

H HEURISTICS

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The Climate–Pollution– Education Trap

Heat, School Disruption, Child Labor, Poverty, and
Long-Run Human Capital in an Age of Polycrisis

Heat · Pollution · School disruption · Child labor · Poverty · Human capital

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H Heuristics · Research Report

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About This Report

This report examines a connected set of harms that rarely appear together in the literature: how extreme heat, polluted air and climate-driven disasters disrupt children’s schooling, how the same shocks push poor households to withdraw children from school or send them to work, and how the resulting loss of learning accumulates into lower human capital for a generation and, through it, a thinner capacity to withstand the next shock. It calls the system the **Climate–Pollution–Education Trap** and treats it as one expression of the [polycrisis](#), the interaction of several crises so that the whole is more damaging than the parts. It follows earlier H Heuristics studies of [cascading risk](#), [the heat trap](#), [human suffering](#) and [the geography of exposure](#) by following one cascade into the life of a child.

The report asks five questions. How many children are exposed to heat, polluted air and disaster, and where? How does each hazard reduce learning, attendance and years of schooling? What happens inside the household when a shock arrives, and how does child labor respond? How large is the long-run cost, and how does it pass between generations? And which interventions would protect schooling most, at what scale? It is written for researchers, policymakers, education and climate practitioners, funders and general readers, and assumes no technical background.

How to read this report

Each section starts on a new page and can be read on its own. The report has four parts (Figure 1). Sections 1 to 3 frame the problem, review the evidence and establish the exposure baseline. Sections 4 to 8 examine the five channels in turn: heat, air and lead, school disruption, poverty and the household decision, and child labor. Sections 9 to 12 trace the consequences and the system: long-run human capital, feedback loops, geography and an original cohort model. Sections 13 to 15 set out the policy portfolio, the measurement and financing agenda, and the conclusions. Appendices give the model specification and data notes.

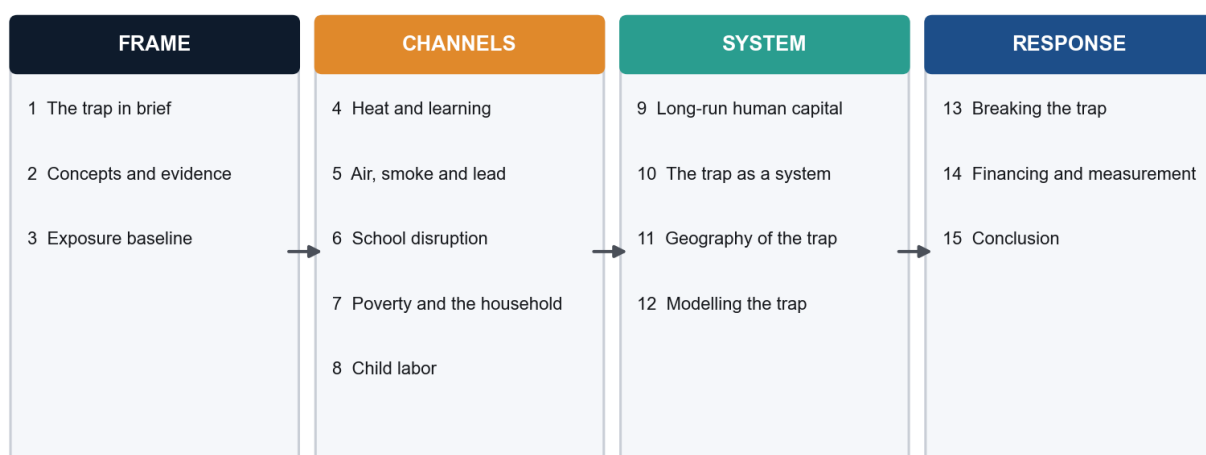


Figure 1. The structure of the report. Three framing sections, five channel sections, four sections on consequences, system and geography, and three on response.

Source: H Heuristics.

Blue underlined text is a hyperlink. Where a specific scientific result is cited, the link goes to the DOI record of the peer-reviewed source, and every DOI was checked against its registered title before publication. Where a statistic comes from an international agency, the link goes to the agency’s report or data page. News sources are linked for 2024 to 2026 events that no peer-reviewed analysis yet covers. The full list of DOI-cited sources is in the References.

Evidence grades

Claims are graded on the four-level scale used across H Heuristics reports. The grade describes the state of knowledge, not the importance of the claim.

Table 1. Evidence grades used in this report

Grade	Meaning	Example from this report
A: Established	Confirmed by multiple independent lines of evidence and assessed as such by major scientific bodies.	Heat lowers learning in classrooms without cooling; lead impairs cognition; years of schooling raise earnings
B: Well supported	Strong evidence from several lines of work, with unresolved detail or some dissent.	Air pollution lowers attention and raises absence; transfers keep children in school; early-life heat lowers later attainment
C: Plausible or contested	A credible argument and partial evidence; specialists disagree about size or mechanism.	Heat raises child labor in low-income countries; disasters displace education budgets
D: Speculative	A scenario or hypothesis offered for evaluation, labelled as such wherever it appears.	The coupling scores; the size of the intergenerational ratchet; the lead risk from battery-based school electrification

A single topic can carry several grades. That heat lowers learning is graded A; that it traps children in poverty is graded B/C; that it does so at a particular rate in a particular country is graded D until measured.

A note on the figures and calculations

The report contains 20 figures and 16 tables. Nine figures chart published data or original analysis of it: global temperature and the child population, the scale of exposure, air pollution and income, power and cooking access, learning-adjusted schooling against heat and air pollution, school disruption, child-labor composition, child employment against agrarian dependence and poverty, and the Trap Exposure Index. The analysis uses World Bank indicators, ERA5 temperature from Copernicus via [Our World in Data](#), and the [UN World Population Prospects 2024](#). Six figures present original calculations: the heat dose-response, the cohort model of schooling under compounding shocks, the threshold map, the intergenerational ratchet, the sensitivity analysis and the intervention comparison. The remaining five are diagrams, including the coupling matrix. The calculations are illustrative: they show how mechanisms behave, not what will happen. Each caption states what was computed, and Appendix A gives the specification.

How to cite

Hughes, H. (2026). *The Climate–Pollution–Education Trap: Heat, School Disruption, Child Labor, Poverty, and Long-Run Human Capital in an Age of Polycrisis*. H Heuristics Research Report, October 2026. The report synthesizes published research and presents original calculations and propositions, which are labelled as such.

Executive Summary

Abstract

Climate change and air pollution are usually discussed as threats to health, food and infrastructure. This report argues that one of their most durable effects is on children’s education, and that the effect is a trap: a self-reinforcing system in which hot classrooms, polluted air, school closures and household income shocks combine to reduce what children learn and how long they stay in school, and in which the resulting loss of human capital leaves the next generation more exposed. The argument is developed in four steps. The report reviews the causal evidence on each channel and grades it. It measures exposure with published estimates and an original country panel. It builds a cohort model of 60,000 to 100,000 households per scenario to show how the mechanisms interact. And it compares four interventions and sets out a policy, measurement and financing agenda. The conclusion is that the trap is real, concentrated and breakable, and that its breaking point is the household’s ability to absorb a shock without removing a child from school.

Key findings

- 1. Exposure is vast and concentrated.** About 2,001 million children are under 15, and 64 percent live in low- and lower-middle-income countries. UNICEF estimates that 242 million students had schooling disrupted by climate hazards in 2024, 171 million of them by heat, and that about 1.1 billion children face three or more overlapping climate hazards ([UNICEF](#); [UNICEF 2026](#)).
- 2. Heat and pollution lower learning directly.** A 1 °F hotter school year lowers learning by 1 percent where classrooms are uncooled ([Park et al., 2020](#)); air pollution on exam days lowers scores and later earnings ([Ebenstein et al., 2016](#)); and about 800 million children have blood lead at or above 5 µg/dL ([UNICEF and Pure Earth](#)). Evidence on the effects in low-income schools, where exposure is highest, is thin.
- 3. The household decision is the pivot.** Hazards that cut income push children out of school where buffers are thin. Workfare in India substantially weakened the link between heat and test scores ([Garg et al., 2020](#)), and a small cash transfer in Ecuador cut paid child work by 78 percent among compliers ([Edmonds and Schady, 2012](#)). The sign of the child-labor response depends on the shock and on credit, and the heat-specific link is the weakest part of the chain.
- 4. The loss is nonlinear and persistent.** In the cohort model, the share of children below a minimal threshold of effective schooling rises from 6 percent today to 18 percent with 1.0 °C of additional warming and 30 percent with 2.0 °C, and reaches 38 percent after five generations at +2.0 °C. Lifetime income for the cohort falls by up to 14 percent.
- 5. The overlap is greatest in a belt from the Sahel to Central Africa.** On a Trap Exposure Index of 150 countries, 18 of the top 20 are in Sub-Saharan Africa and the top 30 hold about 443 million children. The largest absolute numbers of exposed children are in Nigeria and South Asia.
- 6. Household protection is the most powerful lever, and mitigation the most powerful of all.** At +1.0 °C, adaptive cash transfers cut the long-run share trapped from 19 to 7 percent; cooling schools, cleaning the air and protecting continuity each add less alone but improve every child’s learning; and holding warming to +1.0 instead of +2.0 °C halves the long-run share trapped.

