Heat, Adaptation, and Academic Inequality*

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First Draft: January 2025

Abstract

Using data from 22 million students who took nationwide examinations in Japan between 2007 and 2019, we demonstrate that heat disproportionately hinders the human capital accumulation of low-performing students more than their high-performing counterparts. Since school performance closely correlates with a student's socioeconomic background, heat exposure exacerbates pre-existing academic inequality. However, regardless of student achievement levels, the availability of air conditioning in schools largely offsets the negative effects of heat, suggesting that the benefits are progressive. This finding indicates that adequate public school investment may help alleviate the unevenly distributed heat damage to student learning.

Keywords: Heat, Adaptation, Academic inequality, Test score, Air conditioning, Children, Climate change
JEL code: I21, I24, Q54

* The authors thank Joshua Graff Zivin, David Molitor, Soodeh Saberian, Corey White, Chin-Wen Yang and seminar participants at AAERE 2024, ASHEcon 2024, Kansai Labor Workshop, Osaka University (OSIPP) and the Research Institute of Economy, Trade and Industry for their comments and suggestions. We also thank Takahiro Miura for shaping AMeDAS data. Akesaka acknowledges financial support from JSPS KAKENHI (23K12492, 22K01534, 21H04397, 20K13511). Shigeoka acknowledges financial support from JSPS KAKENHI (23H00828, 22H00057, 22H00847, 22H05009), and JST ERATO (JPMJER2301). Any errors are our own.

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1. Introduction

The threat of global warming indicates that people are more prone to severe heat stress. However, the distributional impacts of such environmental stressors, specifically who is more likely to suffer in a warming climate, are not well understood. In particular, previous studies have often failed to differentiate between baseline "exposures" and "vulnerability"—how the same exposure results in damages, based on socioeconomic attributes (Hsiang et al. 2019). This distinction is crucial because the former suggests that the poor can simply relocate from hotter areas to cooler parts of the country where the wealthy may reside to avoid heat exposure. However, if the latter is true, the unequal adaptation potential, such as the availability of air conditioning, between the advantaged and disadvantaged reflects these differences, making spatial relocation to alter "exposure" less effective (Burke et al. 2024).

To address this gap in the literature, we examine the distributional impact of cumulative exposure to extreme temperatures on young children's academic achievement. Previous studies have been unable to investigate these questions, either because their data stem from a *specific* sample or because they lack individual-level information. For instance, both Cho (2017) and Park et al. (2020), which analyze the cumulative exposure to heat's impact on test scores, focus on high school students who took the college entrance exam in Korea and the PSAT in the US. These students are presumably from a higher socioeconomic status group than the general population, making them unsuitable for studying the distributional impacts. Park et al. (2021) utilize standardized achievement data aggregated at the school district level in the US, but such aggregate data cannot differentiate between varying levels of exposure and different vulnerabilities to heat and cold based on socioeconomic status.

We utilize individual-level test score data from nationwide exams administered annually in Japan from 2007 to 2019 to all students in public schools during compulsory education (grades 6 and 9), encompassing nearly 22.8 million students. Importantly, the combination of individual-level data and the nationally representative nature of the exams provides an ideal setting to examine, to our knowledge for the first time, the distributional impact of temperature *within* schools (rather than *across* schools) on test scores while holding "exposure" constant. Empirically, we compare the test scores of students of different ranks within the same school who experienced hotter summer (colder winter) school days with those who experienced milder summer (milder winter) school days to identify the distributional impact of cumulative exposure to extreme temperatures on human capital accumulation.

Cognitive ability serves as a fundamental measure of human capital and is known to predict adult labor market outcomes (Cunha and Heckman 2007). Children's cognitive function may be particularly vulnerable to extreme temperatures due to their physiological and neurocognitive

immaturity (Rowland 2008). Furthermore, the dynamic complementarity of human capital investments—specifically, that investments in human capital during early childhood complement those made later—suggests that interventions at earlier stages could be more beneficial (Heckman 2007). While previous studies on temperature and academic achievement have primarily focused on the effects of heat or cold on the day of testing[1], if these extreme temperatures disrupt students' learning and teachers' teaching abilities, prolonged exposure can have a long-lasting impact on student learning.

There are four main findings. First, we demonstrate that cumulative exposure to both hot and cold days negatively affects children's learning on average. While some studies examine the cumulative impact of heat exposure (Cho 2017; Park et al. 2020, 2021) and cold exposure (Johnston et al. 2021) separately, we show that both extremely hot and cold school days in the prior academic year impair the students' learning environment. Specifically, one additional hot day over 34°C in the previous summer, compared to the normal temperature range of 18-22°C, reduces test scores by 0.19% of a standard deviation (SD). Likewise, replacing a day of normal temperature at 18-22°C with a cold day below 6°C in the previous winter similarly reduces test scores by 0.13% of SD.

Second, and most importantly, we document the significant distributional impact of extreme temperatures on academic inequality. Again, our individual-level test score data, linked to school ID, enable us to examine how temperature affects the test scores of each rank within schools. We find that the negative effects are much larger for students at the bottom of the score distribution compared to those at the top. One additional hot day above 34°C reduces test scores by 0.32% SD for students in the bottom 10th percentile, while the corresponding estimate for students in the top 10th percentile is only 0.12% SD, which is about one third of the estimate for the bottom 10th percentile students.

Importantly, since we are comparing the effect of temperature within the school (i.e., with the school fixed effect), we keep the "exposure" constant. Therefore, this result is not influenced by school-level resources, such as student-teacher ratio, teacher quality, and availability of air conditioning. Rather, it likely reflects different adaptations of advantaged and disadvantaged students at the household or individual level to the same heat exposure. Indeed, a student's rank within a school positively correlates with several measures of socioeconomic status, including

[1] See, for example, Garg et al. (2020), Graff Zivin et al. (2018, 2020), Park (2022), Zhang et al. (2024) regarding hot temperatures, and Suzuki (2024) regarding cold temperatures. The distinction between transitory and cumulative impacts can be crucial since transitory effects might be more easily addressed by, for example, avoiding outdoor activities before cognitively demanding tasks or simply rescheduling those tasks for cooler days. However, cumulative effects indicate that the learning environment is fundamentally disrupted, necessitating more substantial measures to restore it, such as widespread air conditioning installation in classrooms.

household income, parental education, and the father's occupation. This finding suggests that without further investment in school infrastructure, a warming climate is likely to widen the achievement gap between the lowest and highest-performing students and exacerbate existing disparities in academic achievement.

Third, we examine whether adaptation through current heat mitigation technologies, especially school air conditioning (AC), can counteract the negative effects of heat on learning. Strikingly, all negative effects of heat are caused by schools without AC. In contrast, if considered causal, the negative impact of heat on learning can largely be offset by school AC. However, since school air conditioning may be linked to other adaptive technologies in the school or additional resources available to students that could independently enhance student learning, the results should be interpreted with condierable caution.

Finally, we examine the impact of school AC availability on academic inequality within schools and find that while there are still varying effects of heat by rank for schools without AC, there are no negative effects of extreme heat for students of *any* rank in schools with AC. This remarkable finding indicates that adaptation through public investment, such as installing AC at the *school* level (instead of the household level) can mitigate the negative effects of heat for *all* students. Consequently, the benefit of such public investments are likely to be *progressive,* benefiting low-performing students than for high-performing students. This is particularly encouraging since both primary and secondary education are compulsory, where public investment should play a critical role.

The paper contributes to several strands of the literature. First, the paper makes a significant contribution to the sparse body of research on the distribution of climate damage (Hsiang et al. 2019). By comparing the test scores of students of different ranks within the same school, which allows us to hold constant the exposure to extreme temperatures at school, we show that heat disproportionately hinders the human capital accumulation of students from low socioeconomic backgrounds more than their counterparts from higher socioeconomic backgrounds. This suggests that disadvantaged children may not only be more *exposed* to climate risks, but also more *vulnerable* to such risks than advantaged children.

Second, this paper contributes to a growing body of literature exploring adaptation to temperature (Carleton et al. 2022, 2024; Burke et al. 2024). The fundamental question regarding environmental hazards is whether these hazards are largely unavoidable or if individuals can adapt by leveraging current technologies. For instance, the existing evidence indicates some potential for adaptation concerning heat-related mortality (Barreca et al. 2016; Cohen and Dechezleprêtre 2022; Heutel et al. 2021; Mullin and White 2020), violence related to heat (Colmer and Doleac 2023), while the evidence for workplace injuries due to heat is mixed

(Dillender 2021; Park et al. 2021; Ireland et al. 2023).[2] Most relevantly, a seminal study by Park et al. (2020) demonstrates that school air conditioning can lessen the negative impacts of cumulative heat exposure on student learning, based on data from 10 million students who retook the PSATs in the US. In addition to the average effect, we illustrate that the benefits of school air conditioning are progressive and can significantly alleviate the unevenly distributed heat damage to student learning.

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

2. Conceptual framework

This section provides a simple conceptual framework for understanding the distributional impacts of exposure to extreme temperature. The discussion here relies heavily on Hsiang et al. (2019). Let us define damages (or social costs) as a function of two components: the level of exposure to environmental stressors (such as heat, cold, and air pollution) and a vector of socioeconomic status (like income) that may influence how this exposure translates into measures of well-being.

There are two possible explanations for why the empirically measured marginal damages (i.e., the slope of the damage function) might differ by socioeconomic status (SES). As shown in Panel A of Figure 1, heterogeneity in marginal damages may result from nonlinearities in the relationship between exposure and damages, while holding other factors constant. In our setting, test scores of low SES individuals are adversely affected by heat more than those of high SES counterparts, since low SES individuals experience greater exposure to heat than their high SES counterparts. Alternatively, as illustrated in Panel B of Figure 1, the shape of the damage function mapping exposure to damage varies by SES due to many factors correlated with income (e.g., baseline health status or adaptive technologies).

Why is it important to distinguish whether the heterogeneous marginal damages between high and low SES are driven by a single nonlinear damage function or by heterogeneous damage functions (i.e., differing vulnerability)? In the most extreme case, the former suggests that the poor can simply move from hotter areas of the country to cooler regions, where the rich tend to reside, to avoid heat exposure. However, the latter implies that the differential adaptive potential,

[2] See Burke et al. (2024) for adaptation potential to a warming climate on other outcomes such as agricultural yields, economic growth, crime, and violence.

such as AC availability, between the advantaged and disadvantaged reflects these differences, making spatial relocation less effective (Burke et al. 2024). Therefore, policies should target the disadvantaged, such as providing a subsidy for home AC, or should directly address poverty, leading to reduced future vulnerability to heat.

However, distinguishing between these two explanations is challenging because exposure and socioeconomic status, such as income, are highly correlated. For instance, it is well documented that the impacts of climate change are greater in poorer countries (Dell et al. 2012; Burke et al. 2015), yet those countries often tend to be located in hotter regions. Some studies explore the differing effects of heat exposure by race (whites vs. blacks) in the same geographic area by including county or municipality fixed effects (e.g., Park et al., 2020). However, individuals from various socioeconomic statuses still sort into areas with differing exposures at the micro level. For instance, Chakma et al. (2024) note that poorer individuals are more likely than wealthier ones to reside in neighborhoods with heat-absorbing surfaces (i.e., urban heat island neighborhoods), even within narrowly defined regions. Moreover, even if exposure is assumed to be constant within a region, the comparison of heat damage estimates between the black and white populations, for example, still reflects their different exposures due to their uneven distribution across geographic regions. Consequently, such estimates for the white and black populations assign different weights to each region, reflecting different levels of exposure for different demographic groups.

This paper attempts, to our knowledge for the first time, to rigorously distinguish between these two different explanations for *the same* empirical observation. Specifically, the combination of individual-level data and the nationally representative nature of the exams allow us to examine the distributional impact of temperature within schools (rather than across schools) on test scores, holding baseline "exposure" constant, at least in the school environment where most of the learning is supposed to occur. This setting allows us to determine whether marginal damages differ due to variations in baseline exposure or due to differences in vulnerability. If the latter is true, we would expect that the change in damage (i.e., test score reduction) would be greater for low SES than for high SES in response to the change in environmental exposure (i.e., heat). Conversely, if they are not statistically different at the same level of exposure, it's more likely that the former scenario is applicable.

3. Data

We combine temperature data with nationwide test data for nearly 28 million students in Japan. Details about the data sources are available in Appendix B. We discuss school AC penetration data in Section 6.

3.1. Test score

Since 2007, the nationwide exams, called the National Assessment of Academic Ability (hereinafter referred to as "NAAA"), have been annually conducted by the Ministry of Education, Culture, Sports, Science and Technology (MEXT). The exceptions were in 2011, when NAAA was completely canceled due to the Great East Japan Earthquake, and in 2010 and 2012, when NAAA was administered to a random subset of schools.[3]

The NAAA aims to monitor the academic performance and progress of students nationwide and contribute to the improvement of educational policies in schools (MEXT 2024a). As a result, student performance does not affect their promotion to higher grades or better schools. Furthermore, school performance does not lead to explicit consequences for schools, such as a decrease in federal funding, unlike a test-based accountability system (like the No Child Left Behind Act in the US). In summary, the NAAA is not intended to serve as a high-stakes exam for either students or schools, except in terms of concerns about school reputations (Morozumi and Tanaka 2023).

The exams are administered to students in the final years of public primary school (grade 6) and secondary school (grade 9).[4] Both primary and secondary education are compulsory in Japan. Nearly 100% of public primary and secondary schools participated in the NAAA (NIER 2024). The subjects included in the NAAA change slightly over time, but we focus on reading and mathematics, as both subjects are consistently assessed throughout our sample period.

