Environment and Development Economics (2025), 1–21
doi:10.1017/S1355770X25000105

RESEARCH ARTICLE

Climate shocks and human capital:evidence from Uganda

Osaretin Olurotimi

Department of Agricultural and Resource Economics, University of Arizona, Tucson, AZ, USA
Corresponding author: Olurotimi Osaretin; Email: olurotimi@arizona.edu

(Submitted 31 May 2024; revised 30 October 2024, 19 December 2024; accepted 23 January 2025)

Abstract

This research examines whether high temperatures and exposure to childhood rainfall and heat shocks are a cognitive drag on children in Uganda. First, it asks whether students perform worse on a test on hotter days. Second, it examines whether previous longer-term exposure to high temperatures and unusual rainfall influences current test scores and educational outcomes. The analysis shows that high temperatures on test dates harm test performance, especially for girls and children younger than ten, implying additional temperature control considerations for particular demographics. The analysis of childhood climate shocks, which employs within-parish distributions of rainfall and heat, shows that children who experience rain or heat above the 80^{th} percentile of the parish distribution from birth until age 4 have worse learning outcomes in math, English, or local language literacy.

Keywords: climate; heat; human capital; learning outcomes; Uganda

JEL classification: Q54; I21; J13; 015

1. Introduction

Climate change is real, and the effect is felt globally. The Intergovernmental Panel on Climate Change (Panel on Change , IPCC) reports that "each of the last four decades has been successively warmer than any decade that preceded it since 1850". However, there is scant evidence about the impact of climate change on learning outcomes in low-income countries, especially in Africa. Given the centrality of human capital to development trajectories (Lucas, 1988; Hanushek, 2016), research is necessary to unpack the effects of climate shocks on human capital and understand the effect of potential mediators available to households to adapt to such shocks.

Thus, this paper asks whether high temperatures and exposure to climate shocks in childhood are a cognitive drag on children of elementary and early secondary school age in Uganda. First, it asks whether students perform worse on a test on hotter days. Second, it asks whether previous longer-term exposure to high temperatures and unusual rainfall in early childhood influences current test scores and other human capital measures, such as whether a child is in the proper grade for their age. Finally, given that different people may have different thermal reactions to the same thermal environment (Zarghami *et al.*, 2022), this paper explores interesting dimensions of heterogeneous effects of test date temperature among children, including age, gender, and socioeconomic status. Importantly, this paper also asks whether participation in extracurricular instruction provided to students buffers the effect of test date temperature on test outcomes for those who participate in such instruction.

This paper contributes to the literature (see Cho, 2017; Graff Zivin *et al.*, 2020; Park, 2020; Garg *et al.*, 2020; Li and Patel, 2021; Roach and Whitney, 2022; Zhang *et al.*, 2024) on the effect of heat and human capital by generating new knowledge on the impact of heat on cognition in an ordinary setting in a tropical and low-income context. Additionally, this study is the first to distinguish the effect of heat on a literacy test conducted in English versus that conducted in the local language, which is not subject to cross-language processing delays for students whose mother tongue is not English and may best capture general language proficiency for younger children (Knauer *et al.*, 2019). This distinction matters in this context, as the result shows that, although there are no average effects of test date temperature on English literacy, testing on any day with a temperature above 28°C reduces learning outcomes in the local language.

The second research strand this paper addresses is research about the effect of early life exposure to climate shocks on children's human capital (for example, see Maccini and Yang, 2009; Cornwell and Inder, 2015; Shah and Steinberg, 2017; Rosales-Rueda, 2018). This work is inspired by theoretical predictions that exposure to adverse shocks in childhood has a statistically and economically significant adverse effect on human capital (Isen *et al.*, 2017; Almond *et al.*, 2018). Thus, we present the first estimates of the short- and long-term effects of temperature on math, English, and local language literacy in an African setting for children of elementary school age.

Empirically, the paper combines learning outcome data from the UWEZO learning assessments in East Africa, which are annual surveys that measure children's literacy and numeracy skills in Uganda, with the Climate Hazards Group InfraRed Temperature with Station data (CHIRTS) daily temperature data and and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) precipitation data from the Climate Hazard Centre at the University of California, Santa Barbara. The relationship between weather and learning outcomes is analyzed using temperature conditions on the test date at the parish level, which is the fourth administrative level in Uganda, while controlling for typical weather patterns using parish-year fixed effects. We account for a nonlinear relationship between temperature and test scores by employing five bins representing daily mean temperatures.

Additionally, we conduct a heterogeneous analysis of the impact of test date temperature given that the effects of climate shocks could vary by sex due to physiological or sociocultural factors. For instance, there have been studies documenting that girls suffer higher mortality from floods (Pradhan *et al.*, 2007), and experimental studies have documented gender differences in cognitive performance after exposure to high temperatures (Chang and Kajackaite, 2019). Children's response to stressors vary by what is adaptive to them depending on their background characteristics (Heissel *et al.*, 2020). Therefore, as extracurricular activities, including extra tutoring, are associated with skills such as test persistence (Covay and Carbonaro, 2010) and better coping with stress (Heaslip *et al.*, 2021), we check if participation in extra learning has a heterogeneous impact when children experience heat stress during their tests.

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

This paper finds that high temperatures on exam dates are associated with worse test performance in the local language for all children and all subjects tested for girls and children younger than ten. For example, girls' scores decrease additionally by about 1 per cent and 3 per cent in math, in addition to the girl-boy differential, when they take tests on days with temperatures within (32,34]°C and days with temperatures above 34°C, respectively, compared to days with maximum temperature in the (23,28]°C category. Similarly, children younger than ten score additionally about 4 per cent and 8 per cent worse in math when tested on the hottest days with temperatures within (32,34]°C and above 34°C, respectively, compared to days with maximum temperature in the (23,28]°C category. These findings imply a need for temperature control considerations for particular demographics. The results on the effect of test date temperature are generally in line with previous studies; however, we provide two additional findings. First, the analysis shows that although children from households with high socioeconomic status perform better on tests on average, they perform worse when tested on the hottest days, suggesting that access to heat mitigation technology may make a child more susceptible to thermal stress. Socioeconomic status ought to mediate heat stress by making access to cooling technology likelier.[1] However, children from high socioeconomic households may perform worse than others in conditions where that technology is not in use, for instance, when taking tests in the open, as was typically done in this case.

Second, we show that participating in extra instruction before the tests may have some protective effect on the impact of heat on math scores, as children who undergo additional learning outside of school perform better in math and local language when tested on days with temperatures above 34°C. Overall, these heterogeneous effects show that exposure to extreme heat harms all children irrespective of economic status, although ex-ante[2] strategies such as extra learning opportunities may temper the impact of heat stress.

In the estimates of the long-run impact of unusual temperature and rainfall, we utilize within-parish deviations in annual temperature and precipitation by defining positive and negative shocks as temperature and precipitation above the 80^{th} percentile and in the 20^{th} percentile, respectively, of the parish's long-term rainfall and temperature. Thus, we utilize within-parish variation in annual temperature and rainfall to identify children who experience climate shocks in early childhood from the *in utero* period up to age 4.