Table 2. The report's original findings at a glance

Analysis	Result	Section
Learning-adjusted schooling against heat and PM2.5	Spearman $\rho = -0.58$ (heat) and -0.54 (PM2.5); partial $r = -0.45$ and -0.39 after income	3
Air pollution by income group	Population-weighted PM2.5 of $50 \mu\text{g}/\text{m}^3$ in lower-middle-income and 13 in high-income countries; WHO guideline 5	3
Heat dose-response	At $+2.0^\circ\text{C}$, about 4.3% of a year's learning lost; about 93 learning-days over 12 grades	4
Child employment	$r = 0.65$ with agricultural employment; temperature association falls to 0.14 after controls	8
Trap Exposure Index	Top 30 countries hold about 443 million children (22% of the world's)	11
Cohort model: share trapped	$6\% \rightarrow 9\% \rightarrow 18\% \rightarrow 30\%$ at $+0, +0.5, +1.0, +2.0^\circ\text{C}$	12
Intergenerational ratchet	30% in the first cohort and 38% after five generations at $+2.0^\circ\text{C}$	12
Policy comparison at $+1.0^\circ\text{C}$	Transfers: $19\% \rightarrow 7\%$; all four measures: 6%; benefit-cost about 4 to 1 on income alone	13

All original calculations are illustrative; assumptions are in Section 12 and Appendix A.

What to do

1. Make social protection shock-responsive, with payments triggered by heat, rainfall and disaster declarations, starting in the highest-exposure countries.
2. Make classrooms safe to learn in: heat and air-quality protocols, passive cooling, and solar-powered cooling and ventilation, with attention to battery lead.
3. Plan and fund continuity: automatic catch-up after disasters, flexible calendars and a public record of every climate closure.
4. Limit warming and local air pollution at source, because every other measure works against a hazard that is still growing.
5. Build the evidence: a Trap Watch indicator set, and studies of heat and child labor, joint heat and smoke effects and trigger-based transfers in low-income settings.

In one sentence. The harm that heat, smoke and disaster do to a child's schooling is mostly decided in the household, and it can be prevented there. A cohort that learns less carries the loss for a lifetime and hands part of it on, which is why the next hot season is a question about the next generation's future.

01

INTRODUCTION

1. The Trap in Brief

1.1 A school year in a hotter world

In April 2024, heatwaves closed or curtailed schools across South Asia and South-East Asia on a scale rarely documented before. [UNICEF's *Learning Interrupted* snapshot](#) counts at least 242 million students whose schooling was disrupted by climate hazards during 2024, about 171 million of them by heatwaves, and about 118 million by heat in April alone. Three-quarters of the affected students lived in low- and lower-middle-income countries. UNICEF calls its own total conservative, because most countries do not record why a school closed.

The pattern has continued. In April 2026 a severe heatwave led several Indian states to [change school timings, close schools and advance summer holidays](#). In June 2026 a red extreme-heat warning led at least 1,730 schools in England and Wales to close or finish early, and [DeSmog's analysis](#) of the episode estimates that pupils lost more than 15 million teaching hours. These are news-based estimates and should be read as indicative, but they show that the problem is no longer confined to poor countries. What separates the cases is what happens next. A pupil in a wealthy country loses a few days of instruction and returns to a household that can absorb the cost. A pupil in a poor agrarian household may lose far more, because the same heat, dust, flood or drought also strikes the household's harvest, wages and health, and the child becomes one of the household's few adjustable resources.

This report is about that second case. It argues that heat, polluted air and climate-driven disasters do not harm education through one pathway but through several that reinforce each other, and that the people who bear them are the children with the thinnest buffers. We call the result the **Climate–Pollution–Education Trap**.

1.2 What the trap is

A *trap*, in the economics of development, is a self-reinforcing process: a state that persists because the forces that created it are strengthened by its consequences, so that escape requires more than the removal of the original cause ([Carter and Barrett, 2006](#); [Barrett and Carter, 2013](#)). The trap examined here has five linked components.

- 1. Direct learning loss.** Hot classrooms, polluted air and lead exposure reduce what a child learns on the days she is in school (Sections 4 and 5).
- 2. Disrupted schooling.** Heatwaves, floods, storms and smoke close schools, damage buildings and raise absence through illness (Section 6).
- 3. Household shocks.** The same hazards cut crop yields, farm wages and adult health, so family income falls at the moment school costs and food prices rise (Section 7).

4. **Child withdrawal and labor.** Households with no buffer respond by taking children out of school, sending them to work or marrying daughters earlier (Section 8).
5. **Lasting human-capital loss.** Fewer and weaker years of learning lower lifetime earnings and adaptive capacity, which makes the next generation more exposed to the next shock (Sections 9 and 10).

Figure 2 shows how the pieces fit. The diagram has two features worth noting at the outset. First, the household decision is the pivot: the same hazard produces very different educational outcomes depending on whether a family can smooth the shock with savings, credit, transfers or insurance. Second, the arrow that leads back from long-run outcomes to vulnerability is what turns a series of harms into a trap. Without it, each cohort would suffer a loss and the loss would end with the cohort.

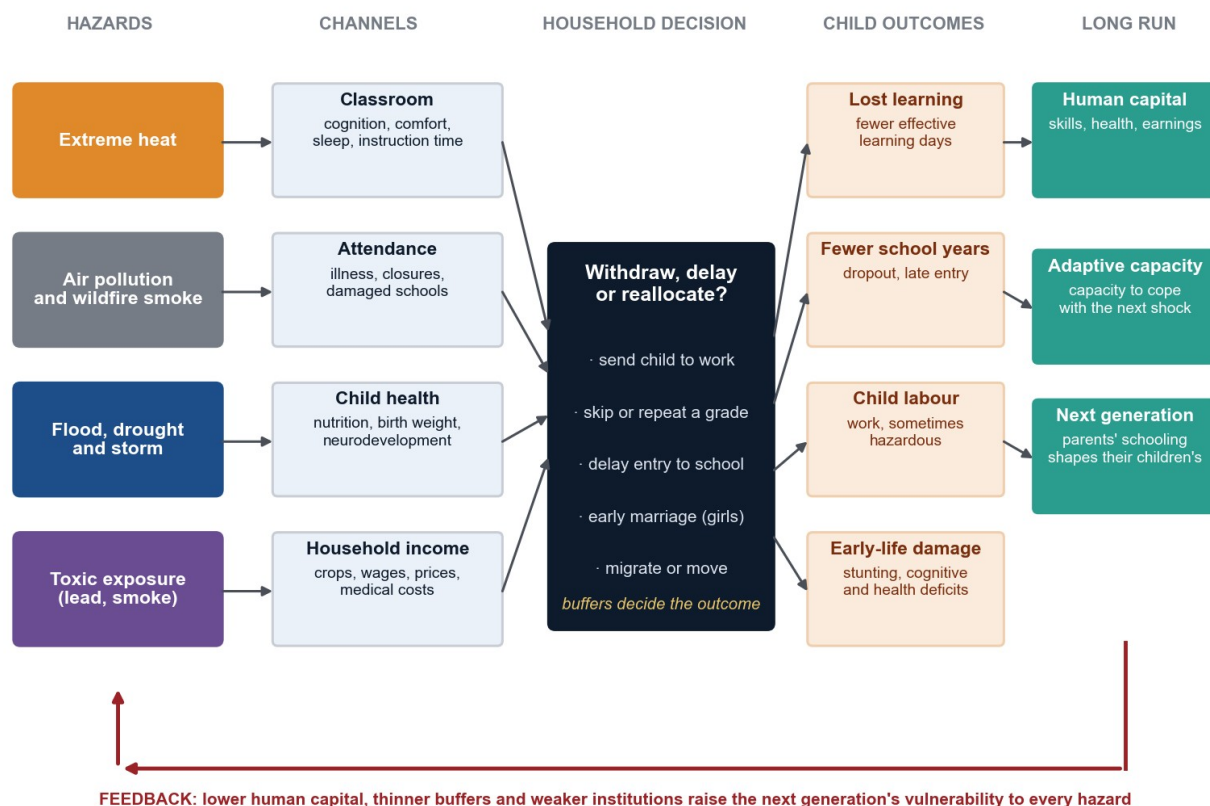


Figure 2. Architecture of the Climate–Pollution–Education Trap. Four families of hazard act through four channels on a household decision about each child; the decision produces child-level outcomes that accumulate into long-run human capital, adaptive capacity and the next generation's starting conditions. The red feedback arrow is what converts repeated harms into a trap.

Source: H Heuristics, drawing on the literature reviewed in Sections 2 to 9.

1.3 Why this belongs in the polycrisis frame

The [polycrisis](#) concept describes situations in which several crises interact so that the whole is more damaging than the sum of the parts. [Lawrence, Janzwood and Homer-Dixon \(2024\)](#) identify three causal pathways that entangle crises: common stresses that hit many systems at once, domino effects in which one failure triggers another, and mutual feedbacks. All three are visible in the education case. Warming is a *common stress* that raises classroom temperatures, farm losses and air pollution together. A flood that

destroys a school and a harvest is a *domino*, in which one event produces both an educational and an economic loss. And poverty, child labor and lost learning form a *feedback* that sustains itself.