The NAAA takes place on either the 3rd or 4th Tuesday of April, the month when the academic year begins in Japan. As a result, the NAAA is designed to assess the student's understanding of the material covered during the previous academic year (NIER 2021).[5] This timing aligns well with our research design, which seeks to evaluate the impact of learning disruptions from the past summer and winter. Since the NAAA exam date is predetermined, there is no room for endogenous choice in the timing of test taking, and because the exam is centrally administered and graded, there is no room to manipulate test scores.

We utilize the 2007-2019 NAAA data with permission from MEXT for the secondary use of confidential information. Appendix Table A1 presents the number of participating schools and

[3] This is entirely due to political reasons. In 2009, there was a change of government, and the new administration chose to cut NAAA's budget.
[4] The share of students attending private primary and secondary schools was 1.3% and 7.7% in 2022, respectively (MEXT 2022). Since compulsory education in Japan consists of 6 years of primary education (ages 6 to 12) followed by 3 years of secondary education (ages 12 to 15), these two grades roughly correspond to ages 12 and 15. In Japan, school grades are nearly entirely determined by age due to the strict enforcement of school entry rules, as well as very rare grade retention and consistent promotion rates (Shigeoka 2015).
[5] The NAAA is not designed to measure general intelligence or IQ.

students each year. From 2007 to 2019, approximately 22.8 million students took the exams (about half from each grade). With the exception of 2010 and 2012, NAAA includes around 30,000 schools nationwide (approximately 20,000 primary schools and 10,000 secondary schools). Generally, this illustrates the education system in Japan, where students from two public primary schools usually attend one public secondary school within the same school district. See Appendix Figure A1 for the location of the schools.

Since we do not observe different patterns by grade, we combine both grades in the main analysis unless stated otherwise to enhance statistical power. Importantly, because the exams are given to both grades on the same day, all conditions, including cumulative heat exposure and concurrent weather conditions on test days, are inherently identical for students in both grades.

Our primary outcome is the combined reading and math scores of students, but we also examine each subject separately. Since exam difficulty and total scores differ from year to year, we calculate the z-scores for each year and grade. Note that throughout the paper, z-scores have been multiplied by 100 to allow for interpretation as percentage changes. The student-level data also include limited demographic information, such as gender. Panel A of Appendix Table A2 presents descriptive statistics of school characteristics in our main sample.

3.2. Temperature

We obtained daily temperature data for 2006–2018 from the Japan Automated Meteorological Data Acquisition System (AMeDAS), operated by the Japan Meteorological Agency. We utilize the AMeDAS data from a subset of 899 weather stations that have daily temperature information available for at least 99 percent of the days from 2006 to 2018. We impute the missing daily observations with data from the nearest stations that have complete information, in order to create a balanced panel of weather stations. Next, we assign each school to the nearest single weather station, ensuring that our estimates remain unaffected by changes in the number or locations 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.[6] Panel B of Appendix Figure A2 illustrates the cumulative distribution of the distance from the nearest station to each school. The mean (median) distance from weather stations is 6.95 (6.48) km, while the corresponding mean distance for Park et al. (2020) in the US is 15.6 km.

Our primary measure of cumulative heat and cold exposure 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

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

of the previous year to March of the test year). We use the daily maximum temperature because these temperatures typically occur when students are still in school. Following Park et al. (2020), we will focus on temperatures during school days and treat school holidays and weekends during school days as separate non-school days (see Appendix Figure A3).[7]

We also use data from weather stations to construct both cumulative and test-date measures of temperature, rainfall, and humidity. Additionally, we include similar pollution data from the nearest monitoring station, as this factor is known to impact short-term cognition (e.g., Ebenstein et al. 2016). Panel B of Appendix Table A2 provides 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 variation in hot and cold days to obtain the causal impact of cumulative exposure to extreme temperatures on human capital accumulation. Specifically, we compare test scores of students in the same school who experienced hotter summer (or cooler winter) school days with those exposed to milder summer (or winter) school days.

Figure 2 illustrates the spatial variation of mean daily maximum temperature between May and October in the previous year relative to the test year (Panel A), along with the temporal variation in the number of school days within each temperature bin from last April to March of the test year (Panel B), as experienced by students on school days. While Panel A highlights ample spatial variation in climate across the countries, Panel B indicates that there is also considerable year-to-year variation in both cold and hot school days.[8]

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:

$$Average_Z\text{-}score_{sy} = \sum_k \beta^k T_{sy}^k + \rho_s + \theta_y + \delta X'_{sy} + \varepsilon_{sy}, \quad [1]$$

where the dependent variable is the average z-score for school s in year y. T_{st}^k represents the number of school days that the maximum temperature in the prior year falls into each of nine temperature 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, where the reference is 18–22°C, the temperature range that has the most optimal

[7] Since no comprehensive national dataset of school calendars covers this period, we assign each school a probable start and end date based on the 2018 calendar of the prefectural capital in the school's prefecture, as illustrated in Appendix Figure A3. Colder regions typically have shorter summer breaks and longer winter breaks, while the opposite is true for warmer regions.

[8] Extremely hot school days are less frequent than extremely cold ones, as the summer break (typically in August) effectively prevents school attendance during excessively hot weather.

effect on test scores. Since the exam is held at the beginning of the academic year to assess students' understanding of the material covered in the previous academic year, it is reasonable to take into account the number of hot and cold days during the previous summer and winter that may disrupt the learning environment.

This specification enables us to flexibly capture the nonlinear effects of temperature impact. Our coefficients of interest are β^k. ρ_s and θ_y are school FE and year FE, respectively. X'_{st} are other time-varying controls at the school level, such as precipitation, pollution, and pollen. We cluster all standard errors at the weather station (N=889), reflecting the underlying variation in our treatment variable (Abadie et al. 2023), to account for potential serial correlation.

Identifying variation—. We leverage year-to-year variation in the previous year's temperature across schools to identify the effects of heat and cold on student test scores. To visualize the identifying variation underlying the baseline specification directly, we present the distribution of residuals from a regression of the number of school days below 6°C and above 34°C against school and year fixed effects. Figure 3 illustrates the interquartile and interdecile range of the residual variations by prefecture and by year. These figures demonstrate that there is ample variation in the number of extremely cold and hot school days within each prefecture and each year, which reassures us that our estimates are not influenced by variation from a specific region or year.

4.2. Estimating heterogeneous marginal damages

The main contribution of this paper is to go beyond the average effect of temperature on test scores and analyze the distributional impacts of extreme weather. Our individual-level test score data, linked to school ID, enable us to assess the effect of temperature on test scores based on the rank of scores within schools. Specifically, for each school, we calculate the following five values: z-scores at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles within schools. Then, we run each value separately as the outcome as follows.

$$Z\text{-}score\ at\ X\ percentile\ (X\ = 10, 25, 50, 75, and\ 90)_{sy}$$

$$= \sum_k \beta^k T^k_{sy} + \rho_s + \theta_y + \delta X'_{sy} + \varepsilon_{sy}, \quad [2]$$

What does the within-school rank capture? The two rounds of NAAA (in 2013 and 2017) included a survey of parents. Figure 4 demonstrates that within-school student rank is monotonically positively correlated with several measures of socio-economic status, including household income (panel A), father's occupation (panel B), father's education (panel C), and mother's education (panel D). For instance, the gap in household income between the 90th and 10th percentiles is 1.79 million yen (approximately 17.9 thousand USD), while the gap in the

proportion of fathers with a university education or higher between these percentiles is 30.4 percentage points. Overall, we view that a student's rank within their school largely reflects their socioeconomic background.

Finally, one might argue that variation in within-school test scores is small; therefore, we may overlook a larger variation in test scores at the national level. To examine this, Figure 5 shows the within-school score distribution by school average score. Specifically, we rank schools according to their average test scores from 2007 to 2019, and we plot the interquartile and interdecile ranges of the within-school score distribution for each five percentile of average test score bins. Although the within-school score distribution is more compressed in higher-ranked schools compared to lower-ranked ones, there is still considerable variation in within-school scores across all school ranks.

5. Baseline results

5.1. Average effects

First, we provide graphical evidence of the average effects of cumulative exposure to heat and cold on test scores. Figure 6 illustrates β^k from equation [1], along with the 95th 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 school days or cold school days increases. The extremely hot days at the right end of the figure (above 34°C) and the extremely cold days at the left end (below 6°C) are especially harmful to student learning, suggesting that the temperature's impact on learning is highly non-linear.

This aligns with the well-documented "u-shaped" mortality-temperature relationship (in our case, "inverse-u-shaped" since the damage is measured as negative), showing that both hot and cold days are linked to increased mortality worldwide (e.g., Barreca et al. 2016; Carleton et al. 2022; Cohen and Dechezleprêtre 2022; Heutel et al. 2021). While a few studies investigate the cumulative impacts of heat exposure (Cho 2017; Park et al. 2020, 2021) and cold exposure (Johnston et al. 2021) individually, we are the first to demonstrate that both extremely hot and cold school days in the previous school year in the same country impair students' learning environments.

In terms of magnitude, one additional cold day below 6°C and one hot day above 34°C in the previous year (compared to the normal temperature of 18–22°C) reduce students' test scores by 0.13% SD and 0.19% SD (p-values < 0.01 for both estimates), respectively. These magnitudes generally fall within the range of previous estimates for cumulative exposure to heat/cold on test scores. Of course, considerable caution is warranted, given the differences in institutions (e.g., teacher quality, class size, and AC availability) and climates across countries.

For example, Cho (2017) demonstrates that one additional day above 34°C (compared to 28-30°C) reduced math test scores by 0.42% SD and English scores by 0.64% SD for G12 students in Korea. Park et al. (2020) show that one extra day above 100°F (37.8°C) and above 90°F (32.2°C) lowered test scores by 0.067% and 0.053% SD, respectively (compared to a school day with temperatures in the 60s °F) for G10/11 students in the US. Additionally, Park et al. (2021) indicate that one extra day above 80°F (26.7°C), relative to 60-69°F, decreased test scores by 0.103% SD for G3-G5 and by 0.027% SD for G6-G8 in the US. Lastly, regarding cold exposure, Johnston et al. (2021) report that experiencing one additional school day with a maximum temperature <60°F (<15.6°C) in the year before the test, compared to a warm school day between 65-75°F, decreases test scores by 0.12% SD.

5.2. Distributional impact

Figure 7 displays β^k from equation [2], where z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools (measured in 0.01σ) are the outcomes. The figure clearly indicates that the negative effects are significantly larger for students at the bottom of the score distribution compared to those at the top. Appendix Table A3 presents the corresponding estimates from the figure. One additional hot day above 34°C reduces test scores by 0.32% SD for students in the bottom 10th percentile, while the corresponding estimate for students in the top 10th percentile is only 0.12%, or about one third of the estimate for the bottom 10th percentile. The magnitude of the adverse effects is consistently increasing as the rank decreases. Similarly, one more cold day below 6°C reduces test scores by 0.28% SD for students in the bottom 10th percentile, while the corresponding estimate for students in the top 10th percentile is just 0.05%. Consequently, both hot and cold temperatures widen the test score gap between the 90th and 10th percentiles by 0.20% and 0.23% SD, *exacerbating* existing inequalities in academic achievement.

Source of heterogeneity—. Importantly, since we are comparing the effect of temperature within the school (i.e., with the school FE), this result is not influenced by school resources (e.g., class size, teacher quality, or school AC). Instead, it is likely to reflect individual-level adaptations occurring outside of school (e.g., the availability of private tutoring).[9] The main contribution of this paper is to uncover the *presence* of heterogeneity in the damage function regarding heat and cold exposure based on socioeconomic status. Consequently, it is beyond the scope of this paper to explore the underlying *sources* of such heterogeneity due to the limited

[9] Of course, we cannot completely rule out the possibility that exposure to extreme temperatures outside of school (e.g., the distance from home to school) may vary based on socioeconomic status and/or differing focus and concentration levels influenced by socioeconomic status in the same classroom temperature environment.

availability of data on detailed student and household behaviors during the hot and cold days of the previous summer and winter.

Nevertheless, Appendix Figure A4 reveals that students in higher ranks within schools are more likely to study longer after school than those in lower ranks. Additionally, Appendix Table A4 suggests that longer hours of after-school study (e.g., in a cram school or at home) may reduce the negative effects of summer heat exposure. However, caution should be needed when interpreting the results, as the out-of-school study time is measured during the April exams, not in the summer or winter. In addition, there are many other factors that could explain the heterogeneity in the damage function, such as better baseline health for students in higher ranks than those in lower ranks (Case et al. 2002). A complete understanding of the underlying sources of heterogeneity in the damage function by socioeconomic status represents a direction for future research.

6. The impact of AC

6.1. Average effects of school AC

Clearly, air conditioning (AC) is the main adaptation technology for heat in schools. However, government statistics show that the notable rise in the availability of AC in public primary and secondary schools in Japan is a relatively recent development. During the sample period from 2006 to 2018, AC penetration in schools rose from approximately 10% to 50%, and by 2022, AC availability nearly reached 100%.[10]

Unfortunately, the government started publishing school air conditioning penetration rates for public primary and secondary schools at the municipal level only in 2017 (MEXT 2024b). We utilized this data in 2018, the last year of the sample period, to categorize schools into municipalities with a 0% share and a 100% share of school AC penetration (and others) as of 2018. Thus, schools with a 0% share ("without AC") indicate that air conditioning was unavailable throughout the *entire* 2006–2018 sample period (without any measurement error). In contrast, schools with a 100% share ("with AC") only indicate that AC became fully available *at some point* during the sample period. Consequently, the impact of school AC on test scores is likely to be underestimated.