The results show positive rain shocks from *in utero* until age 4 reduce test scores in math, English, and the local language. On the other hand, experiencing heat shock *in utero* has some positive effects on test scores in some instances, while heat shocks experienced above age 1 are unequivocally detrimental to test scores in math and English. These results are generally robust to utilizing household fixed effects instead of parish fixed effects, clustering at a higher geographic level, and defining the shock at a larger geographic scale, i.e., at the district level. In this analysis, we have defined a positive rain shock as rainfall above the 80^{th} percentile and found negative results on learning outcomes in math and English, which is contrary to the finding from India that children score 0.012–0.04 points higher on math or reading tests for each year of favorable rainfall compared to drought years (Shah and Steinberg, 2017). However, when the threshold for

[1]In the data, not all households with high socioeconomic status report having electricity. Only 20 per cent do, compared to 11 per cent in the overall sample.

[2]To be sure, parents did not provide extra learning opportunities as a way to cope with climate change. However, we hypothesize that the additional human capital accumulated from the extra instruction may lessen the negative impact that testing on an unusually hot day has on cognition.

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

defining a positive shock is above the median of the long-term within-parish rainfall, the effects of childhood rainfall shocks experienced *in utero* until age four are positive. This result and other analyses suggest that the threshold for defining a positive rainfall shock differs by context.

2. Background

2.1 Literature review

A nascent literature examines the impact of temperature on learning outcomes. For example, hotter school days (Park *et al.*, 2020), and test date temperature in high stakes exams have been associated with cognitive decline (see Cho, 2017; Park, 2020; Graff Zivin *et al.*, 2020; Roach and Whitney, 2022) in Korea, the United States and China and have negligible effects on test scores in Brazil (Li and Patel, 2021). However, most of this research uses the learning outcomes from tests administered at school and in exam settings. The few studies that have examined the effect of high-temperature exposure on cognition in household settings have found adverse effects of test date heat on teenage and adult populations on math scores in China (Zhang *et al.*, 2024) and the United States (Graff Zivin *et al.*, 2018). Also, using similar test measures of learning, Garg *et al.* (2020) find that the previous year's temperature affects children's math and reading scores in India.

Nonetheless, some important questions remain unanswered: first, how generalizable are the findings on the effect of contemporaneous heat and long-run climate change on learning in the African context, where the climate is primarily tropical and where ongoing non-climate vulnerabilities to poverty exacerbate vulnerability to climate? For instance, World Bank Group (2023) estimates that 45 per cent[3] of people have access to electricity in Uganda, compared to 100 per cent in China and the United States. Furthermore, the African context is peculiar because it is characterized by limited uptake and use of formal climate information services in adaptation and response to climate shocks. In addition to socioeconomic differences from the rest of the world, the climate in Africa is peculiar. Although it is the region with the least greenhouse gas emissions, it is predicted to suffer the most disruptions due to climate change (Fonjong *et al.*, 2024). For example, In recent decades, the East African region has experienced a lot of variation in precipitation, including alternating seasons of droughts and floods. The study context, Uganda, has a tropical climate and experiences moderate temperature variations within a year; however, data from the EM-DAT shows that it experienced 15 floods and five droughts between 1990 and 2010. Moreover, research on other outcomes has shown that data from wealthier countries tend to underestimate climate impacts on poorer regions (Carleton *et al.*, 2022).

Second, there is no evidence about how ex-ante coping strategies to boost children's learning mitigate the effect of exposure to climate shock. Third, the paper that the short-term analysis in this work most closely relates to, based on data from China (Zhang *et al.*, 2024), finds no effect on verbal scores measured by word recognition tests and excludes children younger than ten years old, thereby raising the question of how heat affects the cognition of the youngest children and other forms of literacy. This paper contributes to some of these gaps.

[3]This estimate is likely skewed by urban households, as only 11 per cent of households in the data used in this paper report electricity ownership.

Likewise, a rich literature examines the effect of long-term shocks on children's human capital. For instance, variable rainfall (Cornwell and Inder, 2015; Kien and My, 2021), and floods *in utero* (Rosales-Rueda, 2018) have been shown to have adverse effects on children's health and cognitive outcomes. Also, using a similar measure of cognition as in this paper, Shah and Steinberg (2017) finds that positive rainfall shock experienced *in utero* up to age two increases cognition as measured by test scores in English and mathematics. Nonetheless, the findings on long-term climate effects are mixed. Studies have found that long-term effects are relatively muted compared to short-term impacts (Graff Zivin *et al.*, 2018; Garg *et al.*, 2020). Moreover, this literature mostly comes from Asian countries and focuses on educational attainment (Maccini and Yang, 2009; Randell and Gray, 2019; Le and Nguyen, 2023). In Kenya, Nübler *et al.* (2021) examine the effect of childhood rainfall shocks on adolescent girls in a pastoralist setting and find that it decreased achievement in math and English. This research expands the coverage demographically by including primary-aged children, boys, and all regions in Uganda in the analysis. Additionally, this work is the first to examine the effect of childhood heat shocks and rainfall shocks on learning outcomes in an African setting.

2.2 Mechanisms

There are different mechanisms through which heat could affect children in the short and long term. In the short term, heat stress on the test date has been shown to have a cognitive impact on children. This could be due to the effect of heat on physiological factors, including arterial blood oxygen saturation level (Lan *et al.*, 2022) and brain temperature (Yablonskiy *et al.*, 2000), which is related to cognitive performance. In the long term, young children, particularly those below the age of five, may be affected by exposure to extreme weather shocks via physiological, socioeconomic, environmental, and parental pathways. In the case of prolonged exposure to high temperatures, children can suffer heat strokes, which are especially harmful to growth and development during critical periods of vulnerability, including gestation, when vital physiological systems are developing, and early childhood, when the immune and central nervous systems are developing (Bennett and Friel, 2014). Weather shocks could affect children's cognition via low or damaged crop yields in agricultural settings (Schlenker and Lobell, 2010), which could lead to changes in household income (Matyas and Silva, 2013), food availability and related undernourishment, which has been shown to affect later life outcomes (Maccini and Yang, 2009). This mechanism may especially be salient in Uganda, where over 80 per cent of the population is engaged in agricultural activities, and the Agricultural sector contributes up to a quarter of the country's aggregate output.

With regard to precipitation, in tropical African countries, high and heavy rainfall is associated with a rise in vector-borne diseases, such as dengue fever and malaria, which is associated with cognitive declines in some cases (Boivin, 2002; Carter *et al.*, 2005).[4] Also, high and low rainfall extremes have been associated with a rise in diarrhoeal disease (Hashizume *et al.*, 2007). In addition to direct effects, children could be indirectly affected by extreme climate shocks through intergenerational effects because of their dependence on adults. For instance, mothers who themselves suffer any adverse impact of climate shock could transmit the effects genetically to their unborn children or through the quality of nurture they provide their young children. Although this paper

[4] According to the World Health Organisation, African children bear the most significant malaria burden, with over 90 per cent of the global malaria cases reported in the region.

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

does not examine mechanisms empirically, the mechanisms lead one to expect that the impacts of transient test date temperature, which primarily affects children physiologically, are likely to be different from exposure to adverse climate shocks in childhood, which could affect children via multiple pathways.