The education system is also where the long-term costs of the polycrisis are stored. A heatwave leaves no mark on a balance sheet after it ends, but a cohort of children who finished school two years earlier than they would have, or who learned less in the years they attended, carries that loss for the rest of its working life. The earlier H Heuristics studies of [cascading risk](#), [the heat trap](#) and [human suffering across the polycrisis](#) mapped how local shocks spread through systems. This report follows one of those cascades into the life of a child, because children are where the polycrisis becomes irreversible: a lost year of early schooling cannot be recovered later in the way a lost harvest can be replanted.

1.4 Five propositions

The report develops and tests five propositions. Each carries an evidence grade, defined in the front matter.

Table 3. The five propositions of the report

Proposition	Statement	Grade	Where tested
P1	Heat and air pollution reduce what children learn, independently of whether they are in school.	A/B	Sections 4 and 5
P2	Climate hazards are now a major and growing cause of school closure and absence, concentrated in low-income regions.	B	Sections 3 and 6
P3	Where households lack buffers, climate and pollution shocks raise child labor and school withdrawal; the sign depends on the type of shock.	B/C	Sections 7 and 8
P4	Lost schooling is persistent, with large lifetime costs that pass to the next generation.	A/B	Sections 9 and 10
P5	Protecting household income is the most powerful single lever, with cooling, clean air and continuity measures adding to it.	C	Sections 12 and 13

Grades describe the strength of the evidence for the proposition as stated, not its importance.

1.5 What is new in this report

The report makes three contributions. It assembles in one place the evidence on heat, pollution, disruption and poverty as channels of the same trap, which the literature usually treats separately. It builds a country panel of 217 economies from World Bank, ERA5 and UN data to map where the channels overlap, and it ranks 150 countries on a Trap Exposure Index (Section 11). And it presents an original cohort model (Section 12) that simulates 60,000 to 100,000 households per scenario under rising shock frequency, with a sensitivity analysis and a comparison of four interventions. The model is illustrative: its purpose is to show how the mechanisms behave and which assumptions drive the results, not to forecast.

02

LITERATURE REVIEW

2. Concepts and Evidence Foundations

2.1 Human capital and what it is worth

[Human capital](#) is the stock of knowledge, skills and health that a person carries into working life. The economic literature gives it a concrete price. [Psacharopoulos and Patrinos \(2018\)](#) reviewed 1,120 estimates from 139 countries and put the average private return to a year of schooling at about 9 percent. [Hanushek and Woessmann \(2008\)](#) showed that it is cognitive skills, rather than years in a classroom, that are powerfully related to individual earnings and national growth, and [their later work](#) strengthened the case that the relationship is causal. The distinction matters here because heat, air pollution and disruption lower learning *within* the years a child attends, so a country can raise enrolment and still lose human capital.

The World Bank's [Human Capital Project](#) summarizes the idea in one number. The Human Capital Index measures the productivity a child born today can expect to reach by age 18 relative to a benchmark of full health and complete education ([Kraay, 2019](#)). A related measure, learning-adjusted years of schooling (LAYS), discounts the years a child spends in school by how much she learns in them. [Angrist et al. \(2021\)](#) built a globally comparable learning database for 164 countries and showed that global progress in learning has been modest and uneven. The World Bank's most recent [learning-poverty estimate](#) finds that about 70 percent of ten-year-olds in low- and middle-income countries could not read and understand a simple text in 2022, up from about 57 percent before the pandemic. This is the baseline against which the climate effects in this report operate.

2.2 Poverty traps: a conditional claim

The idea that poverty can be self-perpetuating is old and contested. [Kraay and McKenzie \(2014\)](#) reviewed the evidence for classic poverty-trap mechanisms, including S-shaped savings functions and nutrition-based traps, and found limited evidence for several of the classic mechanisms. The argument for traps at the household level rests on different mechanisms. Where credit and insurance are missing, a household that holds few assets must avoid risky but profitable activities, sell productive assets after a shock, or withdraw children from school, and these responses lock in low future income. [Carter et al. \(2007\)](#) found asset thresholds of this kind in Ethiopia and Honduras, where households hit by drought or hurricane either recovered their asset base or fell to a lower equilibrium. [Dercon and Christiaensen \(2011\)](#) showed that consumption risk deters investment in Ethiopian agriculture, which keeps incomes low.

The position of this report follows from that evidence. We do not claim that poverty traps operate everywhere or that every poor household is trapped. We claim that traps are a *conditional* feature of environments in which shocks are frequent, buffers are thin and the cost of a missed investment is high, and that climate and pollution shocks are making such environments more common. The cohort model in

Section 12 makes the condition explicit: it shows how the share of children who fall below a minimal level of effective schooling changes with shock frequency and household buffers.

2.3 Early-life origins of adult outcomes

A second foundation is the finding that conditions in the womb and early childhood leave marks that last for decades. [Almond and Currie \(2011\)](#) surveyed the fetal-origins literature and concluded that the magnitude of the impacts on test scores, educational attainment and income is generally large; a [follow-up review](#) found that relatively mild shocks in early life can have substantial negative effects. [Black, Devereux and Salvanes \(2007\)](#) used Norwegian twins to show that birth weight affects adult height, IQ, earnings and education. [Cunha and Heckman \(2007\)](#) formalized the idea of dynamic complementarity: early inputs raise the productivity of later ones, so a deficit at age three makes schooling at age ten less effective. [Heckman \(2006\)](#) drew the policy lesson that investment in disadvantaged children yields its highest return early. The [Lancet series on early childhood development](#) placed the number of children at risk of not reaching their developmental potential in low- and middle-income countries in the hundreds of millions.

These findings explain why the trap has a temporal structure. Heat and pollution in pregnancy and infancy lower the starting point; shocks in school years remove time and learning; and the effects multiply because each stage builds on the last.

2.4 Climate, temperature and the economy

A third foundation is the evidence that temperature affects economic outcomes through channels that matter for households. [Dell, Jones and Olken \(2012\)](#) found that higher temperatures reduce growth in poor countries and cut agricultural and industrial output. [Burke, Hsiang and Miguel \(2015\)](#) found that production peaks at an annual average of about 13 °C and declines at higher temperatures, a result that places most of the world's poorest countries on the declining side. [Carleton and Hsiang \(2016\)](#) reviewed the broader evidence on health, agriculture, conflict and labor. [Kjellstrom et al. \(2016\)](#) showed that heat reduces work capacity at levels already common in the tropics. For children the relevant implication is indirect but large: when heat lowers adult productivity and farm income, it changes the economic position from which families decide about schooling.

2.5 The evidence map

Table 4 summarizes the main empirical links, the studies that establish them, and the grade assigned in this report. Two points deserve emphasis. The evidence on direct learning effects is strong and mostly causal, because it comes from natural experiments with fixed effects. The evidence on child labor is less uniform, because economic theory predicts that the response to a shock can go either way, depending on whether the shock lowers the household's income (pushing children to work) or lowers the wage a child could earn (pushing children to school). Section 8 returns to this.

Table 4. The empirical links of the trap, with key studies and evidence grades

Link	Key studies	Main finding	Grade
Heat → learning	Park et al. 2020 ; Park et al. 2021 ; Garg et al. 2020	A 1 °F hotter school year lowers that year's learning by 1 percent without air conditioning; hot days reduce scores in 58 countries and in India	A
Heat → exam performance	Graff Zivin et al. 2018 ; Graff Zivin et al. 2020	Hot test days lower math scores above about 26 °C in the US; heat also affects China's national college entrance examination	B
Pollution → learning and attainment	Ebenstein et al. 2016 ; Zhang et al. 2018 ; Sanders 2012	PM2.5 on exam days lowers scores and later attainment and earnings; long-term exposure impairs cognition; prenatal exposure lowers test scores	B
Pollution → absence	Currie et al. 2009 ; Liu and Salvo 2018	Air pollution raises school absence, even at levels below regulatory standards	B
Lead → cognition	Lanphear et al. 2005	IQ deficits at blood lead below 10 µg/dL; no safe threshold identified	A
Early-life heat → attainment	Randell and Gray 2019 ; Isen et al. 2017	Prenatal and early-life heat lowers schooling in 29 tropical countries and adult earnings in the US	B
Shock → child labor and withdrawal	Beegle et al. 2006 ; Duryea et al. 2007 ; Shah and Steinberg 2017	Income shocks raise child labor where credit is constrained; wage shocks can raise it too; the sign depends on the shock	B/C
Shock → child marriage	Corno et al. 2020	Droughts raise the hazard of child marriage in Sub-Saharan Africa and lower it in India	B
Social protection → buffering	Garg et al. 2020 ; Edmonds and Schady 2012	A workfare programme weakens the link between heat and test scores; a small cash transfer cut paid child work sharply in Ecuador	A/B
Lost schooling → earnings	Psacharopoulos and Patrinos 2018	Average private return of about 9 percent per year of schooling	A

Grades follow the scale in the front matter. Studies cited are examples, not an exhaustive list; the full set is in the References.

