated with SES. For example, economic damages from hot temperatures are greater in poorer regions (Dell et al. 2012; Burke et al. 2015), which are also often hotter, reflecting both exposure and vulnerability (Behrer et al. 2021). 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, holding exposure constant, at least in the school environment where most learning is supposed to occur. If the reductions in test scores are greater for low-SES students than for their high-SES counterparts in the same school with identical heat exposure, this suggests that the difference in marginal damages likely arises from the 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 the school AC penetration data in Section 6.

[2] Park et al. (2018) demonstrated that the poor tend to live in hotter locations both within and across countries.

### 3.1. Test score

We use data on the nationwide exams, called the National Assessment of Academic Ability (hereinafter referred to as "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 the improvement of educational policies (MEXT 2024a). The NAAA has been conducted annually since 2007, except in 2011, when the NAAA was completely canceled because of the Great East Japan Earthquake, and in 2010 and 2012, when the NAAA was administered to a random subset of schools.[3]

The NAAA is administered to students in their final years of public primary (grade six) and secondary school (grade nine).[4] Both primary and secondary education are compulsory in Japan. Nearly 100% of public primary and secondary schools participated in the NAAA (NIER 2024). Although the subjects varied slightly over time, we focus on reading and mathematics, which are consistently assessed throughout our sample period.

The NAAA is held on the 3rd or 4th Tuesday of April[5], 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).[6] This timing aligns well 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 the timing of test-taking or score manipulation.

The NAAA is not a high-stakes exam for students or schools. Students' scores do not affect their promotion to higher grades or better schools. Furthermore, school performance has no direct consequences, such as reduced federal funding, unlike test-based accountability systems such as the No Child Left Behind Act in the United States. The only potential stakes are reputation concerns for schools (Morozumi and Tanaka 2023).

We use 2007–2019 NAAA data with MEXT's permission for the secondary use of confidential information. Appendix Table A1 details the number of participating schools and students each year. From 2007 to 2019, approximately 22.8 million students took the exams, with approximately 30,000 schools participating annually (excluding 2010 and 2012). See Appendix Figure A1 for the school locations. For statistical power, we combine both grades in the main analysis unless stated otherwise. Since the exams are administered to both grades on the

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

[4] In 2022, 1.3% of primary and 7.7% of secondary students attended private schools (MEXT 2022). Japan's compulsory education includes six years of primary (ages 6–12) and three years of secondary (ages 12–15). School grades are strictly age-based due to rigid entry rules, rare grade retention, and consistent promotion rates (Shigeoka 2015).

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

[6] The NAAA is not designed to measure general intelligence or IQ.

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 and multiply them by 100 for interpretation as percentage changes. Student-level data include limited demographics such as gender. The NAAA also conducts student surveys in every round and parental surveys in 2013 and 2017. Student surveys capture behaviors (e.g., after-school study), while parental surveys (administered to about 4.8% of randomly selected schools)[7] collect household information such as household income, father's occupation, and parental education. Panel A of Appendix Table A2 provides descriptive statistics of the 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 a subset of 899 weather stations that have daily temperature information available for at least 99% of the days from 2006 to 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 that our estimates remain unaffected by changes in the number or location of the stations.

Panel A of Appendix Figure A2 displays the locations of all 899 weather stations as of 2018. The density of stations is high, given the country's size.[8] Panel B illustrates the cumulative distribution of the distance from the nearest station to each school. The mean (median) distance is 6.95 (6.48) km, compared with 15.6 km in the US (Park et al. 2020).

Our primary measure of cumulative exposure to extreme temperatures is the number of hot and cold school days that 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 use the daily maximum temperature, because it typically occurs during school hours. Following Park et al. (2020), we focus on temperatures during terms as school days and treat school break days and weekends during terms as separate non-school days.[9]

[7] 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 (172,418 responses).

[8] For example, the United States, which is 26 times larger than Japan, has only 3.3 times (nearly 3,000) valid weather stations nationwide (Park et al. 2020).

[9] 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 national school calendar dataset, we assign each school a probable start and end date using the 2018 calendar of its prefectural capital (Appendix Figure A3). Colder regions tend to have shorter summer and longer winter breaks, while warmer regions show the reverse.

We also use weather station data to construct both cumulative and test-date measures for rainfall, wind speed, and relative humidity. We also include pollution data from the nearest monitoring station, as it is known to impact short-term cognition (e.g., Ebenstein et al. 2016). Panel B of Appendix Table A2 presents the descriptive statistics of the weather conditions in our main sample.

## 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 the test scores of students in the same school who experienced hotter summers or cooler winters with those exposed to milder conditions.

Figure 2 shows the spatial variation in the mean daily maximum temperature of the previous year (panel A) and temporal variation in school days within each temperature bin from last April to March of the test year (panel B). Panel A highlights significant climate differences across regions, whereas panel B reveals considerable year-to-year variations in both cold and hot school days.[10]

To reduce the computational burden, we collapse the data into school-year cells and weigh all 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. Since exams are held at the beginning of the academic year to assess material from the previous academic year, considering hot and cold days from the previous summer and winter is reasonable because they may disrupt the learning environment.

This specification enabled us to flexibly capture the nonlinear temperature effects. The coefficient of interest are $\beta^k$. $\rho_s$ and $\theta_t$ 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 variation in our treatment variable (Abadie et al. 2023).

[10] Extremely hot school days are rarer than cold ones since the summer break (typically in August) effectively prevents attendance during peak heat.

The underlying assumption for $\beta^k$ 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.

*Identifying variation*—. To visualize the identifying variation underlying the baseline specification, we plot residuals from a regression of the number of school days below 6°C and above 34°C against school fixed effects. Figure 3 illustrates the interquartile and interdecile ranges of the residual variations by prefecture and year. These distributions confirm ample variation 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 that it moves beyond the effect of temperature on average test scores (Equation [1]) and examines its distributional impacts. Using individual test scores linked to school IDs, we assess the effect of the temperature by the score rank within schools. Specifically, for each school, we compute the z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools. We then run each value separately as the outcome as follows.

$$Z\text{-} score\ at\ X\ percentile\ (X\ = 10, 25, 50, 75, and\ 90)_{st}$$
$$= \sum_k \beta^k T^k_{st} + \rho_s + \theta_t + \delta X'_{st} +\ \varepsilon_{st}, [2]$$

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

What does the within-school rank capture? The 2013 and 2017 NAAA surveys of parents in a subset of schools show a strong positive correlation between student rank and socioeconomic background. Figure 4 illustrates this monotonic relationship with household income (panel A), father's occupation (panel B), and parents' education (panels C and D). For example, the income gap between the 90th and 10th percentiles is 1.79 million yen (approximately 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 is largely indicative of their socioeconomic status.

Finally, we demonstrate that the variation in scores within schools reflects most of the variation in scores at the national level. Figure 5 shows the within-school score distribution by school rank, grouping schools into ventiles based on each year's average scores. 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 in test scores.[11]

# 5. Baseline results

## 5.1. Average effects

First, we present graphical evidence of the average effects of cumulative exposure to heat and cold on test scores. Figure 6 shows $\beta^k$ from equation [1] with 95% confidence intervals, where test scores are measured in hundredths of a standard deviation. The figure indicates that test scores decline as the number of hot or cold school days increases. The extremely hot days at the right end of the figure (above 34°C) and extremely cold days at the left end (below 6°C) are especially harmful to student learning, highlighting the nonlinear impact of temperature on learning.

This aligns with the well-documented “U-shaped” mortality-temperature relationship (or “inverse-U” in our case, 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 the same country impair students’ learning environments and hinder teachers’ abilities to teach by causing distractions and a loss of concentration.

In terms of magnitude, one additional school day below 6°C or above 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 on test scores (see Appendix Table A3 for details). However, differences in institutions across countries (such as teacher quality, class size, and AC availability), along with variations in climate, necessitate caution when making international comparisons. For comparison, Cho (2017) found that in Korea, one extra day above 34°C (vs. 28–30°C) reduces math and English scores by 0.42% and 0.64% SD, respectively, for G12 students. In the US, Park et al. (2020) reported score declines of 0.07% SD for days above 100°F (37.8°C) and 0.05% SD for days above 90°F (32.2°C) (vs. 60s°F) for G10/11 students. Park et al. (2021a) showed that one extra day above 80°F (26.7°C) (vs. 60–69°F) lowers test scores by 0.10% SD for G3–G5 and 0.03% SD for G6–G8. Regarding cold exposure, Johnston et al. (2021) found that one additional day below 60°F (15.6°C) (vs. 65–75°F) decreases test scores by 0.12% SD in Australia.

## 5.2. Distributional impact

Next, we examine whether the negative impacts of extreme temperatures significantly

[11] 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 to private ones. Furthermore, the school curriculum is uniformly determined by the MEXT’s Course of Study.

varies among students across different score distributions. Figure 7 presents $\beta^k$ from Equation [2], where z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools (in 0.01σ) are the outcomes. This figure clearly indicates that the negative effects of extreme temperatures are significantly greater for lower-performing students. Appendix Table A4 provides the corresponding estimates.

One additional hot day above 34°C lowers scores by 0.09% SD for students in the top 10th percentile (i.e., 90th percentile), while the impact on the bottom 10th percentile is 0.30% SD, which is approximately three times larger. Adverse effects consistently increase as the rank decreases. Similarly, an extra cold day below 6°C leads to a negligible reduction of 0.03% SD for students in the top 10th percentile (not statistically significant), while the bottom 10th percentile experiences a decline of 0.26% SD. Consequently, both the extremely hot and cold conditions widen the test score gap between the 90th and 10th percentiles by 0.22% and 0.23% SD, respectively. Given the strong link between academic performance and SES (Figure 4), 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 (with school FE), keeping "exposure" at school constant, our results are not driven by school resources (e.g., class size, teacher quality, or AC). Instead, they likely reflect "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 the underlying *sources* of such heterogeneity in vulnerability owing to limited data on detailed student and household behaviors during the hot and cold days of the previous summer and winter.

Nevertheless, Appendix Figure A4 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, Appendix Table A5 suggests that longer after-school study hours may mitigate the negative effects of heat exposure.[12] However, other factors such as better baseline health among higher-SES students (Case et al. 2002), may also contribute to the observed heterogeneity. Understanding the specific sources of these unequal vulnerabilities is an avenue for future research.

[12] 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.

## 6. The impact of AC

### 6.1. Average effects of school AC

Air conditioning (AC) is the main technology for adapting to heat (Barreca et al. 2016), but its widespread adoption in public primary and secondary schools in Japan has occurred only recently. 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.[13]

Unfortunately, the government began reporting the penetration rates of school AC in public primary and secondary schools at the municipal level only in 2017 (MEXT 2024b). The school council of each municipality determines the installation of AC in public schools within the municipality.[14] 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"), and intermediate AC penetration. 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.

