Policy Research Working Paper 10714

High Temperature and Learning Outcomes

Evidence from Ethiopia

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WORLD BANK GROUP
Development Economics
Development Research Group
March 2024

Policy Research Working Paper 10714

Abstract

This paper uses data from 2003–19 on 2.47 million test takers of a national high stakes university entrance exam in Ethiopia to study the impacts of temperature on learning outcomes. It finds that high temperatures during the school year leading up to the exam reduce test scores, controlling for temperatures when the exam is taken. The results suggest that the scores of female students are less impacted by higher temperatures compared to their male counterparts. Additionally, the analysis finds that the scores of students from schools located in hotter regions are less impacted by higher temperatures compared to their counterparts from cooler regions. The evidence suggests that the adverse effects of temperature are driven by impacts from within-classroom temperatures, rather than from indirect impacts on agriculture.

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High Temperature and Learning Outcomes: Evidence from Ethiopia*

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March 4, 2024

Keywords: *Education; Temperature; Learning Outcomes; Ethiopia; Climate Change.*
JEL Classi ication: *I21; I23; O12; Q54.*

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1 Introduction

There is now abundant evidence from rich counties that heat reduces the formation and utilization of human capital in academic settings.[1] This evidence demonstrates that heat has acute negative impacts, reducing performance on exams on hot days, and longer-term negative effects, reducing the amount that students learn during hotter years. However, how these impacts translate to developing country contexts remains under-investigated. This is especially crucial in low income countries where introducing adaptation measures may be challenging due to generally lower average incomes. The lack of evidence for Sub-Saharan Africa is particularly acute. In this study, we examine the relationship between high temperatures and learning outcomes in Ethiopia in a high stakes exam setting.

While there exists a large literature documenting the negative impacts of extreme ambient temperatures on human capital formation, there remain gaps. Park et al. (2021) find that heat exposure is associated with reduced rate of skill formation or cumulative learning in both the U.S. and internationally. But their sample includes almost no Sub-Saharan African countries. Graff Zivin et al. (2018) find that short-run changes in temperatures in the US beyond 26 degrees Celsius are associated with lower cognitive performance on math, but not on reading. Cho (2017) and Garg, Jagnani, and Taraz (2020) find similar results in the contexts of the Republic of Korea and India, respectively. Park et al. (2020) use data on students who retook the Practice Scholastic Assessment Test (PSAT) in the US to find that high temperatures during school days inhibit learning and thereby reduce test scores. Further, their findings suggest that air conditioning in classrooms can mitigate the adverse effects of high temperatures.

In the developing country context, there is an evidence gap for high-stakes academic settings among older students. Garg et al. (2020) identify that hot days during the agricultural growing season are associated with both lower agricultural yields as well as lower test scores for younger students in rural India. They provide suggestive evidence of the introduction of a workfare program weakening the effects of high temperatures on test scores. Zhang, Chen, and Zhang (in press) find that the prevalence of high temperatures at the time of a low stakes cognitive test evaluated during household surveys in China is associated with reduced cognitive performance, especially for older and less educated respondents. In high stakes settings, evidence from China suggests that that high temperatures during the day of the exam are negatively associated with test performance (Graff Zivin, Song, Tang, & Zhang, 2020).

Existing studies either provide evidence on the impacts of heat on cognitive performance in high-stakes settings in rich countries or in lower-stakes settings in middle income countries.[2] Our paper fills a gap in the literature examining the direct impact of heat

[1]See, for example, Graff Zivin, Hsiang, and Neidell (2018); Park, Behrer, and Goodman (2021); Park, Goodman, Hurwitz, and Smith (2020). For a broad overview of this literature see Park and Heal (2016).

[2]On the separate, but related, question of school attendance, Randell and Gray (2019) study 29 tropical countries, which include 11 African countries (excluding Ethiopia), and find negative impacts of prenatal exposure to higher-than-average temperatures on years of schooling completed. Furthermore, they find that these effects are pervasive across all income groups; especially in the case of West and Central Africa. They

on students using data from a high-stakes exam in a low-income country. More specifically, we examine the relationship between high temperatures and learning outcomes in Ethiopia, with a focus on the national high stakes university entrance exam, the Ethiopian Higher Education Entrance Certificate Examination (EHEECE).

The EHEECE is a critical exam that determines access to higher education and can have important long-term implications for individuals' educational attainment and future labor market outcomes. It determines whether or not students can enroll in undergraduate universities, as well as the undergraduate university in which they enroll. Students who fail the exam usually take up vocational jobs, informal jobs, or work in agriculture; those who pass the exam have the opportunity to take up blue-collar and white-collar jobs, which generally offer higher wages and benefits. The stakes of these exams are high.

We investigate the impact of high temperatures over the school year leading up to the exam, which we will henceforth refer to as the exam year, on the exam performance of 12^{th} grade students in Ethiopia. We present three main findings.

First, exposure to high temperatures during the exam year is associated with poorer performance on exams. These impacts are weakly driven by hot days during the school year as compared to hot days during the winter and summer breaks. On the other hand, unlike the findings from India (Garg et al., 2020), in our setting, we do not find the predominant channel to be hot days that fall during the agricultural growing season. We discuss this result further in the mechanisms section of this paper.

Second, we find evidence of heterogeneity by gender in impacts of heat on exam performance. While, at baseline, women in our sample have significantly lower test scores relative to men, we present suggestive evidence that high temperatures have a smaller adverse impact on women's scores. The current body of literature has not revealed consistent differential effects of temperature on test performance based on gender (Cho, 2017; Park et al., 2020). In contrast to the existing research, our study demonstrates heterogeneous effects based on gender.[3]

Third, we find that students from schools located in hotter regions are better able to cope with higher temperatures compared to their peers who are located in relatively cooler regions. The negative relationship between heat and learning that we find in our study is primarily driven by students in cooler regions. This disparity in impact could be attributed to either physiological adaption or acclimatization to higher temperatures by students in hotter regions (Sexton, Wang, & Mullins, 2022) or due to greater use of climate adaption technologies in hotter regions. Negligible adoption of cooling technologies in Ethiopian schools makes us believe that this is suggestive evidence of heat acclimatization.

The rest of the paper is structured as follows. The next section describes the context for

find that the negative impacts are highest for children whose household heads have attained at least secondary school education. These results are similar to Randell and Gray (2016) who find that early childhood exposure to high temperatures is negatively associated with the likelihood of completing an additional year of schooling in rural Ethiopia.

[3] Graff Zivin et al. (2020) find that heat has more significant impacts in social science (or the arts track), characterized by a relatively higher proportion of women. They suggest that the effects they document might be driven by changes in women's scores due to their propensity to feel more stressed.

our study, section 3 describes the data in detail, section 4 lays out our empirical strategy, section 5 reports our main results, section 6 presents results on potential mechanisms, and section 7 reports robustness checks. Section 8 concludes.

2 Background

2.1 Ethiopian Education System

The Ethiopian education system is structured in three tiers: primary, secondary, and tertiary education. Primary education is mandatory and free for all children aged between seven and fourteen. It consists of two cycles of four years: grades 1-4 and grades 5-8. Secondary education is divided into two cycles of two years each: grades 9-10 and grades 11-12. At the end of grade 10, students take the Ethiopian General Secondary Education Certificate Examination (EGSECE), which grants access to upper secondary education (grades 11 and 12). Those who pass the EGSECE are routed into either natural science or social science streams. Upon completion of upper secondary education, students sit for the EHEECE after grade 12. Those who fail the EGSECE are assigned to a vocational track lasting 2-3 years, depending on the field of study. Tertiary education, which encompasses universities and colleges, is provided to students who complete their secondary education and pass the EHEECE. Depending on the field of study, institutions of tertiary education grant 3-6 years bachelor's degrees and various graduate degrees.

Eligibility for tertiary education in Ethiopia - and in many cases outside of Ethiopia for emigrants - is thus determined by a two step process.[4] First, students must pass the EGSECE and attend upper secondary education in either natural sciences or social sciences stream. Upon completion of upper secondary education students must also take and pass the EHEECE. We study performance on the EHEECE, the exam that directly determines eligibility for college or university.

In recent years, Ethiopia has embarked on a rapid expansion of access to education across all tiers through construction of primary and secondary schools as well as universities. The Ministry of Education reports that from 2000 to 2021-22, the number of primary schools increased from 11,780 to 36,492 and secondary schools from 424 to 3,636.[5] These expansions have also led to a gradual increase in the education access rate of female students from 20% in 2003/04 to 34% in 2017/18. The scale up of tertiary education is equally impressive, with the number of public universities increasing from 2 to 42 in the last two decades. Besides expanding access, the construction of new schools is also aimed at rectifying regional inequities in access to higher education institutions. Despite these efforts to expand access to education by building new schools, little attention is paid to equipping existing and new schools with air conditioning (AC) systems to regulate classroom temperatures. Fewer than 8% schools have any kind of climate control (World Bank Group,

[4]Many U.S. colleges, for example, require applicants from Ethiopia to submit scores on the EHEECE as part of their application.

[5]We refer to reports ESAA 2014 EC (2021-22 G.C) Final and ESSA 2003 EC retrieved from: `https://moe.gov.et/EduStat`.

2018).