Figure 7 illustrates the locations of municipalities with school AC (100% share), without school AC (0% share), and those in between (>0% & <100% share). Clearly, the northern area, characterized by a cooler climate, is more likely to have schools without AC, while schools both with and without AC are broadly distributed in the central region of Honshu Island, Japan's main

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

and largest island.

One concern is that the school AC penetration rate could be correlated with many factors at the school or municipality level, which could directly impact test scores. However, Figure 8 shows that once the average temperature is controlled, the AC penetration rate in 2018 is not strongly correlated with taxable income per capita (Panel A) nor with the student-to-teacher ratio, a measure of per pupil educational expenditure at school (Panel B). Of course, school AC could still be correlated with other adaptive technologies in the school or other resources available to students that could independently enhance student learning; therefore, the results below should be taken with considerable caution.

We now turn to provide graphical evidence of the impact of AC. Figure 9 illustrates β^k from equation [1] separately for schools with 100% AC ("with AC") and 0% AC ("without AC"). Strikingly, all the negative effects of heat are attributed to schools that lack AC throughout the entire sample period. In contrast, the adverse impact of heat on learning can largely be mitigated by AC, if considered causal.

To assess how effectively the school AC can mitigate the negative effects of heat on learning, we interact the cross-sectional measure of AC penetration ("school AC" dummy) with our heat exposure measure and include it in our baseline specification [1]. Here, we limit our sample to municipalities with and without school AC (56.9% of all school-year observations) to most drastically reflect the availability of AC across schools. However, as shown in Appendix Figure A5, our results remain robust even when we include schools from municipalities with a positive share of AC within the municipality (>0% & <100% share) in the "with" school AC category. Specifically, we estimate

$$Average_Z\text{-}score_{sy} = \sum_k \beta^k T_{sy}^k + \sum_k \gamma^k T_{sy}^k * school\ AC + \rho_s + \theta_y + \delta X'_{sy} + \varepsilon_{sy}, \quad [3]$$

where the coefficient β^k now measures the impact of heat on a school without AC, while γ^k represents the difference in that impact compared to a fully air-conditioned school. Table 1 reports β^k and γ^k from equation [3]. Column (1) shows that the negative effects of high temperatures (above 34°C) are mostly offset by the installation of school AC units. For instance, the negative effect of days exceeding 34°C without school AC is as large as 0.54% SD, but the interaction of such temperature bins with the school AC dummy is 0.39% SD. This suggests that, if taken causal, roughly 72% of the adverse effects of heat on learning are mitigated by the availability of school AC.

Of course, this offsetting effect of school AC may pick up the effect of other factors that are cross-sectionally correlated with a school's AC availability. To address this concern, columns (2) and (3) control for the interaction of each temperature bin with two variables examined in Figure

8: municipality-level taxable income per capita and the student-teacher ratio in column (2) to reflect other municipality or school-level resources. It is reassuring that the offsetting effects of school AC are robust to controlling for other factors, which mirrors Figure 7, showing that school AC penetration is uncorrelated with municipal or school-level variables. Finally, column (3) accounts for the interaction of each temperature bin with the share of home AC. Unfortunately, measuring home AC share contains substantial errors because this information is only available at the prefecture level. Nevertheless, the estimates for the interaction of hot temperature with the school AC dummy remain robust, suggesting that our school AC effect does not simply capture the effect of home AC availability.

Other robustness—. Appendix Table A5 presents the results of the additional robustness checks. Column (1) shows the baseline estimate without any controls besides school and year fixed effects. Columns (2) and (3) incorporate test-day temperature and other weather conditions on test days (precipitation, wind speed, and relative humidity) into the baseline specification, yet the estimates remain largely unchanged, indicating that our estimates do not capture the effect of contemporaneous weather conditions. Since the exam takes place in April, when the weather in Japan is relatively mild, this finding is not surprising. Column (4) includes test day air pollution (SO_2, NO, NO_2, CO, OX, and PM_{10}) in the baseline specification for the period of 2009-2019, as pollution data are only available for this period. Column (5) incorporates cumulative weather conditions aside from temperature (precipitation, wind speed, and relative humidity) into the baseline specification; however, the estimates do not change substantially.

Columns (6) and (7) in Appendix Table A5 control for the number of hot days during the non-school period (school holidays and weekends during school days), following Park et al. (2020).[11] We are reassured that the negative effects of heat during school days are not affected by including these controls, suggesting that last summer's heat directly disrupted the classroom learning environment rather than other confounding factors related to hot summers (e.g., student health). Finally, to minimize measurement error in heat exposure, column (8) restricts the sample to schools located within 10 km of the nearest weather stations (72.5% of the sample), but the estimates are little affected.

Heterogeneity—. Appendix Figure A6, along with the corresponding Appendix Table A6, examines the heterogeneous effects of temperature and the offsetting effect of the school AC: by grade (6th vs. 9th), by subject (math vs. reading), by student gender (girls vs. boys), by the

[11] Note that school days, school holidays, and weekends during school days are mutually exclusive. Weekends that fall during school holidays are considered part of the school holidays.

difficulty of the test questions (basic vs. advanced)[12], and finally by the national median temperature between 2006 and 2018 (cool vs. warm regions). Overall, we do not find much heterogeneity in both the negative impact of heat and the offsetting effect of school AC on heat, indicating that the underlying mechanism linking heat exposure to test scores may be generalizable across various contexts. A few notable exceptions are that the negative effect of heat above 34℃ is more than 50 percent greater for grade 6 than for grade 9 (-0.731 vs. -0.443) and for boys than for girls (-0.755 vs. -0.467), possibly indicating that younger children and boys may be more vulnerable to heat. Interestingly, the offsetting effect of school AC is observed only for the basic question, but not for the advanced question, which is consistent with the mitigating effect of school AC on test scores being greater for lower achiveing students, as shown next.

6.2. Distributional impact of school AC

Finally, we examine the distributional impact of school AC on within-school test scores. Figure 10 displays β^k from equation [2], separately for schools without AC (Panel A) and schools with AC (Panel B). While differential effects by rank still exist in schools without AC in Panel A, nearly all negative impacts of extreme heat are absent for *any* rank in schools with AC in Panel B, including those at the lower end of the test score distribution. The benefit is *progressive* (rather than regressive) because school AC benefits those at the lower end of the rank distribution more than those at the higher end. As expected, the school AC does not alter the distributional impact at extremely cold temperatures (below 6°C). However, Panel A without school AC shows that heat is much more likely to exacerbate pre-existing inequalities in academic achievement than cold when there is no intervention.[13]

This finding suggests that adaptation through public investment, such as air conditioning at the school level rather than the household level, can reduce the inequality-enhancing negative effects of heat. Thus, adequate public investment has the potential to mitigate the widening academic gap caused by heat exposure. This is particularly promising since both primary and

[12] Both math and reading are divided into basic and advanced questions (until 2018), where basic skills are practically applied to advanced questions. For instance, in 6th grade math, the basic question simply asks students to multiply two numbers, while the advanced question requires them to read the instructions and use that multiplication to calculate the area of a square. However, the two scores are highly correlated. For 6th graders, the correlation between scores on the basic and advanced questions is 0.90, 0.83, and 0.85 for average, math, and reading, respectively.

[13] Appendix Table A7 indicates that an additional hot day above 34°C can reduce test scores by as much as 0.97% SD for students in the bottom 10th percentile, while the estimate for students in the top 10th percentile is 0.28% SD. To the extent that schools without AC are representative, these are the "pure" estimates that do not reflect any offsetting effects. In contrast, the distributional impact of a cold day below 6°C is similar for schools with and without AC.

secondary education are compulsory in Japan, as in many other countries. It should be emphasized, however, that while school AC can largely eliminate the uneven distribution of heat damage across socioeconomic statuses, the pre-existing inequalities across these statuses still remain.

7. Conclusion

While there are many studies on the average effects of temperature on various outcomes, the distributional impacts of heat and cold based on socioeconomic status are limited. Moreover, the adaptive capacity of individuals with varying socioeconomic statuses to heat is even less understood. In this paper, we investigate the impact of cumulative exposure to extreme temperatures on children's learning, utilizing data from nationwide exams in Japan conducted between 2007 and 2019. We find that extreme temperatures disproportionately affect the human capital accumulation of low-achieving students compared to their high-achieving peers within schools, worsening pre-existing inequalities in academic achievement. However, we demonstrate that introducing air conditioning in schools can largely eliminate the negative effects of heat on learning for students of all levels. This indicates that sufficient investment in public schools has the potential to lessen the inequality-increasing adverse impacts of climate change.

This paper offers several pathways for future research. First, it is essential to determine whether the inequality-enhancing effects of heat exposure on student learning can be observed in different contexts. Second, while we primarily focus on heat due to its relevance in climate change, understanding how to mitigate the negative effects—though smaller than those of heat—of cold exposure may be important in certain situations. Finally, while we highlight the existence of heterogeneity in the damage function concerning heat and cold exposure based on socioeconomic status, understanding the sources of such heterogeneity, supported by richer data on individual and household behavior, is crucial for deepening our insights into the underlying mechanisms.

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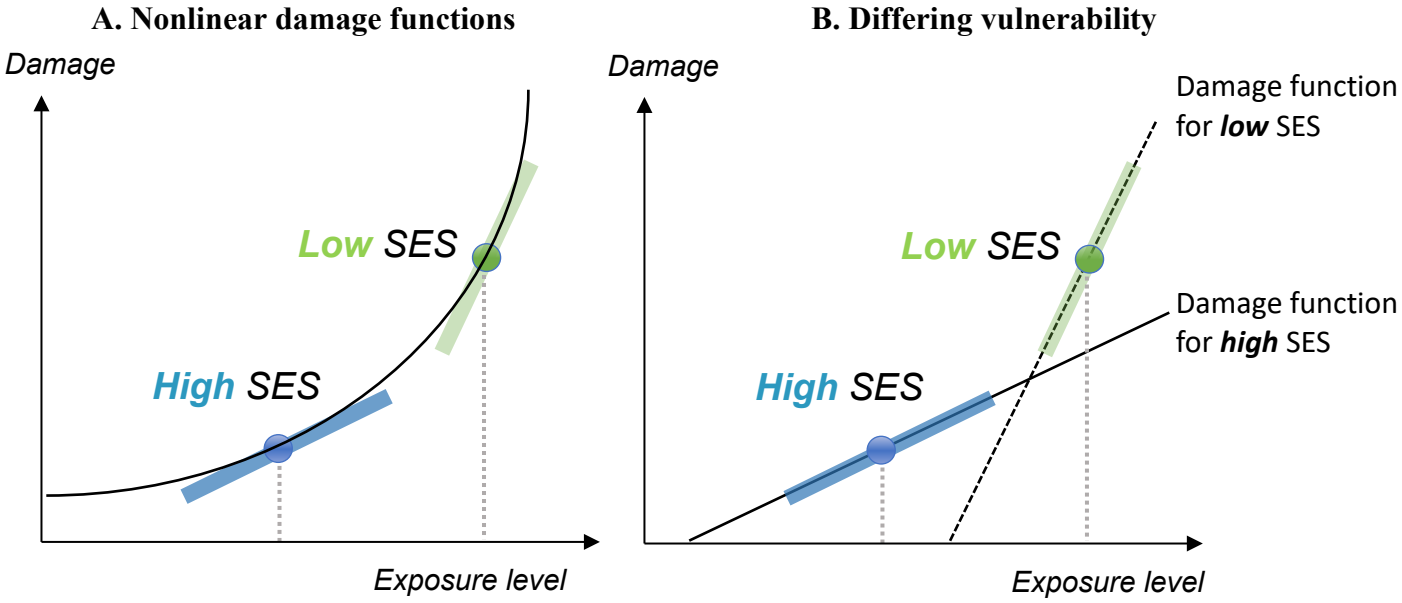
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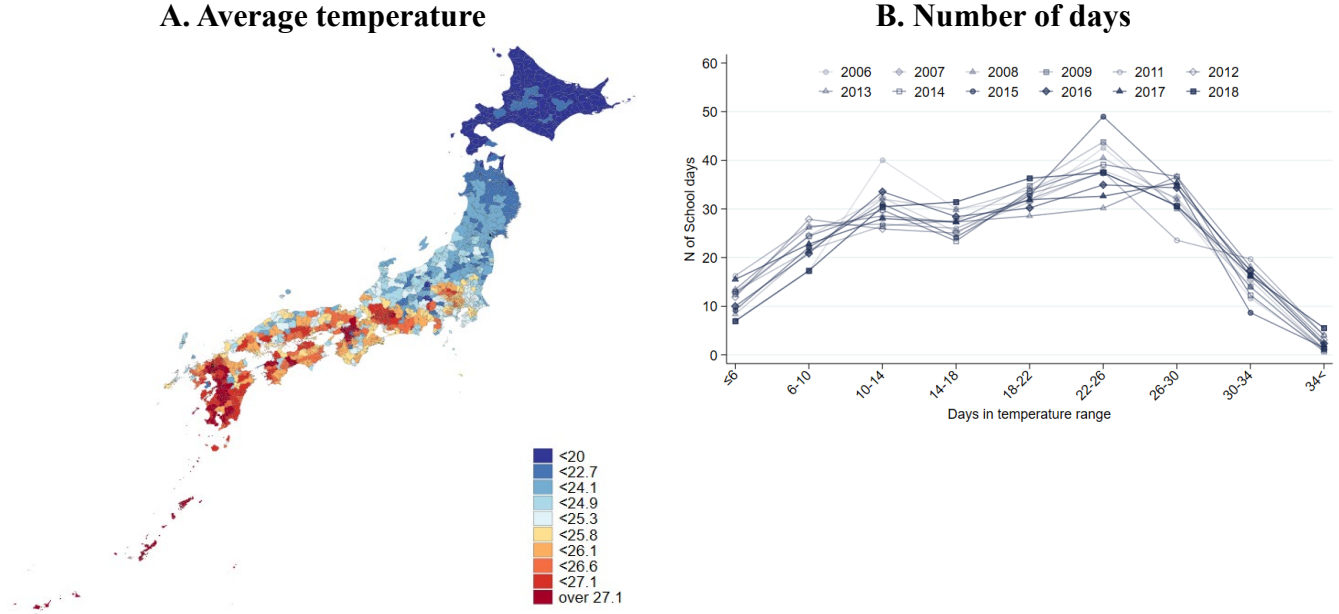
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Figure 1—Heterogeneity in marginal damages from two different explanations