Figure 8 maps municipalities with 100% ("schools with AC"), 0% ("schools without AC"), and partial (>0% & <100%) AC penetration. Clearly, schools without AC are more common in the cooler northern region, while both with and without AC are widely distributed in central Honshu, Japan's main and largest island.

One concern is that school AC penetration may correlate with many factors at the school or municipal levels that could directly impact test scores. However, Figure 9 shows that after controlling for 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, a measure of per-pupil educational expenditure at school (panel B). School AC could still correlate with other adaptive technologies or resources that could independently enhance student learning; therefore, the results below should be interpreted with caution.

We now examine the average impact of access to school AC on test scores. Figure 10 illustrates $\beta^k$ from Equation [1] separately for schools with and without AC. Strikingly, all the negative effects of heat are concentrated 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 formal regression analysis. Specifically, we interact the cross-sectional measure of AC penetration in 2018 ("school AC" dummy) with the number of school days in each temperature

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

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

bin and include them in our 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 Appendix Figure A5 shows, results remain robust when including schools from municipalities with partial AC (>0% & <100%) in the "with AC" category. Specifically, we estimate

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

where the coefficient $\beta^k$ now measures the impact of heat on a school without AC, while $\gamma^k$ represents the difference in that impact compared to a fully air-conditioned school. Table 1 reports $\beta^k$ and $\gamma^k$ from Equation [3]. Column (1) shows that school AC largely offsets the negative effects of extreme heat (above 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 on learning.

The offsetting effect of school AC may reflect other factors that correlate with AC availability. To address this concern, column (2) controls for interactions between temperature bins, municipality-level taxable income per capita, and the student-teacher ratio. The results remain robust and consistent with Figure 9, which shows that school AC is not strongly correlated with these variables. Column (3) further controls for the home AC share, although its measurement at the prefecture level contains significant measurement errors. Nevertheless, the school AC effect persists, suggesting that it does not merely capture the effect of home AC availability.

*Other robustness*—. Appendix Table A6 presents additional robustness checks. The estimates for the days above 34°C and their interaction with the school AC dummy are reported due to their greatest relevance to global warming. Column (1) shows baseline estimates with only school and year fixed effects. Columns (2) and (3) add test-day temperature and weather conditions (precipitation, wind speed, and humidity), yet estimates remain stable, confirming that they do not reflect contemporaneous weather effects. This is expected because the weather in April in Japan is relatively mild. Column (4) includes the test-day air pollution ($SO_2$, NO, $NO_2$, CO, OX, and $PM_{10}$) for 2009–2019, the available period. Column (5) adds cumulative weather conditions beyond temperature; however, the estimates remain largely unchanged. Columns (6) and (7) control for hot days during non-school periods (school break days and weekends), following Park et al. (2020). The results remain unchanged, indicating that our estimates of cumulative heat are not mainly driven by the heat experienced during non-school periods. Finally, to minimize the measurement error in heat exposure, column (8) limits the sample to schools within 10 km of a weather station (72.5% of the sample); however, the estimates remain largely unaffected.

*Heterogeneity*—. Appendix Figure A6 and Table A7 explore the heterogeneous effects of heat above 34℃ 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),[15] and climate (cool vs. warm regions). Overall, the impact of heat and offsetting effect of AC appear to be consistent across contexts, indicating that the underlying mechanism linking heat exposure to test scores may be generalizable across various contexts. A few notable exceptions are that heat above 34°C affects 6th graders more than 9th graders (-0.731 vs. -0.443) and boys more than girls (-0.755 vs. -0.467) by approximately 50%, suggesting greater vulnerability to heat in younger children and boys. Notably, school AC offset the effect on basic but not advanced questions, aligning with its stronger benefit for lower-achieving students, as shown next.

### 6.2. Distributional impact of school AC

Finally, we analyze how the impact of school AC availability differs among students across various score distributions. Figure 11 presents $\beta^k$ from Equation [2], separately for schools without AC (panel A) and with AC (panel B). In schools without AC, heat still disproportionately harms lower-ranked students, whereas in schools with AC, nearly all the negative effects disappear across ranks. Notably, the benefit is *progressive*, favoring lower-performing students over their higher-performing peers. As expected, school AC does not affect performance under extremely cold conditions (below 6°C). However, panel A, without school AC, shows that heat is much more likely to exacerbate pre-existing academic inequalities than cold, without any intervention.

To formally assess how school AC mitigates heat-driven inequality in learning, we estimate a variant of the Equation [3], where the outcomes are z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools (measured in 0.01σ). Table 2 presents the estimates for the 10th and 90th percentile test scores as outcomes in columns (1) and (2) along with the 90th–10th score gap in column (3). The complete table showing the results from the other percentile test scores can be found in Appendix Table A8.

Column (1) shows that high temperatures (above 34°C) without AC reduce scores at the 10th percentile by 0.93% SD. Since these schools lack AC, the estimates reflect the "pure" negative impact of heat without reflecting any offsetting effects.[16] However, the interaction term

[15] 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 (Appendix Figure A7). The two scores are highly correlated, with correlations of 0.90 (average), 0.83 (math), and 0.85 (reading) for 6th graders.

[16] Conversely, the distributional impact of a cold day below 6°C is similar for schools with and without school AC.

is positive and as large as 0.69% SD ($p < 0.01$), indicating that school AC significantly offset the damage from heat exposure. Conversely, column (2) of Table 2 shows that high temperatures above 34°C reduce scores at the 90th percentile only by 0.22% SD ($p < 0.01$), while the offsetting effect of AC is 0.14% SD, though 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.[17]

We demonstrate that school facilities (i.e., school AC) help reduce the widening test score gap between advantaged and disadvantaged students caused by heat. This suggests that the widening gap in the absence of school AC is not primarily caused by differences in *outside-of-school* heat exposure (such as longer commutes for disadvantaged students); if this were the case, we would not expect school AC to counteract the widening of the achievement gap. Simultaneously, school AC did not fully offset the growing gap, likely because of measurement errors in the AC penetration measure and/or remaining outside-of-school adaptations by socioeconomic background (e.g., access to clam school).[18]

This finding suggests that public investment in school AC, rather than household-level adaptation, can largely reduce heat's inequality-enhancing negative effects. Thus, adequate investment in school infrastructure can mitigate unevenly distributed damage caused by heat to student learning. This is particularly encouraging because both primary and secondary education are mandatory in Japan, as in many other countries, where public investment plays a vital role. 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. However, the distributional impact of these temperatures across different socioeconomic statuses remains poorly understood. Even less explored is how different socioeconomic groups adapt to environmental stressors such as heat. Using nationwide exam data from Japan between 2007 and 2019, we find that extreme temperatures disproportionately hinder the human capital accumulation of low-achieving students, deepening academic and social inequalities. However, school air conditioning largely offsets these negative effects, highlighting the potential for public

[17] Appendix Table A9 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.

[18] We cannot entirely dismiss the possibility that this persistent widening gap stems from differing *outside-of-school* exposure, resulting in varying *in-schoo*l vulnerabilities. For example, limited access to AC at home deteriorates sleep quality (outside-of-school exposure), which in turn leads to diminished focus and concentration at school (in-school vulnerability), even within the same classroom environment.

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 different 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 differential vulnerabilities, supported by more comprehensive data on individual and household behaviors, is the key to addressing social disparities. Finally, it is also important to examine whether the inequality-enhancing effects of heat exposure on learning translate into inequalities in long-term economic outcomes such as wages and income.

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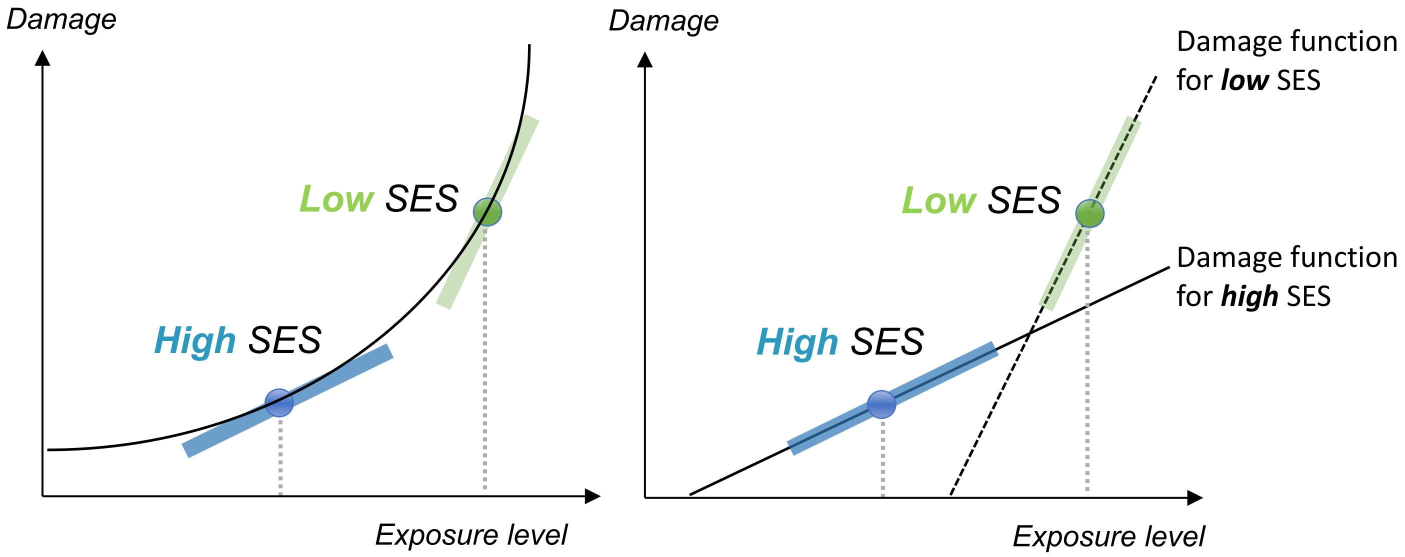
## Figure 1—Heterogeneity in marginal damages from two different explanations