03

CHILDREN, HEAT, AIR AND SCHOOLS

3. The Exposure Baseline

3.1 A warmer world with more children in its hottest places

The [World Meteorological Organization](#) reports that 2024 was the warmest year on record, at about 1.55 °C above the 1850–1900 average, and that 2025 was the second or third warmest at about 1.43 °C. The eleven warmest years in the 176-year record are the eleven most recent. The temperature series in Figure 3a, drawn from the [Our World in Data](#) extract of the HadCRUT5 dataset, shows the same pattern, with 2024 at +1.53 °C against that dataset's baseline.

The demographic picture in Figure 3b matters as much as the thermal one. According to the [UN World Population Prospects 2024](#), the world has about 2,001 million children under 15 in 2025, and 1,278 million of them, 64 percent, live in low- and lower-middle-income countries. The medium projection shows the number of children in low-income countries rising from 318 million in 2025 to 426 million in 2050, while the number in lower-middle-income countries stays near 958 million. Even as the world's total child population plateaus, the share growing up in the hottest, poorest and least-resourced places rises. These are the places with the weakest buffers for the trap described in Section 1.

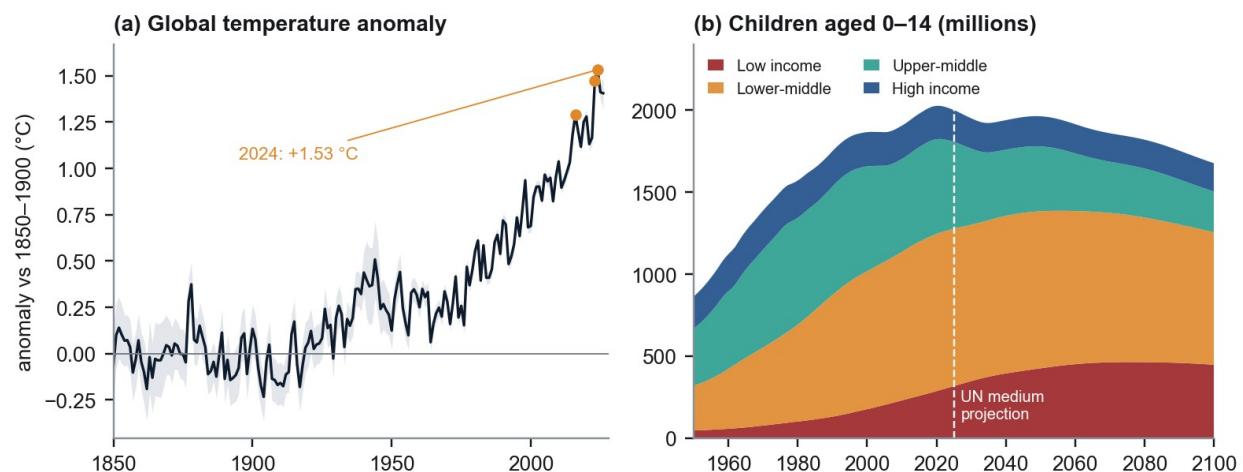


Figure 3. Warming and the geography of childhood. (a) Global near-surface temperature anomaly, 1850–2026, with the 2016, 2023 and 2024 values marked. (b) Population aged 0–14 by World Bank income group, 1950–2100, with the UN medium-variant projection after 2025. The share of the world's children in low-income countries rises through 2050 while high-income countries' share shrinks.

Sources: *Our World in Data* extract of *HadCRUT5* (temperature, baseline 1850–1900); *UN World Population Prospects 2024* via *Our World in Data* (population).

3.2 Counting the exposed

No single statistic captures how many children are exposed to the forces in this report, because exposure, vulnerability and outcome are measured by different agencies in different years. Table 5 gathers the main published estimates, and Figure 4 puts the counts on one axis. Two features stand out. The estimates run from tens of millions (children in hazardous work) to more than a billion (children exposed to overlapping climate hazards), and they overlap heavily: the same child may live in a high-risk country, breathe polluted air, attend a school with no cooling and work after class. The totals cannot be added.

Table 5. Headline estimates of exposure, schooling and child labor

Indicator	Estimate	Source
Global temperature above 1850–1900	About 1.55 °C (2024); about 1.43 °C (2025)	WMO
Children in areas with frequent heatwaves	559 million in 2020; more than 2 billion by 2050	UNICEF, 2022
Children in 33 “extremely high-risk” countries	About 1 billion	UNICEF, 2021
Children exposed to three or more overlapping climate hazards	About 1.1 billion	UNICEF, 2026
Students whose schooling was disrupted by climate hazards	At least 242 million in 2024	UNICEF, 2025
Children and youth out of school	About 272 million	UNESCO GEM Report, 2025
Ten-year-olds in learning poverty, low- and middle-income countries	About 70 percent (2022)	World Bank
Children in child labor; in hazardous work	About 138 million; 54 million (2024)	ILO and UNICEF, 2025
Children with blood lead at or above 5 µg/dL	About 800 million	UNICEF and Pure Earth, 2020
Deaths attributed to air pollution	7.9 million (2023); over 675,000 under age five	State of Global Air 2025
People below the \$3-a-day extreme-poverty line	About 808 million, 9.9 percent (2025 nowcast)	World Bank PIP

Estimates are from different years and methods and overlap; they should not be summed. The 2025 poverty figure is a nowcast, not a survey count.

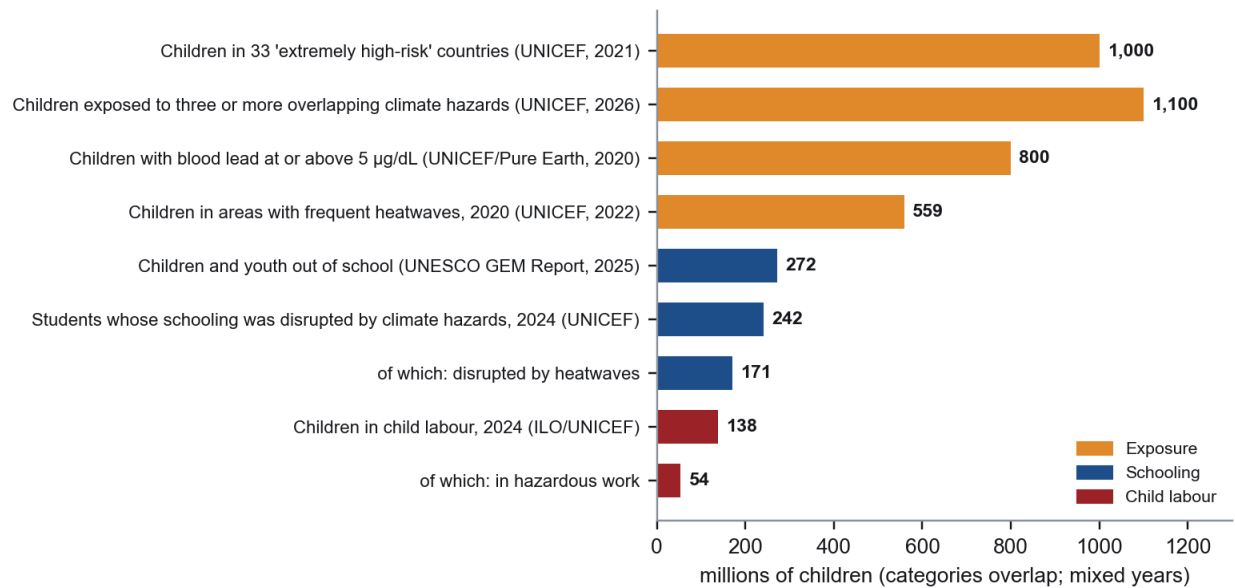


Figure 4. The scale of exposure, schooling disruption and child labor. Bars show published estimates in millions of children; categories overlap and years differ, so the bars are not additive.

Sources: UNICEF (2021, 2022, 2025, 2026); UNICEF and Pure Earth (2020); UNESCO GEM Report (2025); ILO and UNICEF (2025).

The newest of these is the [June 2026 UNICEF Children's Climate Risk Report](#), which finds that nearly half the world's children, about 1.1 billion, are exposed to at least three overlapping climate hazards, and that more than 296 million live where prolonged drought, extreme heat and heatwaves coincide, according to [press coverage of the launch](#). UNICEF's analyst put the problem plainly: children can cope with one or two shocks, but after three, four or five, families' ability to respond becomes severely strained. That is the same threshold logic that the model in Section 12 tests.

3.3 The air children breathe

The [State of Global Air 2025](#) report attributes 7.9 million deaths in 2023 to air pollution, with about 90 percent of them in low- and middle-income countries ([Health Effects Institute](#)). Earlier editions put air-pollution deaths among children under five at about 700,000 in 2021, and the 2025 edition reports over 675,000, though the death rate in this age group has fallen by more than half since 2000. The [Lancet Commission on pollution and health](#) attributed 9 million premature deaths in 2015 to all forms of pollution.

Mortality, however, understates the educational effect, which works through illness, absence, cognition and sleep. To see how the burden varies, the analysis in this report combines World Bank estimates of population-weighted PM_{2.5} exposure for 190 economies ([EN.ATM.PM25.MC.M3](#), 2023) with income data. Figure 5 shows the result. Population-weighted mean exposure is 13 µg/m³ in high-income countries, 27 in upper-middle-income countries, 31 in low-income countries and 50 in lower-middle-income countries, which is the highest of the four because it includes India, Pakistan, Bangladesh and Nigeria. For comparison, the [WHO air-quality guideline](#) for annual PM_{2.5} is 5 µg/m³. Virtually the whole world's population lives in countries whose national average exceeds that guideline, and 98 percent of people in low- and lower-middle-income countries live where the national average exceeds 15 µg/m³, the third interim target in the 2021 WHO guidelines.

