Temperature and Learning in West and Central Africa

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Abstract

Although climate variability and change may present significant challenges to schooling and learning worldwide, its impact on learning in Africa is especially critical but understudied due to the scarcity of nationally comparable and representative micro-data on learning. In this paper, we combine georeferenced temperature data with newly released, standardized reading and math scores from 8 West and Central African countries in the Programme on the Analysis of Education Systems to examine the impact of temperatures on the learning outcomes of primary school students. We find that high temperatures have large negative effects on learning among students at the start and end of primary school. The magnitude of the effects is particularly larger compared to other world regions. Additional analyses suggest that temperature indirectly affects learning by reallocating time away from schooling and toward labor. While the effect of temperature on learning varies little by socioeconomic background and gender, we find that the negative effect of very high temperatures (i.e. above 33° Celsius) on reading and math scores is significantly larger for higher SES students compared to lower SES students. We hypothesize that this finding reflects an erosion of compensatory advantage, wherein wealthier students' typical ability to buffer against adverse conditions is diminished under extreme heat.

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1 Introduction

In the last three decades, the educational landscape in Sub-Saharan Africa (SSA) has been characterized by major policy changes—most notably removal of primary-school fees. Initiated by country-governments with support and funding of international efforts such as the UN's Education for All Initiative (1990), Millennium Development Goals (2000-2015), Global Education First Initiative (2012), and Sustainable Development Goals (2015-present), these policy changes led to dramatic expansion and equalization of primary-school access among diverse strata of society and significantly reduced gender, wealth, and rural-urban gaps in primary-school attendance (Lewin and Sabates 2011). However, the expansion in access to primary schooling corresponded with a crisis in learning. There are an estimated 52 million children in primary school in Sub-Saharan Africa who lack basic skills (UNESCO 2014) and there are vast socioeconomic inequalities in learning outcomes (Gruijters and Behrman 2020).

Changes in the educational landscape of SSA have occurred in the context of increasing severity and frequency of extreme weather events (Collier, Conway, and Venables 2008). Notably, there has been an increase in extreme heat events. For example, between late March and early April 2024 the Sahel region of West Africa experienced a record-breaking five-day heat wave characterized by temperatures reaching 45 ° C (119 ° F) (Barnes et al. 2024). Today it is expected that events of this severity would occur about once every 200 years, and under future warming scenarios it could become a once in 20-year event (ibid). Given that high temperatures have been shown to negatively impact learning in other parts of the world (Park et al. 2020; Park 2022; Park, Behrer, and Goodman 2021; Prentice et al. 2024), there is reason to think temperature extremes might have important implications for Sub-Saharan learning outcomes, as suggested in a recent study on Ethiopia (Srivastava, Hirfrfot, and Behrer 2024). If anything, the high levels of reliance on agriculture for basic livelihoods, the weaker educational infrastructure, and the low levels of climate adaptation mean that many Sub-Saharan countries will be particularly vulnerable to climatic shocks (Emediegwu, Wossink, and Hall 2022).

So far, it has been challenging to empirically explore the effects of temperature on learning in SSA due to a lack of high-quality learning data. This paper addresses this gap by combining georeferenced temperature data with standardized student learning data from the Programme on the Analysis of Education Systems (PASEC) in 8 West and Central African countries. The first aim of our study is to estimate the effect of temperature on learning in 8 West and Central African countries. In doing so, we not only provide an important comparison to other parts of the world where there has been a documented link between heat and learning (Park, Behrer, and Goodman 2021), but also, and most importantly, we focus our analysis on countries that have experienced both an increase in the severity and frequency of extreme heat (Barnes et al. 2024; World Bank 2018) and a learning crisis. Second, informed by economic models of household behavior, we investigate the mechanisms through which temperature affects learning, specifically examining its impact on labor and hunger. Third, using insights from compensatory advantage theory, we explore whether the effects of temperature on learning vary by socioeconomic background or gender. These analyses provide insight into whether privileged backgrounds are protective due to compensatory advantage or whether heat erodes this advantage.

2 Background

2.1 Existing Evidence on Temperature and Learning

There is an increasingly robust evidence base on whether temperature affects learning around the world; yet, to date, there has been insufficient consideration of the effects of temperature on learning in Sub-Saharan Africa. At present, the most globally comprehensive study on heat and learning uses standardized learning data from 58 countries throughout Asia, Europe, the Americas, the Middle East and Australia, drawing on the Programme for International Student Assessment (PISA) between 2000 and 2015 (Park, Behrer, and Goodman 2021). Park and colleagues show that the negative effects of heat on learning are significantly larger in low-income countries compared to high-income countries, presumably due to differences in heat preparation, such as air conditioning. Several other studies focused on high- and middle-income countries in Asia, Europe, and the Americas also document the negative effects of heat on learning (Cho 2017; Garg, Jagnani, and Taraz 2020; Graff Zivin, Hsiang, and Neidell 2018; Park et al. 2020; Prentice et al. 2024; Graff Zivin et al. 2020; Porras-Salazar et al. 2018; Roach and Whitney 2022; Wang et al. 2018; Wargocki, Porras-Salazar, and Contreras-Espinoza 2019). An exception is found in Brazil, where temperature has negligible impacts on college entrance exams (Li and Patel 2021).

To the best of our knowledge, there is only one study focused on Sub-Saharan Africa and, more precisely, on Ethiopia (Srivastava, Hirfrfot, and Behrer 2024). This study reveals that exposure to hot days corresponds to a decrease in performance on university entrance exams in Ethiopia. These effects are particularly strong in the cooler parts of the country, likely due to the lower adaptation to heat in these areas. This study makes an important contribution to the scholarship on temperature and learning by extending the focus to an African setting. However, by focusing on a university population, this study examines a selected group of people who have already overcome significant educational barriers to reach the end of high school. Existing work suggests that climatic shocks experienced at earlier ages have particularly deleterious impacts on later learning (Nubler et al. 2021; Park, Behrer, and Goodman 2021). Younger primary school aged children may therefore be more susceptible to environmental stressors experienced during critical stages of cognitive and educational development than their older counterparts.

The limited exploration of the effects of temperature on learning in Africa is partly due to the absence of learning measures collected in commonly used data sources. Historically, very few African countries have participated in the PISA, which is widely used for international learning assessments. Many of the main sources of data in SSA, such as the Demographic and Health Surveys (DHS) and the Living Standards Measurement Study (LSMS), collect information on school attendance but lack measures of student learning. Existing studies on temperature and schooling in SSA therefore mostly focus on school attendance (Pule et al. 2021; Randell and Gray 2016, 2019). These studies have found heterogeneous results. For example, pooled data from West and Central Africa show no significant link between higher than average temperatures in early childhood and schooling attainment (Randell and Gray 2019), but mild temperatures are associated with increased educational completion in Ethiopia (Randell and Gray 2016). Related work on other types of climatic shocks documents the negative effects of other types of rainfall shocks and droughts on various measures of learning in South and Southeastern Africa (Björkman-Nyqvist 2013; Nordstrom and Cotton 2020; Nubler et al. 2021), albeit with heterogeneity by gender (Björkman-Nyqvist 2013) and the age at which the shock was experienced (Nubler et al. 2021).

2.2 Theoretical Perspectives on why Temperature Might Impact Learning

Educational outcomes have long been understood as the product of both individual cognitive capacities and the broader social and economic environments in which children live. Classical sociological and educational theories emphasize that academic performance is shaped by an interplay of cognitive processes, household resources, and social norms (Coleman et al. 1966; Bourdieu and Passeron 1990; Downey and Condron 2016). More recently, scholars have expanded this focus by examining how external environmental stressors—such as fluctuations in ambient temperature—might disrupt learning (Park, Behrer, and Goodman 2021). Two broad explanations have emerged. The first explanation emphasizes direct effects: extreme heat disrupts students' physical ability to concentrate, retain information, and perform on assessments. The second explanation focuses on indirect effects: heat may alter household routines, leading to increased student absenteeism or shifts in labor responsibility (Conte Keivabu 2024). In what follows we expand on these two explanations by providing further details on the theoretical frameworks that support them.

The primary theoretical perspective behind the hypothesis that temperature has a direct effect on learning is cognitive load theory (CLT). CLT posits that cognitive performance is constrained by the limited capacity of working memory and attention (Sweller 1994). CLT distinguishes between intrinsic cognitive load (task complexity), germane cognitive load (effort devoted to learning), and extraneous cognitive load, which arises from external stressors that interfere with cognition. Environmental conditions, including temperature, may contribute to extraneous cognitive load by increasing physiological strain (Ioannou et al. 2021). High ambient temperatures trigger discomfort, dehydration, and fatigue, all of which reduce cognitive resources available for learning and decision-making (Hancock and Vasmatzidis 2003; Wittbrodt and Millard-Stafford 2018). In the contexts that we study in West and Central Africa the direct effects of temperature on learning may be particularly exacerbated due to inadequate cooling infrastructure: about half the population of West and Central Africa does not have access to electricity (World Bank 2024) and many school facilities lack basic climate controls that require electricity. Furthermore, temperature shocks that lead to crop failure and corresponding hunger and lack of dietary diversity might exacerbate heat-related cognitive overload (Taras 2005).

Scholars have adopted several strategies to test whether cognitive load theory plays a role in explaining the negative effects of heat on learning. One approach has been to explore whether high temperatures impact learning on school – as opposed to vacation – days. For example, Park and colleagues find that high temperatures experienced during school days, but not vacation days, have a negative effect on student learning in 58 OECD countries (Park, Behrer, and Goodman 2021). A similar finding was observed in the U.S. where hotter school days – but not vacation or weekend days – impact standardized test scores (Park et al. 2020). These findings suggest that negative effects of temperature on learning are driven by school-based experiences such as cognitive overload, and not broader changes in environment that might have occurred during non-school days. Another approach used in the literature to helps understand whether cognitive load theory plays a role in explaining the negative effects of heat on learning has been to exploit variation in access to cooling systems within school. For example, an experiment in Costa Rica that randomly varied classroom temperature over a two-week period showed that students performed better on language and logical thinking tasks when classroom temperatures are maintained at neutral levels compared to when they are warm (Porras-Salazar et al. 2018).

In contrast to the focus on direct effects, another body of scholarship highlights the indirect effects that temperature can have on learning. This perspective typically takes economic models of household behavior as its orienting framework. Economic models of household behavior argue that families adjust the allocation of time and labor in response to changing economic and environmental circumstances (Becker 1965). Under normal conditions, households may prioritize educational activities; however, when faced with external stressors that increase the opportunity cost of schooling, families may reassign children's time and energy toward tasks that ensure immediate survival or economic stability (Skoufias and Parker 2002). When extreme heat disrupts daily routines, households may be forced to reallocate children's time to non-academic responsibilities. These responsibilities can include domestic chores or participation in economic activities that can lead to absenteeism among students—absenteeism that has long-term detrimental effects on learning (Cattan et al. 2023). In particular, heat shocks that affect agricultural livelihoods might lead families to diversify livelihoods by reducing school attendance and increasing child labor (Björkman-Nyqvist 2013; Garg, Jagnani, and Taraz 2020). Students may also avoid schools during critically hot days if they have long commutes. While commuting data is hard to come by for the countries in our study, available evidence from Ghana in West Africa shows that 90 percent of primary school children commute on foot with average commutes of about 20 minutes daily (Afoakwah and Koomson 2021).