3. Data and methodology

3.1 Learning outcomes data

The human capital and socioeconomic measures come from the child- and household-level data from the UWEZO East Africa citizen-led assessment, covering Uganda from 2010 to 2015. UWEZO is an adaptation of ASER, an education survey developed by Pratham in India that conducts learning assessments nationally. In Uganda, in rounds 2012 and 2015, the tests were also administered in four local languages, including Ateso, Leblango, Luganda, and Runyoro (ACER, 2014).[5]

The data represents a cross-section of students aged 6 to 16 who were examined using a grade 2-level curriculum and home surveys. Grade 2-level curriculum is used as it coincides with the age at which children are expected to have mastered basic literacy and numeracy skills. For all the relevant years, enumerators visited all census districts in each county. They sampled 30 villages within each district using probability proportional to size, with 20 households sampled in every village using systematic random sampling. Then, each child within the target population in a household is surveyed and tested at the child's home, regardless of whether the child is enrolled in school or not.

Children are typically visited by test-takers recruited from close communities and tested in math, English, and local language literacy. A child is assigned a score on a test based on the number of questions on a test that they answer correctly. In math, the competencies tested are counting, numbers, addition, subtraction, multiplication, and division. In the English language, the levels are letter, word, paragraph, and story. Similarly, in the local language, the levels are syllables, words, paragraphs, and stories. Other child variables collected include age, gender, and type of school attended. In addition, household information collected has parents' age and years of education completed, household size, number of children within a household, asset ownership, and gender of the household head.

The sample used in this paper includes children for whom reliable test dates and GPS information are available, i.e., for years 2010, 2011, 2012, and 2015.

3.2 Weather and climate data

Geographically, Uganda has the following spatial classifications in descending order: region, district, county, sub-county, parish, and village. In 2014, the National Population and Housing Census of Uganda revealed that the average population in a district was about 240,000. More than half of the sub-counties had a population of fewer than 25,000 persons, while parishes have about 4,000 people on average. Therefore, we use unique parish, sub-county, and district names to identify the longitude and latitude of children at the parish level. The GPS information for parishes was then used to obtain the daily maximum temperature, relative humidity, and rainfall data measured in degrees Celsius

[5]The number of children with local language test scores is lower than that of other tests because it is only administered in two out of the four years in the data. The tests are only administered to the subset of children who speak that language.

and millimeters, respectively, from CHIRTS and CHIRPS daily data from the Climate Hazard Centre (CHC) at UC Santa Barbara. The CHC data has a spatial scale of about 0.05°x 0.05°, representing about 5 km by 5 km.

3.3 Data overview

Table 1 shows an overview of the outcome variables and the child and household controls used in the analysis. The average child in the data is 10.6 years old and is in the 3^{rd} grade. Sixty-one per cent and 11 per cent of households have telephones and electric assets, respectively. The average child scores 4 in math and about 3 in English and local language tests, respectively, corresponding to the ability to add and read words.

3.4 Construction of variables

The learning outcomes measured are children's performance in math, English, and local language literacy tests. Also, the long-run estimations look at the probability of a child being "ontrack" in school. Ontrack is defined as the difference between a child's age and grade being at most 6; one reason for using this definition is that it can be seen as a stock variable of human capital that shows how enrolment and advancement have evolved until a child's current grade. The short-run analysis of the effect of test date temperature uses the maximum daily temperature as the measure of temperature. The maximum daily temperature ranged from about 19 to 39°C in the years in the sample.

Long-run temperature and rainfall shocks for a child are based on deviations from the annual long-run average temperature and rainfall over almost three decades from 1985 to 2015. A parish is designated as having a heat shock in a given year if the annual temperature is in the 80^{th} percentile of the long-run temperature in the parish. In contrast, a cool year is defined as having a yearly temperature in the 20^{th} percentile of the long-run temperature. Hence, the variable Temperature Shock at period t is coded one (1) if the annual temperature is in the 80^{th} percentile of the distribution of the parish's long-run temperature and coded -1 if the annual temperature is in the 20^{th} percentile. Any other case is coded as zero. Climate shocks are defined in 6 periods, i.e., t=-1,0,1,2,3,4, where t=0 is the year a child was born, that is, the birth year. The birth year variable is constructed by subtracting the survey year from a child's age. Hence, the *in utero* period is the year preceding the birth year.

3.5 Empirical framework

3.5.1 Short-term effects of test date temperature

To empirically determine the effect of high temperatures on test scores, the analysis exploits the plausible exogeneity of test date temperature given that the tests are administered without prior notice of the exact day to the households. It uses a fixed effect regression to compare outcomes between children living in the same parish and tested in the same year but who take the tests on different days. Hence, it utilizes variations in children's test dates within a parish in a year. The primary treatment variable is test date temperature, while the outcomes are test results in math, English, and local language literacy for children aged 6–15, measured at the individual child level. This estimation strategy implicitly assumes that the daily maximum temperature of the test date indicates the temperature around the time the child took the test, which is plausible given that the tests are administered during the day. Realistically, households have priors about their

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

Table 1. Summary table

	Mean	SD	Min	Max	Count
Dependent variables					
Math	4.38	2.24	1.00	7.00	186359
English	2.83	1.52	1.00	5.00	185500
Local language	2.86	1.84	1.00	6.00	40390
Ontrack (age-grade is at most 6)	0.40	0.49	0.00	1.00	187767
Child and household controls					
Age	10.67	2.97	6.00	16.00	187767
Grade	3.53	2.11	1.00	13.00	187767
Female	0.49	0.50	0.00	1.00	187767
Household size	7.30	3.03	1.00	52.00	187767
Household head is female	0.35	0.48	0.00	1.00	187767
Age of household head	43.49	12.72	15.00	100.00	187767
Mother's education	0.92	0.63	0.00	3.00	187767
Household has electricity	0.11	0.31	0.00	1.00	187767
Household has telephone	0.61	0.49	0.00	1.00	187767
Child partakes in extracurricular instruction	0.20	0.40	0.00	1.00	163785
Rainfall and temperature summary statistics					
Rainshock *in utero*	0.25	0.56	−1.00	1.00	187767
Rainshock in birth year	0.22	0.55	−1.00	1.00	187767
Rainshock at age 1	0.20	0.54	−1.00	1.00	187767
Rainshock at age 2	0.17	0.54	−1.00	1.00	187767
Rainshock at age 3	0.10	0.54	−1.00	1.00	187767
Rainshock at age 4	0.07	0.53	−1.00	1.00	187767
Heat shock *in utero*	0.02	0.56	−1.00	1.00	187767
Heat shock in birth year	0.08	0.57	−1.00	1.00	187767
Heat shock at age 1	0.13	0.57	−1.00	1.00	187767
Heat shock at age 2	0.12	0.59	−1.00	1.00	187767
Heat shock at age 3	0.12	0.61	−1.00	1.00	187767
Heat shock at age 4	0.12	0.62	−1.00	1.00	187767
Maximum test date temperature	30.70	2.92	18.82	39.81	187767
Test date rainfall	3.79	4.75	0.00	36.76	187721
Test date humidity	61.98	12.09	22.57	100.00	187767

Notes: SD: standard deviation. Math, English, and local Language are based on tests administered by UWEZO to children at home. Mother's education is coded 0 "None," 1 "Primary," 2 "Secondary," 3 "More than Secondary.".