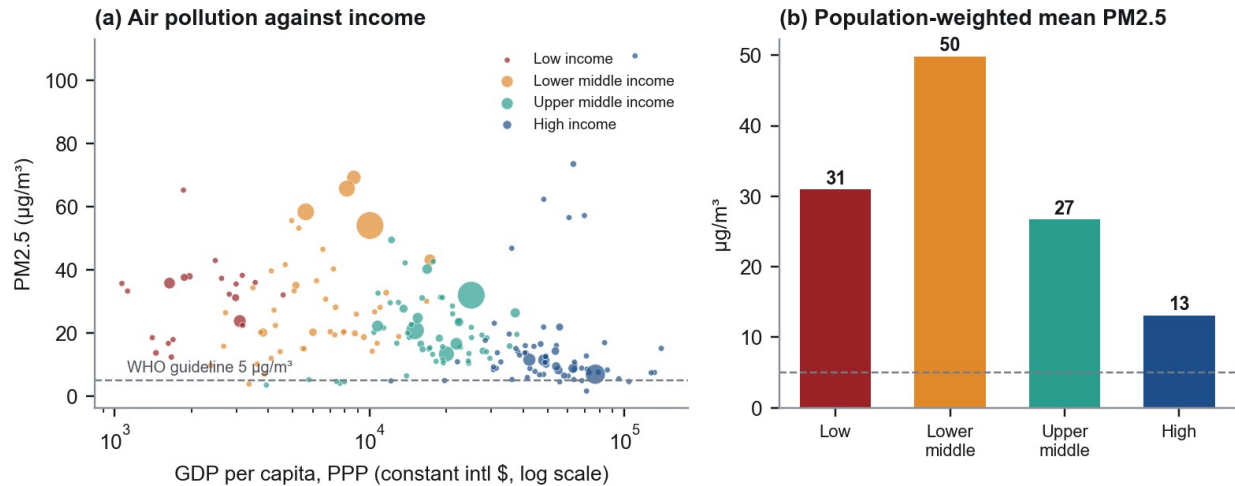


Figure 5. Air pollution and income. (a) National population-weighted PM2.5 against GDP per capita for 190 economies, bubble area proportional to population; the dashed line is the WHO annual guideline of $5 \mu\text{g}/\text{m}^3$. (b) Population-weighted mean PM2.5 by World Bank income group. Country averages conceal large within-country variation, including urban hotspots and seasonal smoke episodes.

Source: H Heuristics analysis of World Bank indicators EN.ATM.PM25.MC.M3 (2023) and NY.GDP.PCAP.PP.KD. PM2.5 values are modelled annual means.

3.4 The infrastructure of coping

Cooling a classroom, filtering its air or cooking cleanly at home all require power or clean fuel. Figure 6 shows the gap. In low-income countries, population-weighted electricity access is 49 percent and access to clean cooking fuels is only 16 percent; in lower-middle-income countries the figures are 91 and 64 percent; in Sub-Saharan Africa as a whole, electricity access is 55 percent. These are national figures for households, not schools, and school electrification is typically lower in rural areas. The point is that the tools that protect children from heat and smoke in rich countries are not available by default where the exposure is greatest.

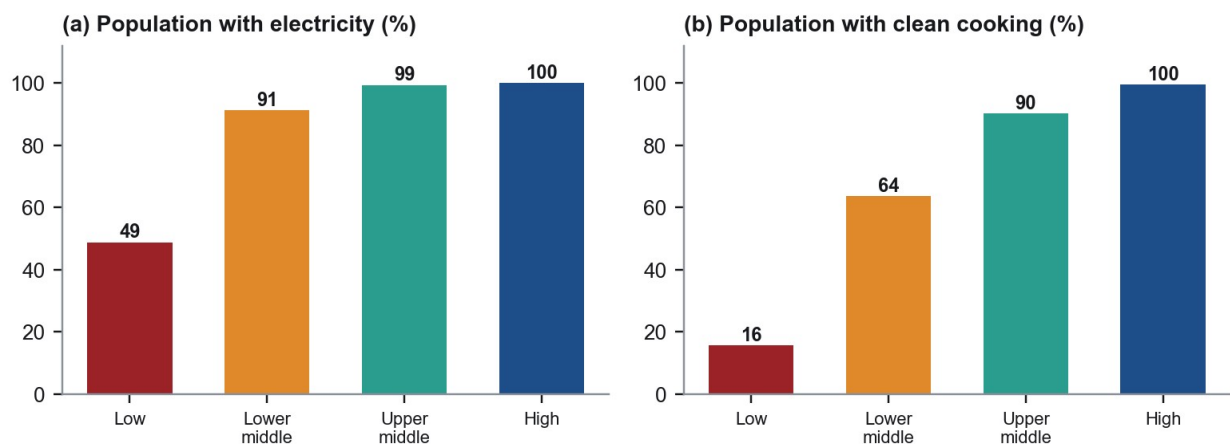


Figure 6. The infrastructure gap. (a) Share of population with access to electricity and (b) with access to clean fuels and technologies for cooking, population-weighted by World Bank income group.

Source: H Heuristics analysis of World Bank indicators EG.ELC.ACCS.ZS (2024) and EG.CFT.ACCS.ZS, most recent year available.

3.5 Hot, polluted places learn less: a descriptive picture

Cross-country data cannot establish cause, but they show where the problem sits. Figure 7 plots the learning-adjusted years of schooling reported in the World Bank's [Human Capital Index data](#) against mean annual temperature for 1991–2020, calculated from ERA5 reanalysis, and against PM2.5. The rank correlation is -0.58 with temperature ($n = 158$) and -0.54 with PM2.5 ($n = 157$). After removing the association with income, by correlating the residuals of each variable on log GDP per capita, the partial correlations remain -0.45 and -0.39 .

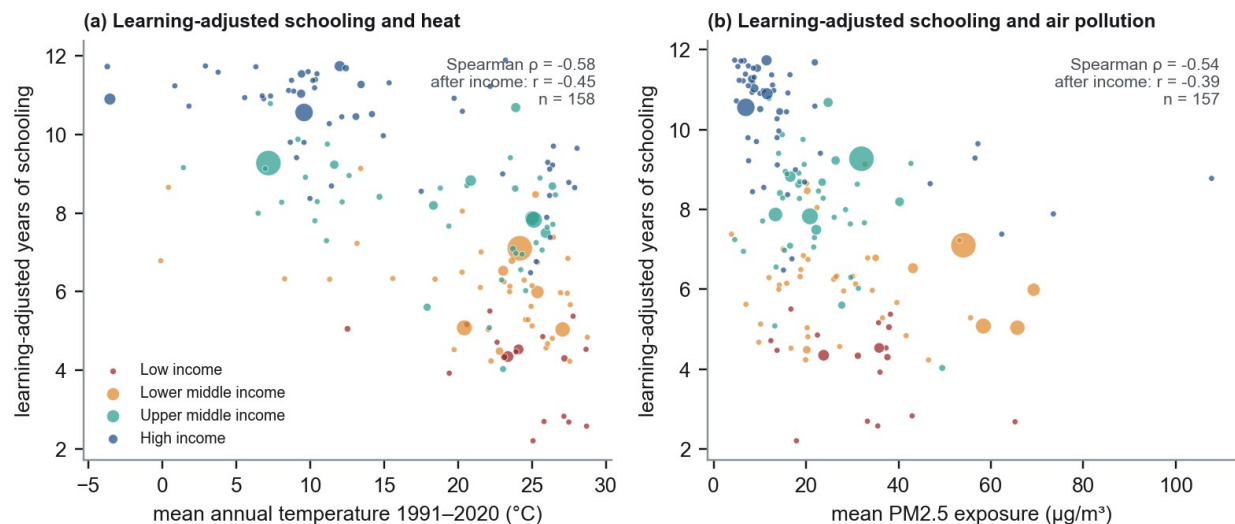


Figure 7. Learning-adjusted years of schooling against heat and air pollution. Each bubble is a country (area proportional to population), coloured by income group. Statistics are Spearman rank correlations and Pearson partial correlations controlling for log GDP per capita. The relationships are descriptive: heat and pollution are correlated with agrarian structure, institutions, conflict and many other determinants of schooling.

Source: H Heuristics analysis of World Bank HCI and indicator data; ERA5 monthly 2 m temperature via Our World in Data and Copernicus (1991–2020 mean).

Reading the scatter. The associations are stronger than income alone would explain, but they cannot be read as the effect of heat or pollution. Hot countries are more agrarian, more exposed to conflict and more recently poor. The evidence for a causal effect comes from the within-country natural experiments reviewed in the next two sections, not from this scatter.