2.3 Socioeconomic and Gender Variation in the Impact of Temperature on Learning

Given the significant disparity in learning outcomes across different socioeconomic groups in West and Central Africa (Gruijters and Behrman 2020), it is highly likely that the effects of temperature shocks on learning will vary depending on socioeconomic background. For example, Park and colleagues show that the negative effects of heat on learning observed in 58 OECD countries are significantly larger for lower income populations (Park, Behrer, and Goodman 2021). Compensatory advantage theory helps explain why heat may differentially affect learning across SES. This theory posits that individuals with greater socioeconomic resources typically have access to buffers (e.g. better learning environments, tutoring, or technological aids) that protect them from adverse shocks (Bernardi 2014). Research in educational sociology shows that higher SES families usually provide additional academic support that promotes educational success or may move their children to a different school (Bernardi 2014; Torche 2018). Climate research from the US supports this view, indicating that the adverse effects of heat on learning are more pronounced among students in lower-income school districts where compensatory resources are limited (Park, Behrer, and Goodman 2021).

Research on socioeconomic variation in the impact of high temperatures on school attendance in West and Central Africa, however, challenges the expectations of compensatory advantage theory. Randell and Gray (2019) find that higher than average temperatures in early childhood lead to larger reductions in years of schooling among children from higher-SES households compared to lower-SES households. This counterintuitive finding may be explained by a phenomenon that we refer to as the erosion of compensatory advantage. This perspective suggests that higher-SES children experience a greater relative learning loss during periods of extreme heat because they normally benefit from better educational environments that facilitate higher academic performance under stable conditions. When heat shocks disrupt learning, higher-SES pupils have more to lose compared to their lower-SES peers, whose baseline educational attainment is already constrained by chronic disadvantages such as poor school infrastructure, lower-quality instruction, and limited access to academic resources (Gruijters and Behrman 2020). In addition, extreme heat may impose new labor demands on high-SES households which can erode learning opportunities. In times of economic stress, students from high-SES backgrounds who would otherwise be focused on school activities may be required to contribute to household economic activities—whether through formal employment, managing family businesses, or assisting with domestic labor. This reallocation of time away from schooling toward labor is particularly relevant in agricultural economies, where wealthier families may own larger farms or businesses that demand additional labor during periods of climate stress. In contrast, lower-SES students who are often already engaged in labor-intensive activities may see less change in their schooling patterns.

The effect of temperature on learning might also differ by gender due to gender differences in the reallocation of time and energy toward non-academic responsibilities during periods of heat. In sub-Saharan African countries, gender norms dictate differential household roles for boys and girls (Webbink, Smits, and Jong 2012). Girls are often expected to take on additional domestic responsibilities, such as caregiving, cooking, and water collection, which may reduce their time for studying or attending school. Heat can exacerbate these patterns, as water shortages and food insecurity—both of which are common consequences of prolonged heat waves—may increase household demands for female labor. When economic or environmental shocks occur, families may favor boys' (over girls') primary educational attainment and achievements. For example, rainfall shocks disproportionately decrease girls' (relative to boys) schooling outcomes in Kenya and Uganda (Björkman-Nyqvist 2013; Nubler et al. 2021). On the other hand, boys may be pulled away from school to engage in income-generating activities to support their families. For example, a study from Ethiopia shows that the negative impact of heat on university entrance exam performance was larger for boys compared to girls (Srivastava, Hirfrfot, and Behrer 2024). Finally, experimental evidence has also shown that heat has differential effects on cognitive performance by gender: at higher temperatures, women perform better on math and verbal tasks, while men experience a decline in performance (Chang and Kajackaite 2019).

3 Data and Sample

We combine data from two sources: (1) micro-data on schooling and learning from PASEC 2014 and 2019; and (2) gridded publicly available temperature data from the ERA5 archive. In what follows we describe each of these data sources in more detail.

First, the micro-data on schooling and learning, PASEC, are standardized learning assessments collected by the Conference of Ministers of Education of Francophone Countries (CONFEMEN) that are nationally representative of students in primary schools. We focus on eight West and Central African countries that participated in both rounds of PASEC data collection in 2014 and 2019: Benin, Burkina Faso, Burundi, Congo, Niger, Senegal, Tchad, and Togo. In each country that participates in PASEC, approximately 150-250 schools are randomly chosen from an official database of all registered public, private, and community schools. Within each selected school, students are randomly chosen from one second-grade class and one sixth-grade class to participate. These students complete a standardized reading and math test and provide basic information about themselves and their families; the test occurs in April at the end of the academic year. Schools participating in the PASEC assessments also provide basic information about school characteristics (i.e. student to teacher ratio etc.). Our final sample includes 80,267 students (Table 1).

The ERA5 gridded temperature data are retrieved from the European Centre for Medium-Term Weather Forecasting (Hersbach et al. 2023). These data contain hourly data on temperature for the whole globe on a grid of parallels and meridians at a 0.25×0.25-degree resolution (approximately 31 km at the equator). Using data on temperature for every hour of all days between 1 September 2013 and 31 March 2014 and 1 September 2018 and 31 March 2019, we calculate a daily average temperature for each stratum (the smallest geographic unit in PASEC) in our sample by averaging the hourly data for each day within each stratum.

To create our final dataset, we match each student in the PASEC dataset with temperature data for the current academic year based on their stratum of residence. Since the PASEC exam is administered in April, we define the academic year as starting on September 1st of 2013 or 2018 (depending on the survey wave) and ending on March 31st of 2014 or 2019 (depending on the survey wave).

4 Measures

Learning: PASEC collects reading and math test scores across countries (similar to the PISA). These test scores, which are standardized to have a mean of 500 and a standard deviation of 100 across all pupils, are our main measure of learning. We look at math and reading scores separately because other scholarship has found temperature has larger impacts on math compared to reading (Park et al. 2020). Table A.2 shows country-level variations in these scores ranging from a low of 467.6 in Togo to a high of 608.4 in Burundi.

Temperature: We construct a stratum-level measure of temperature in the current academic year in Celsius which counts the number of days in six temperature bins: less than 21°C, 21°–24°C, 24°–27°C, 27°–30°C, 30°–33°C, greater than 33°C. This approach to measuring temperature, which allows us to account for non-linearity in the relationship between temperature and learning, is substantively similar to that reported in Park et al.'s international comparative study of the effects of temperature on learning in 58 OECD countries (Park, Behrer, and Goodman 2021). However, it differs from Park et al. in three respects. Firstly, Park et al. focus on temperature over a longer time-frame (i.e three years prior to the exam) whereas we focus on a more narrow time-frame (i.e. the 9 months prior to the exam). We make this change to be able to more precisely estimate how temperature experienced during the current academic year impacts end of year test scores. Secondly, Park et al. use different temperature bins that are cooler than our categories (less than 15°, 16-20°, 21-26°, 27° and greater). While their study looked at a wide range of countries with varying climatic conditions (including hot and cold climates), our analysis focuses on a smaller number of countries with warmer climates. We have therefore modified the temperature bins to more accurately reflect the specific conditions of our setting. Thirdly, Park et al. utilize maximum daily temperature whereas we rely on mean daily temperature calculated by averaging all hourly recordings which allows us to better capture daily temperature exposures.

Precipitation and humidity: To account for other climatic conditions, we control for continuous measures of average precipitation and humidity in the stratum of residence during the current academic year. These variables, calculated in the same way as the temperature variables, come from the ERA5 archive.

Student demographic characteristics: We control for a binary measure of student gender and a continuous measure of student age. Student's age varies from 4 to 27 years old, with grade 2 students being younger (4-22) than grade 6 students (8-27).

Socioeconomic status: We measure socioeconomic status in two ways. We first construct a composite measure of household wealth using principal component analysis on household assets reported by the students (Gruijters and Behrman 2020)[1] . Since information on household assets are only collected for students in grade six, for students in grade two, we create a measure of whether the respondent never speaks French at home, which we use as a proxy of low socioeconomic status (the reference category is speaking French at home sometimes, often or always). Supplementary analyses of students in grade 6 suggest that never speaking French at home is strongly negatively correlated with the composite measure of household wealth,

1. The list of assets used to construct the household assets is as follows: TV, computer, radio, DVD player, hi-fi system, cellphone, fridge, fan, AC, stove, table, sewing machine, electric iron, car or truck, tractor, bicycle, latrines, materials of walls of the house, and electricity

thus giving us confidence that this is an adequate proxy.

Labor: We measure labor with an indicator for whether the student reports to frequently engage in nondomestic work outside of school (framing, commerce or physical labor). This variable is only available for students in grade 6.

Hunger: We measure hunger with a variable for whether the student reports being frequently hungry in school. This variable is only available for students in grade 6.

5 Methods

The first aim of our study is to estimate the effect of temperature on learning in 8 West and Central African countries by assessing how variations in temperature at the stratum level in the 9 months prior to the test (i.e. our "treatment") affect primary-school test scores. Our model reads as follows:

$$y_{isy} = \sum_{k=1}^{K} \beta_k \, \text{Temperature}_{k,sy} + \sigma X_{isy} + \alpha_s + \theta_y + u_{isy}, \tag{5.1}$$

where y is the reading or math test score of student i living in stratum s and surveyed in year y, and temperature represents the number of days in stratum s and year y that fall into the temperature bins k. All models control for a vector of variables X, that are precipitation, humidity, student demographic characteristics, and socioeconomic status, and include stratum α and year θ fixed effects. We use country weights to ensure that our results are representative of the students living in the eight countries[2]. Also, we cluster standard errors at the country levels in line with previous similar work (Park, Behrer, and Goodman 2021). Because prior research suggests that the effects of temperature on learning vary by age (Nubler et al. 2021; Park, Behrer, and Goodman 2021), we conduct analyses separately for students in grades 2 and 6.

The second aim of our study is to provide insight into the mechanisms through which temperature affects learning. To this end, we explore the effects of temperature on labor using the same empirical strategy as above. This secondary analysis investigates the potential indirect effects of temperature on learning by examining whether high temperatures shift students' time allocation toward labor. However, we cannot test for direct temperature effects

2. The country weights are calculated as the ratio of the number of students in each country for a given year and grade to the number of students in our sample for the same year and grade. The number of pupils in each country enrolled in primary education and in the final grade of primary education for 2013 and 2018 was taken from the World Bank Data Bank on Education Statistics - All Indicators, sourced from the UNESCO Institute for Statistics.

on learning with our data. Previous studies have examined these direct effects, showing that temperatures experienced on school days (but not vacation days) have a significant impact on learning outcomes (Park, Behrer, and Goodman 2021). We were unable to do this in our analysis because we focus on temperatures experienced during single academic years as opposed to the three-year window employed by other relevant studies (ibid). While, this focus on heat during the academic year provided a better measure of how recent experiences of heat impact learning, this smaller time frame meant we had insufficient variation in weekend or vacation days to restrict our temperature measures. Furthermore, there is considerable measurement error in reported vacation days in the countries we study. Nonetheless, as an additional analysis, we also look at the effects of temperature on self-reported hunger in school. This is relevant because temperature shocks that lead to crop failure and corresponding hunger and lack of dietary diversity might exacerbate heat-related cognitive overload.