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

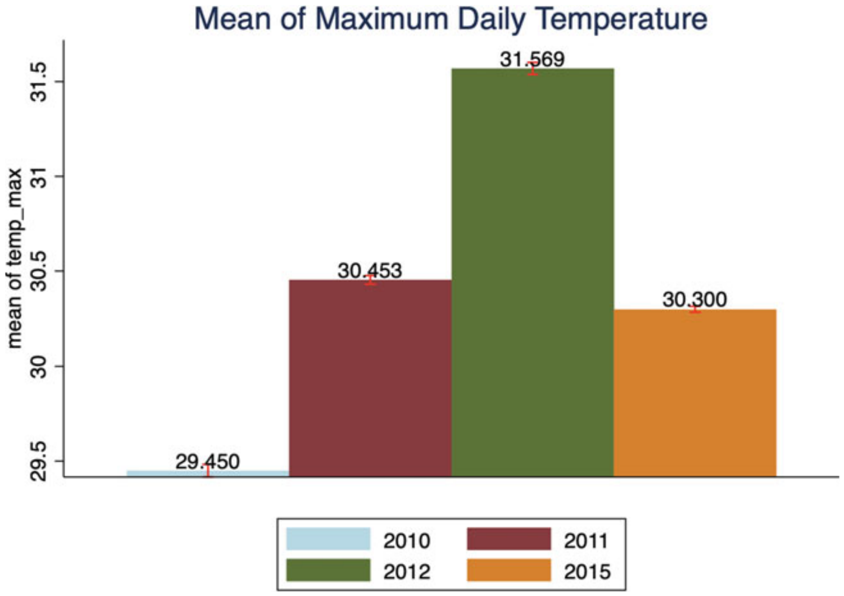

Figure 1. Average maximum daily temperatures by year.

location's climate (Ortiz-Bobea, 2021), and the average monthly maximum temperature is around 30°C in Uganda (see figure 1 for the annual average maximum temperatures recorded for the locations in the dataset) year round.[6] However, the daily weather fluctuations via temperatures we measure will likely be unexpected. Hence, the regressions include parish-year fixed effects for the local region's climate and socio-political conditions in a given year, as well as the month in which a parish is tested in a given year.

The regressions also control for test date rainfall and relative humidity. The regression equation is:

$$Y_{ijt} = \sum_{k=1}^{K} \beta_k T_{ijt}^{k} + X_{ijt}\beta + \tau_{tj} + \epsilon_{ijt}, \tag{1}$$

where Y is an outcome for child i in parish j in survey year t, T_{ijt}^{k} is the k^{th} bin of daily maximum temperature. The test date temperature is binned into the following five bins: $<= 28$, (28, 30], (30, 32], (32, 34], and > 34°C. By utilizing bins, the estimation departs from a linearity assumption of the effects of temperatures on human capital. Child characteristics, including the age, grade, and gender of the child, the age and gender of the household head, the mother's education, and household assets, are included in the vector X. At the same time, parish-year fixed effects are denoted as τ_{tj}. The coefficient β_k on the temperature bins T_{ijt}^{k} can be interpreted as the effect of testing on a day with temperature within a specific bin compared to an omitted bin. In the

[6]The hottest months in Uganda are typically the earliest, i.e., January and February. Interestingly, the school year typically starts in February and ends in December.

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

regressions, the omitted bin is the (23,28]°C bin, chosen because it includes the typical daily temperature in Uganda and the optimal temperature for work (López-Sánchez and Hancock, 2018).

To examine the heterogeneous effect of temperature on human capital, the temperature dummies interacted with variables C_i representing the heterogeneous dimensions of the child or household, i.e., age, gender, household socioeconomic status, and participation in extracurricular instruction. In this case, the regression equation becomes

$$Y_{ijt} = \sum_{k=1}^{K} \beta_k T_{ijt}^{k} + \sum_{k=1}^{K} \beta_c T_{ijt}^{k} * C_i + X_{ijt}\beta + \tau_{tj} + \epsilon_{ijt}. \tag{2}$$

Here, one would interpret the coefficient on the temperature bins β_k as the effect of exposure to high temperature without the individual characteristic C_i. In contrast, the interaction term β_c coefficients will signify the differential impact of temperatures within a particular bin compared to days with maximum temperature in the (23,28]°C category on those with that characteristic or asset compared to children without the characteristic.

One concern with identification is that high temperatures may affect the performance of the test administrators, who may misreport student performance in these tests. However, this measurement error source is unlikely since data collectors follow rigorous training, visit households in pairs, and are supervised by a field supervisor who validates data entries periodically.

3.5.2 Long-term effects of childhood rainfall and temperature

To examine whether climate shocks in early childhood have long-term effects, we determine whether a child experienced abnormal rainfall or heat in early childhood, from the *in utero* period until age 4. Thus, we use lagged climate shocks to assess the effect of early-life rainfall and heat on current human capital outcomes. A climate shock in each of those years is defined as experiencing a childhood period in a year with average annual rainfall in the left (20^{th}) and right (80^{th} percentile) tails of the parish's long-run rain (calculated over about three decades) and temperature distribution. Following Shah and Steinberg (2017), we denote a positive rain shock as 1 if rainfall is in the 80^{th} percentile and above, as -1 if rainfall is in the 20^{th} percentile, while any other case is coded as 0. Temperature shocks are defined similarly. We denote a heat shock 1 if the average annual temperature is in the 80^{th} percentile and above, as -1 if the temperature is in the 20^{th} percentile, while any other case is coded as 0.

The results of experiencing temperature and rainfall shocks in early childhood are presented separately, given that studies have demonstrated their different impact on outcomes in the African context (Burke *et al.*, 2009).[7] We check if experiencing temperature shocks in each period is correlated with experiencing a rainfall shock and find that, on

[7] Using similar data, in other work, we have examined the impact of exposure to the terrorist group, the Lord's Resistance Army (LRA), on children's learning outcomes in Uganda and found significant adverse effects of exposure to conflict on children's learning outcomes (Olurotimi, 2023). Also, given that (Burke *et al.*, 2009) finds that rising temperature increases the risk of conflict in Africa, one may worry that conflict is an important omitted variable that may bias the results. To assuage this concern, we find less than 0.01 correlation between experiencing temperature shocks from *in utero* until age four and being in a parish that experienced LRA conflict. Second, the results are unchanged when one controls for whether a parish was exposed to LRA conflict.

average, there is a weak negative correlation (−0.3) (see table A10 in the online appendix) between experiencing positive rain shock and high heat in the same year. Also, we do not find statistical evidence that experiencing the same type of shock in a year strongly correlates with experiencing the same shock the following year. The effects of long-term climate shocks are estimated using the following equation:

$$Y_{ijyt} = \beta_l \theta_{jk} + X_{ijyt}\beta + \tau_t + \delta_y + \eta_j + \epsilon_{ijyt}, \tag{3}$$

where Y is an outcome for child i in parish j, born in year y and surveyed in year t, θ_{jk} are rainfall or temperature shocks from *in utero* to age 4 ($k = -1, 0, 1, 2, 3, 4$). All variables remain as defined in equation (1) except for δ_y, which represents birth year fixed effects. Our primary variable of interest, β_l, shows the impact of rainfall shock relative to a typical year, and $2\beta_l$ is the impact of experiencing a rainfall shock relative to a drought year. In the case of temperature shocks, β_l shows the effect of experiencing a heat shock relative to a normal year, and $2\beta_l$ is the impact of experiencing a high heat relative to a cool year. The standard errors are clustered at the parish level. Parish fixed effects account for a parish's average rainfall and unchanging geographic characteristics. In contrast, birth year fixed effects control for average rainfall experienced by all the children born in a specific year in Uganda. Thus, identification relies on within-parish variation in rainfall from the long-run rainfall in each parish. Further, as a robustness check, we estimate a version of the regressions using household fixed effects instead of parish fixed effects. Regarding household fixed effects, identification came from households with children born in different years or birth cohorts.