2.2 Ethiopian Climate

Ethiopia's climate is diverse and varies across regions, largely due to differences in topography. It is broadly divided into three main zones: 1) the alpine vegetated cool zone, which covers areas over 2,600 meters above sea level, with temperatures ranging from near freezing to 16°C; 2) the temperate zones covering areas between 1,500 and 2,500 meters above sea level, with temperatures ranging between 16°C and 30°C; and 3) the hot zone, which encompasses both tropical and arid regions. The temperatures in this zone range from 27°C to 50°C.[6]

Since the mid-20th century, the mean annual temperature in Ethiopia has increased by more than 1°C (MEF, 2015). Climate model projections indicate warming across all Ethiopian seasons, with mean annual temperature rising by 1-2°C. By 2060, there is projected to be a significant increase in the number of days with temperatures 2°C above the 1981-2000 baseline, with hot days comprising between 15 and 29 percent of the year (Niang et al., 2014)[7]. This will have serious ramifications for ecosystems, agricultural production, food security, health, and learning outcomes (Trisos et al., 2022).

In Figure 1, we plot the distribution of daily maximum temperatures experienced by schools in our data. We sum the number of days with a maximum temperature in each of 5 three degree Celsius bins between 18°C and 33°C across all schools and all years in our sample (2003-2019). We group days below 18°C and above 33°C into separate bins. In our sample the majority of days fall between 21°C and 30°C. Days in our top bin, above 33°C, are relatively rare in the data. While Ethiopia predominantly experiences moderate temperatures, there exists substantial regional variation in temperatures (refer to Figure A2) resulting from the geographic differences within and between regions in Ethiopia. We will explore these differences in the subsequent sections of this paper.

3 Data

3.1 Educational Outcomes

In the Ethiopian education system, students choose a stream of study between natural sciences and social sciences in the 11th grade. This choice determines the subjects that they will be tested on in the 12th grade. While the total number of subjects is the same between streams, the specific subjects have evolved over the years, particularly following the 2010 secondary school curriculum reform. Before the reform, all students sitting for the grade 12 school leaving/ university entrance exam were required to take english, mathematics, civics, and aptitude. Additionally, they were also required to take stream specific subject

[6]Climate Risk Profile: Ethiopia (2021): The World Bank Group.

[7]See Figure A1 for a visual representation of the rising trend in the average number of days with temperatures surpassing 33 degrees Celsius within the schools in our sample, using 2003 as the baseline year. There is a marked increase in the frequency of hot days starting in 2011.

tests: general science for natural sciences students and social science for those in the social science stream. After the reform, the structure of the stream specific tests changed significantly, with general science split into physics, chemistry, and biology and social science split into geography, history, and economics. Consequently, students in the natural science stream now take physics, chemistry, and biology, while those in the social science stream are tested in history, geography, and economics. Students from both streams continue to take english, mathematics, civics, and an aptitude exam. Each of these exams is scored out of 100 points.

We utilize data from the Ministry of Education, spanning 17 years between 2003 and 2019. The dataset comprises 2.47 million individuals who took the national high stakes exam, the Ethiopian Higher Education Entrance Certificate Examination (EHEECE).[8] The EHEECE tests are highly standardized and administered in a relatively controlled environment. Typically, the exams are administered in June or July at students' schools of enrollment. They follow a uniform schedule across Ethiopia, with tests for each subject administered simultaneously on the same date and time. The exams' timetable is arranged over consecutive days with two testing slots on each day – one in the morning and another in the afternoon. On some days, students from different streams take stream specific subject exams in a single slot. To minimize the possibility of cheating, test invigilators are assigned to schools other than their own.

The passing cut-off for public universities varies by gender, region, and stream. For example, in the 2021/22 academic year, the passing grade for natural science students was 363 for males and 351 for females. For students from rural areas, the cut-off grades were slightly lower, at 351 for males and 339 for females. Additionally, private universities generally have lower cut-offs compared to public universities.[9] Students who fail the exams are allowed to retake them once, but the passing mark for retakes is set higher.

Our sample is restricted to school-going students below the age of 21 and those who have completed the required number of exams. We do not include those students who are re-taking the exams. This results in a sample of 2.13 million test-takers. To account for changes in exam structure and passing requirement over time, we standardize the test scores at the year and stream level[10]. The standardisation is done at the stream level because the distribution of scores differs based on stream, as does the passing score. The exam questions are multiple choice and require students to fill out their answers in an Optical Mark Recognition (OMR) sheet. Anonymity of students is maintained through roll numbers, which reduces the chances of manipulation of grades. Further, the passing

[8] The EHEECE was previously called the Ethiopian School Leaving Certificate Examination (ESLCE) until 2003 before it was replaced by the Ethiopian Higher Education Entrance Certificate Examination (EHEECE), which has since been renamed Ethiopian University Entrance Exam (EUEE) in 2021.

[9] Private higher education in Ethiopia is a relatively recent development, with the enrollment of students in private universities and colleges beginning at the turn of the century. As a result, there is a prevailing perception that the quality of education offered by these private institutions is somewhat inferior. There is, thus, greater competition to join public universities, which may explain the disparity in the passing grades required for entry into public versus private higher education institutions.

[10] To understand the distribution of average scores by region, refer to Figure A3 in the Online Appendix. It provides a map of the average score by geographic location.

cut-off grade is set ex-post based on the distribution of grades, which mitigates the risk of score bunching around the cut-off.

To address potential spatial correlation in learning outcomes within schools, we cluster standard errors of regressions that use test scores as the outcome at the school level.

3.2 Weather Data

We utilize the ERA5-Land dataset to obtain weather information at a spatial resolution of 9 km grid spacing. This dataset, which is available from 1950 onwards, provides hourly information on surface variables such as daily maximum temperature and daily total precipitation for each school in our sample.

To ensure the accuracy of our weather data in relation to the experiences of students, we construct a 10 km buffer around the school's geographic location[11]. We base this on the assumption that students typically reside close to their schools. This assumption is supported by findings from the Living Standard Measurement Study (LSMS) surveys, which indicate that about 90% of students in Ethiopia walk to school, and take less than one hour to reach their school from their homes. Additionally, we re-weight the climate data by population size (from Center for International Earth Science Information Network - CIESIN (2018)) within the buffer, to account for variations in population density.

Overall, our use of the ERA5-Land dataset and the construction of geographic buffers allows us to accurately capture the relationship between extreme temperatures and learning in our study. Our results are robust to variations in buffer size (of 5 km and 20 km) and population density.

3.3 Other Data

3.3.1 Household Survey

We use the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) data for Ethiopia (also known as the Ethiopia Socioeconomic Survey (ERSS)) in order to investigate the time-use patterns of household members as well as the impacts of shocks to agriculture on food consumption within the household (CSA, 2012, 2014, 2016). The LSMS-ISA is a household survey conducted in eight countries in Sub-Saharan Africa (SSA), focusing predominantly on rural households and their agricultural activities. There have been four waves/ survey rounds conducted for Ethiopia in 2011-12, 2013-14, 2015-16, and 2018-19. For our analysis, we specifically concentrate on the second and third waves of data. This selection is based on the sampling consistencies across these waves, ensuring the reliability of the collected data.

The LSMS-ISA surveys employ a two-stage random sampling design. First, enumeration areas (EAs) are selected at random, followed by a random selection of households

[11]To understand the distribution of hot days within these 10 km buffers, refer to Figure A4 in the Online Appendix. It provides a map of the variation in temperatures that is not explained by school, year, and stream fixed effects.

within these EAs. An important feature of these surveys is that households are geo-referenced, which facilitates the mapping of each household's geographic location to its respective agricultural zone. This enables the integration of information on zonal agricultural season cycles with households' self-reported agricultural cycle data.

For our individual level analysis, we further restrict the sample to keep middle and high school students who are currently enrolled in school. That is, our sample consists of students enrolled in 5^{th} through 12^{th} grades. To account for potential spatial correlation within EAs, we cluster the standard errors of all our regressions at the EA level.

4 Empirical Framework

We estimate the effects of temperature during the exam year on standardized total test scores of each student using the following regression specification.

$$Y_{isjt} = \Sigma_{m=1}^{M-1} \beta^m T_{jt}^m + \Sigma_{n=1}^{N-1} \delta^n Prec_{jt}^n + \theta Female_i + \mu_s + \gamma_j + \alpha_t + \epsilon_{isjt} \tag{1}$$

where the outcome variable Y_{isjt} is the standardized test score for student i, in stream s, in school j, and in year t. The variables T_{jt}^m denote the number of days in school *j* and year *t* where the daily maximum temperature was in the m^{th} of the seven bins used in our analysis.[12] Following the literature, we set 18-21°C to be the reference bin. Similarly, variables $Prec_{jt}^n$ denote the number of days in school *j* and year *t* where the daily total precipitation was in the n^{th} of the four bins used in our analysis.[13] We estimate several versions of this specification, dividing the year into school days and non-school days as well as growing season and non-growing season days.

The variable $Female$ is a dummy which takes the value of 1 if the student is female, and 0 otherwise. We include a female control because the level of female students' performance is lower than that of male students, on average. μ_s, γ_j and α_t are the stream, school, and year fixed effects, respectively. We include stream fixed effects as the subjects that students are tested on differ by stream and as do the distribution of scores and the passing cut-off scores. School fixed effects are added to control for school infrastructure and other unobservables which might be location specific. Year fixed effects help to control for year specific shocks as well as curriculum changes or changes in the exams over the years.

We are interested in the semi-elasticity or the β^m coefficients which capture the marginal effect of an additional day during the year in which the temperature is in bin *m* instead of being in the reference temperature bin. The key assumption in this approach is that daily temperature variation is orthogonal to the unobserved determinants of learning outcomes (Deschenes, Greenstone, & Guryan, 2009).

[12] We use the following set of temperature bins in our analysis {≤18°C, (18-21]°C, (21-24]°C, (24-27]°C, (27-30]°C, (30-33]°C, >33°C}.