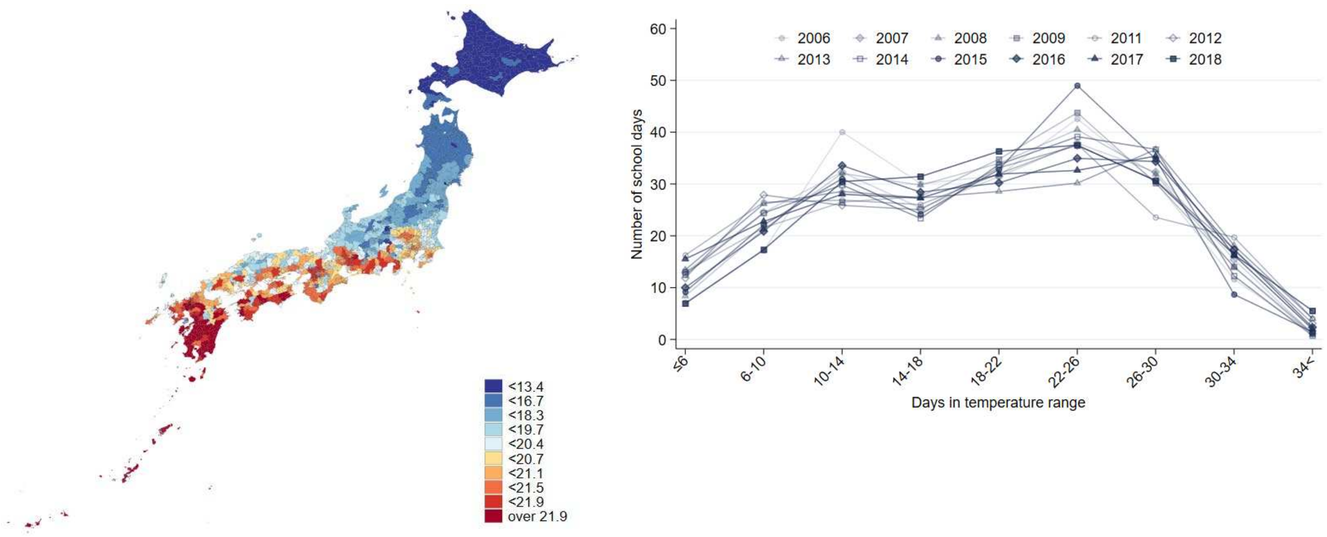
**A. Single nonlinear damage functions** **B. Differing vulnerability**




*Notes:* Adapted from Hsiang et al. (2019, Figure 1), this figure presents two different 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—Spatial and temporal variation in prior year temperature

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

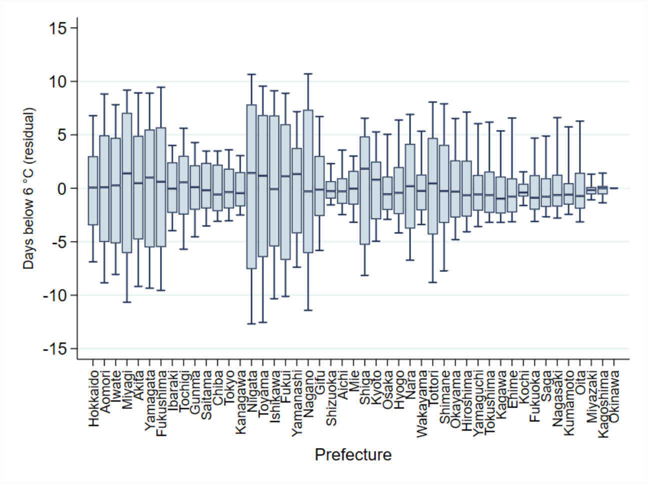



*Notes:* The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The figures illustrate the spatial variation in the mean daily maximum temperature in the year preceding the test year (panel A) and temporal variation in the number of school days within a given maximum temperature bin from last April to March of the test year, as experienced by students on school days (panel B).

# Figure 3—Identifying variation of prior year temperature

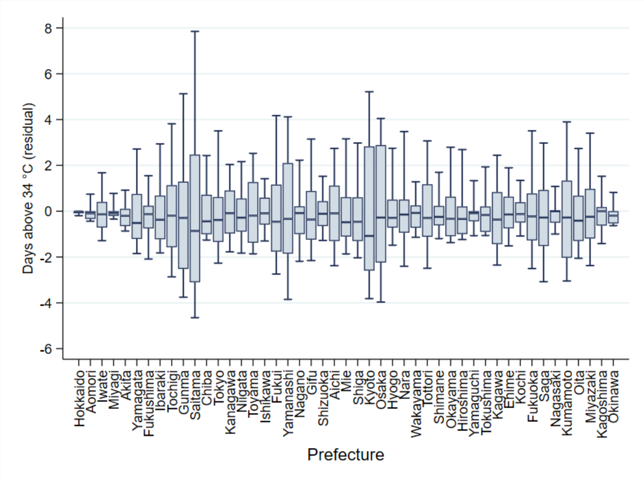
## A. Number of days below 6°C

By prefecture

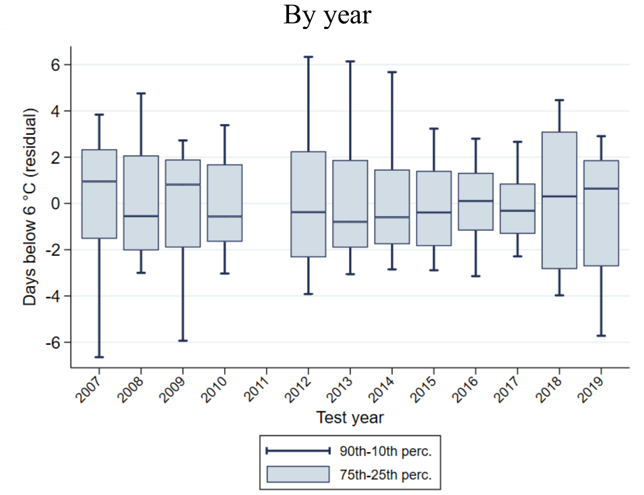



## B. Number of days above 34°C

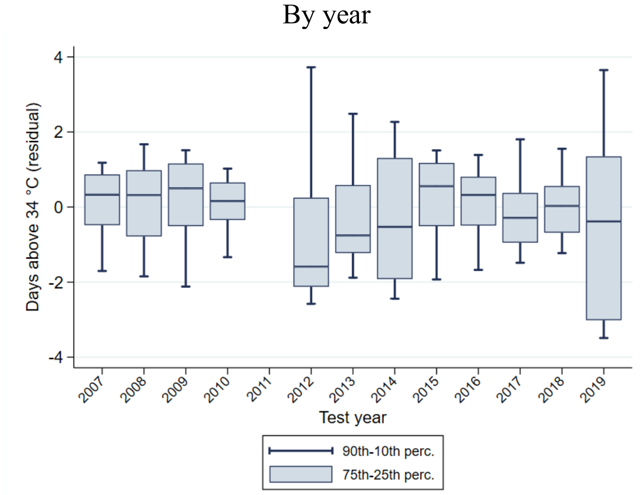
By prefecture




By year



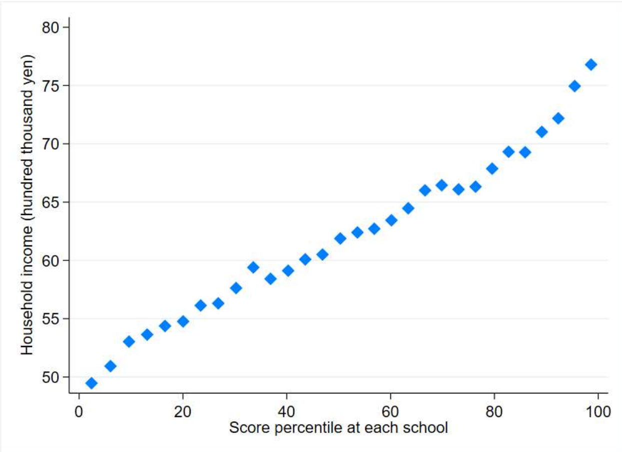

By year



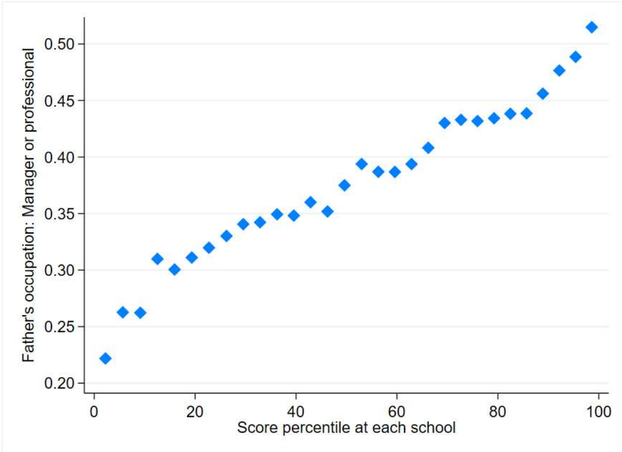

*Notes:* The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. This figure illustrates the interquartile and interdecile ranges of the residual variation, net of school fixed effects, in the number of school days below 6°C in the year prior to the test date (panel A) and the number of school days 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 4—Within-school student rank and socioeconomic status