The third aim of our study is to explore whether the effects of temperature on learning are heterogeneous by socioeconomic background or gender. To this end, we interact our treatment measures of temperature with variables for socioeconomic status and gender, as described in Equation 2. These analyses examine whether high SES buffers the effects of temperature (i.e., a compensatory advantage) or fails to mitigate the impact of temperature (i.e., erosion of compensatory advantage). They also investigate whether temperatures exacerbate gender-based disparities in learning.

$$y_{isy} = \sum_{k=1}^{K} \left(\beta_k + \gamma_k \, \mathrm{SES}_i \right) \mathrm{Temperature}_{k,sy} + \sigma X_{isy} + \alpha_s + \theta_y + u_{isy}. \tag{5.2}$$

6 Results

6.1 Descriptive overview of climatic conditions in our study

Figure 1 shows the average temperature for all the available strata in the eight West and Central African countries during the timeframe of our study. Most strata in our dataset have high average temperatures ranging between 25°C and 28°C. However, as Table 1 shows, students in our sample experience extreme temperatures too (for summary statistics by grade see Table A.1). On average, students in our sample experience 4 days above 33°C, 24 days between 30°C and 33°C, 80 days between 27°C and 30°C, and 60 days between 24°C and 27°C in the academic school years that we study. There is, nonetheless, important variation by country (Table A.2). For example, Burkina Faso, Niger, and Tchad all have an average of 4 to 9 days in the academic year above 33°C, whereas Burundi and Congo have no days in this range. Burundi hosts an equatorial climate with high mean yearly temperatures, but low climatic variations (Figure 1), with an average of 134 days during the school year below 21°C, 77 days between 21°C and 24°C and no days above 27°C (Table A.2). There is also considerable country-level variation in relative humidity and precipitation as well: Benin, Burundi, and Congo have particularly high humidity, whereas Burkina Faso, Niger, Senegal, and Tchad, have particularly low precipitation.

6.2 The effect of temperature on learning

The first aim of our study is to explore the effect of academic-year temperature on primary school students' test scores at the end of the school year. Figures 2 visualizes the effects of temperature on reading and math scores for students in grade 2 (top panel) and grade 6 (bottom panel), respectively, including 95% confidence intervals (see Table A.3 for estimates and standard errors). The patterns observed in these data closely mirror what is observed in previous research (Park, Behrer, and Goodman 2021): cooler temperatures (that is, less than 21°C) lead to higher reading and math scores, and hotter temperatures (that is, greater than 24°C) lead to lower reading and math scores. This general pattern holds for both students in grades 2 and 6, albeit with some differences in statistical significance.

The findings also show a clear temperature-learning gradient. Specifically, high temperatures have large negative effects on learning. For example, each additional day during the academic year between 30° and 33° (compared to 21°-24°) is associated with more than three-point lower reading and math scores among grade 2 students and 1.5-1.8 point lower reading and math scores among grade 6 students. These are remarkably large coefficients if we take into account the high numbers of hot days experienced by students in our sample throughout the academic year (Table 1). For example, the average student in our sample experiences 24 days between 30°C and 33°C throughout the school year. Furthermore, our results reflect one additional day in a given temperature range but do not account for cumulative impacts of several hot days in a specific bin (i.e. experiencing multiple days between 30° and 33° in a row might lead to greater impact). Given that PASEC test scores are standardized to have a mean of 500 and a standard deviation of 100, the cumulative effects of additional hot days we observe in our study are substantial. To provide perspective, days with temperatures above 33°C lead to a decline of about 2 points in math test scores. Given that the gender gap in grade 6 math test scores is approximately 8 points, this means that the impact of one hot day is roughly 25% of the gender gap. The magnitude of our results is particularly striking when we compare them with other research from elsewhere in the world: Park, Behrer, and Goodman (2021) find that each additional day above 26.7°C in the 3 years before the exam lowers the PISA test scores by 0.18 percent of a standard deviation.

To understand the impact of temperature by school grade, we look at the negative effects of high temperatures on learning on both students at the start (Grade 2) and end of primary school (Grade 6). On one hand, the magnitude of the temperature coefficients are larger in most cases for students in Grade 2 compared to Grade 6 at high temperatures (i.e. over 24°C). Yet, the magnitude of Grade 2 vs. Grade 6 temperature coefficients are not statistically different from each other most of the time, which suggests we should be careful over-interpreting age-based differences in the effects of high temperature on learning in our sample. On the other hand, there are age-based differences in the effects of cooler weather on test scores in our data. Among 6 Graders, each additional day during the academic year below 21°C (compared to 21°–24°C) is associated with more than a one-point higher math and reading scores. The magnitudes of the same coefficients are about half the size for Grade 2 students and are not statistically significant.

We find mixed evidence that the other climatic variables in our analyses impact learning (Table A.3). Relative humidity has a negative effect on math and reading scores for students in grade 2 and math scores for students in grade 6, but there is no effect of precipitation on test scores for students in either grade. On the other hand, there is strong evidence of variation in test score performance by SES, gender, and age. Among students in Grade 6, the household asset index is positively correlated with both math and reading test scores, which suggests wealthier students do better on average on math and reading. Among both students in Grades 2 and 6, never speaking French at home (a proxy for low-SES) is associated with performing significantly worse on both math and reading. The magnitude of these coefficients is fairly sizable: for example, never speaking French at home is associated with 50-60 point lower math and reading scores respectively in Grade 2. Females also perform worse on math and reading scores across the board with one exception: in Grade 2, females on average perform only about 1.6 points worse on reading compared to males, which is not statistically significant.

6.3 Exploration of mechanisms

The second aim of our study is to provide insight into the mechanisms through which temperature affects learning. To this end, we explore the effects of temperature on students' labor among Grade 6 students (data on labor is not available for Grade 2 students). A positive effect of temperature on labor would support the perspective that temperature has an indirect effect on learning by reallocating time away from schooling and toward labor. Table 2 shows that the probability of engaging in labor rises significantly for temperatures above 24°C, with the largest effects occurring in the 30°–33°C range ($\beta = 0.008$, $p < 0.01$). At temperatures above 33°C, labor participation remains elevated ($\beta = 0.004$, $p < 0.05$), though the effect size is smaller than in the 30°–33° range (overlapping confidence intervals suggest these coefficients are not statistically different from each other). While the coefficients might appear small (i.e. each additional day between 24°-27°C (compared to 21°–24°C) is associated with half a percentage point higher probability of labor) they become sizable once we take into account their cumulative effects. Interestingly, we find a negative effect of temperatures below 21°C and labor participation ($\beta = -0.003$, $p < 0.01$), suggesting that cooler-than-average conditions may slightly reduce the likelihood of students engaging in work.

Although our data does not permit us to isolate the direct effects of temperature on learning, we are able to explore how temperature impacts hunger, which may exacerbate cognitive overload. We observe that compared to the reference category (21°–24°C), temperatures between 24°–27°C, and 30°–33°C are significantly associated with an increased probability of students reporting frequent hunger. Once again, the magnitude of these coefficients is small, but they could have a substantial cumulative effect. For example, each additional day between 30°C and 33°C increases the probability of frequent hunger by 1 percentage point, and there are, on average, 24 days in this temperature range in our sample.

6.4 Heterogeneous effect of temperature on learning by SES and gender

The third aim of our study is to explore whether the effects of temperature on learning are heterogeneous by SES and gender. We start by interacting the temperature categories with the asset index (our measure of SES where a higher score on the asset index represents greater SES) as described in Equation 2. We limit this analysis to Grade 6 students because the asset index was only available for this subset of students. We present results as the average marginal effect of temperature above 33°C on math scores (top panel) and reading scores (bottom panel) across different levels of the asset index, with 95% confidence intervals (Figure 3). We focus on this threshold only because we do not observe substantial differences in the impact of temperature for other temperature bins—results for all temperature bins are available in Table A.4 which also provides estimates and standard errors. We find that the negative effect of very high temperatures (i.e. above 33°C) on reading and math scores is significantly larger for students with higher scores on the asset index (i.e. higher SES) compared to lower scores on the asset index (i.e. lower SES). This findings align with an erosion of compensatory advantage hypothesis, which suggests that high-SES students, who typically benefit from stable, well-supported educational environments, may experience a greater relative learning loss when these advantages are disrupted by extreme temperatures. Figure 4 provides further insight by showing the heterogeneous effects of temperature above 33°C on labor (top panel) and hunger (bottom panel) by SES among grade 6 students, with 95% confidence intervals (see Table A.5 for estimates and standard errors). These analyses show that the positive effect of very high temperatures (i.e. above 33°C) on labor is significantly larger for higher SES students compared to lower SES students; however, the positive effect of very high temperatures (i.e. above 33°C) on hunger are significantly smaller for higher SES students compared to lower SES students. We hypothesize that due to the erosion of compensatory advantage high-SES students experience significantly higher labor participation during extreme heat, which negatively impacts their learning outcomes; yet, their socioeconomic advantage continues to provide relative protection against hunger.

Next, we examine whether the impact of temperature on learning outcomes varies by gender by interacting the temperature variables with student gender. Table 3 shows that the magnitudes of the effects of temperature on math scores and reading scores are similar for males and females in Grade 2. In most cases, the effects of temperature on learning do not significantly differ by gender. Two exceptions are a significant gender difference in the effect of temperatures below 21°C (compared to the 21°-24°C range) on math scores for Grades 2 and 6 students and a significant gender difference in the effect of temperatures above 33°C (compared to the 21°-24°C range) on reading scores for Grade 6 students. Specifically, the coefficient of temperatures above 33°C on reading scores is not statistically significant for males, but for females each additional day during the academic year above 33°C (compared to 21°–24°C) significantly decrease reading test scores by 1.5 points.

7 Limitations

Our study has several limitations that are important to acknowledge. First, since we use a school-based sample we cannot capture those who are not in school. As a result, our estimates of the effects of heat on learning may be conservative since students who might drop out of school due to heat are not in our data. However, if students who dropped out of school were more likely to be lower SES, it is plausible that some of the larger negative effects of extreme heat on learning for higher (compared to lower) SES populations would have been attenuated. Likewise, if there were gender-based differences in heat-related dropout the effects of temperature on learning may be far greater than what we find here. Second, our analyses of the mechanisms through which heat impacted learning were somewhat constrained by our study design and data. In particular, we were unable to assess the direct effects of heat on learning, a limitation that we share with similar other studies. However, we were able to explore indirect mechanisms through which temperature affects learning by looking at whether heat also affects labor. Nonetheless, we note that our labor measure does not include domestic tasks at home, and thus we may have overlooked some of the gender-differentiated ways in which heat impacts learning. Finally, our identification strategy relies on the assumption that temperate variations are exogenous within a stratum. This is the same strategy as that employed by other scholars of temperature and learning (Park, Behrer, and Goodman 2021).