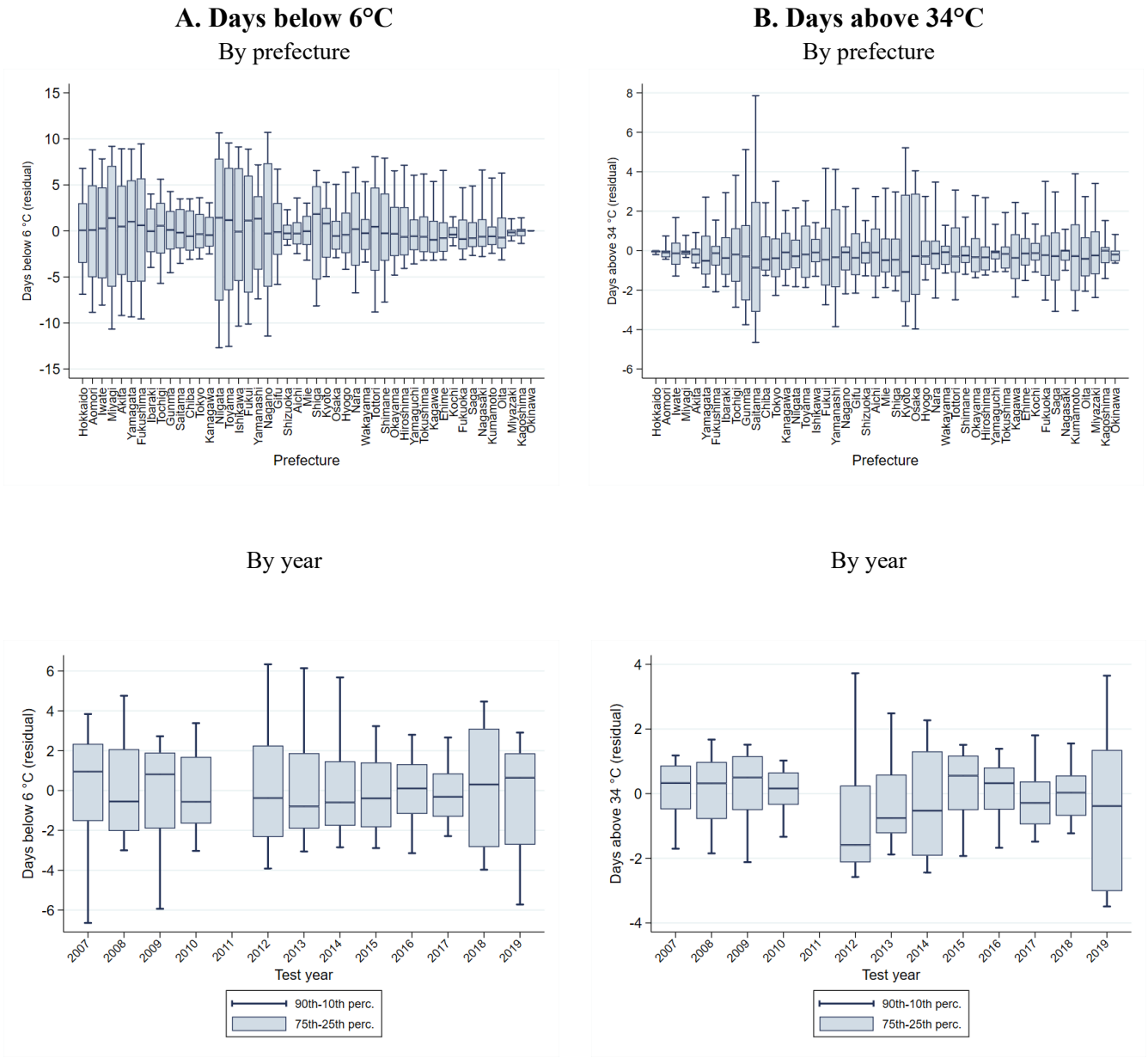
Notes: Adapted from Hsiang et al. (2019, Figure 1), this figure presents two distinct explanations for the empirically observed heterogeneity in marginal damages between high and low socioeconomic status (SES): a single nonlinear damage function, illustrated in Panel A, or different damage functions (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



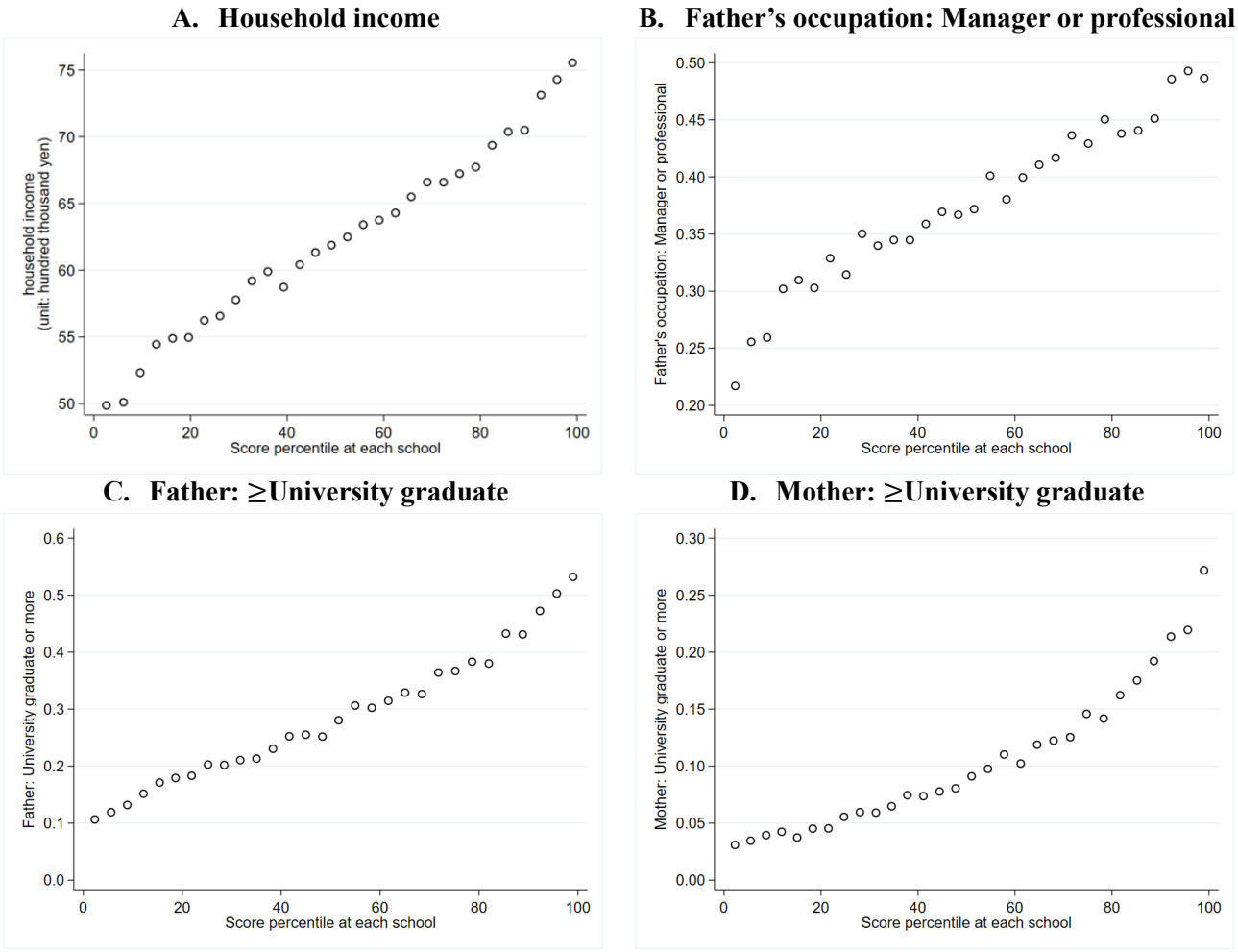
Notes: The data come from 2006-2018 AMeDAS. The figures illustrate the spatial variation of mean daily maximum temperature from May to October in the year preceding the test year (Panel A) and the temporal variation in the number of school days within each temperature bin across years, from last April to March of the test year, as experienced by students on school days (Panel B).

Figure 3—Identifying variation of prior year temperature



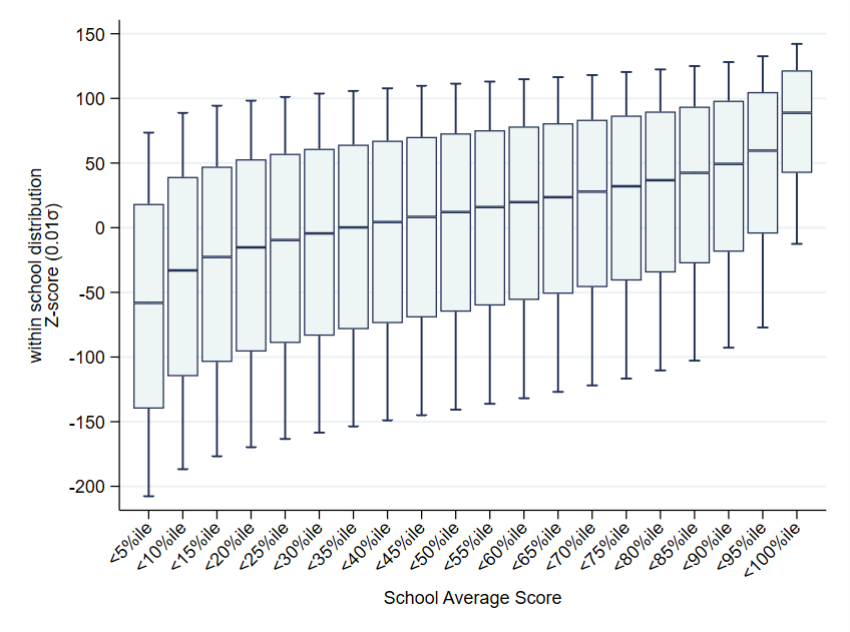
Notes: The data come from 2006-2018 AMeDAS. This figure illustrates the interquartile and interdecile ranges of the residual variation, net of school fixed effects, in the number of days below 6°C in the past year (Panel A) and the number of days above 34°C in the past year (Panel B), by prefecture and year. Estimates are weighted by the number of students in each school.

Figure 4—Within-school student rank and socioeconomic status



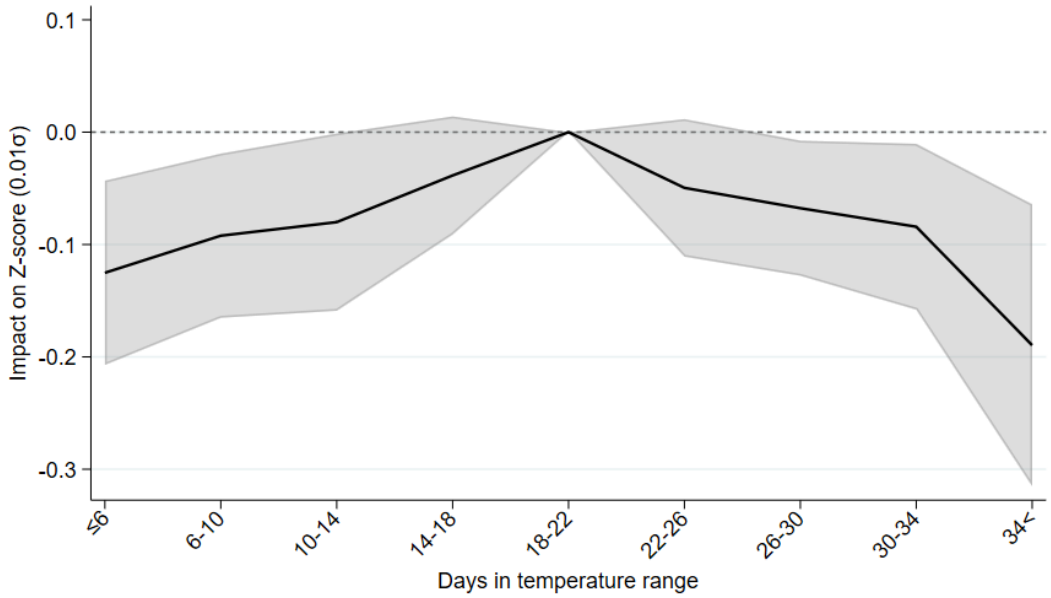
Notes: The data come from parent surveys in 2013 and 2017 NAAA. The binscatter plot illustrates the relationship between within-school student rank and various measures of socioeconomic status, specifically household income (Panel A), the proportion of fathers in managerial or professional occupations (Panel B), fathers with education at or above a 4-year college degree (Panel C), and mothers with education at or above a 4-year college degree (Panel D). Panel A is reported in hundreds of thousands of yen, with US$1 being approximately 100 yen.