[13] We use the following set of precipitation bins in our analysis {0 m, (0-0.01] m, (0.01-0.02] m, >0.02 m }.

5 Results

5.1 Primary Results

Table 1 reports the impact of heat on students' overall test performance measured in standardized total scores of all subjects taken (we also plot the coefficients in Figure 2). We find that heat exposure during the year of the exam has a significant negative impact on students' test performance. An additional day of temperatures above 33°C is associated with $\approx$ one-hundredth of a standard deviation drop in average test scores; thus, our results suggest that 10 additional hot days in a year could reduce test scores by approximately a tenth of a standard deviation. In terms of average performance on the exam over our sample period that represents a decline in performance by 2.28 percent. While temperature deviations from the optimal temperature for learning, measured by the number of days in the temperature bins below and above 18-21°C, negatively affects performance, the impact is 3-4 times higher for extreme temperatures ($>$ 33°C).

Our estimates are robust to inclusion of additional controls such as gender and age of the student, and average temperature in the first half of June which approximately coincides with the week of the exam.[14] Further, our results remain consistent when running the analysis using different buffers around schools (Table A2), when we include annual temperature lags (Table A3), when we divide the sample by stream of study (Table A4), and when we control for the exact week of the exam (Table A1).

Our results align with other papers examining the impact of heat on student performance in terms of average effects. Our estimates are three times larger than the average effects found by Garg et al. (2020) in India and $\sim$ 1.7 times the average effects found by Cho (2017) in the Republic of Korea[15]. In the US, Park et al. (2020) find much larger effect sizes of hot days on test scores; an additional day between 90-100°F (comparable with our T$>$ 33°C bin) is associated with a reduction in scores by 0.061 standard deviations. However, our estimates are well within the range in the existing literature.

In contrast, our effects compared to those for more targeted education interventions are relatively small. Interventions that promoted mother tongue instruction in Ethiopia are associated with gains in math and literacy scores by 0.269 and 0.089 standard deviations, respectively (Seid, 2016). In a similar context Duflo, Dupas, and Kremer (2015) found that hiring an additional local contract teacher in Kenyan schools increased the test scores of students taught by the contract teachers by 0.24 standard deviations, however they found no effect of reduced class size (by half) on test scores. In contrast, Altinok and Kingdon (2012) conduct a meta analysis where they find that a 1 standard deviation increase in class size in developing countries is associated with a reduction in student achievement by 0.03 standard deviations.

[14] Results from our preferred empirical specification are presented in column (2) of Table 1.

[15] Note that these studies presented subject-wise results, and we are comparing our total standardized score results with the average of the results they found for math and reading scores. Additionally, we are comparing our results for the highest temperature bin with the highest temperature bin of these studies, even though these bins are not exactly the same.

5.2 Results by Subject

We present results of our analysis by subject of exam, with a particular focus on english, math, civics, and aptitude, as they are administered to students in both natural science and social science streams. Table 2 reveals that high temperatures have a negative effect on math scores, but this result is not statistically significant. The results for english scores, however, are negative and significant at the 10% significance level. Likewise, the results for civics and aptitude are consistent with our primary findings on the total score, and statistically significant at the 1% significance level.

To understand the difference in results across subjects, we considered the distribution of these subject scores. The distributions of raw scores for civics and aptitude systematically lie to the right of the distributions of english and math (Figure 3). This suggests that civics and aptitude exams are easier than english and math exams. We hypothesize, that students are putting in more effort into learning english and math as a consequence of their greater difficulty. As a result, students (or teachers) may be offsetting some of the negative impacts of high temperature via increased effort. This is consistent with the evidence from the education literature that indicates teachers disproportionately focus instructional effort on more difficult and high stakes subjects like english and math (Jacob, 2005).[16]

We provide the results for other (stream-specific) subjects in Section 8. In Table A5 we report our findings for natural sciences subjects (physics, chemistry, biology, and general science) and in Table A6 we provide results for social sciences (economics, history, geography, and social science). The findings are consistent across these subjects, and similar to our main results in Table 2. We find a negative and significant impact of the highest temperature bin on the test scores for all the core subjects in both natural sciences and social sciences.

Our effect sizes by subject are consistent with other papers examining the impact of heat on student performance for english but not for math. In contrast to other studies, our results for math yield insignificant effects. For instance, Garg et al. (2020) report that the effects of an additional hot day (defined as temperatures above 29°C) decrease math and reading test performance by 0.003 and 0.002 standard deviations, respectively. These effect sizes are slightly smaller than ours for english (0.003) but larger than ours for math (0.001), when comparing the highest temperature bins. Cho (2017) finds that an additional day with a temperature above 34°C in the Republic of Korea decreases the scores of math and english tests by 0.0042 and 0.0064 standard deviations, respectively. These effect sizes are larger than what we observe.

[16]Recall we are measuring temperature in the year leading up to the exam so the negative effects reflect reductions in knowledge accumulated over this time period. If students know that math and english are harder exams they may be applying more effort to learn this material in ways that offset the negative impacts of heat during instructional periods.

6 Mechanisms

In this section we examine the mechanisms that might be driving our results on the negative relationship between heat exposure and test scores.

6.1 Do high temperatures in the agricultural season drive the temperature-test score relationship?

The existing literature provides evidence of heat exposure impacting cognitive performance through the channel of reduced agricultural income in India (Garg et al., 2020). That is, hot days during the agricultural season reduce agricultural yields which reduce parents' investments in children's human capital. To test this mechanism in our data, we construct the temperature bins in our main specification separately for the agricultural growing season and non-growing season. The growing season comprises the main growing season, *meher*, and a shorter minor season called *belg*, which we pool in our analysis.[17] We identify the typical months for these seasons for each administrative zone in Ethiopia.

We do not find strong evidence to support the hypothesis that this mechanism is at play in our setting. When we compare the impacts of hot days during the growing seasons with those in the non-growing season we find slightly larger effects in the non-growing season (column 1 of Table 3). This is consistent with the effects of high temperature being driven by consequences in the classroom as the non-growing season largely overlaps with the school year.[18] To further explore this, we construct the same set of temperature bins for the school year (covering the academic year) and non-school year separately. The results show that the impact of hot days is more pronounced during the school year compared to the non-school year (column 2 of Table 3). This supports the thesis that the effects of heat on test scores we find are primarily associated with conditions within the classroom environment.

Further, we also tested the differences in results by dividing the data into two subsamples: urban and rural (Table 4). We find that the effect sizes for urban areas are larger than those for rural areas (although they are not statistically different), helping us rule out the hypothesis that hot days during the agricultural season are driving our results.

6.2 Do temperature shocks reduce nutrition?

To answer this question, we utilized data from rounds 2 and 3 of the LSMS-ISA surveys for Ethiopia. We identified household food shocks at the month-year level and aggregated the number of negative food shocks experienced by a household in a calendar year.[19] We

[17] *Meher* is the main growing season and lasts from May to September, while the minor growing season, *belg*, starts in February and ends in April. Around 90% of crop production occurs during the main growing season (*meher*).

[18] See Figure 4 for results for all temperature bins in our data.

[19] The LSMS-ISA surveys collect detailed information on food security status of households. Households were asked if they faced a situation where they did not have enough food to feed all members of the household in the past 12 months, and in which months they faced this food insecurity. We added the number of months where the household faced food insecurity to construct an aggregate measure of the number of food shocks

estimate the number of food shocks experienced in a year as a function of temperature shocks in the previous year to account for timing of harvest and storage. We conduct this analysis for a full year as well as by agricultural growing season. We do not find evidence that the previous year temperature shocks we document in our data are leading to significant increase in current year food insecurity (Table 5). These results suggest that our results are unlikely to be driven by a nutrition channel.

6.3 Heterogeneity in Effects by Gender

In our test score data, female students perform relatively poorly compared to male students, on average. Given these baseline differences, we explore whether the effects of temperature on test performance vary by gender. To do this, we add an interaction term between temperature bins and a female dummy to our main empirical specification.

Table 6 shows that coefficient of the interaction term between temperature and female dummy is predominantly positive. Moreover, these effects are positive and statistically significant for temperature bins above 30°C across english, math, and the Total score. This indicates that the effects of heat matter less for female students compared to their male peers. Notably, female students appear able to fully offset the negative effects of temperature on their performance in math. This resilience displayed by female students, despite prevailing societal norms that place them at a disadvantage during weather shocks, is remarkable (Björkman-Nyqvist, 2013).

There are many potential explanations for this including physiological differences in resilience to heat between females and males, and changes in societal norms that benefit females. However, we have limited data to rule out many of these possibilities. One hypothesis that we find particularly interesting is that these exams may be higher stakes for women as the consequence of going to college versus not may be greater for them. As a result, women may put in more effort relative to men, which may compensate for the negative impact of heat exposure.

While we cannot test for gendered differences in effort directly, we check whether female students were absent from school less compared to their male peers. Our data contains information on extended absences from school, but not the number of days of absence. That is, we know if a student was absent during the last semester for more than a week. We also have information on travel time to school, which may reflect the amount of effort that students are putting into attending school. We interact the travel time with female dummy to indirectly isolate gendered differences in effort.

Our results (Table 7) show that there are heterogeneous effects by gender on the probability of extended absence from school. Female students have a lower likelihood of extended absence from school compared to their male counterparts. There are also differential effects of travel time on absenteeism; female students have no effect of an additional minute of travel time to school on absence from school, whereas for male students, an additional minute of travel time increases the likelihood of extended school absence by

experienced in the calendar year.