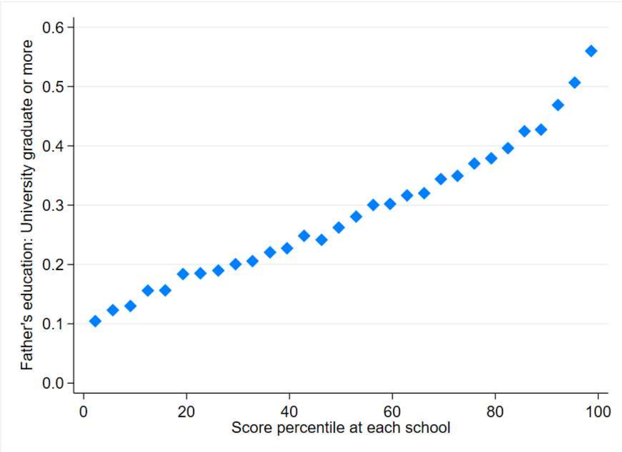
### A. Household income



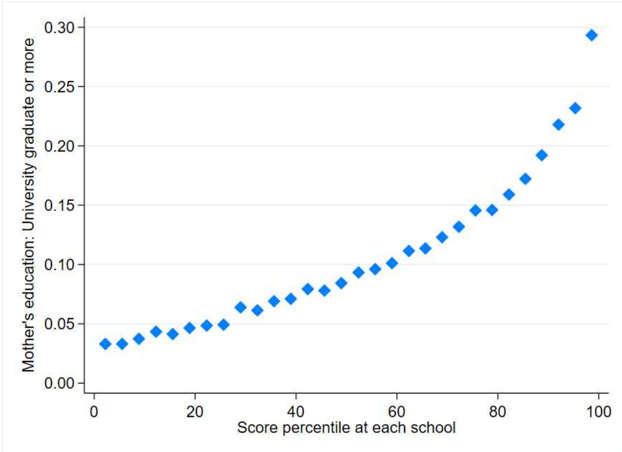

### B. Father's occupation: Manager or professional




### C. Father's education: ≥University graduate

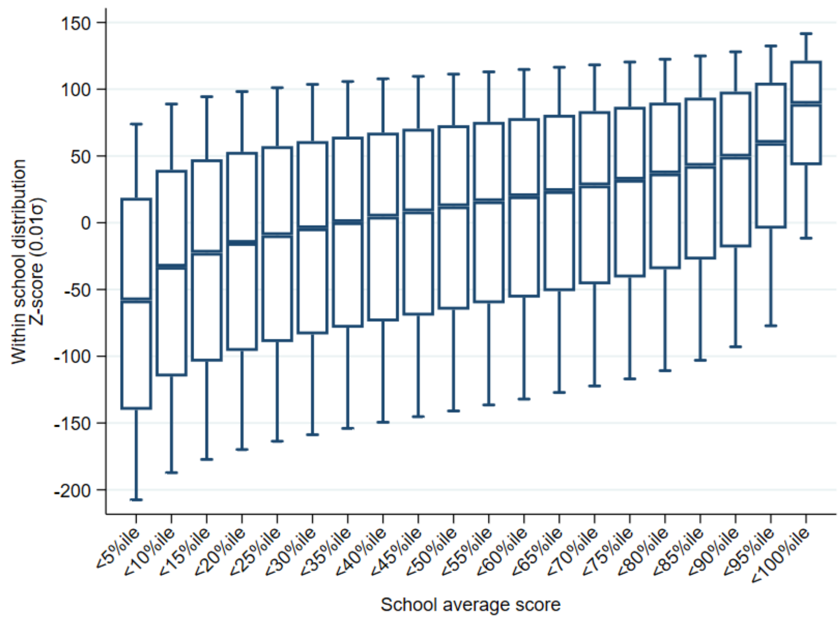



### D. Mother's education: ≥University graduate



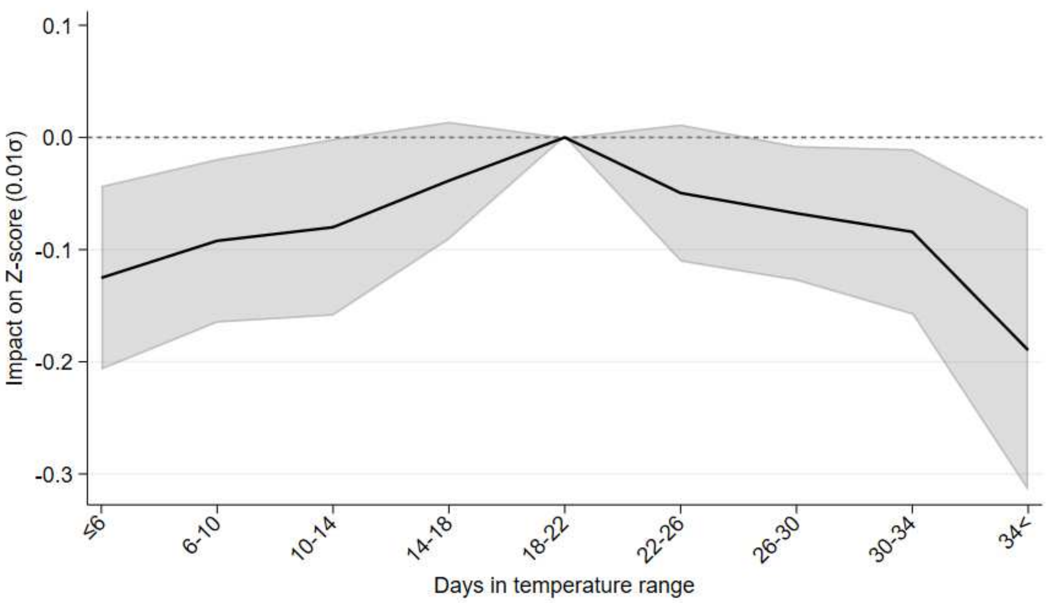

*Notes:* The data are from parent surveys in 2013 and 2017 NAAA. The bin scatter plot illustrates the relationship between within-school student rank and various measures of students' socioeconomic status, net of school fixed effects, specifically household income (panel A), proportion of fathers in managerial or professional occupations (panel B), fathers with education at or above a 4-year university/college degree (panel C), and mothers with education at or above a 4-year university/college degree (panel D). 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 5—Within-school score distribution across school ranks



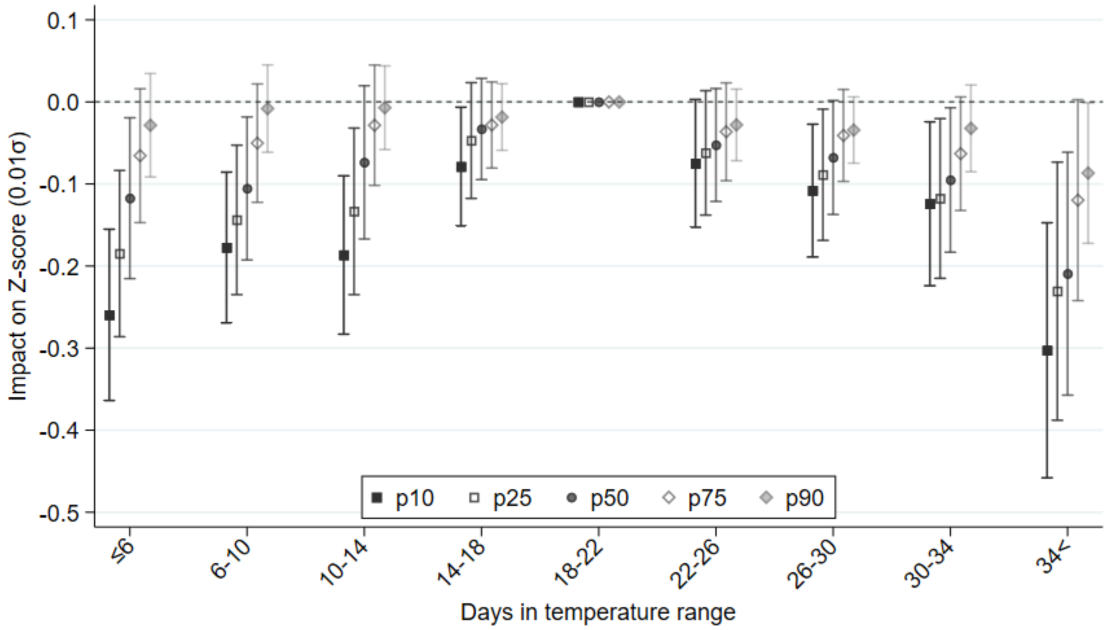

*Notes:* The data are from the 2007–2019 NAAA. This figure illustrates the variation in *within*-school score distribution across school ranks based on the average school scores. Specifically, we group schools into ventiles based on their average scores each year, and plot the average interquartile and interdecile ranges of the within-school score distribution for every ventile.

## Figure 6—Cumulative heat/cold exposure and test performance



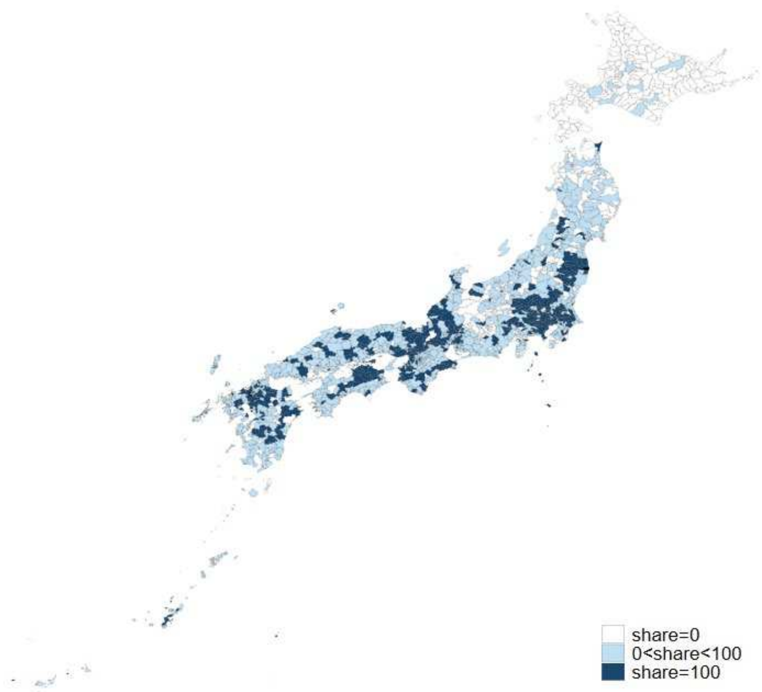

*Notes:* The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The figure plots $\beta^k$ from an estimating Equation [1], where the average z-score (measured in $0.01\sigma$) is regressed on the number of school days within a given maximum temperature bin in the year prior to the test date, along with the 95% confidence intervals. The omitted category is the temperature range between 18–22℃.

## Figure 7—Distributional impact of cumulative heat/cold exposure




*Notes:* The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The figure plots $\beta^k$ from an estimating Equation [2], where z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools (measured in $0.01\sigma$) 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.

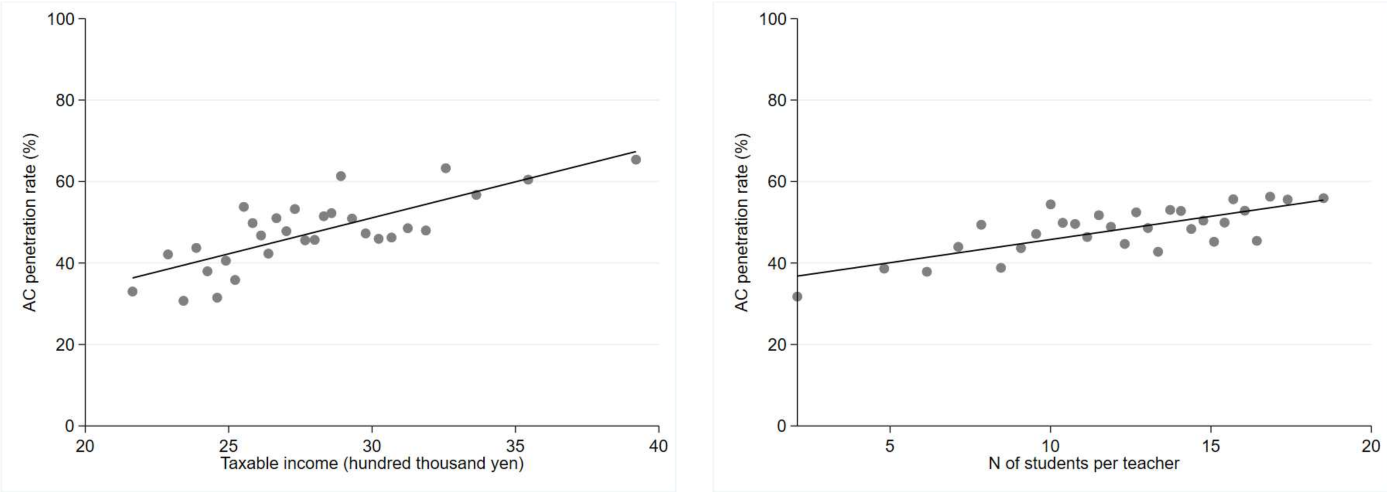
## Figure 8—Map of the school AC penetration




*Notes:* This 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 white), a 100% share (in dark blue), and the remaining (in light blue) of school AC penetration as of 2018. Schools with a 0% share ("without school AC") indicate that school AC was not available throughout the *entire* 2006-2018 sample period (without any measurement error), while schools with a 100% share ("with school AC") indicate that school AC became fully available *at some point* during the sample period.