04

CHANNEL I · HEAT

4. Heat and Learning

4.1 How heat reaches the classroom

Heat affects learning through at least four mechanisms. It impairs cognitive performance on the day, so a hot child learns less per hour. It disrupts sleep: [Obradovich et al. \(2017\)](#) found that warmer nights raise reported insufficient sleep, with the largest effects in lower-income respondents, and [Minor et al. \(2022\)](#), using wearable-device data from dozens of countries, found that hot nights shorten sleep, with larger effects in lower-income countries. It raises illness, dehydration and hunger, which cause absence. And it cuts instructional time when schools close, shorten the day or move activities outdoors. The first and last of these show up in the test-score studies below; the second and third show up in absence records and survey data.

4.2 What the best evidence shows

The most rigorous study is [Park, Goodman, Hurwitz and Smith \(2020\)](#), which follows students who retook the PSAT and compares their scores across school years that differed in heat. Without air conditioning, a 1 °F hotter school year reduces that year's learning by 1 percent. Weekend and summer heat has little effect, which indicates that heat disrupts learning time directly. School air conditioning largely offsets the damage, and hot school days account for roughly 5 percent of the racial achievement gap in the United States. [Park, Behrer and Goodman \(2021\)](#) extended the finding to standardized achievement data from 58 countries and to 12,000 US school districts, and found that learning slows as the number of hot school days rises.

The evidence from developing countries is thinner but consistent. [Garg, Jagnani and Taraz \(2020\)](#) show that high temperatures reduce math and reading scores of school-age children in India. They also show that agricultural income is one of the mechanisms: hot days during the growing season reduce yields and test scores, with much smaller effects of hot days in the off-season, and the roll-out of a rural workfare programme substantially weakened the link between temperature and test scores. This single study carries three lessons for the trap. Heat harms learning through the household as well as through the classroom, so the income channel is not separate from the learning channel. Social protection can sever the link. And the burden falls on the poor in agrarian economies. [Graff Zivin, Hsiang and Neidell \(2018\)](#) found that short-run temperature changes reduce math performance beyond about 26 °C in a US longitudinal survey, while the long-run effect of climate was smaller and imprecise, which suggests that adaptation can offset some of the damage. [Graff Zivin et al. \(2020\)](#) studied China's national college entrance examination, one of the highest-stakes tests in the world, and found that temperature affects performance on it.

4.3 A dose-response calculation

To see how large these effects could become, we apply the Park et al. coefficient to future warming. The calculation is deliberately simple. Local warming over land is assumed to be 1.4 times the global mean change, in line with the faster warming of land than ocean; school-year temperature is assumed to rise by that amount; and learning falls by 1 percent per °F, reduced in proportion to the share of classrooms effectively cooled. The result is a lower-bound illustration, since the US estimate comes from a setting with mild climate and substantial adaptation, and the true effect in a hot, uncooled school may be larger or smaller.

Figure 8a shows the dose-response lines. At 2 °C of additional global warming above the mid-2020s level, local school-year temperatures rise by about 5.0 °F, which, with 15 percent of classrooms effectively cooled, reduces annual learning by about 4.3 percent, or roughly 8 of 180 school days. Over twelve grades that adds to about 93 days of learning lost, a little over half a school year; with 60 percent of classrooms cooled the loss falls to about 44 days (Figure 8b). At 1 °C of additional warming the twelve-year loss is about 46 days.

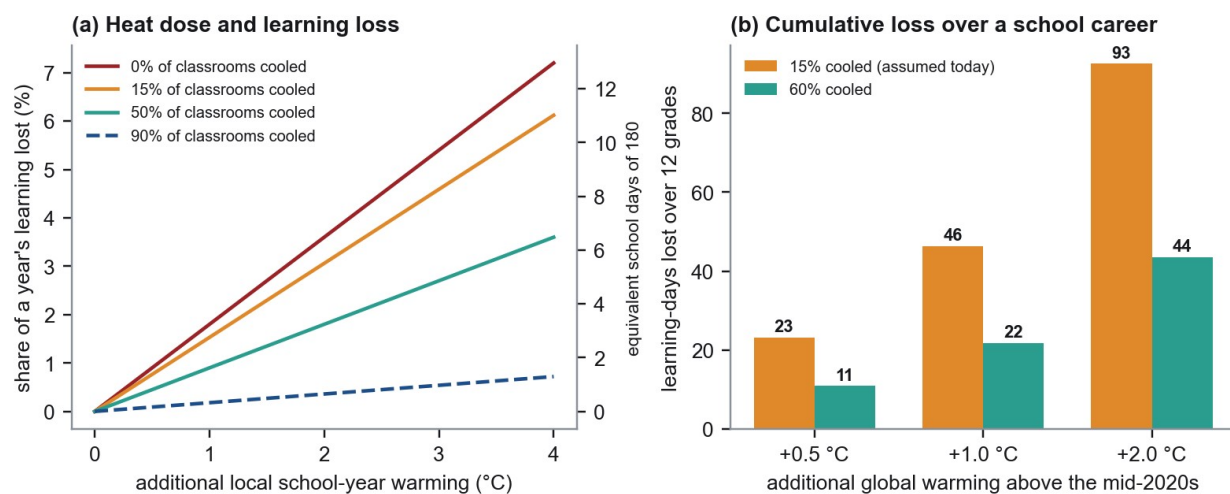


Figure 8. Original calculation: heat dose and learning loss. (a) Share of a year's learning lost against additional local school-year warming, by share of classrooms cooled; the right axis converts to school days of 180. (b) Cumulative learning-days lost across 12 grades under +0.5, +1.0 and +2.0 °C of additional global warming for 15 percent and 60 percent of classrooms cooled.

Source: H Heuristics calculation. $\text{Loss} = 1\% \times \Delta T(^{\circ}\text{F}) \times (1 - \text{share cooled})$, with local warming = $1.4 \times \text{global}$; $\Delta T(^{\circ}\text{F}) = 1.8 \times \Delta T(^{\circ}\text{C})$. The 1% per °F coefficient is from Park et al. (2020), a US estimate extrapolated linearly; see Appendix A.

Two points follow. Direct heat effects on learning, by themselves, are real but modest compared with the losses the model finds from household withdrawal (Section 12): a few percent of a year's learning per degree, against children who leave school altogether. And cooling is a high-leverage but partial measure, since it addresses the classroom and leaves the household untouched.

4.4 Heat before school begins

The largest effects of heat on schooling may occur before a child enters a classroom. [Isen, Rossin-Slater and Walker \(2017\)](#) followed more than 12 million Americans from birth and found that each extra day above 32 °C in utero or in the first year of life is associated with a 0.1 percent reduction in adult annual earnings at age 30. [Randell and Gray \(2019\)](#) linked census data for 29 tropical countries to climate data and found that a child in South-East Asia who experienced prenatal and early-life temperatures two

standard deviations above average attained 1.5 fewer years of schooling by ages 12 to 16, with rainfall effects in West and Central Africa and Central America. [Baker and Anttila-Hughes \(2020\)](#) found that higher temperatures worsen child undernourishment across 30 Sub-Saharan African countries. Together these results mean that a child’s educational outcome can be shaped by a heatwave that occurred before she was born.

The [2025 Lancet Countdown report](#) documents rising heat exposure, with infants and adults over 65 among the most vulnerable groups, and a [summary of its findings](#) puts annual potential labor-hours lost to heat at about 640 billion, equivalent to US\$1.09 trillion in lost income. Those labor losses are the income channel in aggregate: parents who work in heat earn less, and their children bear part of the loss.

4.5 What is not yet known

- **Effect size in hot, unprotected schools.** Almost all causal estimates come from the United States, India, China and a handful of other countries. We lack estimates for low-income Sub-Saharan Africa, where both exposure and vulnerability are highest.
- **Nonlinearity and acclimatization.** Effects are concentrated on the hottest days, and children in persistently hot places may adapt through behavior and physiology. The 1-percent-per-°F figure should be treated as an average over a mild-to-hot range.
- **Closure and absence data.** Few countries record why schools close. UNICEF’s 242 million figure and the UK analysis both rely on reconstruction from media and administrative sources.
- **Interaction with pollution.** Hot days raise ozone and wildfire smoke, which act on the same children; Section 5 shows that the combined effect has not been measured.

Key point. Heat lowers learning on the days children attend, before birth and through the household income it destroys. The direct classroom effect is modest per degree but is borne by the children with the fewest protections, and the income effect that travels alongside it is larger.

05

CHANNEL II · POLLUTION

5. Air, Smoke and Lead

5.1 The pollution channels

Pollution reaches schooling through the same four doors as heat, plus a fifth that heat lacks: it can alter the developing brain directly. Fine particles and gases cause respiratory illness and absence. They impair attention and memory on the day. Exposure in pregnancy and infancy lowers the starting point for learning. Illness among working adults reduces household income. And toxic metals, above all lead, damage neural development at doses that cause no obvious symptoms. [Aguilar-Gomez et al. \(2022\)](#) reviewed the economic research on these “nonhealth” effects and concluded that subclinical effects on cognitive performance, productivity and decision-making may be more pervasive than hospital-based measures suggest, because they touch otherwise healthy people.