0.2 percentage points. This provides suggestive evidence that female students exert more effort to attend school as compared to their male counterparts.

Our overall findings are consistent with the education literature which has found some evidence for female students taking high stakes exams more seriously compared to their male peers (Brunello & Kiss, 2022). More specifically, evidence suggests that female students put in more time on homework compared to male students (Wagner, Schober, & Spiel, 2008), and that these results did not differ by grade among the sample of high school students (Xu, 2006).

6.4 Does school location affect students' adaptation to higher temperatures?

Response to temperature may vary based on region as humans adapt to their physical environment (or heat) and these adaptations reduce the performance losses associated with heat exposure. Medical research suggests that the "effect of heat acclimation on submaximal exercise performance can be quite dramatic, such that acclimated individuals can easily complete tasks in the heat that earlier were difficult or impossible" (Périard, Racinais, & Sawka, 2015). Students from schools located in hotter areas might be better at adapting to higher temperatures as compared to the students who live in relatively colder areas. There is abundant evidence from high-income settings that hotter places have more physical infrastructure adaptations to high temperatures, such that the adverse effects of temperature on a variety of measures of human performance are reduced in these locations relative to their colder counterparts (Carleton et al., 2022; Heutel, Miller, & Molitor, 2021; Park & Behrer, 2017).

We test this adaptation hypothesis in Table 8 by dividing schools into quartiles depending on the mean number of days across years when their temperature exposure exceeds 30°C. We find that heat has larger effects on test scores for students in schools located in colder regions (Column 1 of Table 8). The impact is smaller and/or statistically insignificant for the upper (hotter) quartiles.

Since the locations in the first three quartiles experience relatively low mean number of days where the temperature exceeds 30°C, we divide the sample into two groups: the first three quartiles, and the fourth quartile. We present the results for this break up in Table 9. We find that the negative association between high temperatures and test scores is driven by the first three quartiles (schools in colder locations). In hotter regions, though the relationship between hot days and test scores is negative, it is statistically insignificant. These results of hotter regions being able to cope with heat better are consistent with the findings of Zhang et al. (in press).

It is not obvious what kinds of adaptation are leading to these reduced effects in hotter regions. Based on data from World Bank Group (2018), only 8% (11 out of 137 schools) of Ethiopian schools have any adoption of heat adaptation technologies including fans or evaporative air cooling, and air conditioning[20]. This suggests that mechanical cooling is

[20]Notably, this survey sampled the largest school in each location, implying that the true number of Ethiopian schools with cooling technologies might be even lower than 8%.

not the predominant means of adaptation in this setting. It is possible that the construction of schools differs across settings, such that materials or ventilation approaches result in a greater ability to keep classrooms cool in hotter areas. We leave further examination of these important questions around adaptation to future work.

7 Robustness Checks

7.1 Does temperature affect stream choice?

One potential source of endogeneity in our model could arise from stream choice being a function of temperature. Since the stream of study is chosen at the start of 11^{th} grade, it could be that temperature during the 10^{th} grade affected performance on end-of-year exams, which, in turn, affected the choice of stream.

We know that for a given location, temperature across years is correlated.

If there is selection into streams based on temperature exposure during 10th grade, then our results might be biased. To test this, we run equation 2.

$$PS_{jt} = \Sigma_{m=1}^{M-1}\beta^m Lag_2T_{jt}^m + \Sigma_{n=1}^{N-1}\delta^n Lag_2Prec_{jt}^n + \theta Female\ Share_{jt} + \gamma_{r(j)} + \alpha_t + \epsilon_{jt} \quad (2)$$

where the outcome variable PS is the proportion of students in the science stream in school j in year t. Lag_2T is the second-year lag of temperature bin M. Lag_2Prec is the second-year lag of precipitation bin N. $Female\ Share$ is the share of women in school j and year t. We include the share of female students to control for gender specific preferences on which stream to enroll in. $\gamma_{r(j)}$ and α_t are the region (which the school is mapped to), and year fixed effects, respectively.

The results presented in Table 10 are all economically insignificant, suggesting temperature is not playing a large roll in stream selection. While the point estimates of 10^{th} grade exposure to heat are negative, the effect size is infinitesimal.

7.2 Does temperature affect grade progression?

It could be that our population of students is a selected sample of students who are resilient to or more adapted to higher temperatures. This would occur if only the students who can adapt remain in school long enough to appear in our sample. If this was true, we would be underestimating the effects of high temperature exposure on test performance.

To address this concern, we consider data on grade progression within the schools in our sample and check grade progression of each school from 11^{th} grade to 12^{th} grade. (We do not have cohort information prior to the 11^{th} grade.) We have this information for approximately 83% of school x exam year combinations between 2017-2019.

We do not find any effects of high temperature exposure in the 11^{th} grade on drop out rates and grade progression rates in our sample (Table 11). This is true for both male and female students, suggesting that our estimates are valid.

7.3 Are the results sensitive to changes in the way the dependent variable is defined?

We test whether our main specification is sensitive to changes in results by considering variations in the way we define out dependent variable (students' scores). In Table 12 we compare the results for the standardized total scores with those using average scores and relative scores. We consider the average score across subjects instead of the total raw score because the required number of subjects vary by year: it was five in 2003 and increased to seven from 2004 onward. The relative score is defined as the student's score as a percentage of the highest score within each stream and year; this allows us to test for the effects of high temperatures on the distribution of scores while controlling for the level of difficulty of the exam, using the highest score as reference. We find that our results remain consistent across these different specifications. We also tested all of our regression specifications using these three dependent variables and found no significant differences in the direction and significance of our results.

8 Conclusion

In this paper, we study the effect of high temperatures on test scores in the context of a high-stakes exam in Ethiopia. We find that each additional day with temperatures above 33°C reduces the standardized total test score of students by 0.009 standard deviations.

Delving into the potential channels that drive this negative association, we find that the effects are driven by hot days that fall in the school year (as compared to hot days that fall in the summer and winter breaks). Contrary to findings from India, we do not find evidence of the results being driven by hot days during the agricultural growing season. We further substantiate this result by finding that as compared to their counterparts in rural areas, students in urban areas experience larger negative effects of temperatures on test performance. We also rule out the channel of high temperatures worsening exam performance due to poor nutrition caused by increased food insecurity.

We then proceed to present the first significant findings of heterogeneity of temperature effects on exam performance by gender and show that female students' scores suffer smaller declines caused by higher temperatures. We do not have conclusive evidence for why female students are less impacted, but we do find that female students are less likely to take extended absences from school as compared to their male counterparts. Thus, we believe that the heterogeneity in effects by gender may be explained by female students putting in more effort on their academic performance, conditional on temperature, as compared to their male counterparts.

Consistent with our hypothesis about female students offsetting the negative impact of heat with greater effort, we find that the negative effects of temperature for all students are larger for easier subjects (civics and aptitude) as compared to the more challenging subjects (english and math). We believe that this is because, conditional on temperature, students exert higher levels of effort on more difficult subjects as compared to the easier ones. We are unable to directly test this, and leave it for future work.

Further, we find that students from schools located in hotter regions are better able to cope with higher temperatures as compared to their counterparts from cooler regions. This provides suggestive evidence of heat acclimatization since Ethiopian schools have negligible adoption of cooling technologies as heat adaptation measures.

Overall our results add to the growing body of literature indicating that high temperatures during the school year reduce the amount that students learn. Our estimates are some of the first from Sub-Saharan Africa and thereby add important additional context to this literature. Our overall effect sizes from Ethiopia are substantially larger than those found in other developing country contexts, but are not as large as the estimates found in the US. Future work should examine how adaptation, such as investments in fans and air-conditioning in schools, might help students cope better with higher temperatures, and might indirectly also reduce absenteeism.

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Tables

Table 1: Impact of Heat Exposure on Standardized Scores

	Standardized Score			
	(1)	(2)	(3)	(4)
$T > 33C$	-0.009^{***}	-0.009^{***}	-0.007^{**}	-0.007^{**}
	(0.002)	(0.002)	(0.003)	(0.003)
T 30-33C	-0.003^{**}	-0.004^{***}	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)
T 27-30C	-0.00004	-0.001	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.002)
T 24-27C	-0.002^{**}	-0.002^{***}	-0.003^{*}	-0.003^{*}
	(0.001)	(0.001)	(0.001)	(0.001)
T 21-24C	-0.002^{**}	-0.002^{***}	-0.002^{**}	-0.002^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
$T < 18C$	-0.003^{**}	-0.003^{**}	0.0003	0.0004
	(0.001)	(0.001)	(0.002)	(0.002)
Female Control		X	X	X
Avg T in First Half of June Control			X	X
Age Control				X
Fixed Effects				
Year	X	X	X	X
School	X	X	X	X
Stream	X	X	X	X
Observations	2,132,635	2,132,635	1,082,496	1,082,496
R^2	0.189	0.247	0.332	0.339

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable is the standardized test scores of students taking the 12th grade exams and is constructed to have mean of (or close to) zero. All regressors include the number of days in the temperature bin for the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table 2: Impact of Heat Exposure on Performance in Common Subjects