Figure 5—Within-school score distribution by school average score



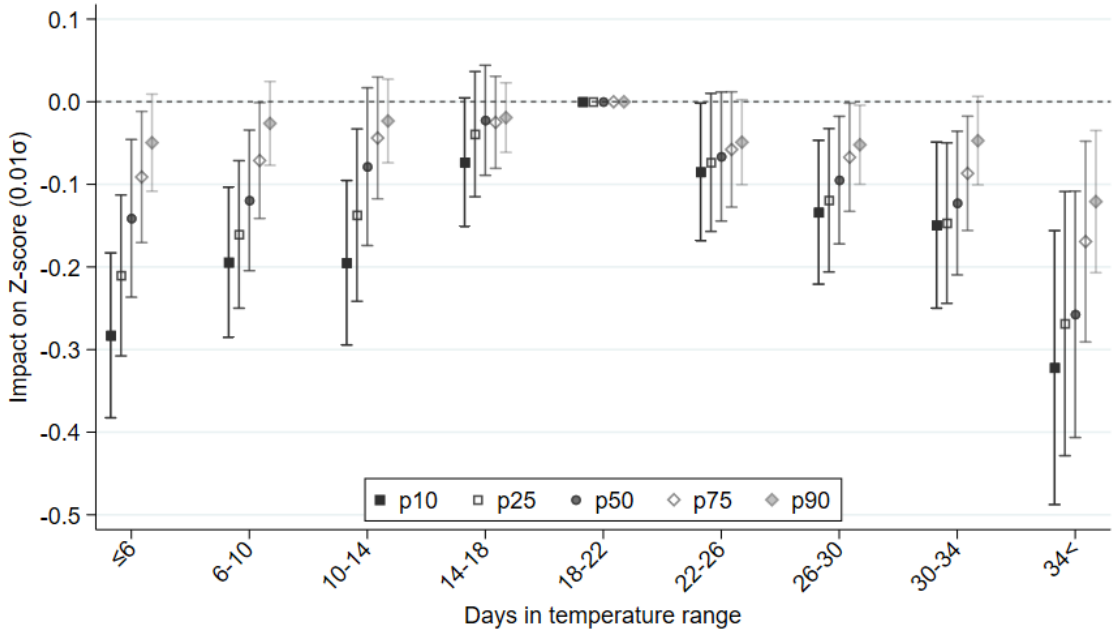
Notes: The data come from the 2007-2019 NAAA. The figure illustrates the *within*-school score distribution based on the average school scores. Specifically, we rank schools according to their average test scores from 2007 to 2019 and display the interquartile and interdecile ranges of the within-school score distribution for schools in each five percentile of average test score bins.

Figure 6—Cumulative heat/cold exposure and test performance



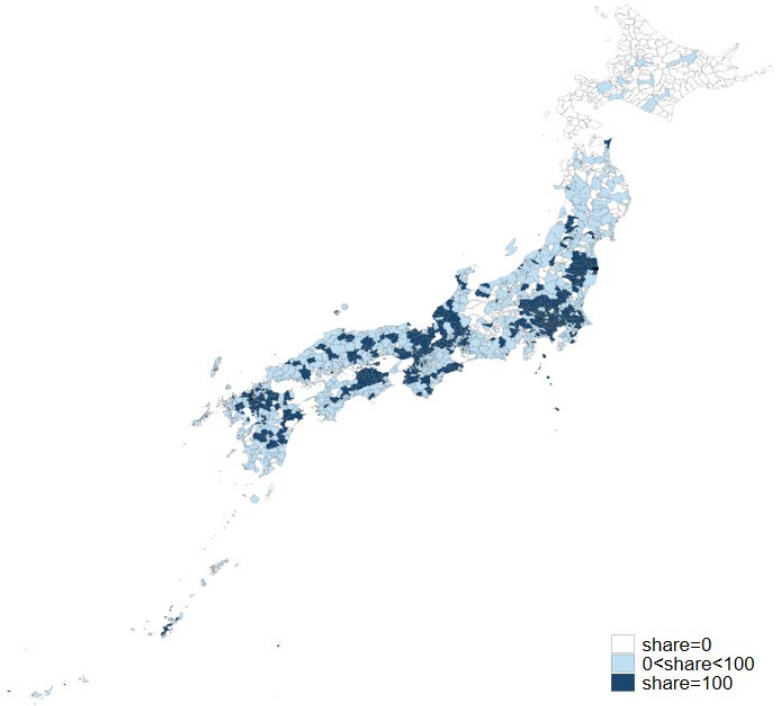
Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The figure plots β^k from an estimating equation [1], where the average z-score (measured in 0.01σ) is regressed on the number of school days within a given maximum temperature bin in the year prior to the test date, along with the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

Figure 7—Distributional impact of cumulative heat/cold exposure



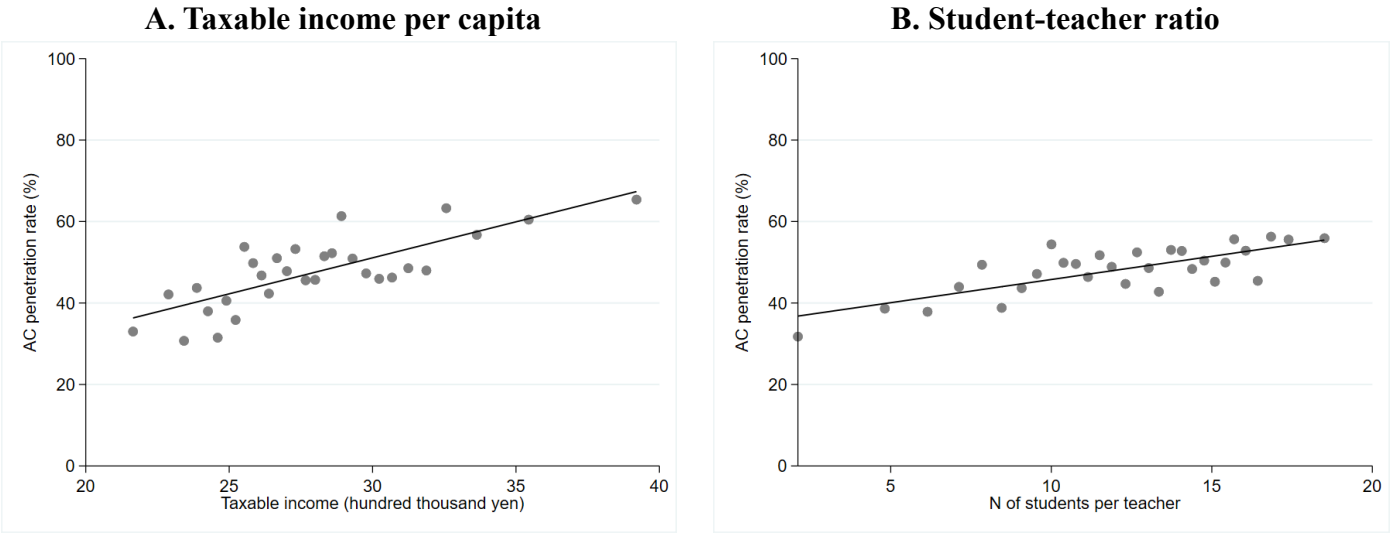
Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The figure plots β^k from an estimating equation [2], where z-scores at the 10th, 25th, 50th, 75th, and 90th percentiles within schools (measured in 0.01σ) are regressed separately on the number of school days within a given maximum temperature bin from the year prior to the test date, along with the 95th confidence intervals. The omitted category is the temperature range between 18-22°C.

Figure 7—Map of the AC penetration in schools



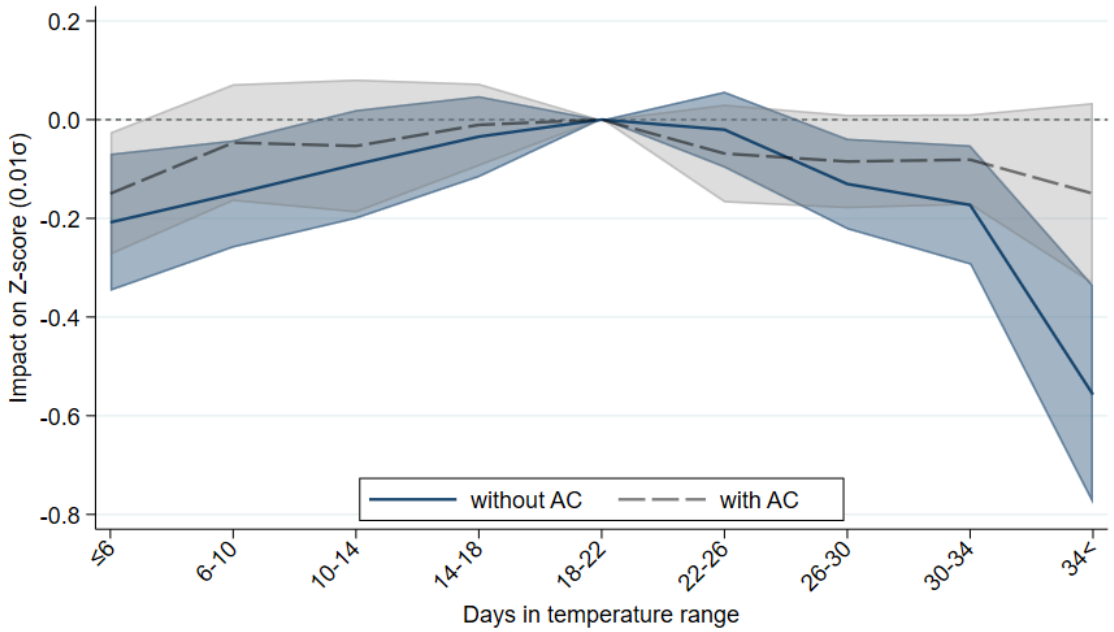
Notes: The figure displays the locations of municipalities "with AC" and "without AC." Schools are categorized based on their municipalities: those with 0% share (in white), 100% share (in dark blue), and those with a remaining share (in light blue) of school AC availability as of 2018. Schools with a 0% share indicate that school AC was not available throughout the *entire* 2006-2018 sample period (without any measurement error), while schools with a 100% share indicate that school AC became fully available *at some point* during the sample period.

Figure 8—Correlation with AC penetration



Notes: The binscatter plot illustrates the cross-sectional relationship between the school AC penetration rate and taxable income per capita (Panel A), as well as the student-teacher ratio (Panel B) for 2018, after controlling for average temperature from 2006 to 2018. Similarly, both taxable income per capita and the student-teacher ratio are averaged over the period from 2006 to 2018.

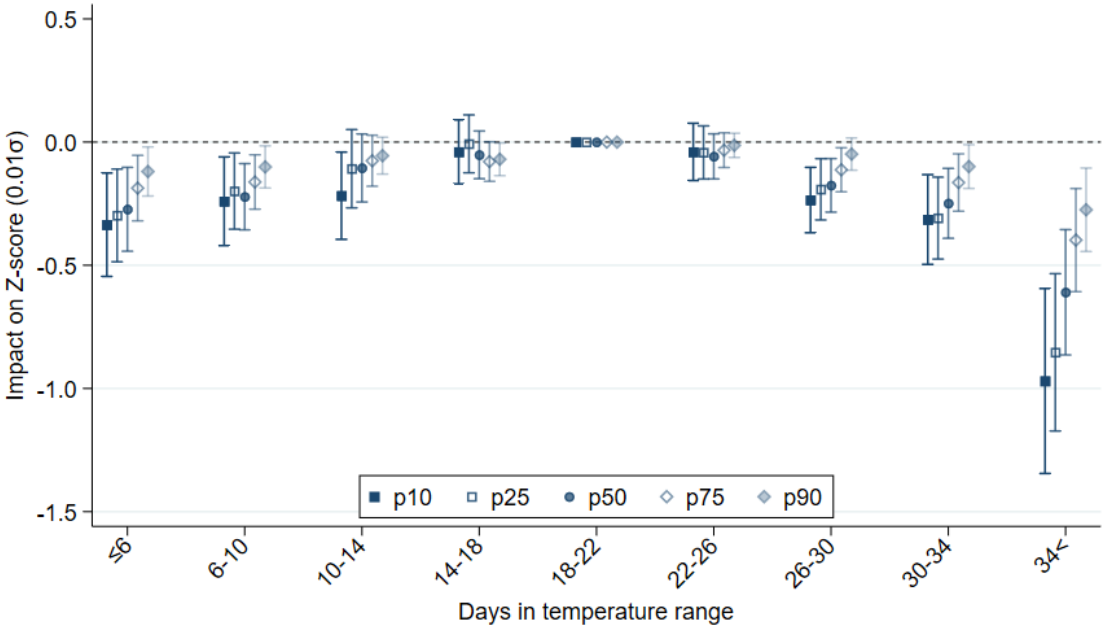
Figure 9—Cumulative heat/cold exposure and test performance (with and without school AC)



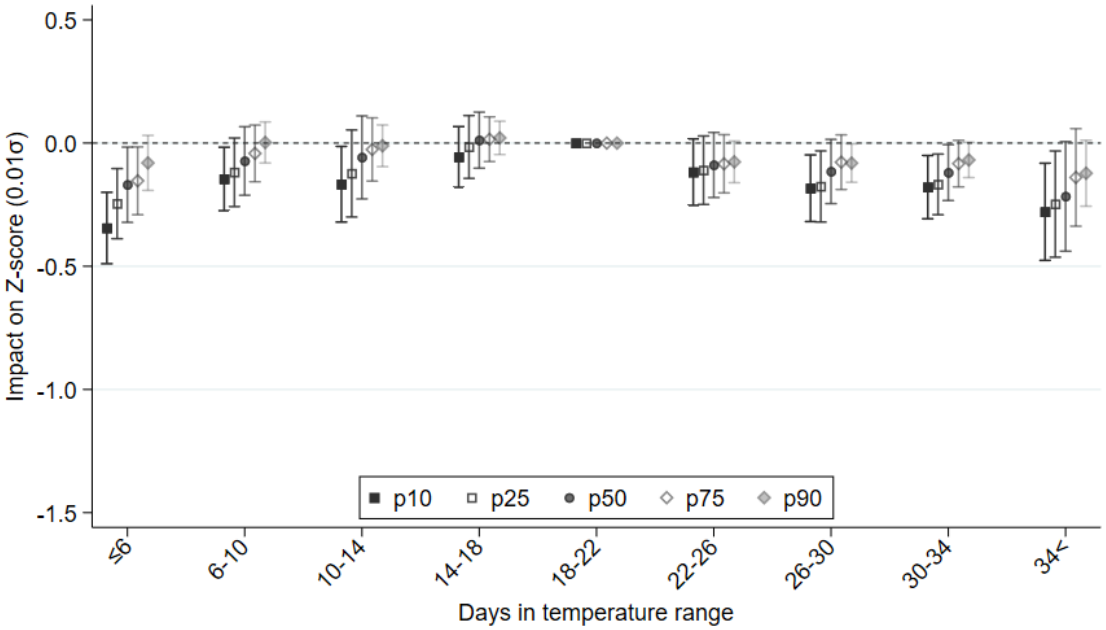
Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The figure plots β^k from estimating equation [1], separately for schools with 100% AC ("with AC") and 0% AC ("without AC") in 2018, along with the 95th confidence intervals. See Figure 7 for the locations of schools within each AC penetration category. The omitted category is the temperature range between 18-22℃.