8 Discussion

Climate variability and change may pose significant challenges to education in coming years, particularly in SSA and the Global South more broadly. Yet, existing work on climatic shocks and schooling in Africa has been limited by the lack of nationally comparable and representative micro-data with information on learning. Our study contributes by exploring how temperature shocks affect learning outcomes in 8 West and Central African countries, where high temperatures are expected to increase in frequency and duration in the coming years (Barnes et al. 2024). In empirical analyses, we show that high temperatures have large negative effects on learning among students at the start and end of primary school. Crucially the magnitude of the effects we find in our study is particularly large compared to other regions of the world (Park, Behrer, and Goodman 2021). These findings are particularly concerning because the countries in our study face both an increase in the severity and frequency of extreme heat (Barnes et al. 2024; World Bank 2018) and a learning crisis (UNESCO 2014). Our study demonstrates the potential for temperature shocks to exacerbate already poor learning outcomes, with profound implications for the generation of young people in West and Central Africa today.

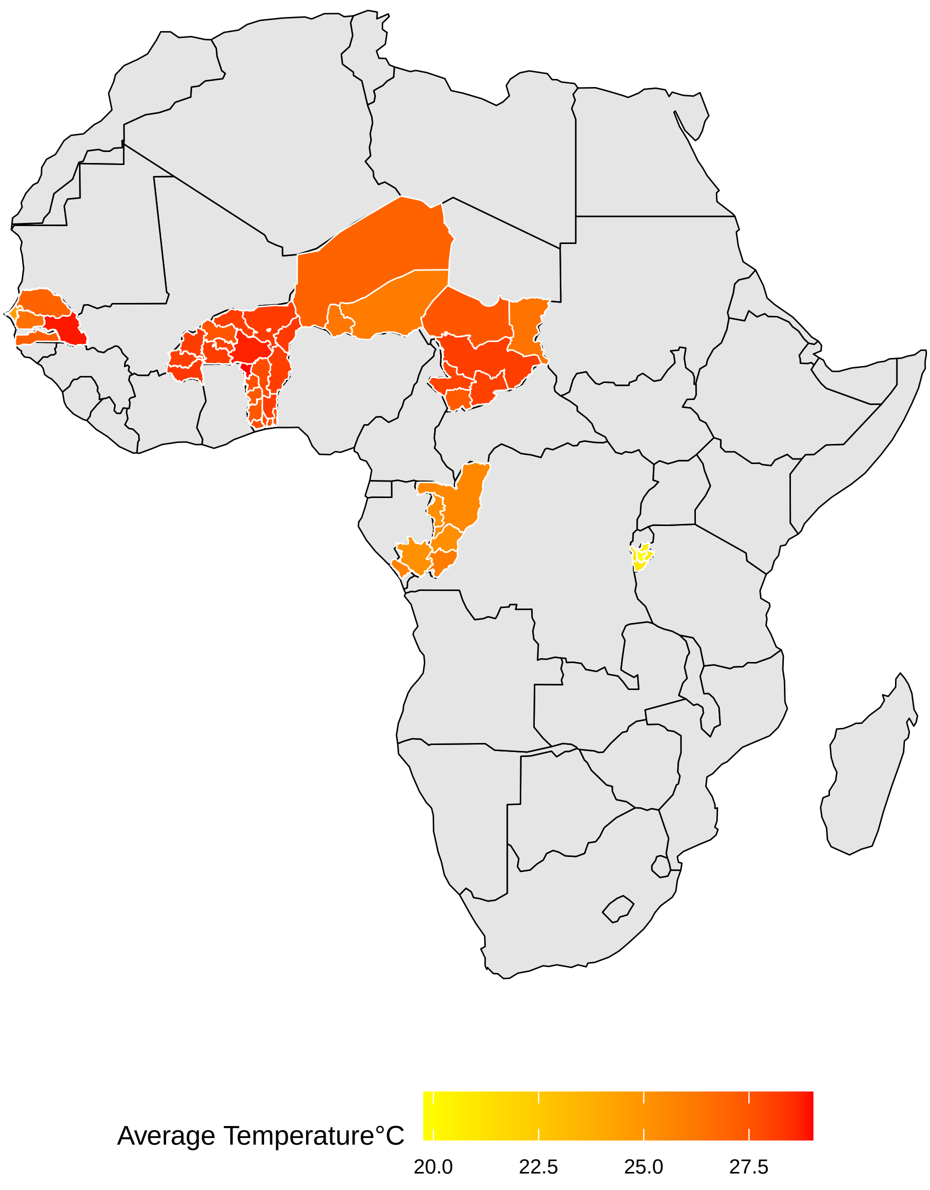
This finding that high temperatures reduce the learning outcomes of primary school students may be explained either via direct effects, where heat disrupts concentration and performance, or indirect effects, such as reallocation of time away from schooling. In the second part of our analysis, we therefore explored the mechanisms through which temperature might affect learning. We found evidence that hotter temperatures lead to increases in labor, and conversely, cooler temperatures lead to decreases in labor. These findings support the perspective that temperature has an indirect effect on learning by reallocating time away from schooling and toward labor. At the same time, temperature may also directly affect learning by increasing cognitive strain; unfortunately, we were unable to test for this possibility using our data. Nonetheless, we found clear evidence that hot temperatures lead to increases in frequent hunger in schools. To the extent that hunger makes concentration more difficult, it is plausibly that the direct effects of temperature on learning are exacerbated by hunger (Afridi, Barooah, and Somanathan 2019; Kroeger 2023).

In the final part of our analyses, we found that the effect of temperature on math and reading scores does not vary by SES for most of our temperature bins. Yet, there is one important exception: the negative effect of very high temperatures (i.e. above 33° C) on reading and math scores is significantly larger for higher SES students compared to lower SES students. Furthermore, the positive effect of very high temperatures on labor is significantly larger for higher SES students compared to lower SES students. This finding challenges the compensatory advantage mechanism (Bernardi 2014) positing that individuals with greater socioeconomic resources tend to have access to buffers that protect them from adverse shocks. We find evidence of an erosion of compensatory advantage, with high-SES students experiencing significantly higher labor participation during extreme heat, which in turn impacts their learning. This finding aligns with another study showing that above-average temperatures in early childhood lead to greater reductions in years of schooling among children from higher-SES households compared to lower-SES households in West and Central Africa (Randell and Gray 2019). These findings run counter to what is observed in OECD countries in other parts of the world where the negative effects of heat on learning are significantly larger for lower-income populations (Park, Behrer, and Goodman 2021). This discrepant finding suggests that the ways in which socioeconomic status interacts with learning are heterogeneous across contexts.

Our analyses show that heat has dramatic effects on learning in the West and Central African countries that we study. From a policy perspective, the implications of our study raise a host of complications. A major strategy to deal with the adverse effects of temperature on learning is based on air conditioning and other electricity-intensive climate controls. However, this is not a realistic solution in the countries we study: about half of the population of West and Central Africa does not have access to electricity (World Bank 2024) and many school facilities lack basic climate controls that require electricity. These realities suggest a need to innovate in creative ways that might provide students in West and Central Africa with better conditions that facilitate learning. Alternative approaches could include restructuring the school year or the timing of the school to maximize attendance during cooler periods; introducing school-based feeding programs to help with temperature-related hunger; or providing agricultural support that would reduce labor needs among primary-aged students. Identifying how a scalable solution to the challenges of heat and learning is crucially important: at present, Sub-Saharan Africa has among the largest population of young people in the world, and it is projected that by 2030 young Africans are projected to comprise 42 percent of the world's youth population (PRB 2019). Continued investment in schooling and learning for young Africans is essential to improve the well-being outcomes of the next generation of Africans.