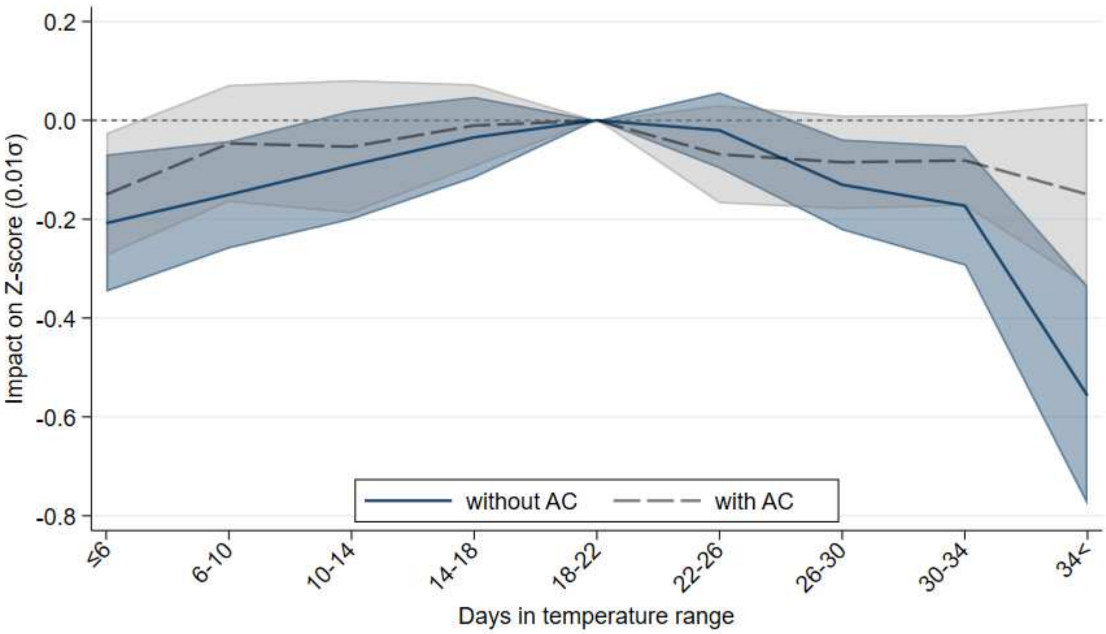
## Figure 9—Correlation with school AC penetration rates

**A. Taxable income per capita** **B. Student-teacher ratio**




*Notes:* The binscatter plot illustrates the cross-sectional relationship between school AC penetration rates at the municipality level and taxable income per capita (panel A) as well as the student-teacher ratio (panel B) for 2018, after controlling for the average temperature between 2006 and 2018. Both taxable income per capita and the student-teacher ratio were averaged over the period from 2006 to 2018.

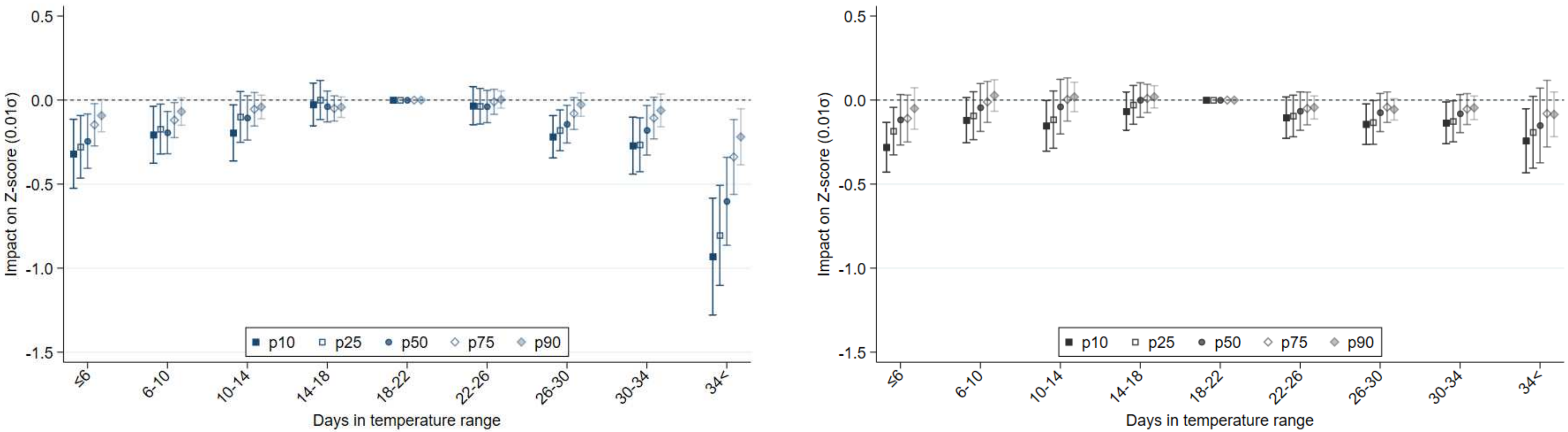
## Figure 10—Cumulative heat/cold exposure and test performance (with and without school AC)




*Notes:* The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The figure plots $\beta^k$ from estimating Equation [1], separately for schools with and without school AC in 2018, along with the 95% confidence intervals. Figure 8 shows the locations of the schools within each AC penetration category. The omitted category is the temperature range between 18–22℃.

## Figure 11—Distributional impact of cumulative heat/cold exposure (with and without school AC)

**A. Without school AC** **B. With school AC**




*Notes*: The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The figures plot $\beta^k$ from estimating Equation [2], separately for schools with AC in panel A and schools without AC in 2018 in panel B, along with the 95% confidence intervals. Figure 8 shows the locations of the schools within each AC penetration category. The omitted category is the temperature range between 18–22℃.

## 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 are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The unit of observation is the school-year. The dependent variable is the average test score at the school-year level, measured in $0.01\sigma$. 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 8 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), with 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 between 18–22℃.

## Table 2—The distributional impact of school AC

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| **Outcomes:** | **$10^{th}$ percentile score** | | **$90^{th}$ percentile score** | | **$90^{th}$-$10^{th}$ 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 are from the 2007–2019 NAAA and the 2006–2018 AMeDAS. The unit of observation is the school -year. Columns (1) and (2) present the estimates from the variant of the Equation [3], where the outcomes are z-scores at the $10^{th}$ and $90^{th}$ percentiles within schools (measured in $0.01\sigma$), 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 8 shows the locations of the schools within each AC penetration category. The complete table showing the results for the other percentiles is presented in Appendix Table A7. Column (3) presents the estimate of the score gap between the $90^{th}$ and $10^{th}$ percentiles within the school measured at $0.01\sigma$. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range between 18–22℃. 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