	Standardized Score			
	English	Math	Civics	Aptitude
	(1)	(2)	(3)	(4)
T > 33C	-0.003^{*}	-0.001	-0.011^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.002)	(0.002)
T 30-33C	0.00001	0.001	-0.005^{***}	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
T 27-30C	0.001^{**}	0.002^{***}	-0.003^{**}	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
T 24-27C	-0.00002	0.001^{**}	-0.003^{***}	-0.0002
	(0.0005)	(0.001)	(0.001)	(0.001)
T 21-24C	-0.0004	0.0005	-0.003^{***}	-0.001
	(0.0004)	(0.0005)	(0.001)	(0.0005)
T < 18C	-0.002^{***}	-0.003^{*}	-0.002	-0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Female Control	X	X	X	X
Fixed Effects				
Year	X	X	X	X
School	X	X	X	X
Stream	X	X	X	X
Observations	2,132,635	2,132,635	2,104,972	2,132,635
R^2	0.271	0.140	0.144	0.196

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variables are the subject-wise standardized test scores of students taking the 12th grade exams (for the common subjects across both streams) and is constructed to have a mean of (or close to) zero. All regressors include the number of days in the temperature bins during the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table 3: Impact of Heat Exposure on Standardized Scores

	Standardized Score	
	(1)	(2)
T > 33C: Not Growing	-0.012^{***}	
	(0.003)	
T 30-33C: Not growing	-0.007^{***}	
	(0.002)	
T 27-30C: Not growing	-0.002^{*}	
	(0.001)	
T > 33C: Any growing	-0.008^{***}	
	(0.003)	
T 30-33C: Any growing	-0.002	
	(0.002)	
T 27-30C: Any growing	-0.0001	
	(0.001)	
T > 33C: School Year		-0.010^{***}
		(0.003)
T 30-33C: School Year		-0.005^{***}
		(0.002)
T 27-30C: School Year		-0.001
		(0.001)
T > 33C: Not School Year		-0.008^{*}
		(0.005)
T 30-33C: Not School Year		-0.006
		(0.004)
T 27-30C: Not School Year		-0.001
		(0.003)
Female Control	X	X
Other Temperature Bins:	X	X
Fixed Effects		
Year	X	X
School	X	X
Stream	X	X
Observations	2,132,635	2,132,635
R^2	0.248	0.248

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable for all regressions is the standardized test scores of students taking the 12th grade exams and is constructed to have a mean of (or close to) zero. All regressors include the number of days in the temperature bin by season-school year. All regressions control for the number of days in the corresponding season-school year precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table 4: Impact of Heat Exposure on Standardized Scores

	Standardized Score	
	Urban	Rural
	(1)	(2)
T > 33C	-0.009^{***}	-0.007^{**}
	(0.003)	(0.003)
T 30-33C	-0.007^{***}	-0.0001
	(0.002)	(0.002)
T 27-30C	-0.002	0.001
	(0.001)	(0.001)
T 24-27C	-0.004^{***}	-0.0003
	(0.001)	(0.001)
T 21-24C	-0.003^{***}	-0.001
	(0.001)	(0.001)
T < 18C	-0.005^{*}	-0.003^{*}
	(0.003)	(0.002)
Outcome Mean:	0.09	-0.09
Female Control	X	X
Fixed Effects		
Year	X	X
School	X	X
Stream	X	X
Observations	1,232,230	900,405
R^2	0.260	0.224

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable is the standardized test scores of students taking the 12th grade exams in urban and rural areas. All regressors include the number of days in the temperature bin for the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table 5: Impact of Heat Exposure on Number of Negative Food Consumption Shocks

	Number of Negative Food Consumption Shocks		
	(1)	(2)	(3)
Lag T > 33C			−0.006
			(0.006)
Lag T 30-33C			0.013**
			(0.006)
Lag T 27-30C			−0.004
			(0.004)
Lag T > 33C: Growing Season		−0.026*	
		(0.015)	
Lag T 30-33C: Growing Season		0.013	
		(0.009)	
Lag T 27-30C: Growing Season		−0.014*	
		(0.008)	
Lag T > 33C: Major Season	0.007		
	(0.021)		
Lag T 30-33C: Major Season	0.016		
	(0.014)		
Lag T 27-30C: Major Season	0.001		
	(0.011)		
Lag T > 33C: Non-Major Season	−0.016*		
	(0.009)		
Lag T 30-33C: Non-Major Season	0.005		
	(0.012)		
Lag T 27-30C: Non-Major Season	−0.013*		
	(0.007)		
Lag T > 33C: Non-Growing Season		0.010	
		(0.008)	
Lag T 30-33C: Non-Growing Season		0.006	
		(0.009)	
Lag T 27-30C: Non-Growing Season		0.003	
		(0.007)	
Outcome Mean	0.871	0.871	0.871
Fixed Effects			
Year	X	X	X
Enumeration Area	X	X	X
Observations	10,207	10,207	10,207
R^2	0.331	0.332	0.328

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable is the number of negative food consumption shocks experienced by the household in a given calendar year. The regressors represent the number of days in the temperature bins during the previous calendar year. All regressions control for precipitation bins from the previous calendar year. Errors are clustered at the enumeration area level. *p<0.1 **p<0.05 ***p<0.01.

Table 6: Impact of Heat Exposure on Standardized Scores

	Standardized Score		
	Total	English	Math
	(1)	(2)	(3)
T > 33C	-0.010^{***}	-0.003^{*}	-0.001
	(0.002)	(0.001)	(0.001)
T 30-33C	-0.005^{***}	-0.0003	0.0003
	(0.001)	(0.001)	(0.001)
T 27-30C	-0.001	0.001^{**}	0.002^{**}
	(0.001)	(0.001)	(0.001)
T 24-27C	-0.002^{***}	0.0001	0.001
	(0.001)	(0.0005)	(0.001)
T 21-24C	-0.002^{***}	-0.0004	0.0003
	(0.001)	(0.0004)	(0.001)
T < 18C	-0.003^{**}	-0.002^{**}	-0.003^{**}
	(0.001)	(0.001)	(0.001)
Female * T > 33C	0.001^{***}	0.0002	0.001^{***}
	(0.0002)	(0.0002)	(0.0002)
Female * T 30-33C	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0004)	(0.0003)	(0.0003)
Female * T 27-30C	0.0004	0.0001	0.0004^{*}
	(0.0003)	(0.0002)	(0.0002)
Female * T 24-27C	0.0001	-0.0003^{*}	0.001^{***}
	(0.0002)	(0.0002)	(0.0002)
Female * T 21-24C	0.0004	0.0001	0.001^{**}
	(0.0003)	(0.0002)	(0.0002)
Female * T < 18C	0.00005	-0.0005^{*}	0.001^{**}
	(0.0004)	(0.0003)	(0.0004)
Female	-0.598^{***}	-0.359^{***}	-0.441^{***}
	(0.058)	(0.039)	(0.052)
Fixed Effects			
Year	X	X	X
School	X	X	X
Stream	X	X	X
Observations	2,132,635	2,132,635	2,132,635
R^2	0.248	0.271	0.141

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable is the standardized test scores of students taking the 12th grade exams and is constructed to have a mean of (or close to) zero; we consider the total score in all exams, and then the separate scores by subject. All regressors include the gender of the student and the number of days in the temperature bin in the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins for the school year. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table 7: Impact of Gender on Absenteeism

	Absent from School > 1 Week	
	(1)	(2)
Female	-0.035^{***}	0.018
	(0.013)	(0.017)
Travel Time to School		0.002^{**}
		(0.001)
Female X Travel Time to School		-0.002^{***}
		(0.001)
Outcome Mean:	0.063	0.063
Fixed Effects		
Year	X	X
Enumeration Area	X	X
Observations	5,398	5,393
R^2	0.337	0.343

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable is whether school going students (5th grade and above) in the LSMS household survey were absent from school for more than a consecutive week in the past 6 months. The regressors identify whether or not the student was female and what the travel time to school (in minutes) for the student was. Errors are clustered at the enumeration area level. *p<0.1 **p<0.05 ***p<0.01.

Table 8: Impact of Heat Exposure on Standardized Scores

	Standardized Score			
	Quartiles			
	(1)	(2)	(3)	(4)
T > 33C			−0.014	−0.003
			(0.048)	(0.006)
T 30-33C		−0.017	−0.005*	−0.003
		(0.015)	(0.003)	(0.006)
T 27-30C	−0.010***	−0.001	−0.001	−0.001
	(0.003)	(0.002)	(0.002)	(0.006)
T 24-27C	−0.003**	−0.002*	−0.001	−0.007
	(0.001)	(0.001)	(0.002)	(0.006)
T 21-24C	−0.003**	−0.003***	−0.002	−0.007
	(0.001)	(0.001)	(0.002)	(0.007)
T < 18C	−0.001	−0.001	0.001	−0.017
	(0.002)	(0.001)	(0.008)	(0.029)
Outcome Mean:	0.028	0.102	-0.009	-0.133
No of Schools:	300	300	300	299
Mean Days T > 30C:	0	0.152	10.689	107.428
Female Control	X	X	X	X
Fixed Effects				
Year	X	X	X	X
School	X	X	X	X
Stream	X	X	X	X
Observations	574,115	588,150	650,821	319,549
R^2	0.236	0.293	0.234	0.219

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable is the standardized test scores of students taking the 12th grade exams. We divide the the schools into quartiles based on the mean number of days that each school experienced temperatures above 30°C; the sub-headers represent the subsample of quartile 1-3 and quartile 4. All regressors include the number of days in the temperature bin. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table 9: Impact of Heat Exposure on Standardized Scores