Figure 10—Distributional impact of cumulative heat/cold exposure (with and without school AC)

A. Without school AC



B. With school AC



Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The figures plot β^k from estimating equation [2], separately for schools with 100% AC ("with AC") in Panel A, and 0% AC ("without AC") in 2018 in Panel B, along with the 95th confidence intervals. The omitted category is the temperature range between 18-22℃.

Table 1—The impact of school AC

	(1)		(2)		(3)	
		× 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		188,913		190,210	

Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The unit of observation is school-year. The dependent variable is the average test score of math and reading at the school-year level, measured in 0.01σ. Column (1) presents estimates from an estimating 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 is available at the school in 2018. Column (2) adds the interaction of municipality-level taxable income per capita and the student-teacher ratio in 2018 with the number of days in each temperature bin during school days in the previous year. Column (3) adds the interaction of prefecture-level home AC shares in 2014 with the number of days in each temperature bin during school days in the previous year. Estimates are weighted by the number of students in each school year. The omitted category is the temperature range between 18-22℃.

Online Appendix
(Not for Publication)

Heat, Adaptation, and Academic Inequality

By Mika Akesaka, and Hitoshi Shigeoka

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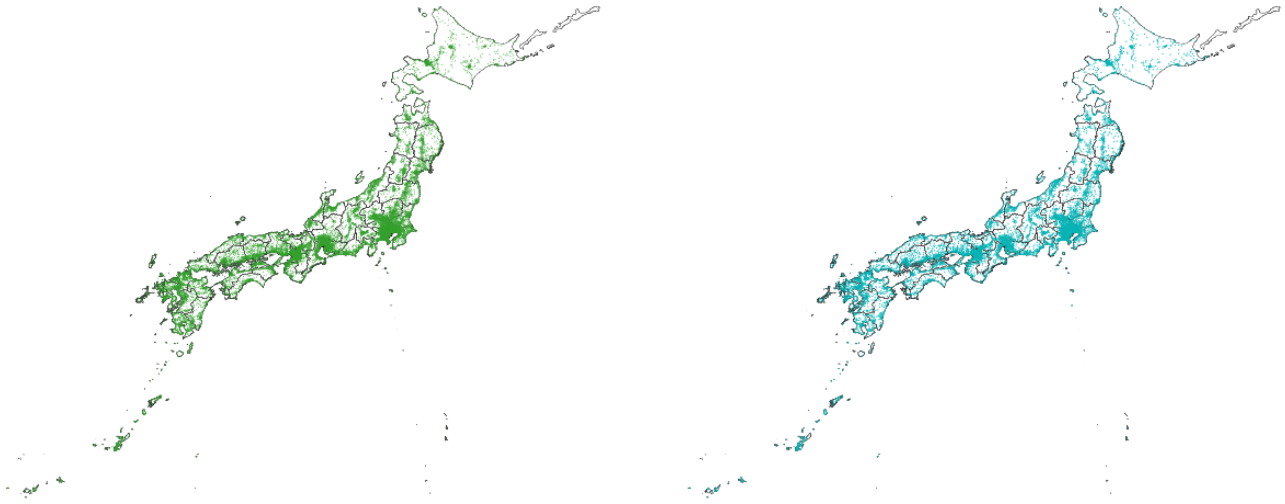
Section A Additional Figures and Tables

Section B Data Appendix

Appendix A: Additional figures and tables

Figure A1—Location of schools

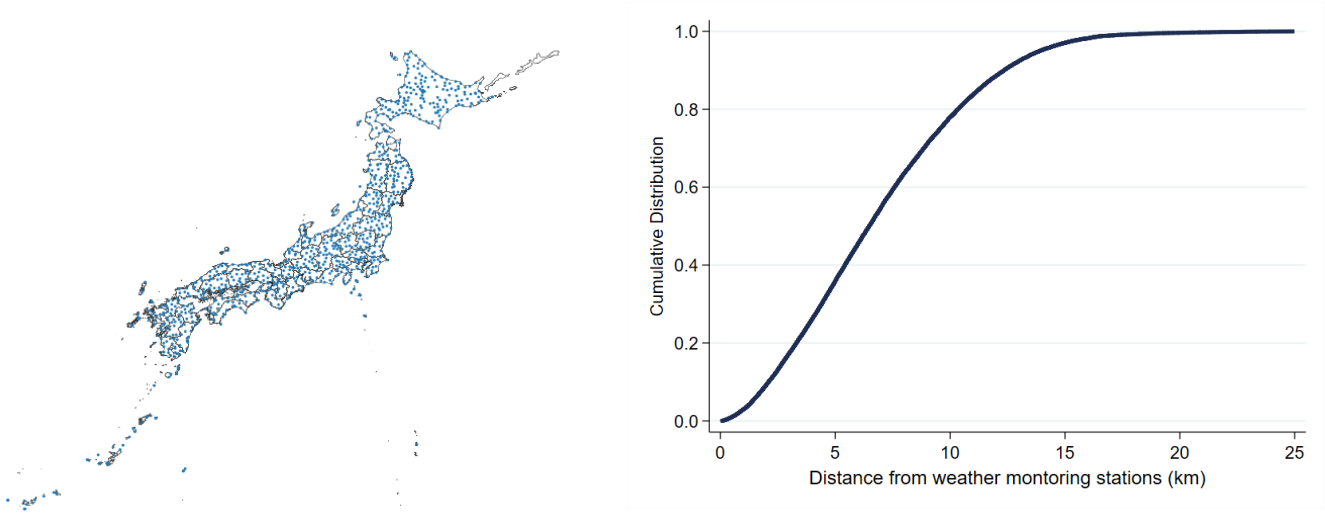
A. Primary schools (grade 6) **B. Secondary schools (grade 9)**



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.

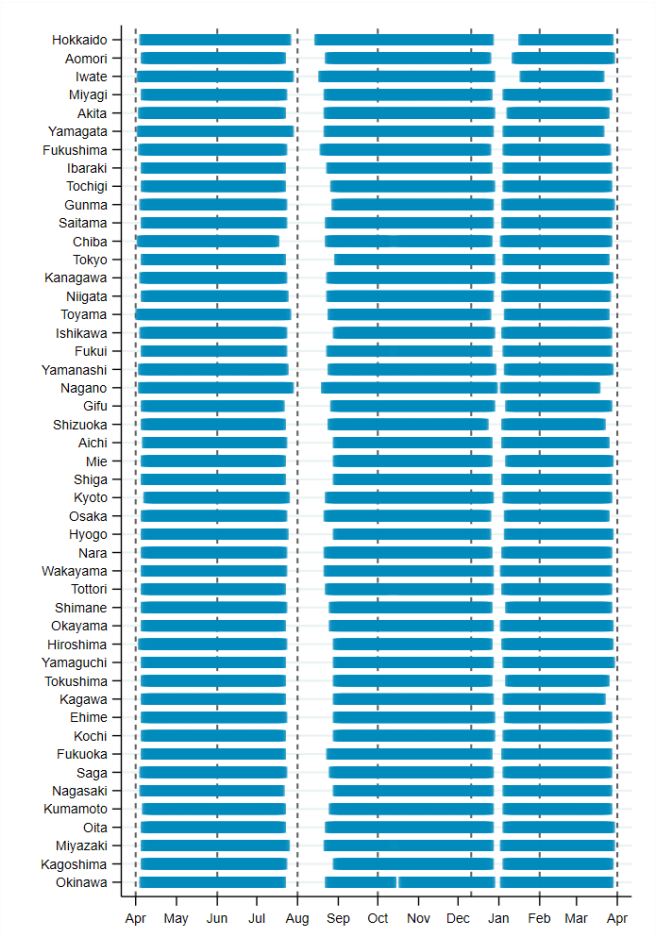
Figure A2—Weather stations

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.

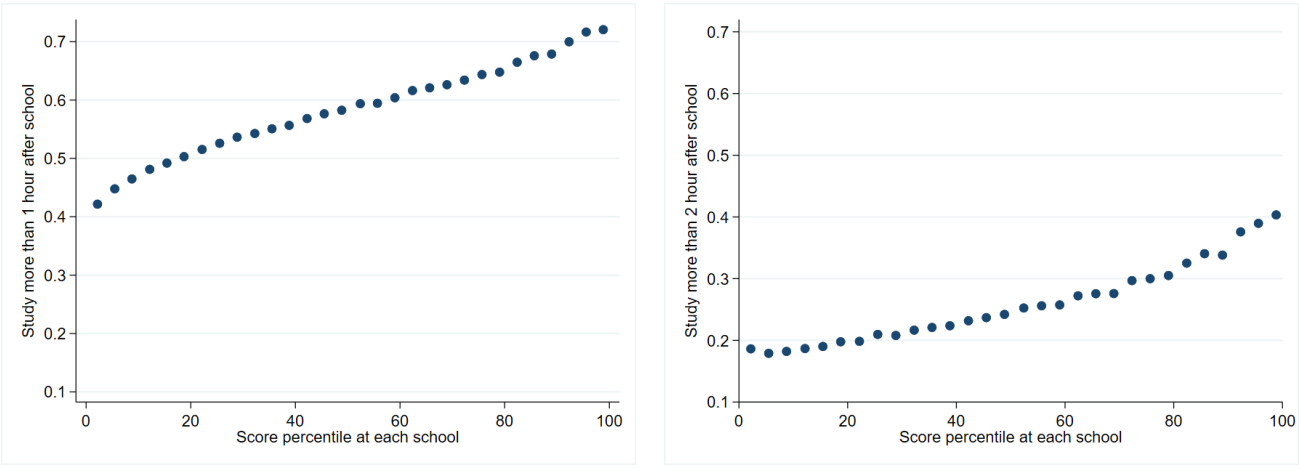
Figure A3—School days by region



Notes: The figure displays the academic calendar of the prefectural capital within the school's prefecture for 2018. There is a total of 47 prefectures in Japan. The academic calendar consists of three terms: spring, fall, and winter.

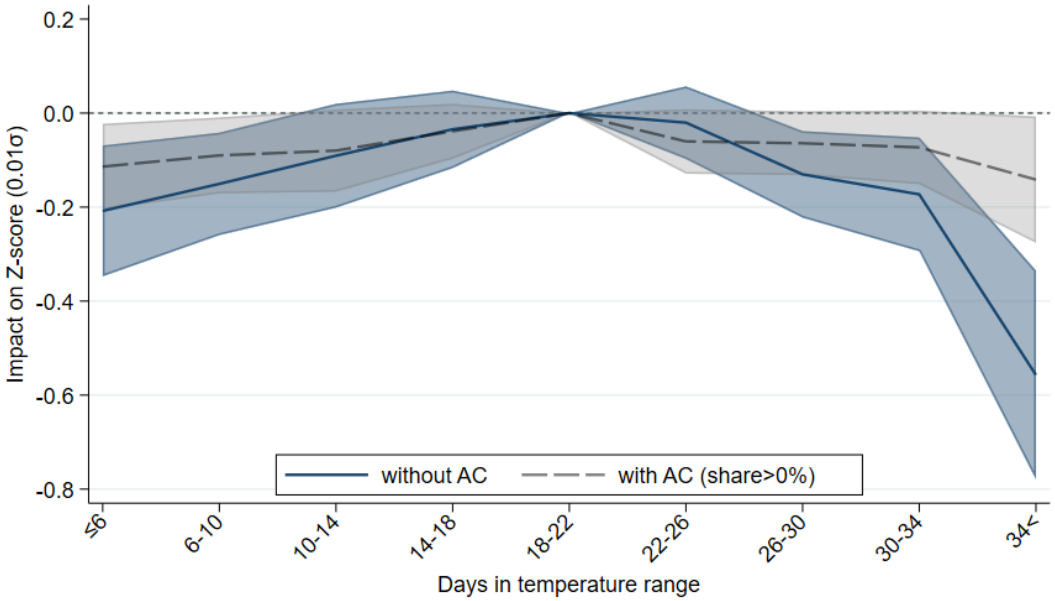
Figure A4—Within-school student rank and studying outside of school

A. Study outside of school over 1 hour **B. Study outside of school over 2 hours**



Notes: The data come from student surveys from the 2007-2019 NAAA. The binscatter plot illustrates the relationship between within-school student rank and the fraction of students studying outside of school for over 1 hour (Panel A), and the fraction of students studying outside of school for over 2 hours (Panel B).