4. Results

4.1 Short run: the effect of test date temperature on learning outcomes

We present the first results on the effect of high temperatures on learning outcomes in (1) math, (2) English literacy, and (3) local language literacy. In the base regression in table 2, the coefficients on each temperature bin are relative to the lowest temperature bin of (23,28]°C. There is no significant effect of testing on hotter days on children's learning outcomes in math and English literacy relative to testing on a date with a temperature below 28°C. However, when tested in the local language, temperature has a monotonically increasing negative effect on students' local language test scores.

On days with temperatures in the (28,30]°C range, children scored about 0.12 (4 per cent) less in the local language than the mean score of 2.9. Likewise, children scored about 0.16, 0.16, and 0.22 less in the local language when tested on days with temperatures in the (30,32]°C, (32,34]°C, and (34,40]°C range, respectively.

Thus, the result on English literacy is similar to the finding from China (Zhang *et al.*, 2024), where the authors do not find any effect on verbal scores of an older demographic. However, the significant effect on the local language test scores demonstrates that the language in which the test is administered matters. The results are unchanged when the regressions control for heat and rainfall shocks in early childhood, explored in the secondary part of the analysis.

4.1.1 Heterogeneous effect of test date temperature on learning outcomes

Next, the heterogeneous effects of test date temperature produce a more nuanced result. To understand the distributional impacts of heat on children, we examine the heterogeneous impact of test date temperature by child and household characteristics,

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

Table 2. Effect of test date temperature on learning outcomes

Variables	(1) Math	(2) English	(3) Local language
Temperature (28,30]	0.028 (0.027)	0.002 (0.018)	−0.118 (0.057)
Temperature (30,32]	−0.006 (0.035)	−0.023 (0.023)	−0.155 (0.076)
Temperature (32,34]	−0.015 (0.043)	−0.030 (0.029)	−0.162 (0.090)
Temperature (34,40]	−0.039 (0.057)	−0.029 (0.039)	−0.220 (0.120)
Observations	186,288	185,426	40,383
R-squared	0.597	0.641	0.530
Controls	YES	YES	YES
Parish-Year FE	YES	YES	YES
Mean of dependent variable	4.381	2.835	2.857

Notes: Math, English, and Local language are based on tests administered by UWEZO to children at home. All regressions control for the child and household controls, including the child's age, grade, gender, household size, age and gender of household head, mother's education level, possession of household assets, test date rainfall, and humidity, and a vector of rainfall and temperature shocks experienced in childhood. Local language has fewer observations as the tests were only administered in 2012 and 2015, compared to the others for which we have 4 years of observations and only to children who spoke a local language. Standard errors clustered at the parish level are in parentheses.

including gender, age, socioeconomic status, and parental investment in additional learning opportunities.

By gender: Table 3 presents the heterogeneous impact of testing on hotter days for girls. Girls perform significantly worse than boys in all the subjects tested when examined on dates with temperatures higher than 32°C. In addition, the coefficients on the interaction between test date temperature and the female variable are monotonically increasing in the temperature bin for all the subjects. For instance, in comparison to boys, girls score an additional −0.06 (1 per cent) and −0.13 (3 per cent) less in math when they test on days with maximum temperature in the (32,34]°C and (34,40]°C categories, respectively, compared to days with maximum temperature in the (23,28]° C category. As with math, girls also scored additionally worse in English and the local language when tested on days with temperatures above 32° C, although females scored higher in the literacy tests on average.

By age: Table A1 (online appendix) presents heterogeneous effects by age. A younger child is defined as a child younger than ten, while an older child is between the ages of 11 and 16. This differentiation also coincides with primary school and secondary school ages. On average, younger children score less in all subjects. However, the effect of being a young child differs negatively and significantly in all subjects when tested on days with temperatures above 32 °C compared to days with maximum temperature in the (23,28]° C category and in math when tested on any day with a temperature above 30°C. In math, English, and local language literacy, the coefficient on the interaction term of younger children and the temperature bin of (32,34]°C and (34,40]°C is negative and

Table 3. Effect of test date temperature on learning outcomes of girls

Variables	(1) Math	(2) English	(3) Local language
Temperature (28,30]	0.026 (0.029)	−0.006 (0.020)	−0.121 (0.063)
Temperature (30,32]	0.008 (0.036)	−0.015 (0.024)	−0.087 (0.080)
Temperature (32,34]	0.017 (0.044)	0.003 (0.030)	−0.071 (0.094)
Temperature (34,40]	0.027 (0.059)	0.025 (0.041)	−0.109 (0.124)
Temperature (28,30] *Female	0.006 (0.022)	0.019 (0.015)	0.007 (0.044)
Temperature (30,32]*Female	−0.026 (0.022)	−0.015 (0.014)	−0.130 (0.044)
Temperature (32,34]*Female	−0.063 (0.022)	−0.066 (0.015)	−0.176 (0.046)
Temperature (34,40]*Female	−0.130 (0.026)	−0.106 (0.017)	−0.217 (0.054)
Female	−0.012 (0.016)	0.025 (0.011)	0.092 (0.036)
Observations	186,288	185,426	40,383
R-squared	0.597	0.641	0.530
Controls	YES	YES	YES
Parish-Year FE	YES	YES	YES
Mean of dependent variable	4.381	2.835	2.857

Notes: Math, English, and local language are based on tests administered by UWEZO to children at home. Standard errors are clustered at the parish level.

monotonically increasing in temperature, suggesting that younger children are less able to perform cognitive tasks better under thermal stress.

By socioeconomic status: Additionally, we examine the heterogeneity in the effect of test scores by stratifying the children into those from high and low socioeconomic backgrounds. To determine socioeconomic status, we calculate an aggregate asset index by summing household possession of assets, including television, phone, bicycle, motorcycle, and radio, and then classify a household as having high socioeconomic status (SES) if they have an above-average value of the household index.[8] The estimates in table A2 (online appendix) show that although high SES students tend to score higher in math and English on average, compared to children from low SES households, being a high SES child reduces test scores in math and English when tested on the hottest days, i.e., days with temperatures above 34°C compared to days with maximum temperature in the (23,28]°C category. For instance, students from high SES households score about 0.05 (2

[8]These households are not high SES households in an absolute sense, but only relative to other households in the data. For instance, only 20 per cent of these households have electricity compared to 11 per cent in the data.

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

per cent) less in English when tested on days with temperatures above 34°C compared to days with maximum temperature in the (23,28]°C category.

Does extra learning make children resistant to temperature shocks: Like parents elsewhere who are eager to provide the best opportunities for their children to thrive academically and economically in the future, some parents in Uganda pay for additional learning beyond the regular schooling that happens in schools. We check whether participating in these extra lessons, called tuition, provides accumulated cognitive advantages that reduce the impact of temperature shocks. The results, as presented in table A3 in the online appendix, show that in addition to the fact that children who participate in extra learning score better in math and English when tested on average, students who undergo extra instruction score an additional 0.1 and 0.2 points better in math and local language when tested on days with temperatures above 34°C compared to days with maximum temperature in the (23,28]°C category. The choice to participate in tuition is selective and positively associated with household SES and parents' educational level. Still, after controlling for these variables and finding a negative heterogeneous impact by high SES, this result suggests that extra learning may provide a cognitive buffer in the face of temperature shocks.