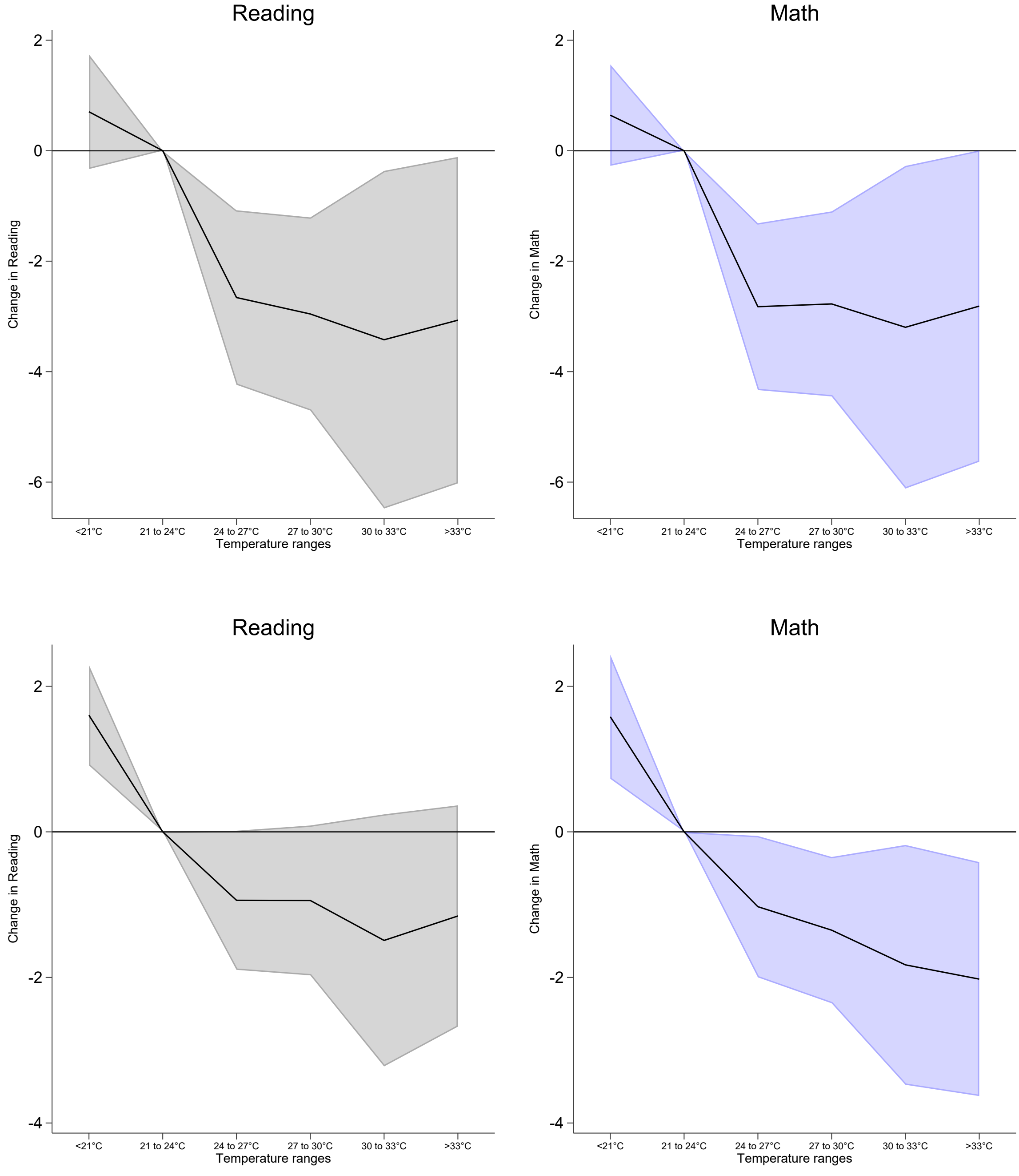
Tables and Figures

Fig. 1. Average temperature for the countries in our study



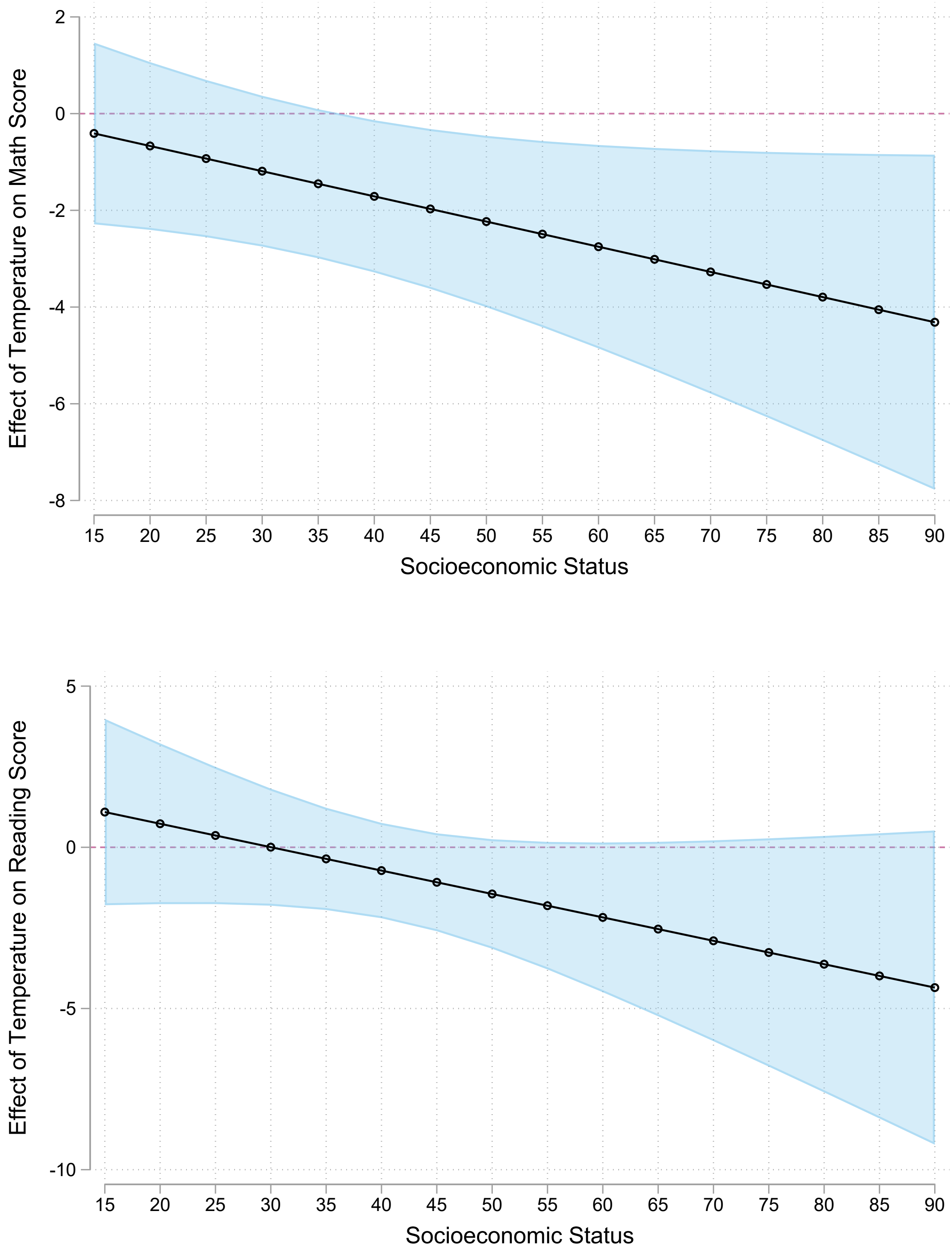
Note: Average temperature over the study time frame (2014-2019) in Benin, Burkina Faso, Burundi, Congo, Niger, Senegal, Tchad and Togo.

Fig. 2. Visualization of change in reading and math score by temperature for grade 2 (top panel) and grade 6 (bottom panel).



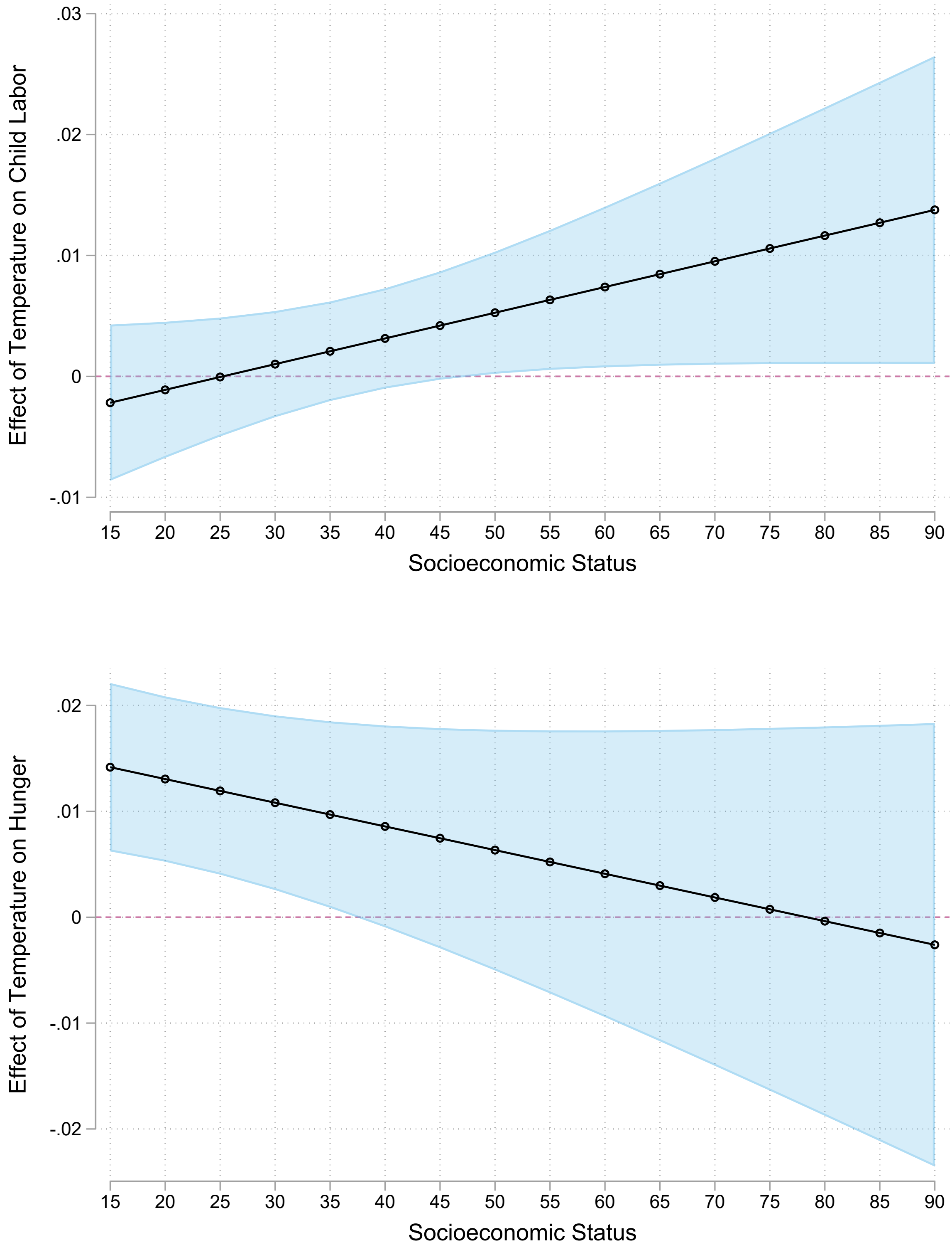
Note: This figure plots the effect of accumulated exposure over the previous academic year, including vacation days on student test score. Generated following multi-variable regression of the association between temperature and learning.

Fig. 3. Heterogeneity in the effect of temperature above 33 C on child labor (top panel) and hunger (bottom panel) by SES among students in Grade 6



Note: Results presented as Average Marginal Effect of temperature above 33 C on learning over different levels of asset index. Generated following multi-variable regression of the association between temperature and child labor and hunger including interactions between SES (asset index) and temperature.

Fig. 4. Heterogeneity in the effect of temperature above 33 C on child labor (top panel) and hunger (bottom panel) by SES among students in Grade 6



Note: Results presented as Average Marginal Effect of temperature above 33 C on learning over different levels of asset index. Generated following multi-variable regression of the association between temperature and child labor and hunger including interactions between SES (asset index) and temperature.

Table 1: Summary Statistics

	Mean	SD	Min	Max	N
Outcome Variables					
Mean Math Score	516.924	104.167	82.326	968.807	80267
Mean Reading Score	514.321	110.238	21.323	965.824	80267
Absolute Temperature					
# of Days Below 21° C	18.861	45.327	0.000	201.000	80267
# of Days Between 21 and 24° C	25.040	29.482	0.000	154.000	80267
# of Days Between 24 and 27° C	60.313	29.829	0.000	189.000	80267
# of Days Between 27 and 30° C	80.073	39.975	0.000	165.000	80267
# of Days Between 30 and 33° C	24.036	19.112	0.000	70.000	80267
# of Days Above 33° C	3.677	5.087	0.000	22.000	80267
Other Variables					
Child is Often Hungry	0.476	0.499	0.000	1.000	58760
Child Labor Index	0.583	0.493	0.000	1.000	60373
Relative Humidity	47.761	17.888	22.976	85.964	80267
Precipitation	15.725	21.193	1.120	92.625	80267
Student's Age	8.526	1.668	4.000	27.000	80267
Female (=1 if student is female)	0.484	0.500	0.000	1.000	80267
Never Speaks French at Home	0.577	0.494	0.000	1.000	80267
Household asset index	48.861	10.113	17.544	88.340	60499

Note: Data on students is from a program that evaluates learning in francophone countries in Africa. Data on temperature is from ERA5 archive. The analyses use two cross sectional datasets collected in 2014 and 2019. The first panel displays the main outcomes of this paper. The two main outcomes are Math Score and Reading Score. The second panel shows the average number of days of a giving temperature bin for all countries in our sample between both years, accounting for vacation days. The third panel shows other variables use as control in our specification, including additional weather variables, children's background characteristics, as well as 2 mechanisms outcomes which are hunger and child labor. To generate the statistics, we first generate country weights, and then multiply country weights by sampling weights and we use the latter.