	Standardized Score	
	Quartiles 1-3	Quartile 4
	(1)	(2)
T > 33C	−0.018	−0.003
	(0.048)	(0.006)
T 30-33C	−0.008***	−0.003
	(0.002)	(0.006)
T 27-30C	−0.002*	−0.001
	(0.001)	(0.006)
T 24-27C	−0.003***	−0.007
	(0.001)	(0.006)
T 21-24C	−0.003***	−0.007
	(0.001)	(0.007)
T < 18C	−0.003*	−0.017
	(0.001)	(0.029)
Outcome Mean:	0.039	-0.133
No of Schools:	900	299
Mean Days T > 30C:	3.886	107.428
Female Control	X	X
Fixed Effects		
Year	X	X
School	X	X
Stream	X	X
Observations	1,813,086	319,549
R^2	0.252	0.219

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable is the standardized test scores of students taking the 12th grade exams. We divide the the schools into quartiles based on the mean number of days that each school experienced temperatures above 30°C; the sub-headers represent the subsample of quartile 1-3 and quartile 4. All regressors include the number of days in the temperature bin. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table 10: Impacts of Heat Exposure on Stream Choice

	Fraction of Students in Science
Lag 2: T > 33C	-0.0001
	(0.0001)
Lag 2: T 30-33C	-0.0004^{***}
	(0.0001)
Lag 2: T 27-30C	-0.0001
	(0.0001)
Lag 2: T 24-27C	0.00002
	(0.0001)
Lag 2: T 21-24C	-0.0003
	(0.0002)
Outcome Mean:	0.63
Female Share Control	X
Fixed Effects	
Year	X
Region	X
Observations	9,616
R^2	0.322

Notes. Estimates are from linear regressions using panel fixed effects run at the school level. The dependent variable is the fraction of students in each school who enroll in the science stream. All regressors include the number of days in the temperature bin during the time when these students were in their 10th grade. All regressions control for the number of days in the precipitation bins during the time that the current cohort of students were in their 10th grade. Errors are clustered at the region level. *p<0.1 **p<0.05 ***p<0.01.

Table 11: Impact of Heat Exposure on Grade Progression

	Grade Progression (Fraction)		
	All	Male	Female
	(1)	(2)	(3)
Lag 1: T > 33C	−0.0004	−0.0003	−0.001
	(0.0005)	(0.0005)	(0.0005)
Lag 1: T 30-33C	0.001	0.0005	0.0003
	(0.001)	(0.001)	(0.0004)
Lag 1: T 27-30C	−0.0002	−0.0001	0.00004
	(0.0003)	(0.0004)	(0.0003)
Lag 1: T 24-27C	0.00004	0.0001	−0.0002
	(0.0002)	(0.0002)	(0.0003)
Lag 1: T 21-24C	0.0004	0.0005	0.0005
	(0.0004)	(0.0004)	(0.0004)
Lag 1: T < 18C	0.00001	0.0001	−0.0002
	(0.0005)	(0.0005)	(0.0004)
Outcome Mean:	-0.016	-0.011	0.017
Female Control			
Fixed Effects			
Year	X	X	X
Region	X	X	X
Observations	2,482	2,475	2,475
R^2	0.015	0.014	0.016

Notes. Estimates are from linear regressions using panel fixed effects run at the school level. The dependent variable is the fraction of students in each school who enrolled in grade 12 as compared to the class composition in the previous year (grade 11). All regressors include the number of days in the temperature bin during the time when these students were in their 11th grade. All regressions control for the number of days in the precipitation bins during the time that the current cohort of students were in their 11th grade. Errors are clustered at the region level. *p<0.1 **p<0.05 ***p<0.01.

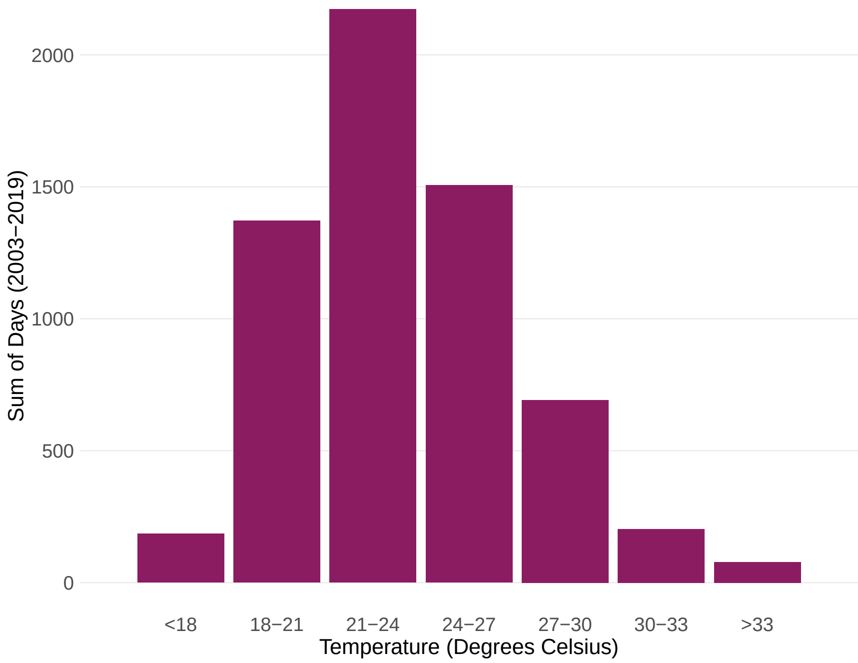
Table 12: Impact of Heat Exposure on Different Outcomes

	Dependent Variable		
	Standardised Score	Relative Score (%)	Average Score (%)
	(1)	(2)	(3)
T > 33C	-0.009^{***}	-0.104^{***}	-0.090^{***}
	(0.002)	(0.024)	(0.021)
T 30-33C	-0.004^{***}	-0.040^{**}	-0.035^{**}
	(0.001)	(0.016)	(0.014)
T 27-30C	-0.001	-0.006	-0.005
	(0.001)	(0.012)	(0.010)
T 24-27C	-0.002^{***}	-0.024^{***}	-0.021^{***}
	(0.001)	(0.009)	(0.008)
T 21-24C	-0.002^{***}	-0.026^{***}	-0.023^{***}
	(0.001)	(0.007)	(0.007)
T < 18C	-0.003^{**}	-0.031^{*}	-0.029^{*}
	(0.001)	(0.017)	(0.015)
Outcome Mean:	0.01	55.21	49.07
Female Control	X	X	X
Fixed Effects			
Year	X	X	X
School	X	X	X
Stream	X	X	X
Observations	2,132,635	2,132,635	2,132,635
R^2	0.247	0.287	0.320

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variables are listed as column headers. All regressors include the number of days in the temperature bin for the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

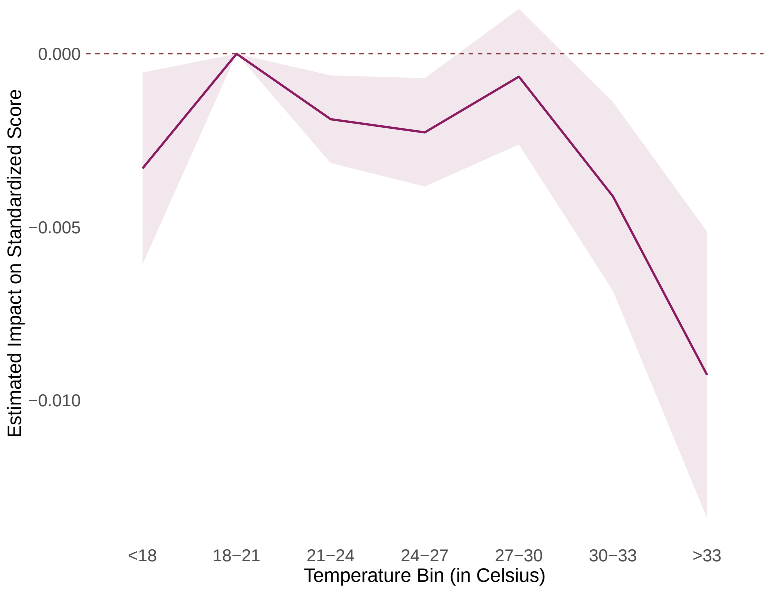
Figures

Figure 1: Distribution of Daily Max Temperature Over the Years



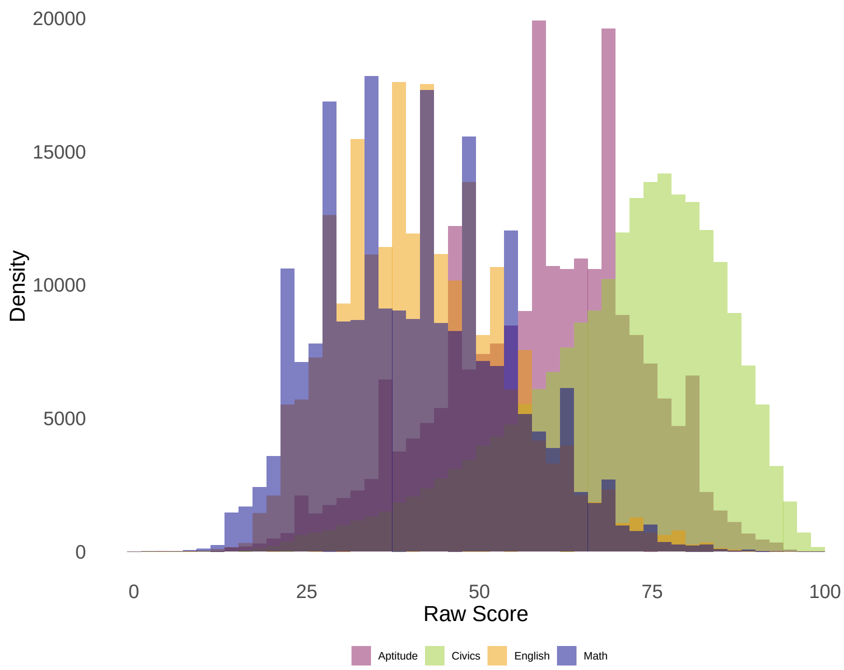
Notes: In this figure, we illustrate the cumulative sum of days within various temperature bins spanning the years 2003-2019. The calculation involves initially deriving the weighted average of the days in each temperature bin for every unique school location in our dataset for each year. The weights are determined by the number of students taking the exam in the respective location. Subsequently, we aggregate the weighted mean of the number of days falling within each temperature bin over the course of multiple years, encompassing the period from 2003-2019.