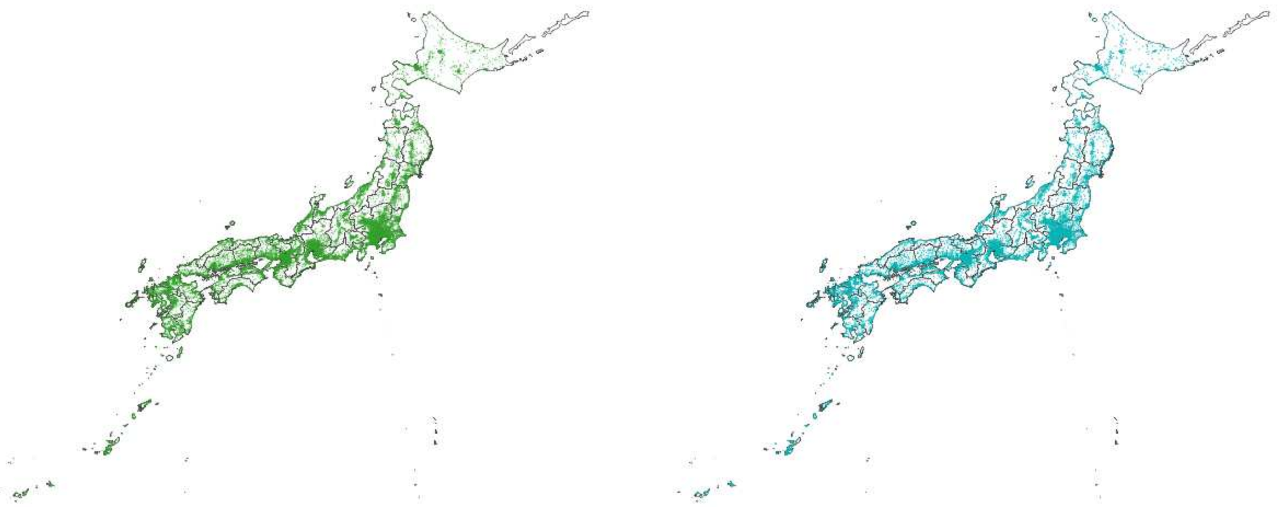
By Mika Akesaka and Hitoshi Shigeoka

## Table of Contents

# Appendix A: Additional figures and tables

## Figure A1—Location of schools

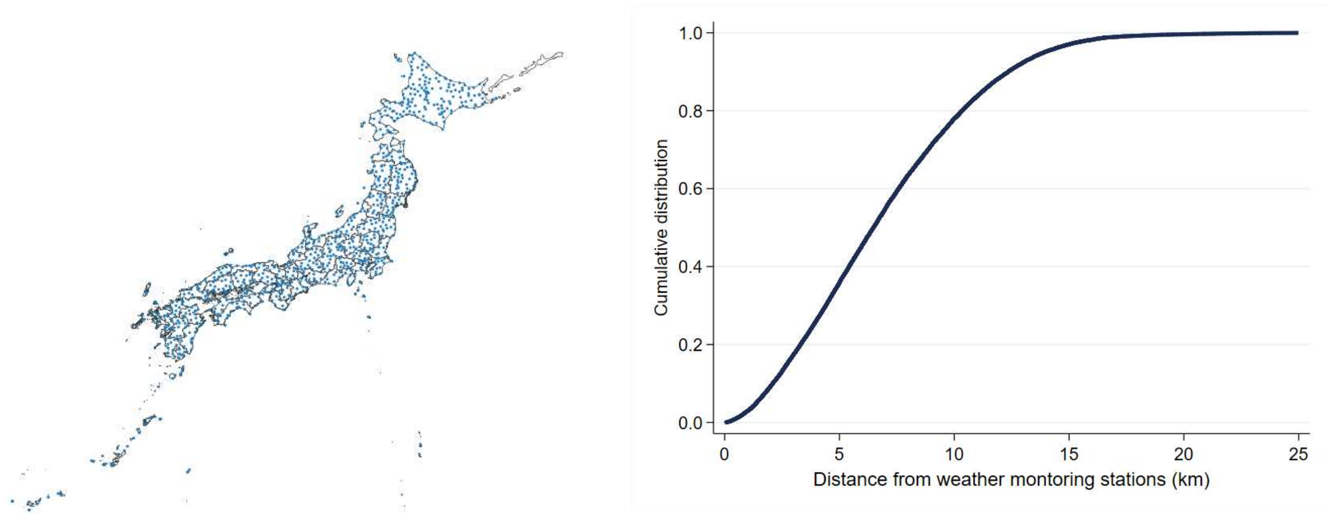
**A. Primary schools (grade 6)** **B. Secondary schools (grade 9)**



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

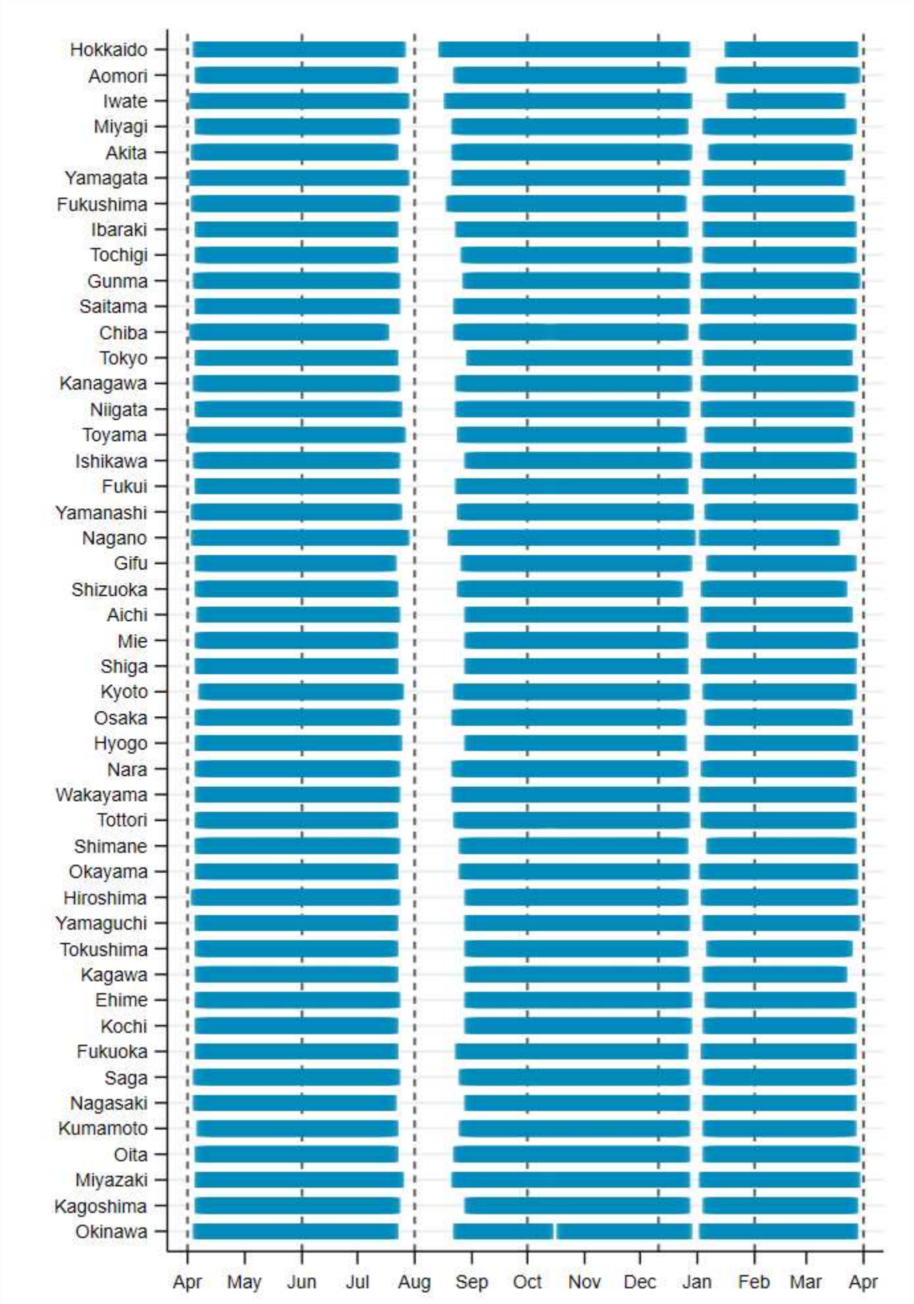
## Figure A2—Weather stations

**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) distances from the weather stations are 6.95 (6.48) km.

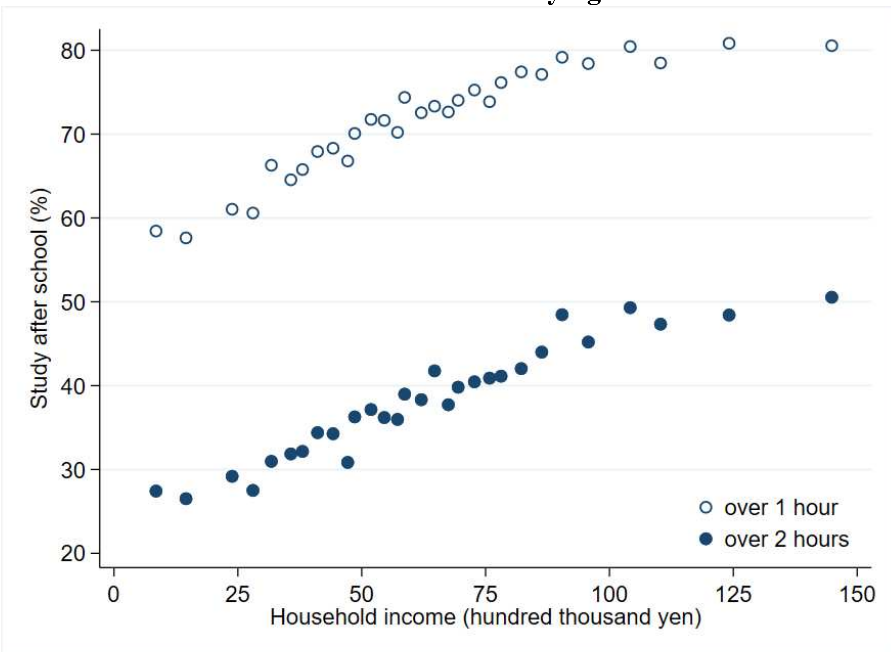
## Figure A3—School days by region



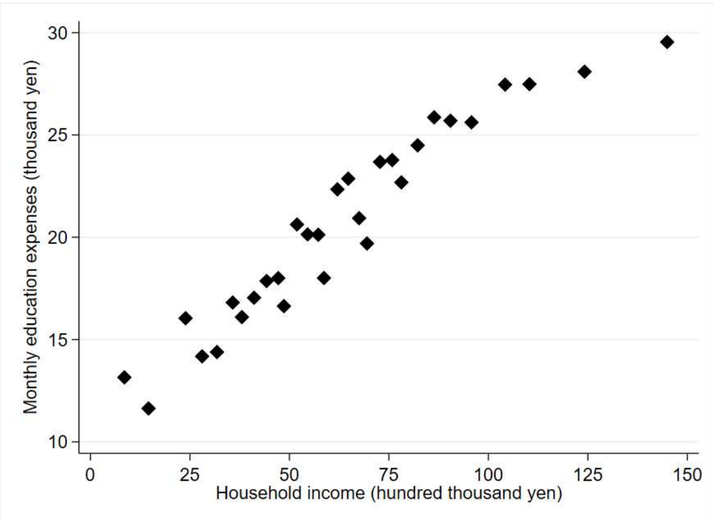

*Notes:* The figure displays the academic calendar of the prefectural capital in the school's prefecture for 2018. A total of 47 prefectures exist in Japan. The academic calendar mostly comprises three terms: spring, fall, and winter.