Overall, these heterogeneous effects show that exposure to heat affects cognition in most children, especially girls and younger children, irrespective of SES.

4.1.2 Robustness check on the effect of test date temperature

As a robustness check, we check whether the effect of heat is affected by weather conditions the week after a child takes the test (see table A4 in the online appendix). Although next week's temperature positively correlates with today's temperature (correlation coefficient of 0.7), this check reveals that next week's temperature does not affect the learning outcomes, on average. The results are also robust to including months of survey fixed effects to address concerns that differences in learning outcomes are related to how far along in a school year children are tested. Additionally, we look at the impact of average daily temperature rather than the maximum daily temperature. As presented in table A5 (online appendix), we still see a significant negative effect of testing on a day above 32°C on local language test results. However, one now sees a negative impact of testing with temperature between (28,30]°C on math test scores.

4.2 The effect of early life rainfall shocks on human capital

Table 4 presents the results of estimating the effect of early life rainfall shocks from in-utero up to age four on a broader set of human capital measures, including (1) math, (2) English literacy, (3) local language literacy, and (4) the likelihood of being at the right age for a grade, i.e., on track. Following (Shah and Steinberg, 2017), we define a parish as having a rain shock in a given year if the annual rainfall exceeds the 80^{th} percentile of long-run rainfall. In contrast, a drought year is defined as having yearly rainfall in the 20^{th} percentile of the long-run parish rainfall. These regressions control for the vector of temperature shocks and test date weather variables. The results show that experiencing a rainfall shock at birth leads to significant scoring about 1 per cent less in math (−0.08), English (−0.08), and local language (−0.20) compared to drought years. One also sees similar negative and significant coefficients with some variation in the subjects for those who experience a rain shock in the year they are *in utero*, at ages 2, 3, and 4. Also, there

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

Table 4. The effect of childhood rainfall shocks on human capital

Variables	(1) Math	(2) English	(3) Local language	(4) Ontrack
Rainshock *in utero*	−0.027 (0.011)	−0.020 (0.015)	−0.088 (0.034)	0.004 (0.004)
Rainshock in birth year	−0.040 (0.012)	−0.041 (0.012)	−0.100 (0.026)	0.004 (0.004)
Rainshock at age 1	−0.051 (0.012)	−0.047 (0.014)	−0.098 (0.032)	−0.006 (0.004)
Rainshock at age 2	−0.063 (0.012)	−0.047 (0.011)	−0.073 (0.047)	−0.006 (0.004)
Rainshock at age 3	−0.053 (0.011)	−0.044 (0.014)	−0.053 (0.043)	−0.010 (0.004)
Rainshock at age 4	−0.040 (0.011)	−0.040 (0.015)	0.049 (0.043)	−0.006 (0.003)
Observations	186,299	184,029	39,844	186,299
R-squared	0.582	0.629	0.527	0.666
Controls	YES	YES	YES	YES
Parish FE	YES	YES	YES	YES
Birth year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Mean of dependent variable	4.381	2.837	2.858	0.396

Notes: Ontrack is a dummy variable coded if a child is at the right age for a grade, i.e., the difference between a child's age and grade is no more than six years. All regressions control for the child and household controls, including the child's age, grade, gender, household size, gender of household head, mother's age and education level, father's age and possession of household assets, and test date weather variables, including rainfall and humidity. Standard errors clustered at the parish level are in parentheses.

is a statistically significant decrease in the probability of being on track in school when you experience a rain shock at ages 3 and 4.

4.2.1 Robustness checks on the effect of rainfall shocks

The findings on the effect of rain shocks are robust to other regression specifications, such as replacing the parish fixed effects with household fixed effects, as seen in table A6 (online appendix). The table shows that rain shocks *in utero* until age four still lead to statistically negative impacts on math and English scores. However, in the version with household fixed effects, one now observes that a rain shock *in utero* and at birth increases the likelihood of being on track, i.e., in the right age for a grade, by 1 and 1.2 percentage points, respectively, compared to a drought year. Also, to address concerns about spatial correlation, we conduct a version of the regression that clusters at a higher geographic level, i.e., at the sub-county, and find that the results are unchanged from the base results on the effect of rainfall shocks presented in table 4.

In a different set of regressions, we use a different source of data and a higher geospatial level, i.e., district-level average rainfall obtained from the World Bank Climate Knowledge Portal (World Bank Group, 2023) to calculate rainfall and heat shocks as before, i.e., defining a rain shock depending on the percentiles of the within-district distribution. The district is the second administrative level, while the parish is the fourth

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

administrative level in Uganda. As with the parish level data, we define a child within a district as having a rain shock in a given year if the annual district rainfall exceeds the 80^{th} percentile of long-run rainfall. In contrast, a drought year is defined as having yearly rainfall in the 20^{th} percentile of the district's long-run rainfall. Using this measure leads to bigger coefficients (see online appendix table A7); for instance, the coefficient of experiencing a positive rain shock *in utero* almost doubles the base result on math (−0.08 compared to −0.15). Nonetheless, these results also confirm that experiencing rain above the 80^{th} percentile from *in utero* until age 4 reduces learning outcomes in math, English, and the local language in Uganda.

4.2.2 Additional analysis using different threshold of positive rain shock

Hitherto, we have defined a positive rain shock as rainfall above 80^{th} percentile and found negative results on learning outcomes in math and English, which is contrary to the finding from India that children score 0.012–0.04 points higher on math or reading tests for each year of favorable rainfall compared to drought years (Shah and Steinberg, 2017). This difference may likely be related to differences in country climactic contexts, as a rainfall shock above the 80^{th} percentile may be too much rain (say flooding) in Uganda.[9] Alternatively, we recode a rain shock as one (1) if rain is above the 50^{th} but beneath the 80^{th} percentile of the long-run rainfall while still representing a drought year as rain below the 20^{th} percentile. The results are shown in table 5. In that regression with rain shock defined as rain above the 50^{th} percentile, one now sees a 0.08 (1.2 per cent) increase in math scores for children who experienced a rainfall shock from birth until age 3. In the case of English, one sees a positive effect of rain shocks from *in utero* up to age 4. Also, exposure to a positive rainfall shock *in utero*, at birth, and at ages 1 and 2 is now associated with at least a one percentage point increase in the probability of being on track in school compared to those who did not. These results show that positive effects of rain shocks are observed when a rain shock is defined at the 50^{th} percentile versus at the 80^{th} percentile, as has been done in the literature, highlighting that the thresholds of climate shocks may be different across various country contexts.

4.3 The effect of early life heat on human capital

We define a parish as having a heat shock in a given year if the annual temperature is above the 80^{th} percentile of the long-run temperature in the parish. In contrast, a cool year is defined as having a yearly temperature in the 20^{th} percentile of the long-run temperature. These regressions also control for exposure to rain shocks, as defined previously.

Table 6 reports the results of estimating the effect of early-life heat shocks from *in utero* up to age 4. Compared to those who experience cooler years, children who experience hotter years *in utero* and at birth have better learning outcomes in math. At age 1, experiencing a heat shock is associated with having higher test scores in the local language and a 0.8 percentage point reduction in the probability that a child is at the right age for a grade, significant only at the 90 per cent level. However, after age 1, we see consistently adverse effects of heat shocks on math and English. For instance, children who experience a heat shock *in utero* and at birth score about 0.04 more in math, but those

[9] According to data from the EM-DAT, Uganda has experienced 15 floods and five droughts over the period (1997–2008) during which up to 90 per cent of the children in this data were born.