Table 6. Pathways from pollution to schooling

Pathway	Mechanism	Key evidence	Most affected
Acute cognition	Particulates and gases impair attention, memory and test performance on high-exposure days	Ebenstein et al. 2016 (Israel); Zhang et al. 2018 (China)	Children in high-PM2.5 cities; examinees
Illness and absence	Respiratory illness, asthma and eye irritation keep children home	Currie et al. 2009 (Texas); Liu and Salvo 2018 (China)	Younger children; those with asthma
Prenatal and early life	Exposure lowers birth weight and neural development	Sanders 2012 ; Currie et al. 2014	Infants of poor, urban or rural-fuel-burning households
Neurotoxic metals	Lead damages neurodevelopment at low blood levels	Lanphear et al. 2005 ; Grandjean and Landrigan 2014	Children near battery recycling, mining or leaded products
Household air pollution	Smoke from solid cooking fuels harms infants and adults	WHO	Households without clean cooking, mainly in Sub-Saharan Africa and South Asia
Income loss	Adult illness and death reduce household earnings	Lancet Commission 2018	Workers in dusty, smoky or informal settings

The lead-pathway evidence concerns IQ and cognitive tests; effects on schooling attainment are inferred rather than directly measured in most studies.

5.2 What the evidence shows

The cleanest evidence comes from studies of exam days, where random variation in air quality can be linked to individual scores. [Ebenstein, Lavy and Roth \(2016\)](#) followed Israeli students who took several

matriculation exams and found that transitory PM_{2.5} exposure on exam days reduced performance, and that those same students had lower postsecondary attainment and earnings when observed in 2010. The result shows that pollution on a single day can have permanent consequences when the day carries high stakes. [Zhang, Chen and Zhang \(2018\)](#) found, using a longitudinal Chinese survey, that long-term exposure impedes cognitive performance in verbal and math tests, with the damage more pronounced for the less educated. [Sanders \(2012\)](#) found that prenatal exposure to total suspended particulates lowered later high-school test scores. On absence, [Currie et al. \(2009\)](#) found that carbon monoxide at levels below federal standards raised absences in 39 Texas school districts, and a [study of expatriate children in northern China](#) examined how absence responds to severe air pollution when schools and parents take protective action.

Nearly all of this evidence comes from the United States, Israel and China, and none directly measures long-term pollution effects on learning in Sub-Saharan Africa or South Asia, where pollution is highest. The research gap itself is a finding. Exposures in those regions are higher and protective responses weaker, so there is no reason to expect smaller effects, but that remains an inference and not a finding.

5.3 Smoke, ozone and the climate link

Climate change and air pollution are not independent. Higher temperatures speed the chemistry that forms ozone, and drier fuels and longer fire seasons produce more wildfire smoke. [Burke et al. \(2023\)](#) showed that wildfire smoke has become a major contributor to PM_{2.5} trends in the United States, offsetting some of the gains from emission controls. In South Asia, crop-residue burning, dust and heat coincide in the pre-monsoon and winter seasons. The result for schools is that the days when classrooms are hottest are not always different from the days when the air is worst, and the two exposures compound on the same child. No study we are aware of has measured the joint effect of heat and particulate exposure on learning, which is one reason the combined cost is likely understated.

5.4 Lead: the silent subtraction

Lead is the best-documented neurotoxin in the environment of children. [Lanphear et al. \(2005\)](#) pooled seven cohort studies and found measurable IQ deficits at blood lead concentrations below 10 µg/dL, with the steepest decline per unit of exposure at low levels, and no evidence of a safe threshold. UNICEF and Pure Earth's [Toxic Truth report](#) estimates that about 800 million children, roughly one in three worldwide, have blood lead levels at or above 5 µg/dL, nearly half of them in South Asia. It identifies informal recycling of lead-acid batteries as a leading source and estimates the lifetime economic cost to low- and middle-income countries at nearly US\$1 trillion. [Grandjean and Landrigan \(2014\)](#) described the wider class of developmental neurotoxicants as a silent pandemic.

Lead belongs in a report on climate and education for a specific reason. The expansion of off-grid solar, backup power and cooling in the places that need them most will rely heavily on batteries, and where lead-acid batteries are used and recycled informally the transition could widen the very exposure that lowers children's cognition. This is an inference from the sources above and not a documented trend (grade D), but it argues for planning battery supply chains and recycling alongside school electrification.

5.5 Smoke at home

Household air pollution from cooking with solid fuels is the largest source of exposure for many young children. The [WHO fact sheet](#) documents the health burden, and the data in Section 3 show that clean-

cooking access is 16 percent in low-income and 64 percent in lower-middle-income countries. Clean cooking is at once a health, climate and time-poverty problem; for the trap, it matters because the smoke exposure is concentrated on the same infants and mothers who face the heat and income shocks described elsewhere in this report.

5.6 What the model says about pollution

The cohort model in Section 12 represents pollution as an absence-day burden of 1 to 6 school days a year, an assumption within the range implied by the absence studies but not calibrated to any particular country. In the sensitivity analysis (Figure 18) that range shifts mean learning-adjusted schooling by about 0.1 years and does not move the share of children below the trap threshold. This looks small, and for the model's limited purpose it is: the absence channel alone does not trap anyone. The model does not capture the cognitive, prenatal, lead and household-income channels, which the evidence suggests are larger, so it should be read as a lower bound on the contribution of pollution.

Key point. Pollution lowers the starting point and the learning rate of children who are already behind. Because the evidence base is concentrated in rich and middle-income settings, the true cost in the poorest countries is more likely to be understated than overstated.

06

CHANNEL III · DISRUPTION

6. School Disruption

6.1 The scale of climate-related disruption

Disruption is the most visible link between climate and education, and the one most often reported. UNICEF's [Learning Interrupted snapshot](#) compiled climate-related school closures in 2024 from official sources, UN reports and media, and found that at least 242 million students in 85 countries and territories had their schooling disrupted, with at least 20 countries suffering nationwide disruptions. Figure 9 shows the breakdown. Heatwaves were the leading hazard, affecting about 171 million students, with about 118 million affected in April alone, mainly in Bangladesh, Cambodia, India, the Philippines and Thailand. South Asia accounted for 128 million students and East Asia and the Pacific for 50 million. About 74 percent of affected students lived in low- and lower-middle-income countries.

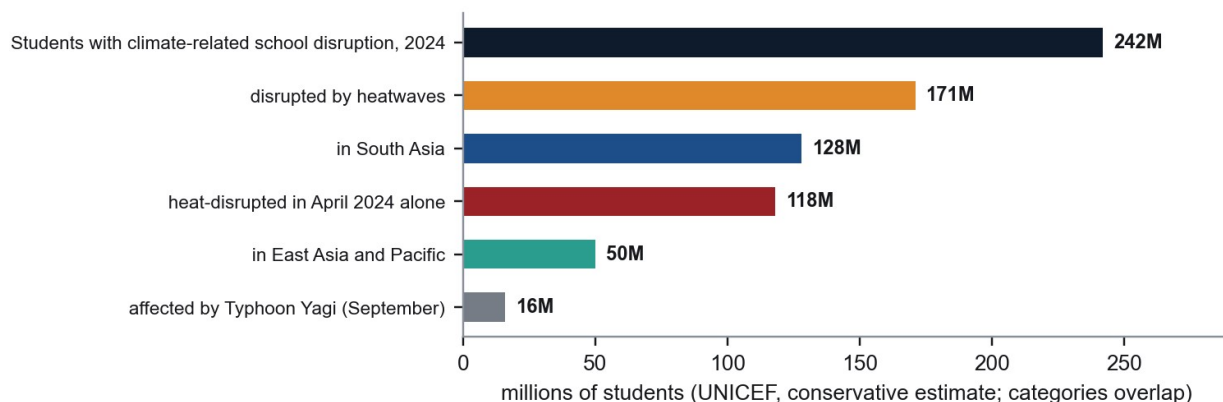


Figure 9. Climate-related school disruption in 2024. Headline numbers from UNICEF's global snapshot, in millions of students. UNICEF describes its total as conservative; hazard and region categories overlap.

Source: UNICEF (2025), *Learning Interrupted: Global snapshot of climate-related school disruptions in 2024*.

Table 7 lists recent events with documented scale. They differ in cause, geography and quality of data, but they share a pattern: the disruption is large, it recurs, and the official record is incomplete.

Table 7. Recent climate-related school disruption events

Event	Documented scale	Source
Pakistan floods, 2022	Nearly 27,000 schools damaged or destroyed; more than 2 million children without access to classes; more than 3.5 million children's education interrupted	UNICEF
South and South-East Asia heatwaves, April 2024	At least 118 million children affected in April, mainly in Bangladesh, Cambodia, India, the Philippines and Thailand	UNICEF
Typhoon Yagi, September 2024	About 16 million children affected in East Asia and the Pacific	UNICEF
Indian heatwave, April 2026	Several states revised school timings, closed schools or advanced summer holidays; Bihar districts closed classes up to Class 8	Careers360
England and Wales heatwave, June 2026	At least 1,730 schools closed or shortened days; at least 760,000 students missed lessons through closures; absence reached 36.5 percent in Wales on 25 June; more than 15 million teaching hours lost	DeSmog analysis

Figures from news and agency summaries; closures are not systematically recorded in most countries. The 2026 events are reported estimates.