## Figure A4—Socioeconomic status and studying after school

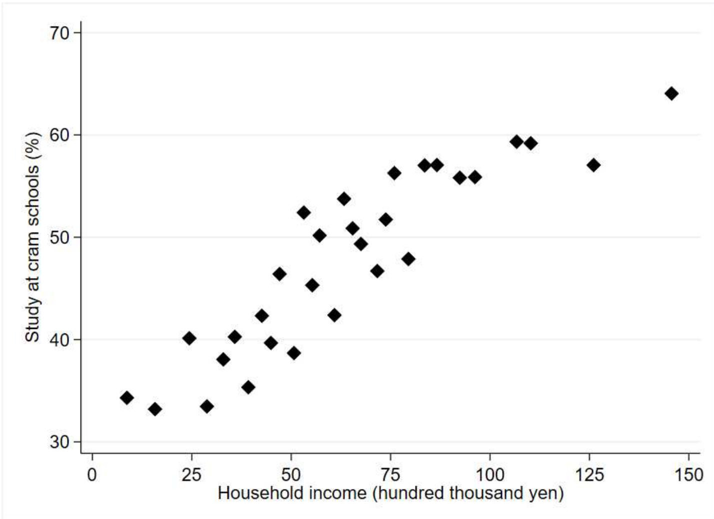
### A. Household income and studying after school




### B. Household income and education expenses



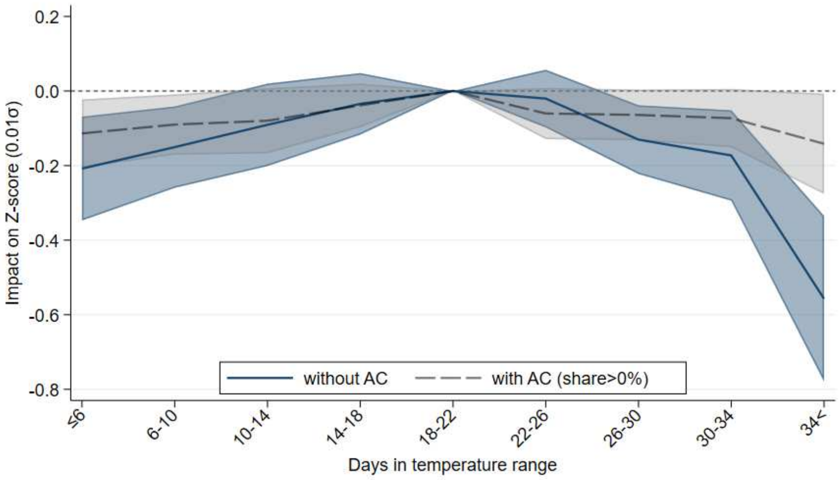

### C. Household income and clam school




*Notes:* The data come from parent surveys in the 2013 and 2017 NAAA, except for the fraction of students who study for more than 1 hour or 2 hours in panel A, which comes 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 hour or more than 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 A5—Cumulative heat/cold exposure and test performance

(school AC 0% vs. AC>0%)

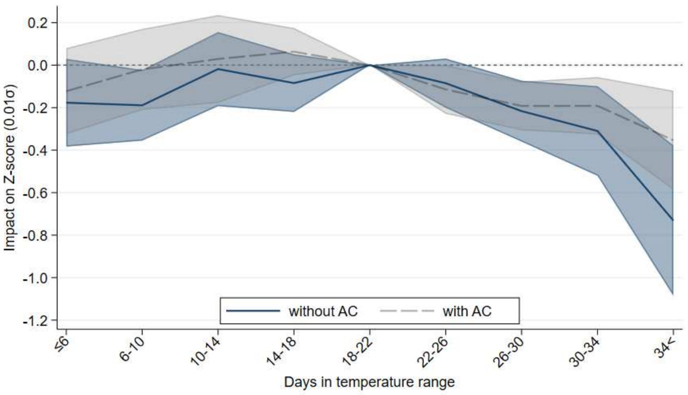



*Notes:* The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The figure displays $\beta^k$ from an estimating Equation [1], separately for schools in municipalities with a positive share of AC and those in municipalities with 0% AC availability in 2018, along with the 95% confidence intervals. The omitted category is the temperature range between 18–22℃. Figure 8 shows the locations of schools for each school AC penetration category.

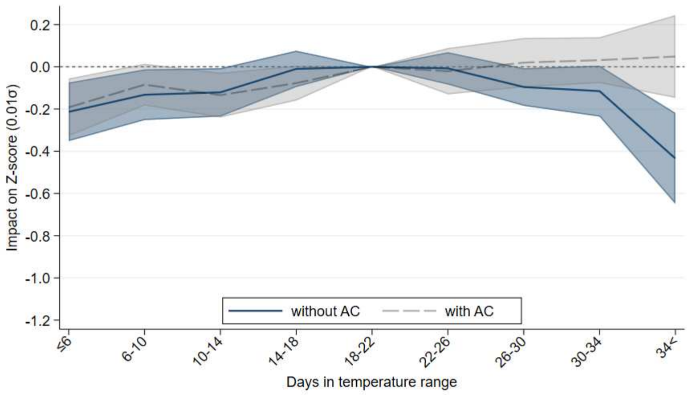
## Figure A6—Heterogeneity: Cumulative heat/cold exposure and test performance (with and without school AC)

### A. By grade

Grade 6

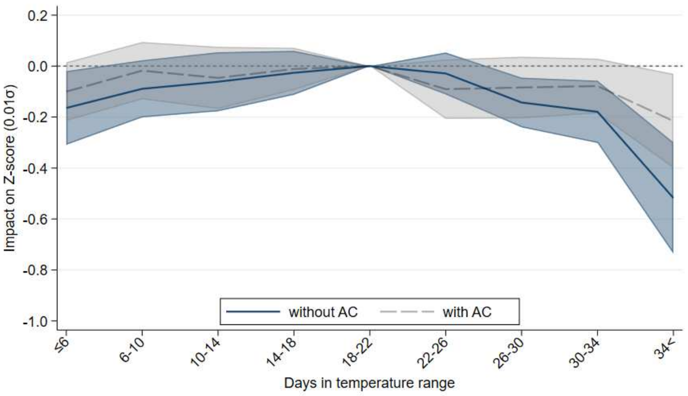



Grage 9

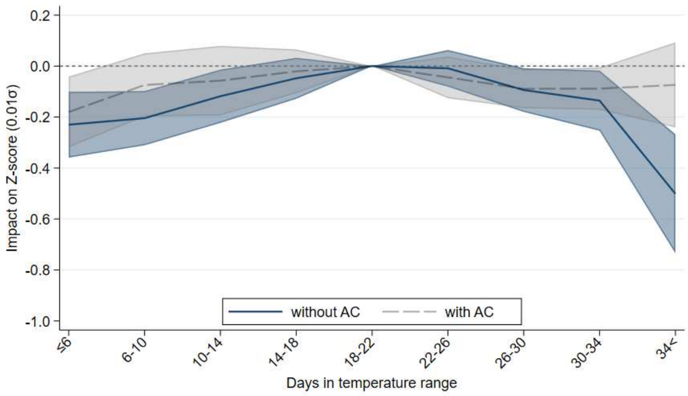



### B. By subjects

Math

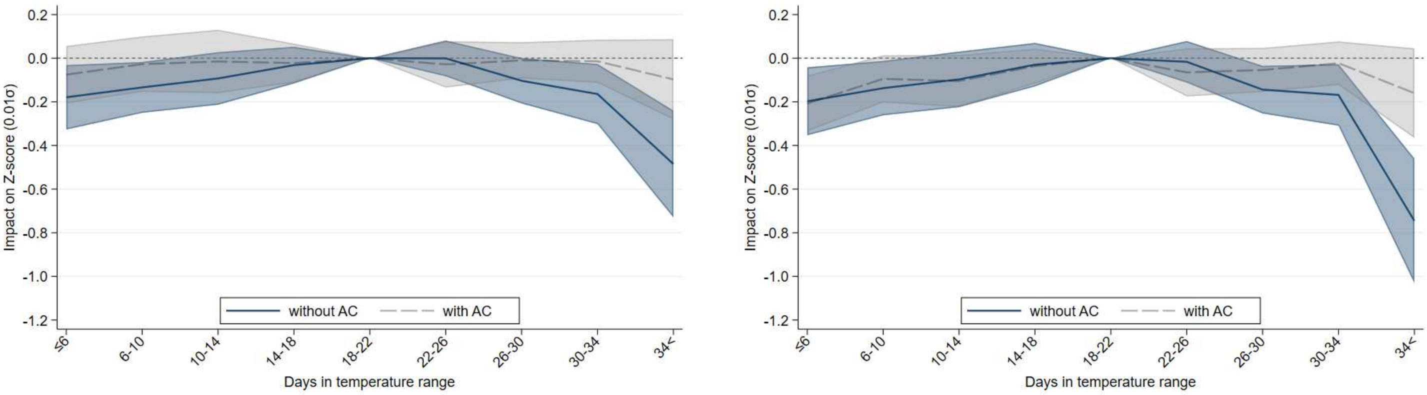



Reading



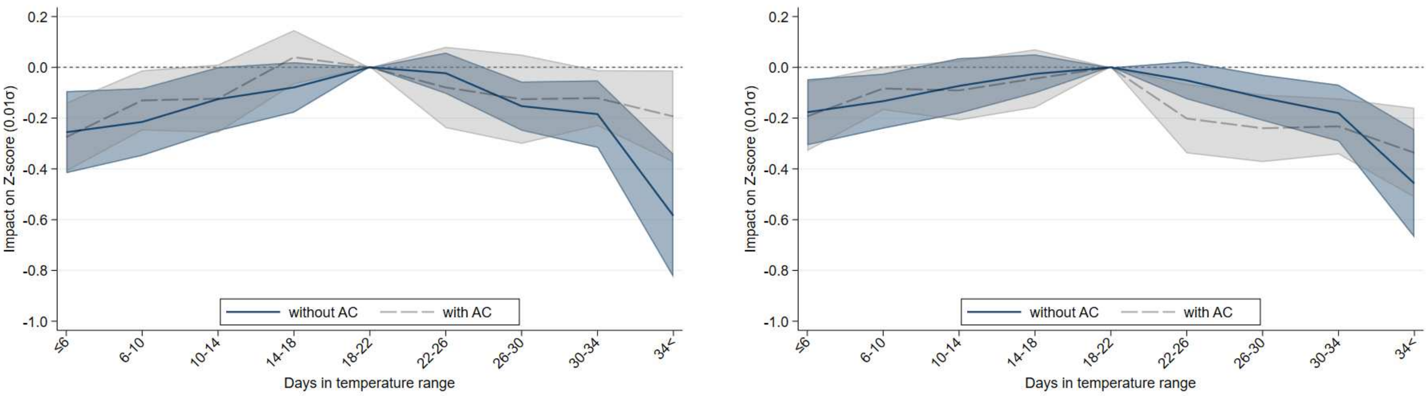
## C. By gender

Girls | Boys



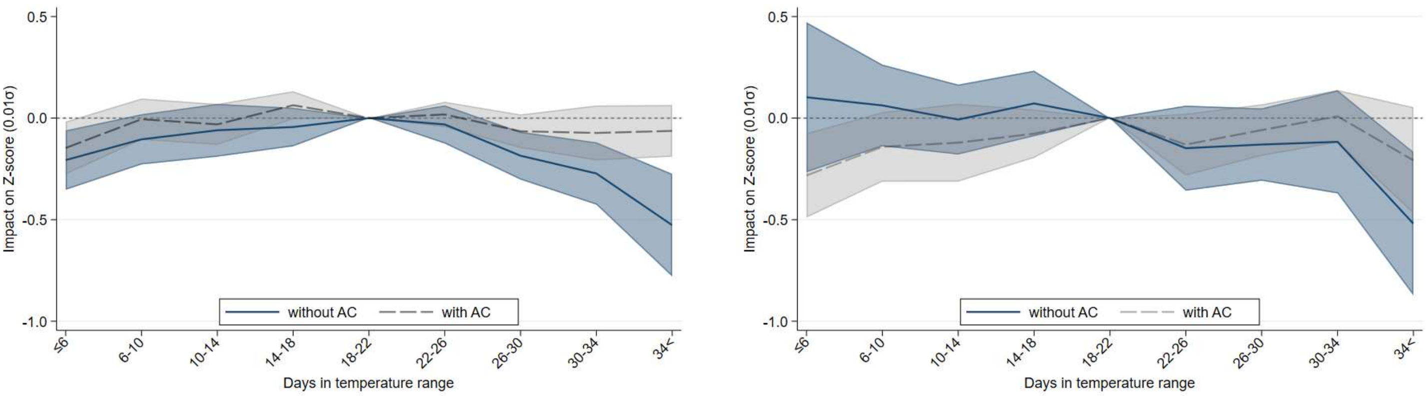

## D. By difficulty

Basic | Advanced




## E. By region

Cold region | Warm region




*Notes:* The data are from the 2007–2019 NAAA and the 2006–2018 AMeDAS. The figures plot $\beta^k$ from an estimating Equation [1], separately for schools with and without AC in 2018, along with the 95% confidence intervals. Figure 8 shows the locations of schools for each school AC penetration category. The omitted category is the temperature range between 18–22℃. Panel A divides the sample by grade (grade 6 vs. grade 9). Panel B divides the sample by subject (math vs. reading). Panel C divides the sample by student gender (girls vs. boys). Panel D divides the sample by the difficulty level of the test questions (basic vs. advanced). Finally, panel E divides the sample into cool and warm regions by the national median temperature between 2006 and 2018.