Figure A5—Cumulative heat/cold exposure and test performance (school AC 0% vs. AC>0%)

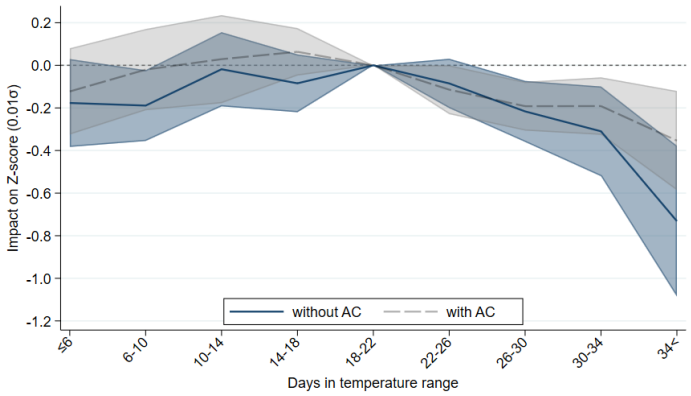


Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The figure displays β^k from an estimating equation [1], separately for schools in municipalities with a positive share of AC and those in municipalities with 0% AC availability in 2018, along with the 95% confidence intervals. The omitted category is the temperature range between 18-22°C. See Figure 7 for the locations of schools for each school AC penetration category.

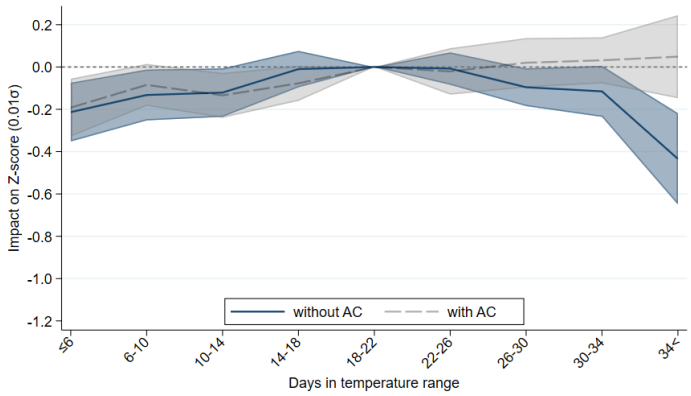
Figure A6—Heterogeneity: Cumulative heat/cold exposure and test performance (with and without school AC)

A. By grade

Grade 6

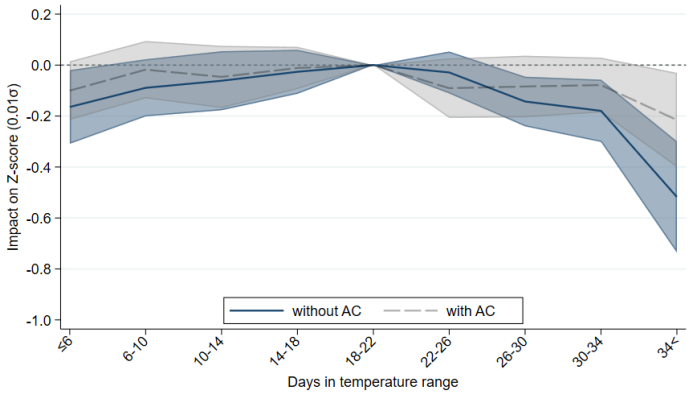


Grage 9

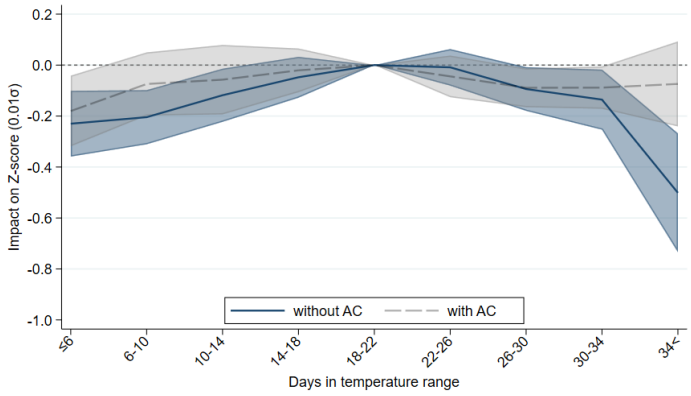


B. By subjects

Math

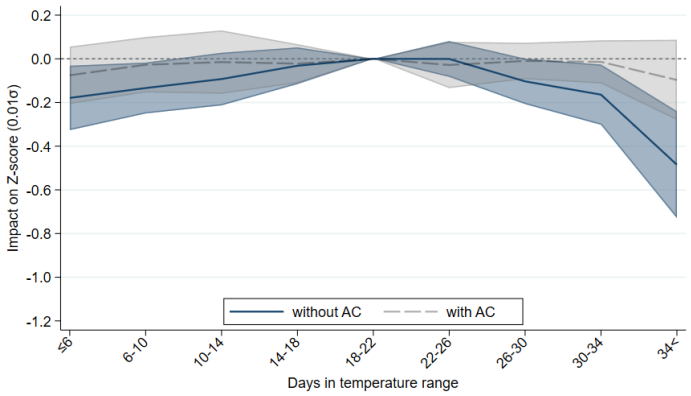


Reading

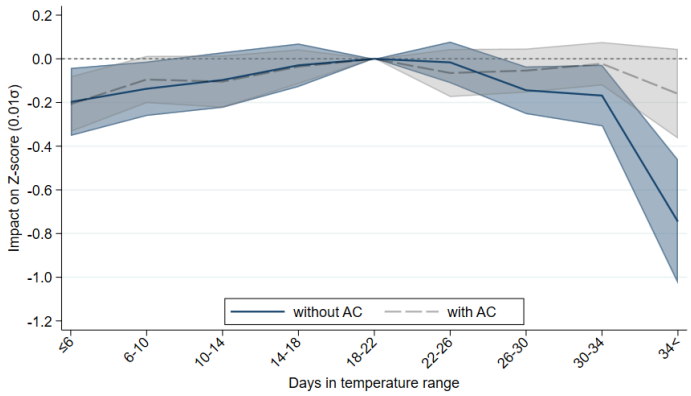


C. By gender

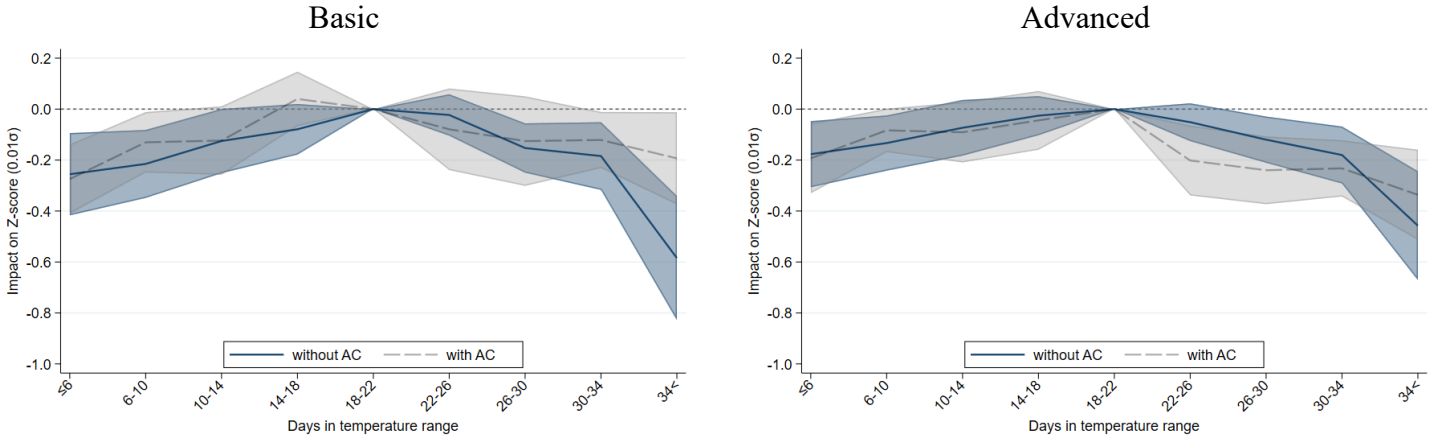
Girls



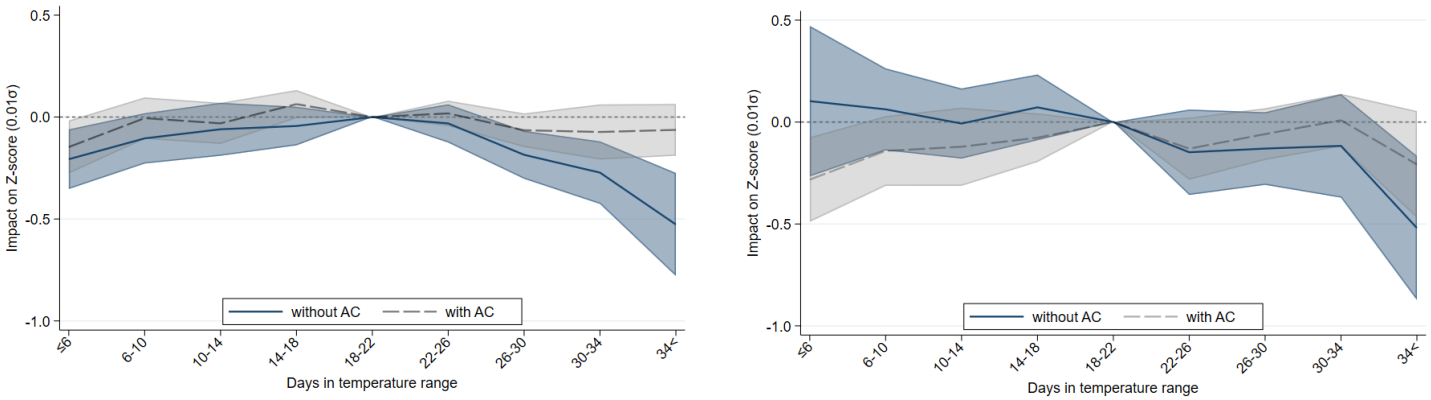
Boys



D. By difficulty



E. By region



Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The figures plot β^k from an estimating equation [1], separately for schools with 100% AC ("with AC") and 0% AC ("without AC") in 2018, along with the 95th confidence intervals. See Figure 7 for 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 grades (grade 6 vs. grade 9). Panel B divides the sample by subjects (math vs. reading). Panel C divides the sample by student gender (girls vs. boys). Panel D divides the sample by the difficulty 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.

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	32,326	21,816	10,510	2,217,644	1,120,072	1,097,572
2008	32,127	21,695	10,432	2,244,103	1,162,703	1,081,400
2009	31,848	21,505	10,343	2,264,518	1,153,072	1,111,446
2010	9,868	5,421	4,447	709,114	271,004	438,110
2011	-	-	-	-	-	-
2012	9,550	5,178	4,372	703,865	262,232	441,633
2013	30,574	20,472	10,102	2,209,163	1,124,218	1,084,945
2014	30,236	20,222	10,014	2,162,958	1,097,586	1,065,372
2015	29,964	20,032	9,932	2,136,318	1,076,834	1,059,484
2016	29,127	19,397	9,730	2,076,525	1,037,066	1,039,459
2017	29,195	19,376	9,819	2,048,161	1,018,543	1,029,618
2018	29,259	19,431	9,828	2,013,346	1,041,474	971,872
2019	29,079	19,304	9,775	2,030,382	1,048,815	981,567
Total	323,153	213,849	109,304	22,816,097	11,413,619	11,402,478

Notes: This table shows the number of schools and students participating in the National Assessment of Academic Ability (NAAA) each year. 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 due to 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:	Obs	Mean	Std. dev.	Min	Max	N of station	Period
Panel A. School characteristics							
Female share	301,821	0.485	0.123	0	1	-	2007-2019
School type:							
Private school	322,531	0.005	0.072	0	1	-	2007-2019
Public school	322,531	0.979	0.142	0	1	-	2007-2019
National school	322,531	0.015	0.123	0	1	-	2007-2019
Number of classes:							
5≤	321,987	0.159	0.366	0	1	-	2007-2019
6-11	321,987	0.378	0.485	0	1	-	2007-2019
12-17	321,987	0.281	0.449	0	1	-	2007-2019
≥18	321,987	0.183	0.386	0	1	-	2007-2019
Region size:							
Metropolitan area	315,036	0.180	0.384	0	1	-	2007-2019
Core city	315,036	0.121	0.326	0	1	-	2007-2019
Other city	315,036	0.531	0.499	0	1	-	2007-2019
Town or Village	315,036	0.168	0.374	0	1	-	2007-2019
Panel B. Weather conditions							
Number of days							
6℃≤	322,531	13.99	19.58	0	194	891	2007-2019
6-10℃	322,531	22.46	8.53	0	53	891	2007-2019
10-14℃	322,531	30.04	8.82	0	60	891	2007-2019
14-18℃	322,531	27.39	6.03	0	58	891	2007-2019
18-22℃	322,531	32.76	6.61	0	71	891	2007-2019
22-26℃	322,531	38.22	8.89	0	88	891	2007-2019
26-30℃	322,531	31.94	10.44	0	97	891	2007-2019
30-34℃	322,531	13.90	9.14	0	79	891	2007-2019
34℃>	322,531	1.96	2.79	0	20	891	2007-2019
Precipitation (mm)	322,531	4.66	1.56	0.82	21.48	1165	2007-2019
Wind speed (m/s)	322,531	2.43	0.95	0.26	8.75	887	2007-2019
Relative humidity	322,531	69.59	5.12	58.39	82.94	153	2007-2019
SO_2 (ppb)	226,633	1.79	1.33	0.04	46.06	839	2010-2019
NO_2 (ppb)	226,702	12.04	6.62	0.71	51.01	1433	2010-2019
CO (0.1ppm)	226,702	3.81	1.30	1.07	11.01	236	2010-2019
OX (ppb)	226,690	29.31	3.79	11.61	54.56	1017	2010-2019
PM_{10} ($\mu g/m^3$)	226,702	18.05	4.47	3.27	42.77	1425	2010-2019

Notes: Panels A and B present the descriptive statistics of school characteristics and weather characteristics, respectively. Gender information for grade 6 in Panel A was not collected in 2015. Pollution information is available from 2009 to 2019.