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

Table 5. The effect of childhood rainfall shocks on human capital with alternative threshold

Variables	(1) Math	(2) English	(3) Local language	(4) Ontrack
Rainshock *in utero*	0.038 (0.009)	0.027 (0.006)	0.043 (0.017)	0.004 (0.002)
Rainshock in birth year	0.044 (0.010)	0.037 (0.006)	0.029 (0.017)	0.007 (0.002)
Rainshock at age 1	0.043 (0.010)	0.034 (0.007)	0.032 (0.019)	0.005 (0.002)
Rainshock at age 2	0.027 (0.010)	0.023 (0.006)	−0.027 (0.017)	0.008 (0.002)
Rainshock at age 3	0.030 (0.009)	0.014 (0.006)	−0.050 (0.017)	0.001 (0.002)
Rainshock at age 4	0.012 (0.009)	0.011 (0.006)	−0.027 (0.016)	−0.001 (0.002)
Observations	186,299	184,029	39,844	186,299
R-squared	0.582	0.629	0.527	0.666
Controls	YES	YES	YES	YES
Parish FE	YES	YES	YES	YES
Birth year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Mean of dependent variable	4.381	2.837	2.858	0.396

Notes: Math, English, and local language are based on tests administered by UWEZO to children at home. Rainfall shock is coded 1 if annual parish rainfall exceeds the 50^{th} percentile of long-run parish rainfall. Standard errors are clustered at the parish level.

who experience a heat shock at ages 2 and 3 score (−0.04) less. Unlike the results on rainfall shocks, the direction of the effect of heat shocks tends to vary by age at exposure.

4.3.1 Robustness checks on the effect of heat shocks

The results on the effect of heat shocks are generally robust to utilizing household fixed effects instead of parish fixed effects, as seen in table A8 (online appendix). Household fixed effects address unobservables at the family level that could drive the observed results. Reassuringly, when the regressions are estimated with household fixed effects instead of parish fixed effects, one no longer sees any divergence in the sign of the coefficient by subjects. In sum, experiencing a heat shock from age one until age three has a negative and economically significant impact on math and English scores. Also, to address concerns about spatial correlation, we conduct a version of the regression that clusters at a higher geographic level, i.e., at the sub-county, and find that the results are unchanged from the base results on the effect of temperature shocks presented in table 6. Additionally, when the results are estimated using district-level long-term temperature (see table A9, online appendix), one no longer sees any positive effect of childhood heat shocks experienced *in utero* on learning outcomes or the probability of being on track. Together, these results on the impact of heat shocks discussed thus far suggest that heat shocks harm children's learning outcomes in early childhood, especially after a child is born.

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

Table 6. The effect of childhood temperature shocks on human capital

Variables	(1) Math	(2) English	(3) Local language	(4) Ontrack
Heat shock *in utero*	0.021 (0.011)	−0.001 (0.007)	−0.050 (0.021)	−0.000 (0.002)
Heat shock in birth year	0.019 (0.011)	−0.002 (0.007)	−0.007 (0.022)	−0.004 (0.002)
Heat shock at age 1	−0.013 (0.012)	−0.014 (0.008)	0.037 (0.022)	−0.005 (0.002)
Heat shock at age 2	−0.026 (0.012)	−0.032 (0.007)	−0.001 (0.022)	0.003 (0.003)
Heat shock at age 3	−0.026 (0.012)	−0.037 (0.007)	0.013 (0.020)	−0.001 (0.002)
Heat shock at age 4	0.003 (0.011)	0.002 (0.007)	0.026 (0.018)	−0.002 (0.002)
Observations	186,299	184,029	39,844	186,299
R-squared	0.582	0.629	0.527	0.666
Controls	YES	YES	YES	YES
Parish FE	YES	YES	YES	YES
Birth year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Mean of dependent variable	4.381	2.837	2.858	0.396

Notes: Ontrack is a dummy variable coded if a child is at the right age for a grade, i.e., the difference between a child's age and grade is no more than six years. All regressions control for the child and household controls, including the child's age, grade, gender, household size, age and gender of household head, mother's education level, possession of household assets, and test date weather variables, including rainfall and humidity. Standard errors clustered at the parish level are in parentheses.

5. Conclusion

This study examines the effect of test date temperature and long-run climate shocks on measures of children's human capital in Uganda. Compared to an omitted category of (23,28]°C, taking the test on hotter days significantly reduces learning outcomes in local language literacy. Also, this effect increases monotonically as the temperature rises. Additionally, heterogeneous analysis shows that girls and younger children perform worse in math, English, and local language when tested on days with temperatures above 32°C. We also find that children in households with high SES performed worse on days with temperatures above 34°C. This finding highlights that thermal sensations may differ even when children experience the same thermal stress.

Overall, these results inform the need for adaptive testing environments for particular demographics, such as girls and children younger than ten. In addition, this paper provides evidence that high SES alone does not provide a cognitive buffer. On the other hand, extra learning before a heat shock may provide a cognitive buffer; however, experimental research is needed to ascertain if this is the case under various testing and temperature conditions.

In measuring long-run temperature and rainfall shocks, we utilize within-parish variation by denoting a parish as experiencing a shock if the temperature or rainfall is within

https://doi.org/10.1017/S1355770X25000105 Published online by Cambridge University Press

the 80^{th} percentile(positive shock) or 20^{th} percentile(negative shock) of the parish's long-run annual temperature and precipitation. The analysis shows that heat shocks *in utero* and at birth affect learning outcomes positively, while heat shocks experienced above age 1 harm learning outcomes. Second, the estimates show that experiencing rainfall above the 80^{th} percentile from *in utero* to age 4 leads to worse learning outcomes than those for children who do not experience a positive rain shock, which differs from results in other country contexts, like in India, for instance, where rainfall shocks similarly defined increase test scores (Shah and Steinberg, 2017). On the contrary, when one defines a positive rain shock as experiencing rainfall above the 50^{th} percentile, one observes the positive impact of rainfall on learning outcomes and the probability of a child being in the right age for their grade.

This paper indicates that early childhood climate shocks impact cognition in low-income countries. Also, the result suggests that the thresholds for defining climate shocks differ across country contexts. This necessitates further research into how varying thresholds affect other outcomes and how stakeholders such as insurers and policy-makers define climate shocks ex-ante in low-income settings, especially those in the tropics.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1355770X25000105

Acknowledgements. I thank Jeremy Foltz, Paul Dower, Priya Mukherjee, Andrew Stevens, Bridget Hoffman, and Nancy Kendall for helpful feedback. I am also grateful to seminar participants at the Eastern Economic Association and Arizona Workshop on Environment, Natural Resource, and Energy Economics and the referees for their comments. All errors are mine.

Competing interest. The author declares none.

References

ACER (2014) Uwezo: monitoring children's competencies in East Africa. ACER Assessment Gems series No. 7.

Almond D, Currie J and Duque V (2018) Childhood circumstances and adult outcomes: Act II. *Journal of Economic Literature* **56**, 1360–1446.

Bennett CM and Friel S (2014) Impacts of climate change on inequities in child health. *Children* **1**, 461–473.