Figure 2: Impact of Heat Exposure on Test Performance



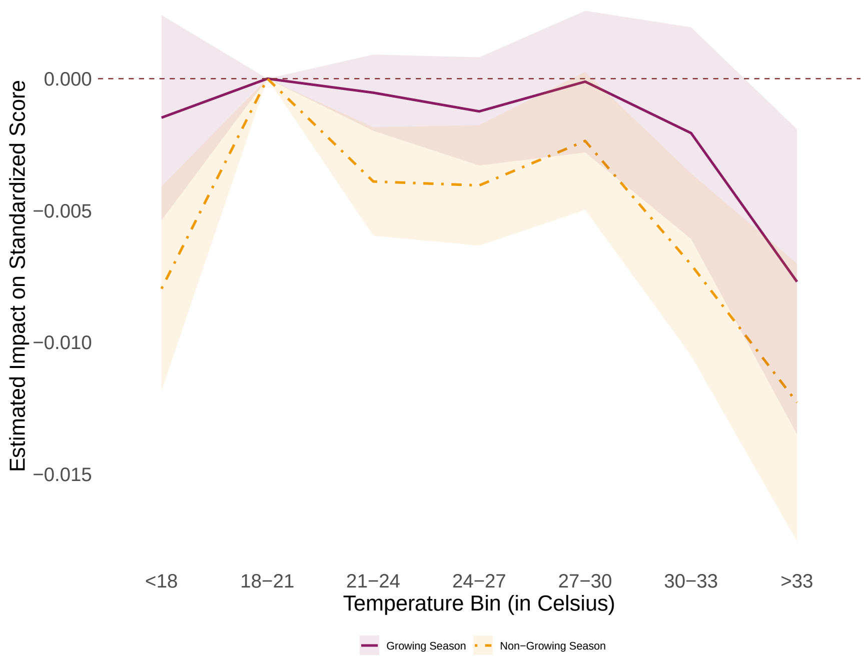
Notes: This figure plots the results from Column (2) of Table 1 where we run a fixed effects regression of the standardized scores of 12^{th} grade students on the number of hot days in each temperature bin (excluding the reference bin) controlling for precipitation bins as well as the gender of the student. The x-axis represents various temperature bins, while the y-axis illustrates their respective coefficients. These coefficients signify the effect on standardized test scores resulting from an additional hot day in the temperature bin of interest compared to the reference bin.

Figure 3: Distribution of Subject-wise Raw Scores in 2018



Notes: This figure illustrates the distribution of raw scores for the 2018 12^{th} grade exam in four common subjects: civics, aptitude, math, and english, each assessed on a scale of 0 to 100. Comparable distributions are observed for other years.

Figure 4: Impact of Heat Exposure on Test Performance by Season



Notes: This figure plots the results from Column (1) of Table 3 where we run a fixed effects regression of the standardized scores of 12^{th} grade students on the number of hot days in each temperature bin disaggregated by growing and non-growing seasons (excluding the reference bin) controlling for precipitation bins as well as the gender of the student. The x-axis represents various temperature bins, while the y-axis illustrates their respective coefficients. These coefficients signify the effect on standardized test scores resulting from an additional hot day in the temperature bin x season of interest compared to the reference bin. We find that the effects for non-growing season are larger than those for the growing season in the highest temperature bin, although the results are not statistically different.

Appendix: For Online Publication

Appendix Tables

Table A1: Impact of Heat Exposure on Standardized Scores

	Standardized Score			
	(1)	(2)	(3)	(4)
T > 33C	-0.009^{***}	-0.009^{***}	-0.008^{**}	-0.008^{**}
	(0.002)	(0.002)	(0.003)	(0.003)
T 30-33C	-0.003^{**}	-0.004^{***}	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)
T 27-30C	-0.00004	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)
T 24-27C	-0.002^{**}	-0.002^{***}	-0.002^{*}	-0.003^{*}
	(0.001)	(0.001)	(0.001)	(0.001)
T 21-24C	-0.002^{**}	-0.002^{***}	-0.002^{*}	-0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.001)
T < 18C	-0.003^{**}	-0.003^{**}	0.0002	0.0003
	(0.001)	(0.001)	(0.002)	(0.002)
Female Control		X	X	X
Avg T in Exam Week Control			X	X
Age Control				X
Fixed Effects				
Year	X	X	X	X
School	X	X	X	X
Stream	X	X	X	X
Observations	2,132,635	2,132,635	1,082,496	1,082,496
R^2	0.189	0.247	0.331	0.338

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable is the standardized test scores of students taking the 12th grade exams and is constructed to have a mean of (or close to) zero. All regressors include the number of days in the temperature bin for the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table A2: Impact of Heat Exposure on Standardized Score

	Standardized Score	
	5 Km Buffer	20 Km Buffer
	(1)	(2)
T > 33C	-0.009^{***}	-0.009^{***}
	(0.002)	(0.002)
T 30-33C	-0.004^{***}	-0.004^{***}
	(0.001)	(0.001)
T 27-30C	-0.001	-0.001
	(0.001)	(0.001)
T 24-27C	-0.002^{***}	-0.002^{***}
	(0.001)	(0.001)
T 21-24C	-0.002^{***}	-0.002^{***}
	(0.001)	(0.001)
T < 18C	-0.003^{**}	-0.003^{**}
	(0.001)	(0.001)
Female Control	X	X
Fixed Effects		
Year	X	X
School	X	X
Stream	X	X
Observations	2,132,635	2,132,635
R^2	0.247	0.248

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variable the standardized test scores of students taking the 12th grade exams across different school-buffer constructions and has a mean of (or close to) zero. All regressors include the number of days in the temperature bin. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table A3: Impact of Heat Exposure on Standardized Scores

	Standardized Score			
	No Lags	1 Year Lags	2 Year Lags	3 Year Lags
	(1)	(2)	(3)	(4)
T > 33C	-0.009^{***}	-0.009^{***}	-0.009^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
T 30-33C	-0.004^{***}	-0.004^{***}	-0.005^{***}	-0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
T 27-30C	-0.001	-0.001	-0.002^{*}	-0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.001)
T 24-27C	-0.002^{***}	-0.002^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
T 21-24C	-0.002^{***}	-0.002^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
T < 18C	-0.003^{**}	-0.003^{**}	-0.003^{**}	-0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Female Control	X	X	X	X
Fixed Effects				
Year	X	X	X	X
School	X	X	X	X
Stream	X	X	X	X
Sum T > 33C	-0.009	-0.01	-0.007	-0.004
Sum T 30-33C	-0.004	-0.005	-0.003	0
Observations	2,132,635	2,132,635	2,132,635	2,132,635
R^2	0.247	0.248	0.250	0.251

Notes. Estimates are from linear regressions using panel fixed effects run at the school level. The dependent variable is the standardized test scores of students taking the 12th grade exams and is constructed to have a mean of (or close to) zero. All regressors include the number of days in the temperature bin. All regressions control for the number of days in the precipitation bins and the lags of temperature bins as specified in the sub-column headers. Errors are clustered at the region level. *p<0.1 **p<0.05 ***p<0.01.

Table A4: Impact of Heat Exposure on Standardized Scores

	Standardized Score	
	Natural Science Stream	Social Science Stream
	(1)	(2)
T > 33C	-0.009^{***}	-0.009^{***}
	(0.002)	(0.003)
T 30-33C	-0.005^{***}	-0.002
	(0.001)	(0.002)
T 27-30C	-0.002^{*}	0.001
	(0.001)	(0.001)
T 24-27C	-0.003^{***}	-0.001
	(0.001)	(0.001)
T 21-24C	-0.002^{***}	-0.002^{*}
	(0.001)	(0.001)
T < 18C	-0.002^{*}	-0.005^{***}
	(0.001)	(0.002)
Female Control	X	X
Fixed Effects		
Year	X	X
School	X	X
Stream		
Observations	1,359,565	773,070
R^2	0.269	0.234

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variables are the standardized test scores of students taking the 12th grade exams by stream and is constructed to have a mean of (or close to) zero. All regressors include the number of days in the temperature bins during the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

Table A5: Impact of Heat Exposure on Performance in the Sciences

	Standardized Score			
	Physics	Chemistry	Biology	General Science
	(1)	(2)	(3)	(4)
T > 33C	-0.005^{***}	-0.008^{***}	-0.008^{***}	-0.003
	(0.002)	(0.002)	(0.002)	(0.004)
T 30-33C	-0.002	-0.004^{***}	-0.004^{***}	-0.002
	(0.001)	(0.002)	(0.002)	(0.002)
T 27-30C	0.001	-0.002^{*}	-0.001	0.0003
	(0.001)	(0.001)	(0.001)	(0.002)
T 24-27C	-0.001	-0.003^{***}	-0.003^{***}	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
T 21-24C	0.001	-0.001^{**}	-0.001^{**}	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
T < 18C	-0.001	-0.001	-0.0002	0.002
	(0.001)	(0.001)	(0.001)	(0.003)
Female Control	X	X	X	X
Fixed Effects				
Year	X	X	X	X
School	X	X	X	X
Stream				
Observations	1,169,633	1,169,633	1,169,633	189,932
R^2	0.162	0.177	0.175	0.139