Table 2: Multi-variable regression of the association between temperature and hunger and child labor for students in Grade 6.

	(1) Child is Often Hungry	(2) Child Labor
Temperature (Ref. Cat.: # of Days Between 21 and 24° C)		
# of Days Below 21° C	0.001	-0.003***
	(0.001)	(0.001)
# of Days Between 24 and 27° C	0.005**	0.005***
	(0.003)	(0.001)
# of Days Between 27 and 30° C	0.006**	0.003*
	(0.003)	(0.001)
# of Days Between 30 and 33° C	0.009*	0.008***
	(0.004)	(0.002)
# of Days Above 33° C	0.007	0.004*
	(0.006)	(0.002)
Relative Humidity	0.041***	0.031***
	(0.009)	(0.008)
Rain	-0.018**	-0.001
	(0.008)	(0.005)
Student's Age	0.007**	0.020***
	(0.003)	(0.003)
Sex (Ref. Cat.: Male)		
Female (=1 if student is female)	0.003	-0.071***
	(0.005)	(0.011)
French at Home (Ref. Cat.: Always Speaks French at Home)		
Never Speaks French at Home	0.001	0.014
	(0.009)	(0.009)
Household asset index	-0.003***	-0.005***
	(0.001)	(0.001)
Observations	58760	60373
Year FE	Yes	Yes
Strate FE	Yes	Yes

Notes: The table reports the results of a multi-variable regression of the association between temperature and hunger and child labor for students in Grade 6. Robust standard errors clustered at strata level in parentheses. Reported estimates describe how hunger and child labor for pupils in grade 6 change when one day with mean temperature 21-24° C is replaced by one day of a given other temperature category. Vacation days are included. We generate country weights and use them in our regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Heterogeneity by Gender.

	Grade 2		Grade 6	
	(1) Mean Math Score	(2) Mean Reading Score	(3) Mean Math Score	(4) Mean Reading Score
Temperature (Ref. Cat.: # of Days Between 21 and 24° C)				
# of Days Below 21° C	0.560	0.672	1.474***	1.588***
	(0.451)	(0.517)	(0.428)	(0.340)
Female × # of Days Below 21° C	0.131***	0.042	0.224**	0.040
	(0.036)	(0.043)	(0.094)	(0.051)
# of Days Between 24 and 27° C	−2.864***	−2.655***	−1.083**	−0.957**
	(0.750)	(0.784)	(0.483)	(0.474)
Female × # of Days Between 24 and 27° C	0.061	−0.016	0.087	0.024
	(0.044)	(0.043)	(0.058)	(0.041)
# of Days Between 27 and 30° C	−2.784***	−2.944***	−1.413***	−0.948*
	(0.827)	(0.867)	(0.496)	(0.505)
Female × # of Days Between 27 and 30° C	0.001	−0.033	0.080	−0.018
	(0.042)	(0.039)	(0.054)	(0.041)
# of Days Between 30 and 33° C	−3.227**	−3.435**	−1.900**	−1.494*
	(1.448)	(1.512)	(0.812)	(0.854)
Female × # of Days Between 30 and 33° C	0.041	0.021	0.118	−0.015
	(0.117)	(0.099)	(0.076)	(0.063)
# of Days Above 33° C	−2.656*	−3.030*	−1.957**	−0.941
	(1.405)	(1.569)	(0.798)	(0.748)
Female × # of Days Above 33° C	−0.363	−0.089	−0.176	−0.532*
	(0.563)	(0.496)	(0.196)	(0.283)
Relative Humidity	−7.640**	−11.943***	−6.300*	−5.248
	(3.561)	(4.058)	(3.431)	(3.148)
Rain	0.828	1.297	0.937	1.521
	(2.810)	(3.234)	(1.997)	(1.728)
Student's Age	6.746***	1.821	−7.036***	−8.530***
	(1.031)	(1.249)	(0.894)	(0.947)
Sex (Ref. Cat.: Male)				
Female (=1 if student is female)	−18.101***	1.033	−25.979**	−2.578
	(5.951)	(5.728)	(10.577)	(7.000)
French at Home (Ref. Cat.: Always Speaks French at Home)				
Never Speaks French at Home	−49.588***	−59.096***	−23.843***	−24.873***
	(4.380)	(5.305)	(2.457)	(2.789)
Household asset index			0.960***	1.575***
			(0.131)	(0.163)
Observations	19768	19768	60499	60499
Year FE	Yes	Yes	Yes	Yes
Strate FE	Yes	Yes	Yes	Yes

Notes: Table reports the results of an heterogeneity by gender of the main effect. Reported estimates describe how hunger and child labor for pupils in grade 2 and grade 6 when they are exposed to different temperature percentiles. Vacation days are included. We generate country weights and multiply country weights by sampling weights and use the latter in our regressions. *** p<0.01, ** p<0.05, * p<0.1.

References

Afoakwah, Clifford, and Isaac Koomson. 2021. "How Does School Travel Time Impact Children's Learning Outcomes in a Developing Country?" *Review of Economics of the Household* 19, no. 4 (December): 1077–1097. https://doi.org/10.1007/s11150-020-09533-8. https://doi.org/10.1007/s11150-020-09533-8.

Afridi, Farzana, Bidisha Barooah, and Rohini Somanathan. 2019. "Hunger and Performance in the Classroom."

Barnes, Clair, Friederike Otto, Ben Clarke, and Pinto Izidine. 2024. *Extreme Sahel Heatwave That Hit Highly Vulnerable Population at the End of Ramadan Would Not Have Occurred Without Climate Change.* Technical report. Imperial College. https://www.worldweatherattribution.org/extreme-sahel-heatwave-that-hit-highly-vulnerable-population-at-the-end-of-ramadan-would-not-have-occurred-without-climate-change/.

Becker, Gary S. 1965. "A Theory of the Allocation of Time." *The Economic Journal* 75, no. 299 (September): 493–517. https://doi.org/10.2307/2228949. https://doi.org/10.2307/2228949.

Bernardi, Fabrizio. 2014. "Compensatory Advantage as a Mechanism of Educational Inequality: A Regression Discontinuity Based on Month of Birth." *Sociology of Education* 87, no. 2 (April): 74–88. https://doi.org/10.1177/0038040714524258. https://doi.org/10.1177/0038040714524258.

Björkman-Nyqvist, Martina. 2013. "Income Shocks and Gender Gaps in Education: Evidence from Uganda." *Journal of Development Economics* 105 (November): 237–253. https://doi.org/10.1016/j.jdeveco.2013.07.013. https://www.sciencedirect.com/science/article/pii/S0304387813001120.

Bourdieu, Pierre, and Jean Claude Passeron. 1990. *Reproduction in Education, Society, and Culture.* 1990 ed. Theory, culture & society. London ; Newbury Park, Calif: Sage in association with Theory, Culture & Society, Dept. of Administrative / Social Studies, Teesside Polytechnic.

Cattan, Sarah, Daniel A Kamhöfer, Martin Karlsson, and Therese Nilsson. 2023. "The Long-Term Effects of Student Absence: Evidence from Sweden." *The Economic Journal* 133, no. 650 (February): 888–903. https://doi.org/10.1093/ej/ueac078. https://doi.org/10.1093/ej/ueac078.

Chang, Tom Y, and Agne Kajackaite. 2019. "Battle for the Thermostat: Gender and the Effect of Temperature on Cognitive Performance." *PloS one* 14 (5): e0216362.

Cho, Hyunkuk. 2017. "The Effects of Summer Heat on Academic Achievement: A Cohort Analysis." *Journal of Environmental Economics and Management* 83 (May): 185–196. https://doi.org/10.1016/j.jeem.2017.03.005. https://www.sciencedirect.com/science/article/pii/S0095069616301887.

Coleman, James, Campbell Ernest, Carol Hobson, James McPartland, Alexander Mood, Frederick Weinfield, and Robert York. 1966. *Equality of Educational Opportunity.* Technical report. Washington D.C.: U.S. Government Printing Office.

Collier, Paul, Gordon Conway, and Tony Venables. 2008. "Climate Change and Africa." *Oxford Review of Economic Policy* 24, no. 2 (July): 337–353. https://doi.org/10.1093/oxrep/grn019. https://doi.org/10.1093/oxrep/grn019.

Conte Keivabu, Risto. 2024. "Temperature and School Absences: Evidence from England." *Population and Environment* 46, no. 6 (February). https://doi.org/10.1007/s11111-024-00448-5.

Downey, Douglas B., and Dennis J. Condron. 2016. "Fifty Years Since the Coleman Report: Rethinking the Relationship Between Schools and Inequality." *Sociology of Education* 89, no. 3 (July): 207–220. https://doi.org/10.1177/0038040716651676. https://doi.org/10.1177/0038040716651676.

Emediegwu, Lotanna E., Ada Wossink, and Alastair Hall. 2022. "The Impacts of Climate Change on Agriculture in Sub-saharan Africa: A Spatial Panel Data Approach." *World Development* 158 (October): 105967. https://doi.org/10.1016/j.worlddev.2022.105967. https://www.sciencedirect.com/science/article/pii/S0305750X22001577.

Garg, Teevrat, Maulik Jagnani, and Vis Taraz. 2020. "Temperature and Human Capital in India." *Journal of the Association of Environmental and Resource Economists* 7, no. 6 (November): 1113–1150. https://doi.org/10.1086/710066. https://www.journals.uchicago.edu/doi/full/10.1086/710066.

Graff Zivin, Joshua, Solomon M. Hsiang, and Matthew Neidell. 2018. "Temperature and Human Capital in the Short and Long Run." *Journal of the Association of Environmental and Resource Economists* 5, no. 1 (January): 77–105. https://doi.org/10.1086/694177. https://www.journals.uchicago.edu/doi/abs/10.1086/694177.

Graff Zivin, Joshua, Yingquan Song, Qu Tang, and Peng Zhang. 2020. "Temperature and High-Stakes Cognitive Performance: Evidence from the National College Entrance Examination in China." *Journal of Environmental Economics and Management* 104 (November): 102365. https://doi.org/10.1016/j.jeem.2020.102365. https://www.sciencedirect.com/science/article/pii/S0095069620300887.

Gruijters, Rob J., and Julia A. Behrman. 2020. "Learning Inequality in Francophone Africa: School Quality and the Educational Achievement of Rich and Poor Children." *Sociology of Education* 93, no. 3 (July): 256–276. https://doi.org/10.1177/0038040720919379. http://journals.sagepub.com/doi/10.1177/0038040720919379.

Hancock, P. A., and I. Vasmatzidis. 2003. "Effects of Heat Stress on Cognitive Performance: The Current State of Knowledge." *International Journal of Hyperthermia* 19, no. 3 (January): 355–372. https://doi.org/10.1080/0265673021000054630. https://doi.org/10.1080/0265673021000054630.