Boivin MJ (2002) Effects of early cerebral malaria on cognitive ability in Senegalese children. *Journal of Developmental & Behavioral Pediatrics* **23**, 353–364.

Burke MB, Miguel E, Satyanath S and Lobell DB (2009) Warming increases the risk of civil war in Africa. *Proceedings of the National Academy of Sciences* **106**, 20670–20674.

Carleton T, Jina A, Delgado M, Greenstone M, Houser T, Hsiang S, Hultgren A, Kopp RE, McCusker KE, Nath I, Rising J, Rode A, Seo HK, Viaene A, Yuan J and Zhang AT (2022) Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics* **137**, 2037–2105.

Carter JA, Mung'ala-Odera V, Neville BGR, Murira G, Mturi N, Musumba C and Newton CRJC (2005) Persistent neurocognitive impairments associated with severe falciparum malaria in Kenyan children. *Journal of Neurology, Neurosurgery Psychiatry* **76**, 476–481.

Chang TY and Kajackaite A (2019) Battle for the thermostat: gender and the effect of temperature on cognitive performance. *PLOS One* **14**, e0216362.

Cho H (2017) The effects of summer heat on academic achievement: a cohort analysis. *Journal of Environmental Economics and Management* **83**, 185–196.

Cornwell K and Inder B (2015) Child health and rainfall in early life. *The Journal of Development Studies* **51**, 865–880.

Covay E and Carbonaro W (2010) After the bell: participation in extracurricular activities, classroom behavior, and academic achievement. *Sociology of Education* **83**, 20–45.

Fonjong L, Matose F and Sonnenfeld DA (2024) Climate change in Africa: impacts, adaptation, and policy responses. *Global Environmental Change* **89**, 102912.

Garg T, Jagnani M and Taraz V (2020) Temperature and human capital in India. *Journal of the Association of Environmental and Resource Economists* **7**, 1113–1150.

Graff Zivin J, Hsiang SM and Neidell M (2018) Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists* **5**, 77–105.

Graff Zivin J, Song Y, Tang Q and Zhang P (2020) Temperature and high-stakes cognitive performance: evidence from the national college entrance examination in China. *Journal of Environmental Economics and Management* **104**, 102365.

Hanushek EA (2016) Will more higher education improve economic growth? *Oxford Review of Economic Policy* **32**, 538–552.

Hashizume M, Armstrong B, Hajat S, Wagatsuma Y, Faruque AS, Hayashi T and Sack DA (2007) Association between climate variability and hospital visits for non-cholera diarrhoea in Bangladesh: effects and vulnerable groups. *International Journal of Epidemiology* **36**, 1030–1037.

Heaslip GP, Davis H and Barber BL (2021) Extracurricular activity participation in early adolescence predicts coping efficacy one year later. *Australian Journal of Psychology* **73**, 306–315.

Heissel JA, Adam EK, Levy DJ, Kemeny M, Shalowitz MU, Quinn KA and Chen E (2020) Testing, stress, and performance: how students respond physiologically to high-stakes testing. *Education Finance and Policy* **16**, 183–208.

Intergovernmental Panel on Climate Change (IPCC) (2021) Summary for policymakers. In Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M, Leitzell K, Lonnoy E, Matthews JBR, Maycock TK, Waterfield T, Yelekçi O, Yu R and Zhou B (eds), *Climate change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, pp. 3–32.

Isen A, Rossin-Slater M and Walker R (2017) Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Sciences* **114**, 13447–13452.

Kien L and My N (2021) In-utero exposure to rainfall variability and early childhood health. *World Development* **144**, 105485.

Knauer HA, Kariger P, Jakiela P, Ozier O and Fernald LC (2019) Multilingual assessment of early child development: analyses from repeated observations of children in Kenya. *Developmental Science* **22**, e12875.

Lan L, Tang J, Wargocki P, Wyon DP and Lian Z (2022) Cognitive performance was reduced by higher air temperature even when thermal comfort was maintained over the 24–28° C range. *Indoor Air* **32**, e12916.

Le K and Nguyen M (2023) Early-life rainfall and long-term human capital accumulation of African women. *Economic Development and Cultural Change* **72**, 361–387.

Li X and Patel PC (2021) Weather and high-stakes exam performance: evidence from student-level administrative data in Brazil. *Economics Letters* **199**, 109698.

López-Sánchez JI and Hancock PA (2018) Thermal effects on cognition: a new quantitative synthesis. *International Journal of Hyperthermia* **34**, 423–431.

Lucas RE (1988) On the mechanics of economic development. *Journal of Monetary Economics* **22**, 3–42.

Maccini S and Yang D (2009) Under the weather: health, schooling, and economic consequences of early-life rainfall. *American Economic Review* **99**, 1006–10026.

Matyas CJ and Silva JA (2013) Extreme weather and economic well-being in rural Mozambique. *Natural Hazards* **66**, 31–49.

Nübler L, Austrian K, Maluccio JA and Pinchoff J (2021) Rainfall shocks, cognitive development and educational attainment among adolescents in a drought-prone region in Kenya. *Environment and Development Economics* **26**, 466–487.

Olurotimi O (2023) The effect of conflict on children's learning outcomes: evidence from Uganda [Manuscript submitted for publication].

Ortiz-Bobea A (2021) Climate, agriculture and food. Papers No. 2105.12044, arXiv.org.

Park RJ (2020) Hot temperature and high stakes performance. *Journal of Human Resources* **57**, 400–434.

Park RJ, Goodman J, Hurwitz M and Smith J (2020) Heat and learning. *American Economic Journal: Economic Policy* **12**, 306–39.

Pradhan EK, West KPJ, Katz J, LeClerq SC, Khatry SK and Shrestha SR (2007) Risk of flood-related mortality in Nepal. *Disasters* **31**, 57–70.

Randell H and Gray C (2019) Climate change and educational attainment in the global tropics. *Proceedings of the National Academy of Sciences* **116**, 8840–8845.

Roach T and Whitney J (2022) Heat and learning in elementary and middle school. *Education Economics* **30**, 29–46.

Rosales-Rueda M (2018) The impact of early life shocks on human capital formation: evidence from El Niño floods in Ecuador. *Journal of Health Economics* **62**, 13–44.

Schlenker W and Lobell DB (2010) Robustness of climate impact estimates. *Environmental Research Letters* **5**, 014010.

Shah M and Steinberg BM (2017) Drought of opportunities: contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy* **125**, 527–561.

World Bank Group (2023) Climate Change Knowledge Portal. Available at https://climate.copernicus.eu/ESOTC/2023.

Yablonskiy DA, Ackerman JJ and Raichle ME (2000) Coupling between changes in human brain temperature and oxidative metabolism during prolonged visual stimulation. *Proceedings of the National Academy of Sciences of the United States of America* **97**, 7603–7608.

Zarghami E, Yazdanfar SA, Hosseini Yekta N and Dadras F (2022) Effect of environmental temperature on working memory in military personnel. *Journal of Archives in Military Medicine* **10**, e128528.

Zhang X, Chen X and Zhang X (2024) Temperature and low-stakes cognitive performance. *Journal of the Association of Environmental and Resource Economists* **11**, 75–96.

Cite this article: Olurotimi O (2025). Climate shocks and human capital:evidence from Uganda. *Environment and Development Economics* 1–21. https://doi.org/10.1017/S1355770X25000105