# Figure A7—Examples of basic and advanced questions (math for grade 6)

| Basic | Advanced |
|---|---|

**Basic**

**1**

次の計算をしましょう。

(1) $28+72$

(2) $27\times 3.4$

(3) $9.3\times 0.8$

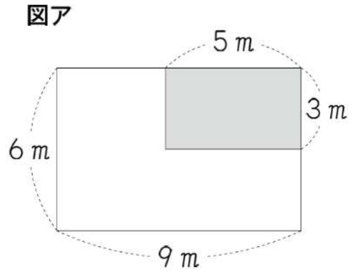
(4) $12\div 0.6$

**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**




(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 A1—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 A2—Descriptive statistics

| Variable: | N of schools | Mean | Std. dev. | Min | Max | N of station | 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 occup: Manager/Professional | 1,949 | 0.40 | 0.49 | 0 | 1 | - | 2017 |
| Father's educ: ≥University graduate | 2,779 | 0.31 | 0.46 | 0 | 1 | - | 2013, 2017 |
| Mother's educ: ≥University graduate | 2,784 | 0.13 | 0.33 | 0 | 1 | - | 2013, 2017 |
| Education expenses | 2628 | 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 condition** | | | | | | | |
| 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 A3—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<br>Above 34°C<br>↓0.19% SD<br>Below 6°<br>↓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<br>Above 34°C<br>↓0.42% SD (Math)<br>↓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)<br>Above 100°F (37.8°C)<br>↓0.07% SD<br>Above 90°F (32.2°C)<br>↓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)<br>Above 80°F (26.7°C)<br>↓0.10% SD (G3–G5)<br>↓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)<br>Below 60°F (15.6°C)<br>↓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.

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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 A4—Distributional impact of cumulative heat/cold exposure

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Outcomes:** | **$10^{th}$ percentile** | **$25^{th}$ percentile** | **$50^{th}$ percentile** | **$75^{th}$ percentile** | **$90^{th}$ percentile** | Resulting score gap | | |
| | | | | | | $90^{th}$-$10^{th}$ | $90^{th}$-$50^{th}$ | $50^{th}$-$10^{th}$ |
| 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 are from the 2007–2019 NAAA and 2006–2018 AMeDAS. 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 $10^{th}$, $25^{th}$, $50^{th}$, $75^{th}$, and $90^{th}$ percentiles within school (measured in $0.01\sigma$), along with standard errors clustered at the weather station level in parentheses. Columns (6)–(8) present the estimate of the score gap between the $90^{th}$ and $10^{th}$ percentiles, $90^{th}$ and $50^{th}$ percentiles, and $50^{th}$ and $10^{th}$ percentiles within the school, measured in $0.01\sigma$. The estimates are weighted by the number of students in each school-year. The omitted category is the temperature range between 18–22℃. Significance levels: *** $p$<0.01, ** $p$<0.05, * $p$<0.10.

## Table A5—The impact of studying after school

| | (1) | | (2) | |
|---|---|---|---|---|
| **Outcomes:** | **Average Z-score** | | **Average Z-score** | |
| | | × study over 1 hour | | × study over 2 hour |
| 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 are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The unit of observation is the school-year. The dependent variable is the average test score at the school-year level, measured in $0.01\sigma$. 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 the fractions of students studying after school for more than one hour (column 1) and for 2 hours (column 2) are demeaned by the average between the 2007–2019 NAAA. 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 between 18–22°C. Significance levels: *** $p$<0.01, ** $p$<0.05, * $p$<0.10.

## Table A6—Robustness on the impact of heat

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Outcomes:** | **Average Z-score** | | | | | | | |
| Days above 34°C | -0.562*** | -0.568*** | -0.557*** | -0.278*** | -0.503*** | -0.493*** | -0.482*** | -0.551*** |
| | (0.112) | (0.113) | (0.111) | (0.105) | (0.113) | (0.105) | (0.130) | (0.123) |
| Days above 34°C × school AC | 0.413*** | 0.425*** | 0.421*** | 0.401*** | 0.363** | 0.386*** | 0.409** | 0.440*** |
| | (0.145) | (0.145) | (0.139) | (0.126) | (0.146) | (0.130) | (0.164) | (0.150) |
| R-squared | 0.751 | 0.751 | 0.751 | 0.772 | 0.751 | 0.751 | 0.751 | 0.759 |
| Observations | 190,210 | 190,210 | 190,210 | 145,769 | 190,210 | 190,210 | 190,210 | 141,733 |
| Sample period | Full | Full | Full | 2009-2019 | Full | Full | Full | Full |
| Temperature (test day) | | X | | | | | | |
| Weather (test day) | | | X | | | | | |
| Pollution (test day) | | | | X | | | | |
| Weather (cumulative) | | | | | X | | | |
| Temperature (school holidays) | | | | | | X | | |
| Temperature (weekend) | | | | | | | X | |
| Stations within 10 km | | | | | | | | X |

*Notes:* The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The unit of observation is the school-year. The dependent variable is the average test score at the school-year level, measured in $0.01\sigma$. The estimates come from Equation [3], along with the standard errors clustered at the weather station level in parentheses. The estimates for the number of school days above 34℃ 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 8 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 between 18–22°C. Full-year mean from 2007–2019. Column (1) presents the baseline estimate without any controls other than school and year fixed effects, as reported in column (1) of Table 1. Column (2) adds the test-day temperature and column (3) includes additional test-day weather conditions (precipitation, wind speed, and relative humidity). Column (4) includes test-day air pollution ($SO_2$, NO, $NO_2$, CO, OX, and $PM_{10}$) for the 2009-2019 period, as pollution data are only available for this period. Column (5) includes other cumulative weather conditions (precipitation, wind speed, and relative humidity). Columns (6) and (7) control the number of days during school break days and weekends, respectively, within a given maximum temperature bin from the year prior to the test date. Finally, column (8) 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 A7—Heterogeneous impacts of heat

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Outcomes:** | **Average Z-score** | | **Average Z-score** | | **Average Z-score** | | **Average Z-score** | | **Average Z-score** | |
| | *By grade* | | *By subject* | | *By gender* | | *By difficulty* | | *By region* | |
| | 6th | 9th | Math | Reading | Girls | Boys | Basic | Advanced | Cool | Warm |
| Days above 34℃ | -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℃ × 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 |
| Observations | 115,312 | 74,898 | 190,210 | 190,210 | 176,297 | 176,169 | 173,005 | 173,005 | 105,672 | 84,538 |

*Notes:* The data are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The unit of observation is the school-year. The dependent variable is the average test score at the school-year level, measured in $0.01\sigma$. The estimates come from Equation [3], along with the standard errors clustered at the weather station level in parentheses. The estimates for the number of school days above 34℃ 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 8 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 between 18–22℃. 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-year 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 A8—Distributional impact of school AC (full)

| | (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 are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The unit of observation is the school-year. Columns (1)–(5) present the estimates from the variant of the 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 8 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 between 18–22°C. Significance levels: *** $p$<0.01, ** $p$<0.05, * $p$<0.10.

## Table A9—Robustness: The impact of school AC on academic inequality

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| **Outcomes:** | **$90^{th}$-$10^{th}$ score gap** | | **$90^{th}$-$10^{th}$ score gap** | | **$90^{th}$-$10^{th}$ 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 are from the 2007–2019 NAAA and 2006–2018 AMeDAS. The unit of observation is the school-year. 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 8 shows the locations of the schools within each AC penetration category. The outcome is the gap between the $90^{th}$ and $10^{th}$ percentile scores within the school, measured at $0.01\sigma$. 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 between 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<br>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)<br>Source: The National Institute for Educational Policy Research<br>https://www.nier.go.jp/kaihatsu/zenkokugakuryoku.html |
| Weather | Years: 2006–2019<br>Data description: daily temperature (maximum, average, minimum)<br>Source: Japan Automated Meteorological Data Acquisition System (AMeDAS) operated by the Japan Meteorological Agency (JMA)<br>https://www.data.jma.go.jp/obd/stats/etrn/ |
| Pollution | Years: 2009 April–2019 March<br>Data description: hourly $SO_2$, NO, $NO_2$, CO, OX, $PM_{10}$<br>Source: National Institute for Environmental Studies<br>https://tenbou.nies.go.jp/download/ |
| Taxable income | Years: 2006–2018<br>Data description: taxable income per capita at the municipality level<br>Source: Survey on Municipal Taxation Status (Shichōsonzei kazeijōky tou no shirabe)<br>https://www.soumu.go.jp/main_sosiki/jichi_zeisei/czaisei/czaisei_seido/ichiran09.html |
| Student-teacher ratio | Years: 2006–2018<br>Data description: student-teacher ratio at municipality level<br>Source: School Basic Survey<br>https://www.mext.go.jp/b_menu/toukei/chousa01/kihon/1267995.htm |
| School AC penetration rate | Year: 2018<br>Data description: school AC penetration rate for public primary and secondary schools at the municipality level<br>Source: Survey of Air Conditioning Installation Status in Public School Facilities<br>https://www.mext.go.jp/a_menu/shotou/zyosei/mext_01278.html |
| Home AC share | Year: 2014<br>Data description: home AC share at the prefecture level<br>National Survey of Family Income and Expenditure<br>https://www.stat.go.jp/data/zensho/2014/index.html |