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variables are the subject-wise standardized test scores of students taking the 12th grade exams for the science stream and is constructed to have a mean of (or close to) zero. All regressors include the number of days in the temperature bins during the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

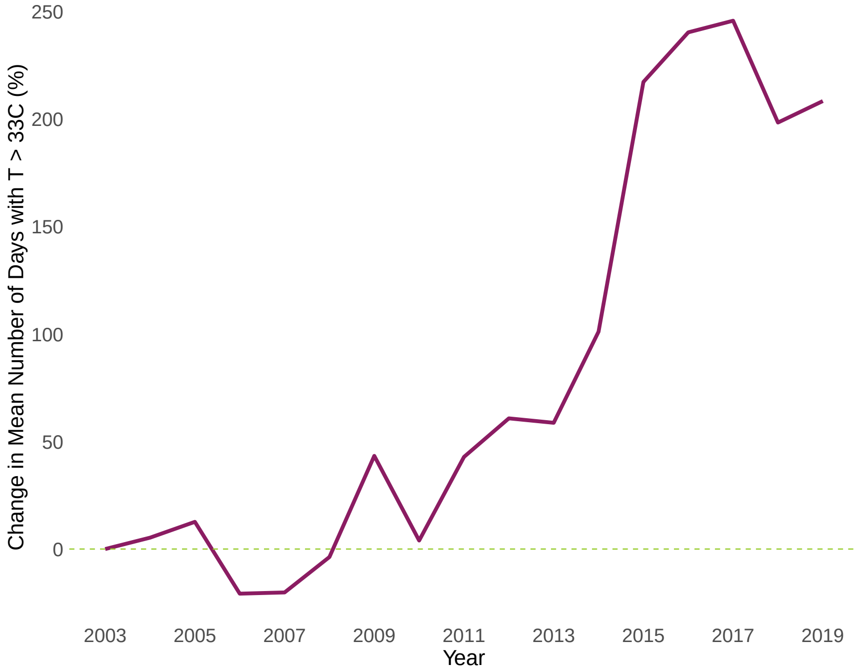
Table A6: Impact of Heat Exposure on Performance in the Social Sciences

	Standardized Score			
	Economics	History	Geography	Social Science
	(1)	(2)	(3)	(4)
T > 33C	-0.005^{**}	-0.007^{***}	-0.004^{*}	-0.002
	(0.002)	(0.002)	(0.002)	(0.004)
T 30-33C	-0.002	-0.001	0.002	0.001
	(0.002)	(0.002)	(0.001)	(0.002)
T 27-30C	0.002	0.002	0.003^{***}	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
T 24-27C	-0.001^{*}	-0.001	0.00004	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
T 21-24C	-0.001	-0.001	-0.0001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
T < 18C	-0.002	-0.003^{*}	-0.003^{**}	-0.001
	(0.001)	(0.001)	(0.001)	(0.003)
Female Control	X	X	X	X
Fixed Effects				
Year	X	X	X	X
School	X	X	X	X
Stream				
Observations	571,536	571,536	571,536	201,534
R^2	0.175	0.157	0.202	0.150

Notes. Estimates are from linear regressions using panel fixed effects. The dependent variables are the subject-wise standardized test scores of students taking the 12th grade exams for the social science stream and is constructed to have a mean of (or close to) zero. All regressors include the number of days in the temperature bins during the school-year cycle: June-May. All regressions control for the number of days in the precipitation bins. Errors are clustered at the school level. *p<0.1 **p<0.05 ***p<0.01.

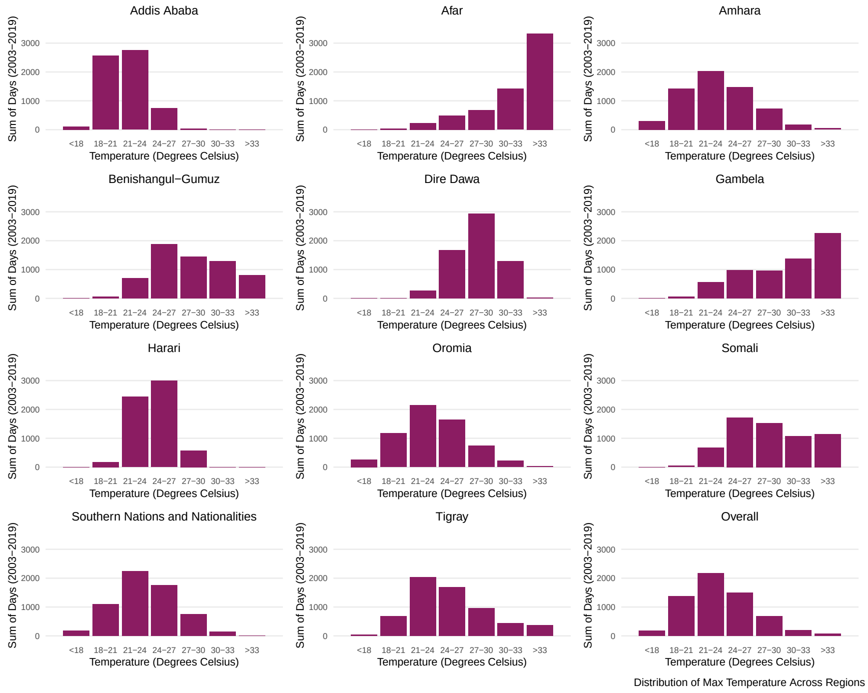
Appendix Figures

Figure A1: Percentage Change in Average Number of Days with T > 33°C Over the Years



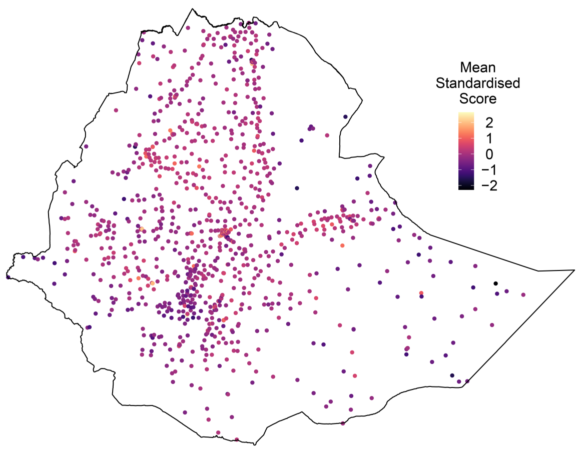
Notes: The solid line illustrates the percentage change in the mean number of days with T > 33°C over the years. We use the number of hot days in 2003 as our index. We compute the mean number of hot days in each year by deriving the weighted average of the days in the highest temperature bin for every unique school location in our dataset for each year. The weights are determined by the number of students taking the exam in the respective location. We then compute the percentage change in the average number of hot days in each year as compared to the average number of hot days in 2003. The temperature data utilized in this analysis is sourced from the ERA5-Land dataset. The dashed line represents no change in the number of hot days.

Figure A2: Distribution of Daily Max Temperature Over the Years by Region



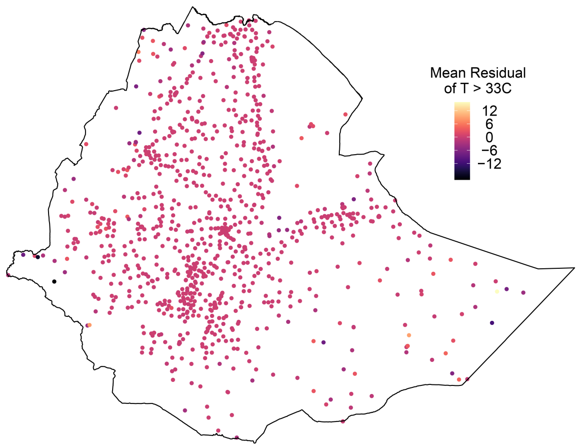
Notes: In this figure, we illustrate the cumulative sum of days within various temperature bins spanning the years 2003-2019 for each region in Ethiopia. The calculation involves initially deriving the weighted average of the days in each temperature bin for every unique school location in our dataset for each year and each region. The weights are determined by the number of students taking the exam in the respective location. Subsequently, we aggregate the weighted mean of the number of days falling within each temperature bin over the course of multiple years, encompassing the period from 2003-2019, for each region. The temperature bins were defined using ERA5 Land dataset.

Figure A3: Map of Mean Standardised Scores by School



Notes: We map the mean standardized score of students in distinct geographic locations. The mean is computed by initially averaging the standardized scores for each geographic location in each year and subsequently calculating the overall average across multiple years for each specific geographic location. These standardized scores are derived from data encompassing 2.13 million test-takers who participated in the EHEECE exam in Ethiopia between 2003 and 2019.

Figure A4: Map of Mean Days with Temperature Above 33°C by School



Notes: We calculate the mean residual from a regression model, incorporating the number of days in the highest temperature bin (T >33°C) as the dependent variable. This regression includes fixed effects for stream, year, and school as the regressors, with standard errors clustered at the school level. To obtain the mean residual, we initially compute the residual for each unique geographic location in each year. Subsequently, we calculate the overall average across multiple years (from 2003 to 2019) for each geographic location. This residual allows us to capture the variation in the number of days in the highest temperature bin that remains unexplained by the fixed effects. The temperature data utilized in this analysis is sourced from the ERA5-Land dataset.