Ioannou, Leonidas G., Konstantinos Mantzios, Lydia Tsoutsoubi, Zoe Panagiotaki, Areti K. Kapnia, Ursa Ciuha, Lars Nybo, et al. 2021. "Effect of a Simulated Heat Wave on Physiological Strain and Labour Productivity." *International Journal of Environmental Research and Public Health* 18, no. 6 (January): 3011. https://doi.org/10.3390/ijerph18063011. https://www.mdpi.com/1660-4601/18/6/3011.

Kroeger, Carolin. 2023. "Heat is Associated with Short-Term Increases in Household Food Insecurity in 150 Countries and This is Mediated by Income." *Nature Human Behaviour* 7 (10): 1777–1786.

Lewin, Keith, and Ricardo Sabates. 2011. *Changing Patterns of Access to Education in Anglophone and Francophone Countries in Sub Saharan Africa.* Is Education for All Pro-Poor? Anchor Books, January. http://r4d.dfid.gov.uk/PDF/Outputs/ImpAccess_RPC/PTA52.pdf.

Li, Xiaoxiao, and Pankaj C. Patel. 2021. "Weather and High-Stakes Exam Performance: Evidence from Student-Level Administrative Data in Brazil." *Economics Letters* 199 (February): 109698. https://doi.org/10.1016/j.econlet.2020.109698. https://www.sciencedirect.com/science/article/pii/S0165176520304584.

Nordstrom, Ardyn, and Christopher Cotton. 2020. *Impact of a Severe Drought on Education: More Schooling but Less Learning.* SSRN Scholarly Paper ID 3601834. Rochester, NY: Social Science Research Network, May. https://doi.org/10.2139/ssrn.3601834. https://papers.ssrn.com/abstract=3601834.

Nubler, Laura, Karen Austrian, John A. Maluccio, and Jessie Pinchoff. 2021. "Rainfall Shocks, Cognitive Development and Educational Attainment Among Adolescents in a Drought-Prone Region in Kenya." *Environment and Development Economics* 26, nos. 5-6 (October): 466–487. https://doi.org/10.1017/S1355770X20000406. https://www.cambridge.org/core/journals/environment-and-development-economics/article/rainfall-shocks-cognitive-development-and-educational-attainment-among-adolescents-in-a-droughtprone-region-in-kenya/E432EC63DAD24849A991E67C7B387844.

Park, R. Jisung. 2022. "Hot Temperature and High-Stakes Performance." *Journal of Human Resources* 57, no. 2 (March): 400–434. https://doi.org/10.3368/jhr.57.2.0618-9535R3. https://jhr.uwpress.org/content/57/2/400.

Park, R. Jisung, A. Patrick Behrer, and Joshua Goodman. 2021. "Learning is Inhibited by Heat Exposure, Both Internationally and Within the United States." *Nature Human Behaviour* 5, no. 1 (January): 19–27. https://doi.org/10.1038/s41562-020-00959-9. https://www.nature.com/articles/s41562-020-00959-9.

Park, R. Jisung, Joshua Goodman, Michael Hurwitz, and Jonathan Smith. 2020. "Heat and Learning." *American Economic Journal: Economic Policy* 12, no. 2 (May): 306–339. https://doi.org/10.1257/pol.20180612. https://www.aeaweb.org/articles?id=10.1257/pol.20180612.

Porras-Salazar, Jose Ali, David P. Wyon, Beatriz Piderit-Moreno, Sergio Contreras-Espinoza, and Pawel Wargocki. 2018. "Reducing Classroom Temperature in a Tropical Climate Improved the Thermal Comfort and the Performance of Elementary School Pupils." *Indoor Air* 28 (6): 892–904. https://doi.org/10.1111/ina.12501. https://onlinelibrary.wiley.com/doi/abs/10.1111/ina.12501.

PRB. 2019. *Africa's Future: Youth and the Data Defining Their Lives.* https://www.prb.org/resources/africas-future-youth-and-the-data-defining-their-lives/.

Prentice, Caitlin M., Francis Vergunst, Kelton Minor, and Helen L. Berry. 2024. "Education Outcomes in the Era of Global Climate Change." *Nature Climate Change* 14, no. 3 (March): 214–224. https://doi.org/10.1038/s41558-024-01945-z. https://www.nature.com/articles/s41558-024-01945-z.

Pule, Vicky, Angela Mathee, Paula Melariri, Thandi Kapwata, Nada Abdelatif, Yusentha Balakrishna, Zamantimande Kunene, et al. 2021. "Classroom Temperature and Learner Absenteeism in Public Primary Schools in the Eastern Cape, South Africa." *International Journal of Environmental Research and Public Health* 18, no. 20 (January): 10700. https://doi.org/10.3390/ijerph182010700. https://www.mdpi.com/1660-4601/18/20/10700.

Randell, Heather, and Clark Gray. 2016. "Climate Variability and Educational Attainment: Evidence from Rural Ethiopia." *Global Environmental Change* 41 (November): 111–123. https:

//doi.org/10.1016/j.gloenvcha.2016.09.006. https://www.sciencedirect.com/science/article/pii/S0959378016302643.

Randell, Heather, and Clark Gray. 2019. "Climate Change and Educational Attainment in the Global Tropics." *Proceedings of the National Academy of Sciences* 116, no. 18 (April): 8840–8845. https://doi.org/10.1073/pnas.1817480116. http://www.pnas.org/lookup/doi/10.1073/pnas.1817480116.

Roach, Travis, and Jacob Whitney. 2022. "Heat and Learning in Elementary and Middle School." *Education Economics* 30, no. 1 (February): 29–46. https://doi.org/10.1080/09645292.2021.1931815. https://turing.library.northwestern.edu/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=tfh&AN=154955888&site=ehost-live.

Skoufias, Emmanuel, and Susan W. Parker. 2002. "Labor Market Shocks and Their Impacts on Work and Schooling: Evidence from Urban Mexico." https://doi.org/10.22004/ag.econ.16405.

Srivastava, Bhavya, Kibrom Tafere Hirfrfot, and Arnold Patrick Behrer. 2024. *High Temperature and Learning Outcomes: Evidence from Ethiopia.* Washington, DC: World Bank, March. https://doi.org/10.1596/1813-9450-10714. https://hdl.handle.net/10986/41155.

Sweller, John. 1994. "Cognitive Load Theory, Learning Difficulty, and Instructional Design." *Learning and Instruction* 4, no. 4 (January): 295–312. https://doi.org/10.1016/0959-4752(94)90003-5. https://www.sciencedirect.com/science/article/pii/0959475294900035.

Taras, Howard. 2005. "Nutrition and Student Performance at School." *Journal of School Health* 75 (6): 199–213. https://doi.org/10.1111/j.1746-1561.2005.tb06674.x. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1746-1561.2005.tb06674.x.

Torche, Florencia. 2018. "Prenatal Exposure to an Acute Stressor and Children's Cognitive Outcomes." *Demography* 55, no. 5 (October): 1611–1639. https://doi.org/10.1007/s13524-018-0700-9. https://doi.org/10.1007/s13524-018-0700-9.

UNESCO. 2014. *Teaching and Learning: Achieving Quality for All — Global Education Monitoring Report.* Technical report. UNESCO. https://en.unesco.org/gem-report/report/2014/teaching-and-learning-achieving-quality-all.

Wang, Dengjia, Yanchao Xu, Yanfeng Liu, Yingying Wang, Jing Jiang, Xiaowen Wang, and Jiaping Liu. 2018. "Experimental Investigation of the Effect of Indoor Air Temperature on Students' Learning Performance Under the Summer Conditions in China." *Building and Environment* 140 (August): 140–152. https://doi.org/10.1016/j.buildenv.2018.05.022. https://www.sciencedirect.com/science/article/pii/S0360132318302828.

Wargocki, Pawel, Jose Ali Porras-Salazar, and Sergio Contreras-Espinoza. 2019. "The Relationship Between Classroom Temperature and Children's Performance in School." *Building and Environment* 157 (June): 197–204. https://doi.org/10.1016/j.buildenv.2019.04.046. https://www.sciencedirect.com/science/article/pii/S0360132319302987.

Webbink, Ellen, Jeroen Smits, and Eelke de Jong. 2012. "Hidden Child Labor: Determinants of Housework and Family Business Work of Children in 16 Developing Countries." *World Development* 40, no. 3 (March): 631–642. https://doi.org/10.1016/j.worlddev.2011.07.005. https://www.sciencedirect.com/science/article/pii/S0305750X1100180X.

Wittbrodt, Matthew T., and Melinda Millard-Stafford. 2018. "Dehydration Impairs Cognitive Performance: A Meta-Analysis." *Medicine & Science in Sports & Exercise* 50, no. 11 (November): 2360–2368. https://doi.org/10.1249/MSS.0000000000001682. https://journals.lww.com/00005768-201811000-00021.

World Bank. 2018. *LEARNING to Realize Education's Promise. The World Development Report 2018.* Technical report. Washington D.C.: The World Bank.

———. 2024. *Powering Up Western and Central Africa.* Text/HTML. https://www.worldbank.org/en/programs/powering-up-western-and-central-africa.

ONLINE APPENDIX

Temperature and Learning in West and Central Africa

A Appendix Figures and Table

Table A.1: Summary Statistics by Grade.

	Grade 6	Grade 2
Mean Math Score	508.024	517.187
	(98.470)	(104.339)
Mean Reading Score	508.367	514.488
	(102.486)	(110.482)
# of Days Below 21° C	15.503	18.974
	(39.922)	(45.490)
# of Days Between 21 and 24° C	24.334	25.066
	(27.459)	(29.551)
# of Days Between 24 and 27° C	61.978	60.258
	(29.005)	(29.858)
# of Days Between 27 and 30° C	80.961	80.037
	(38.165)	(40.035)
# of Days Between 30 and 33° C	25.591	23.986
	(19.126)	(19.111)
# of Days Above 33° C	3.634	3.680
	(5.003)	(5.092)
Relative Humidity	46.294	47.808
	(17.677)	(17.894)
Precipitation	14.215	15.776
	(19.933)	(21.233)
Student's Age	12.989	8.380
	(1.558)	(1.458)
Female (=1 if student is female)	0.486	0.484
	(0.500)	(0.500)
Never Speaks French at Home	0.263	0.588
	(0.440)	(0.492)
Child is Often Hungry	0.476	
	(0.499)	
Child Labor Index	0.575	
	(0.494)	
Household asset index	48.861	
	(10.113)	

Notes: Data on students is from a program that evaluates learning in francophone countries in Africa. Data on temperature is from ERA5 archive. The analyses use two cross sectional datasets collected in 2014 and 2019. We show the same variables as in Table 1 by country for our sample. To generate the statistics, we first generate country weights, and then multiply country weights by sampling weights and we use the latter.

Table A.2: Summary Statistics by Country.