Table A3—Distributional impact of cumulative heat/cold exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	Resulting gap		
						90th-10th	90th-50th	50th-10th
Days 6℃≤	-0.283***	-0.210***	-0.141***	-0.091**	-0.050*	0.233***	0.092***	0.142***
	(0.051)	(0.050)	(0.049)	(0.040)	(0.030)	(0.043)	(0.026)	(0.038)
Days 6-10℃	-0.194***	-0.161***	-0.119***	-0.071**	-0.026	0.168***	0.093***	0.075**
	(0.046)	(0.045)	(0.043)	(0.036)	(0.026)	(0.040)	(0.024)	(0.034)
Days 10-14℃	-0.195***	-0.137**	-0.079	-0.044	-0.023	0.172***	0.055**	0.116***
	(0.051)	(0.053)	(0.049)	(0.038)	(0.026)	(0.039)	(0.027)	(0.029)
Days 14-18℃	-0.073*	-0.039	-0.022	-0.025	-0.019	0.054	0.003	0.051*
	(0.040)	(0.039)	(0.034)	(0.028)	(0.021)	(0.037)	(0.019)	(0.028)
Days 22-26℃	-0.085**	-0.073*	-0.066*	-0.058	-0.049*	0.036	0.017	0.019
	(0.042)	(0.043)	(0.040)	(0.036)	(0.026)	(0.031)	(0.019)	(0.024)
Days 26-30℃	-0.134***	-0.119***	-0.095**	-0.067**	-0.052**	0.082**	0.043**	0.039
	(0.044)	(0.044)	(0.039)	(0.033)	(0.024)	(0.036)	(0.021)	(0.026)
Days 30-34℃	-0.149***	-0.147***	-0.123***	-0.087**	-0.047*	0.102**	0.076***	0.027
	(0.051)	(0.049)	(0.044)	(0.035)	(0.027)	(0.045)	(0.028)	(0.030)
Days 34℃>	-0.322***	-0.269***	-0.257***	-0.169***	-0.121***	0.201***	0.136***	0.065
	(0.084)	(0.081)	(0.076)	(0.062)	(0.044)	(0.066)	(0.044)	(0.047)
R-squared	0.646	0.687	0.692	0.649	0.577	0.527	0.531	0.355
Observations	312,764	312,764	312,764	312,764	312,764	312,764	312,764	312,764

Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The unit of observation is school-year. Columns (1)-(5) present the estimates from equation [2], along with standard errors clustered at the weather station level in parentheses. Columns (6)-(8) show the within-school differences in estimates for the 90th–10th percentile, 90th-50th percentile, and 50th-10th percentile. 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 A4—The impact of studying outside of school

	(1)		(2)	
		× study over 1 hour		× study over 2 hour
Days 6℃≤	-0.1167***	0.0015***	-0.1263***	-0.0004
	(0.0405)	(0.0004)	(0.0409)	(0.0005)
Days 6-10℃	-0.0637*	0.0038***	-0.0947**	0.0060***
	(0.0363)	(0.0005)	(0.0368)	(0.0006)
Days 10-14℃	-0.0799**	0.0033***	-0.0840**	0.0032***
	(0.0393)	(0.0005)	(0.0390)	(0.0006)
Days 14-18℃	-0.0525**	0.0041***	-0.0471*	0.0019**
	(0.0264)	(0.0006)	(0.0254)	(0.0008)
Days 22-26℃	-0.0527	0.0004	-0.0468	0.0001
	(0.0324)	(0.0004)	(0.0306)	(0.0004)
Days 26-30℃	-0.0753**	0.0029***	-0.0771**	0.0021***
	(0.0303)	(0.0004)	(0.0304)	(0.0005)
Days 30-34℃	-0.0937**	0.0025***	-0.1009***	0.0015**
	(0.0373)	(0.0007)	(0.0381)	(0.0007)
Days 34℃>	-0.1858***	0.0040**	-0.2057***	0.0015
	(0.0601)	(0.0017)	(0.0617)	(0.0020)
R-squared	0.748		0.737	
Observations	322,523		322,523	

Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The unit of observation is school-year. The dependent variable is the average test score of math and reading at the school-year level, measured in 0.01σ. Estimates from a variant of equation [1], which additionally includes the interaction between the fraction of students studying outside of 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. School AC is a dummy that takes one if an AC is available at the school in 2018. 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—Robustness on the impact of heat

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Days above 34℃	-0.536***	-0.546***	-0.521***	-0.348***	-0.531***	-0.535***	-0.445***	-0.575***
	(0.117)	(0.118)	(0.117)	(0.127)	(0.122)	(0.113)	(0.138)	(0.131)
Days above 34℃ × school AC	0.385***	0.400***	0.380***	0.478***	0.442***	0.440***	0.361**	0.466***
	(0.149)	(0.149)	(0.141)	(0.147)	(0.143)	(0.135)	(0.176)	(0.153)
R-squared	0.748	0.748	0.748	0.769	0.749	0.748	0.748	0.756
Observations	190,214	190,214	190,214	145,780	190,214	190,214	190,214	141,736
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	
Sensor within 10 km								X

Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The unit of observation is school-year. The dependent variable is the average test score of math and reading at the school-year level, measured in 0.01σ. The estimates come from an estimating equation [3], along with the standard errors clustered at the weather station level in parentheses. Here, the estimates for the number of 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 that takes one if an AC is available at the school in 2018. Estimates are weighted by the number of students in each school-year. The omitted category is the temperature range between 18-22℃. Full years mean from 2007-2019. Column (1) presents the baseline estimate without any controls other than school and year fixed effects. Column (2) adds test-day temperature into the baseline specification. Column (3) further includes additional weather conditions (precipitation, wind speed, and relative humidity). Column (4) includes test-day air pollution (SO_2, NO, NO_2, CO, OX, PM_{10}) in the baseline specification for the 2009-2019 period, as pollution data is only available for this period. Column (5) adds other cumulative weather conditions (precipitation, wind speed, and relative humidity. Columns (6) and (7) control for the number of days in each temperature bin during school holidays and weekends in the prior year, respectively. 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 A6—Heterogeneous impacts of heat

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	By grade		*By subject*		*By gender*		*By difficulty*		*By region*	
	6th	9th	Math	Reading	Girls	Boys	Basic	Advanced	Cool	Warm
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℃×AC dummy	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 come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The unit of observation is school-year. The dependent variable is the average test score of math and reading at the school-year level, measured in 0.01σ. The estimates come from an estimating equation [3], along with the standard errors clustered at the weather station level in parentheses. Here, the estimates for the number of 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 that takes one if an AC is available at the school in 2018. 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 level (grade 6 vs. grade 9). Columns (3) and (4) show the estimates by subject area (math vs. reading). Columns (5) and (6) show the estimates by student gender (girls vs. boys). Columns (6) and (7) show 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, so we observe the average test score of each school-year for each subject, gender, and the 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 either columns (3) or (4). The slightly smaller observations for columns (5) and (6), compared to either columns (3) or (4), are due to the fact that gender information was not collected for grade 6 in 2015. Similarly, the slightly smaller observations for columns (7) and (8), compared to either columns (3) or (4), are due to the absence of such a distinction in 2019. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A7—Distributional impact of cumulative heat/cold exposure (with and without school AC)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Without AC					**With AC**				
	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Days 6℃≤	-0.336***	-0.298***	-0.273***	-0.187***	-0.119**	-0.345***	-0.246***	-0.169**	-0.153**	-0.080
	(0.107)	(0.096)	(0.087)	(0.068)	(0.051)	(0.074)	(0.072)	(0.078)	(0.070)	(0.057)
Days 6-10℃	-0.240***	-0.199**	-0.222***	-0.162***	-0.101**	-0.146**	-0.118*	-0.073	-0.042	0.003
	(0.092)	(0.079)	(0.068)	(0.056)	(0.044)	(0.065)	(0.071)	(0.071)	(0.059)	(0.042)
Days 10-14℃	-0.218**	-0.108	-0.105	-0.076	-0.055	-0.167**	-0.123	-0.058	-0.026	-0.011
	(0.090)	(0.081)	(0.070)	(0.053)	(0.038)	(0.078)	(0.090)	(0.086)	(0.065)	(0.043)
Days 14-18℃	-0.040	-0.007	-0.052	-0.079*	-0.070**	-0.056	-0.016	0.012	0.016	0.021
	(0.066)	(0.060)	(0.049)	(0.041)	(0.034)	(0.063)	(0.065)	(0.058)	(0.046)	(0.034)
Days 22-26℃	-0.040	-0.042	-0.058	-0.033	-0.013	-0.118*	-0.110	-0.089	-0.084	-0.076*
	(0.059)	(0.055)	(0.047)	(0.036)	(0.025)	(0.069)	(0.071)	(0.067)	(0.060)	(0.043)
Days 26-30℃	-0.235***	-0.192***	-0.176***	-0.112**	-0.049	-0.183***	-0.176**	-0.115*	-0.077	-0.081**
	(0.068)	(0.063)	(0.055)	(0.045)	(0.033)	(0.069)	(0.073)	(0.066)	(0.056)	(0.040)
Days 30-34℃	-0.314***	-0.308***	-0.249***	-0.164***	-0.099**	-0.179***	-0.168***	-0.120**	-0.083*	-0.068*
	(0.093)	(0.085)	(0.072)	(0.059)	(0.045)	(0.065)	(0.063)	(0.058)	(0.048)	(0.036)
Days 34℃>	-0.970***	-0.853***	-0.609***	-0.398***	-0.275***	-0.279***	-0.248**	-0.216*	-0.139	-0.122*
	(0.191)	(0.163)	(0.129)	(0.107)	(0.086)	(0.100)	(0.110)	(0.113)	(0.101)	(0.068)
R-squared	0.544	0.590	0.605	0.566	0.491	0.692	0.731	0.737	0.698	0.631
Observations	48,938	48,938	48,938	48,938	48,938	134,551	134,551	134,551	134,551	134,551

Notes: The data come from the 2007-2019 NAAA and the 2006-2018 AMeDAS. The unit of observation is school-year. The dependent variable is the percentile test score at the school-year level, measured in 0.01σ. Estimates from equation [2] are reported, along with standard errors clustered at the weather station level in parentheses, separately for schools without AC (columns 1-5) and without AC (columns 6-10) as of 2018. Estimates are weighted by the number of students in each school-year. The omitted category is the temperature range between 18-22℃. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Appendix B: Data Appendix

Data	Source
National Assessment of Academic Ability (NAAA)	Years: 2007–2019 Data description: reading and math scores for grades 6 and 9 Source: The National Institute for Educational Policy Research https://www.nier.go.jp/kaihatsu/zenkokugakuryoku.html
Weather	Years: 2006–2019 Data description: daily temperature (maximum, average, minimum) Source: Japan Automated Meteorological Data Acquisition System (AMeDAS) operated by the Japan Meteorological Agency (JMA) https://www.data.jma.go.jp/obd/stats/etrn/
Pollution	Years: 2009 April–2019 March Data description: hourly SO_2, NO, NO_2, CO, OX, PM_{10} Source: National Institute for Environmental Studies https://www.nies.go.jp/igreen/index.html
Taxable income	Years: 2006–2018 Data description: taxable income per capita at municipality level Source: Survey on Municipal Taxation Status (Shichōsonzei kazeijōky tou no shirabe) https://www.soumu.go.jp/main_sosiki/jichi_zeisei/czaisei/czaisei_seido/ichiran09.html
Student-teacher ratio	Years: 2006–2018 Data description: student-teacher ratio at municipality level Source: School Basic Survey https://www.mext.go.jp/b_menu/toukei/chousa01/kihon/1267995.htm
School AC penetration rate	Year: 2018 Data description: school AC penetration rate for public primary and secondary schools at the municipality level Source: Survey of Air Conditioning Installation Status in Public School Facilities https://www.mext.go.jp/a_menu/shotou/zyosei/mext_01278.html
Home AC share	Year: 2014 Data description: home AC share at prefecture level National Survey of Family Income and Expenditure https://www.stat.go.jp/data/zensho/2014/index.html