	BENIN	BURKINA FASO	BURUNDI	CONGO	NIGER	SENEGAL	TCHAD	TOGO
Mean Math Score	480.833	503.921	608.407	562.022	492.014	545.707	503.175	467.576
	(97.071)	(95.200)	(55.448)	(91.409)	(117.611)	(98.245)	(94.459)	(86.559)
Mean Reading Score	483.666	505.447	624.347	550.122	485.570	533.956	491.420	459.383
	(87.109)	(108.233)	(92.730)	(99.650)	(107.348)	(115.410)	(78.446)	(88.150)
# of Days Below 21° C	0.000	0.119	134.276	0.000	13.771	3.348	1.634	0.000
	(0.000)	(0.381)	(44.631)	(0.000)	(14.371)	(6.867)	(3.313)	(0.000)
# of Days Between 21 and 24° C	0.556	12.240	76.740	19.869	31.317	34.594	12.175	3.150
	(1.425)	(9.779)	(43.935)	(9.137)	(11.103)	(24.725)	(9.692)	(2.772)
# of Days Between 24 and 27° C	72.544	62.405	0.984	172.442	50.632	77.292	67.871	81.524
	(16.649)	(9.313)	(1.333)	(9.622)	(10.113)	(14.087)	(13.107)	(22.964)
# of Days Between 27 and 30° C	128.676	100.722	0.000	19.689	62.135	79.025	93.994	107.883
	(20.757)	(15.896)	(0.000)	(16.436)	(18.214)	(20.913)	(12.873)	(20.543)
# of Days Between 30 and 33° C	9.924	30.179	0.000	0.000	49.641	17.521	26.891	16.034
	(13.285)	(7.836)	(0.000)	(0.000)	(11.880)	(17.041)	(7.460)	(15.141)
# of Days Above 33° C	0.299	6.335	0.000	0.000	4.504	0.220	9.434	3.409
	(1.415)	(4.350)	(0.000)	(0.000)	(4.334)	(0.876)	(5.707)	(7.366)
Child is Often Hungry	0.375	0.519	0.530	0.363	0.561	0.385	0.463	0.417
	(0.484)	(0.500)	(0.499)	(0.481)	(0.496)	(0.487)	(0.499)	(0.493)
Child Labor Index	0.508	0.648	0.634	0.396	0.663	0.380	0.662	0.606
	(0.500)	(0.478)	(0.482)	(0.489)	(0.473)	(0.485)	(0.473)	(0.489)
Relative Humidity	71.343	37.526	72.534	81.744	28.081	47.985	38.845	60.504
	(13.580)	(3.261)	(3.129)	(2.602)	(2.866)	(8.728)	(6.079)	(10.808)
Precipitation	21.733	6.240	65.600	43.183	1.996	6.971	6.983	18.723
	(5.646)	(1.899)	(21.832)	(8.885)	(0.625)	(3.654)	(2.100)	(5.853)
Student's Age	7.209	8.834	9.585	8.002	8.360	8.429	8.962	7.847
	(1.570)	(1.762)	(1.715)	(1.506)	(1.111)	(1.310)	(1.728)	(1.438)
Female (=1 if student is female)	0.478	0.491	0.512	0.500	0.449	0.517	0.463	0.468
	(0.500)	(0.500)	(0.500)	(0.500)	(0.497)	(0.500)	(0.499)	(0.499)
Never Speaks French at Home	0.563	0.593	0.017	0.456	0.781	0.721	0.559	0.728
	(0.496)	(0.491)	(0.128)	(0.498)	(0.413)	(0.449)	(0.496)	(0.445)
Household asset index	52.419	49.661	42.754	53.800	44.625	55.617	45.513	47.592
	(9.082)	(7.781)	(7.319)	(9.604)	(11.280)	(8.335)	(10.278)	(8.726)

Notes: Data on students is from a program that evaluates learning in francophone countries in Africa. Data on temperature is from ERA5 archive. The analyses use two cross sectional datasets collected in 2014 and 2019. We show the same variables as in Table 1 by country for our sample. To generate the statistics, we first generate country weights, and then multiply country weights by sampling weights and we use the latter.

Table A.3: Multi-variable regression of the association between temperature and math and reading test scores for students in Grades 2 and 6.

	Grade 2		Grade 6	
	(1) Mean Math Score	(2) Mean Reading Score	(3) Mean Math Score	(4) Mean Reading Score
Temperature (Ref. Cat.: # of Days Between 21 and 24° C)				
# of Days Below 21° C	0.644	0.706	1.582***	1.602***
	(0.456)	(0.515)	(0.423)	(0.342)
# of Days Between 24 and 27° C	−2.824***	−2.658***	−1.028**	−0.940*
	(0.750)	(0.785)	(0.482)	(0.475)
# of Days Between 27 and 30° C	−2.774***	−2.956***	−1.350***	−0.942*
	(0.832)	(0.868)	(0.499)	(0.511)
# of Days Between 30 and 33° C	−3.197**	−3.422**	−1.827**	−1.491*
	(1.450)	(1.518)	(0.818)	(0.860)
# of Days Above 33° C	−2.813*	−3.068**	−2.023**	−1.156
	(1.399)	(1.467)	(0.798)	(0.755)
Relative Humidity	−7.639**	−11.947***	−6.148*	−5.205
	(3.562)	(4.057)	(3.414)	(3.153)
Rain	0.810	1.294	0.781	1.445
	(2.803)	(3.230)	(1.978)	(1.717)
Student's Age	6.773***	1.833	−7.021***	−8.531***
	(1.033)	(1.245)	(0.896)	(0.950)
Sex (Ref. Cat.: Male)				
Female (=1 if student is female)	−12.289***	−1.633	−8.220***	−4.045***
	(2.299)	(1.774)	(1.075)	(1.142)
French at Home (Ref. Cat.: Speaks French at Home)				
Never Speaks French at Home	−49.642***	−59.095***	−23.948***	−24.921***
	(4.386)	(5.305)	(2.429)	(2.769)
Household asset index			0.957***	1.571***
			(0.132)	(0.164)
Observations	19768	19768	60499	60499
Year FE	Yes	Yes	Yes	Yes
Strate FE	Yes	Yes	Yes	Yes

Notes: The table reports the results from a multi-variable regression of the association between temperature and math and reading test scores for students in Grades 2 and 6. Robust standard errors clustered at strata level in parentheses. Reported estimates describe how learning in math and reading change for pupils in grade 2 and grade 6 when one day with mean temperature 21-24° C is replaced by one day of a given other temperature category. Vacation days are included. We generate country weights and use them in our regressions. Asset information is not collected for Grade 2 students. We do find a significant correlation between the variable "Never Speaks French at Home" and the variable "Pupil Asset Index" for Grade 6. *** The variable "Never Speaks French at Home" is 1 if the student never speaks French at home, 0 if the student speaks french sometimes, often and always. The reference is "Speaks French sometimes, often and always". I will modify the tables accordingly. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Heterogeneity by SES for Grade 6 in Math and Reading

	(1) Mean math score	(2) Mean reading score
Temperature (Ref. Cat.: # of Days Between 21 and 24° C)		
# of Days Below 21° C	1.716***	1.824***
	(0.534)	(0.414)
# of Days Below 21° C × Household Asset Index	-0.003	-0.005
	(0.008)	(0.008)
# of Days Between 24 and 27° C	-1.113*	-1.088*
	(0.559)	(0.548)
# of Days Between 24 and 27° C × Household Asset Index	0.001	0.002
	(0.005)	(0.006)
# of Days Between 27 and 30° C	-1.543**	-1.148**
	(0.579)	(0.547)
# of Days Between 27 and 30° C × Household Asset Index	0.003	0.003
	(0.005)	(0.006)
# of Days Between 30 and 33° C	-1.794*	-1.484
	(1.012)	(1.065)
# of Days Between 30 and 33° C × Household Asset Index	-0.002	-0.002
	(0.007)	(0.008)
# of Days Above 33° C	0.372	2.183
	(1.253)	(2.134)
# of Days Above 33° C × Household Asset Index	-0.052*	-0.073
	(0.028)	(0.049)
Relative Humidity	-6.235*	-5.286
	(3.420)	(3.168)
Rain	0.965	1.707
	(1.974)	(1.743)
Student's Age	-6.999***	-8.510***
	(0.904)	(0.949)
Sex (Ref. Cat.: Male)		
Female (=1 if student is female)	-8.218***	-4.043***
	(1.071)	(1.127)
Never Speaks French at Home	-23.987***	-24.970***
	(2.437)	(2.785)
French at Home (Ref. Cat.: Always Speaks French at Home)		
Household Asset Index	0.991	1.658*
	(0.809)	(0.915)
Observations	60499	60499
Year FE	Yes	Yes
Strate FE	Yes	Yes

Notes: Table reports the results of an heterogeneity analysis by socioeconomic status of the main effect. Reported estimates describe how Math and Reading for pupils in grade 6 change by socioeconomic groups when they are exposed to different temperature percentiles. Vacation days are included. We generate country weights and multiply country weights by sampling weights and use the latter in our regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.5: Heterogeneity by SES in Hunger and Child Labor.

	(1) Child is Often Hungry	(2) Child Labor
Temperature (Ref. Cat.: # of Days Between 21 and 24° C)		
# of Days Below 21° C	-0.00152	-0.00312
	(-0.78)	(-1.59)
# of Days Below 21° C × Household Asset Index	0.0000593	0.0000139
	(1.55)	(0.34)
# of Days Between 24 and 27° C	0.00110	0.00234
	(0.42)	(1.05)
# of Days Between 24 and 27° C × Household Asset Index	0.0000808***	0.0000527
	(3.32)	(1.32)
# of Days Between 27 and 30° C	0.00416	0.00125
	(1.46)	(0.62)
# of Days Between 27 and 30° C × Household Asset Index	0.0000384	0.0000297
	(1.54)	(0.93)
# of Days Between 30 and 33° C	0.00306	0.00628*
	(0.79)	(1.83)
# of Days Between 30 and 33° C × Household Asset Index	0.000104**	0.0000360
	(2.42)	(0.70)
# of Days Above 33° C	0.0175***	-0.00537
	(3.55)	(-1.12)
# of Days Above 33° C × Household Asset Index	-0.000224	0.000213*
	(-1.57)	(1.83)
Relative Humidity	0.0405***	0.0308***
	(4.71)	(4.16)
Rain	-0.0169**	-0.0000527
	(-2.29)	(-0.01)
Student's Age	0.00702**	0.0199***
	(2.32)	(7.42)
Sex (Ref. Cat.: Male)		
Female (=1 if student is female)	0.00325	-0.0717***
	(0.68)	(-6.78)
French at Home (Ref. Cat.: Always Speaks French at Home)		
Never Speaks French at Home	0.000350	0.0128
	(0.04)	(1.38)
Household Asset Index	-0.0137***	-0.0130*
	(-3.30)	(-1.89)
Observations	58760	60373
Year FE	Yes	Yes
Strate FE	Yes	Yes

Notes: Table reports the results of an heterogeneity analysis by socioeconomic status of the main effect. Reported estimates describe how hunger and child labor for pupils in grade 2 and grade 6 change by different socioeconomic groups when they are exposed to different temperature percentiles. Vacation days are included. We generate country weights and multiply country weights by sampling weights and use the latter in our regressions. *** p<0.01, ** p<0.05, * p<0.1.