The Pakistan floods show how a climate disaster compounds an existing education deficit. According to figures cited by UNICEF, Pakistan already had an estimated 22.8 million children aged 5 to 16 not attending school before the floods. Flood damage to nearly 27,000 schools adds to the stock of children for whom school is already inaccessible. It also shows the long tail: rebuilding schools takes years, and children who miss a semester or a year may not return.

6.2 The case of a rich country

The England and Wales episode is useful as a test of the argument. A wealthy country with near-universal schooling, free school meals and a functioning welfare state still saw hundreds of thousands of pupils miss lessons in a few days, and absence that reached more than a third of pupils in Wales on the hottest day. According to DeSmog, the government's climate adviser has estimated that without action to avoid 4 °C of warming, students would lose around 14 days of learning to extreme heat each year. That the loss can be offset in a rich country by classroom retrofits, meal programmes and make-up lessons does not make it vanish. It means the cost is borne by the system rather than by the child. In poor countries, the system cannot absorb it, and the cost falls on the child.

6.3 What disruption costs: lessons from the pandemic

The pandemic is the closest natural experiment on the effect of school closure on learning. [Engzell, Frey and Verhagen \(2021\)](#) exploited the timing of national exams in the Netherlands, a best-case setting with a short lockdown, equitable funding and wide broadband access, and found that students made little or no progress while learning from home, with the largest losses among disadvantaged students. In developing countries the stakes were higher. [Azevedo et al. \(2021\)](#) simulated that closures could cost between 0.3 and 1.1 years of schooling adjusted for quality, and that about 11 million students could drop out because of the income shock of the pandemic alone. The second finding is the more relevant one here. School closure damages learning directly, but the income shock that accompanies it is what removes children from school permanently. A climate disaster has the same structure: the closed school is the visible harm and the lost household income is the lasting one.

Climate closures differ from the pandemic in three respects. They are local rather than global, so recovery help is available from neighboring areas. They recur, so catch-up is repeatedly interrupted. And they are associated with physical damage to buildings, transport and water supply rather than only with a decision to close. Evidence on recovery is encouraging in one respect: [Banerjee et al. \(2017\)](#) showed that structured instruction pitched at the child’s actual learning level, the Teaching at the Right Level approach, can be integrated into government schools in India at scale. Catch-up can work, if it is funded and triggered by the disruption itself.

6.4 Hidden disruption

Closures are the visible part of disruption. Below them lies attendance loss that never makes headlines: children who stay home because of heat, smoke, illness or a flooded road; teachers who cannot reach schools; water points that fail; and school buildings used as shelters. [Education Cannot Wait](#) and other humanitarian funds focus on crisis-affected children, but the day-to-day losses in places that are not declared emergencies are almost entirely unmeasured. Girls can be disproportionately affected when disruption raises the cost of schooling, a pattern taken up in Section 8. The practical conclusion is that the 242 million is a floor and that without a standard reporting system the true burden cannot be known or managed.

Key point. Disruption itself costs learning, but it matters most as the point where a physical event becomes a household decision. The heat that closes a school also hits the harvest, and the closure is the moment at which the family decides whether the child returns.

07

CHANNEL IV · POVERTY

7. Poverty and the Household Decision

7.1 The household as the pivot

Whether a hazard becomes an educational loss is decided in the household. A flood, a failed harvest or a long heatwave reduces the household's income or raises its costs. The family can absorb the loss from savings, borrow against the future, draw on relatives or public transfers, or cut something. What it cuts depends on what it can least afford to lose in the short run and what it values least in the long run, and in poor households the investment in a child's schooling often falls into the second category because its returns come years later. This is the logic of the poverty-trap models reviewed in Section 2: where insurance and credit are missing, a transitory shock can produce a permanent loss, because the coping strategies that protect consumption today lower income tomorrow ([Carter and Barrett, 2006](#)).

Not every response is damaging. [Jacoby and Skoufias \(1997\)](#) studied rural India and found that seasonal fluctuations in school attendance functioned as self-insurance, with children attending less in lean periods, and that this did not on average result in a substantial loss of human capital. The distinction between a temporary, reversible adjustment and a permanent withdrawal is the heart of the trap. A child who misses a month in a bad season and returns is not trapped. A child who misses a year, falls behind and does not return is. What decides between the two is whether the household recovers its buffer before the next shock arrives.

7.2 Poverty today and what climate adds

The [World Bank's June 2025 update](#) of the international poverty line, to \$3 a day in 2021 prices, estimates that about 808 million people, 9.9 percent of the world, live in extreme poverty in 2025. The rate has fallen since 2022 but the number of people close to the line is large, and these are the households for which a single shock moves them across it. The analysis in this report using [World Bank survey data](#) shows that extreme poverty and child labor are strongly related across countries (Section 8). The earlier [Shock Waves](#) analysis by the World Bank estimated that climate change could push as many as 100 million or more additional people into poverty by 2030 in a pessimistic scenario, largely through agriculture, health and disasters. The mechanism it identified, that poor households are more exposed, lose a larger share of their income, and recover more slowly, is the household side of the trap.

7.3 The coping menu and its educational cost

Table 8 lists the responses a poor rural household has to an income shock, ordered roughly from least to most damaging to long-run human capital. The ordering is a judgement, and the actual choices depend on local markets and norms. The evidence cited in Section 8 shows that where the lower-cost options are exhausted, the later items on the list come into use.

Table 8. Household coping responses to a climate or pollution shock and their schooling cost

Response	What it protects	Cost to schooling and human capital	Reversible?
Draw down savings or stocks	Consumption and school fees	None, if savings exist; this is the buffer the model tracks	Yes, slowly
Receive transfers or remittances	Consumption	None; protects schooling directly	Yes
Take high-cost loans	Consumption	Debt service later crowds out school spending	Partly
Sell livestock, land or tools	Consumption	Lowers future income and therefore later school investment	Rarely
Cut food, health or sanitation spending	Cash	Child illness, undernourishment and absence rise	Partly
Cut school spending (fees, uniforms, books)	Cash	Attendance and learning fall; dropout becomes more likely	Partly
Children work part-time, seasonally	Income	Absence and fatigue; may be reversible	Often
Withdraw children from school	Income and cost saved	Permanent loss of years; re-entry is difficult	Rarely
Marry daughters earlier	Consumption smoothing via marriage payments	School ends; early childbearing follows	No
Migrate	Income	Disrupts schooling for children who move; may raise remittances	Mixed

Compiled from the empirical literature cited in Sections 2 and 8, including Carter et al. (2007), Jacoby and Skoufias (1997), Beegle et al. (2006) and Corno et al. (2020). The ordering is a judgement.

7.4 Sex, age and timing

The costs of a shock are not shared equally within a household. [Maccini and Yang \(2009\)](#) found that Indonesian women exposed to higher rainfall in their birth year were taller, completed more years of school and lived in wealthier households, with no comparable effect for men. [Corno, Hildebrandt and Voena \(2020\)](#) showed that droughts raised the hazard of child marriage by about 3 percent in Sub-Saharan Africa, where families receive a bride price, and lowered it by about 4 percent in India, where families pay a dowry. The sign differs because the institution differs, which is a warning against assuming that one pattern holds everywhere. Timing also matters. [Shah and Steinberg \(2017\)](#) found that in rural India, higher wages raise human capital from in utero to age two, but reduce it from age five to sixteen, because children switch from school to work when wages rise. The same shock can help a baby and harm a ten-year-old.

7.5 Social protection as the counterfactual

If the household's buffer is the pivot, then raising the buffer should protect schooling. Three studies show that it does. [Garg et al. \(2020\)](#) found that the roll-out of India's rural workfare programme substantially weakened the link between temperature and test scores. [Edmonds and Schady \(2012\)](#) studied a randomly assigned cash transfer in Ecuador worth less than 20 percent of median child earnings and found that students in families induced to take it up reduced paid employment by 78 percent and unpaid economic activity inside their home by 32 percent, with a rise in unpaid household services. [Baird, McIntosh and Özler \(2011\)](#) compared unconditional and school-conditional transfers to adolescent girls in

Malawi: the unconditional transfer produced a modest decline in dropout, 43 percent as large as the conditional one, but teenage pregnancy and marriage were substantially lower in the unconditional arm, entirely among girls who dropped out. These results are from non-climate settings, with the exception of Garg et al., but they show that the response of households to income shocks can be changed by policy, which is the premise of Section 13.

Key point. Shocks become educational losses where the buffer is too thin. That makes household buffers the most important single variable in the system, and it is the variable the cohort model in Section 12 shows to be decisive.

08

CHANNEL V · CHILD LABOR

8. Child Labor

8.1 The global picture

The [ILO and UNICEF's 2024 global estimates](#) put 138 million children, 59 million girls and 78 million boys, in child labor, almost 8 percent of all children, with 54 million in hazardous work likely to harm their health, safety or morals. The number fell by more than 22 million from 2020 and by over 100 million since 2000, reversing the rise recorded between 2016 and 2020, but progress is uneven. Sub-Saharan Africa has 87 million children in child labor, close to two-thirds of the global total, and the number there has not fallen since 2020 because population growth offset the fall in prevalence. Agriculture accounts for 61 percent of child labor globally, mostly on family and smallholder farms, with services at 27 percent and industry at 13 percent. The ILO's definition excludes household chores in a child's own home, so unpaid care work, which falls heavily on girls, is not counted.

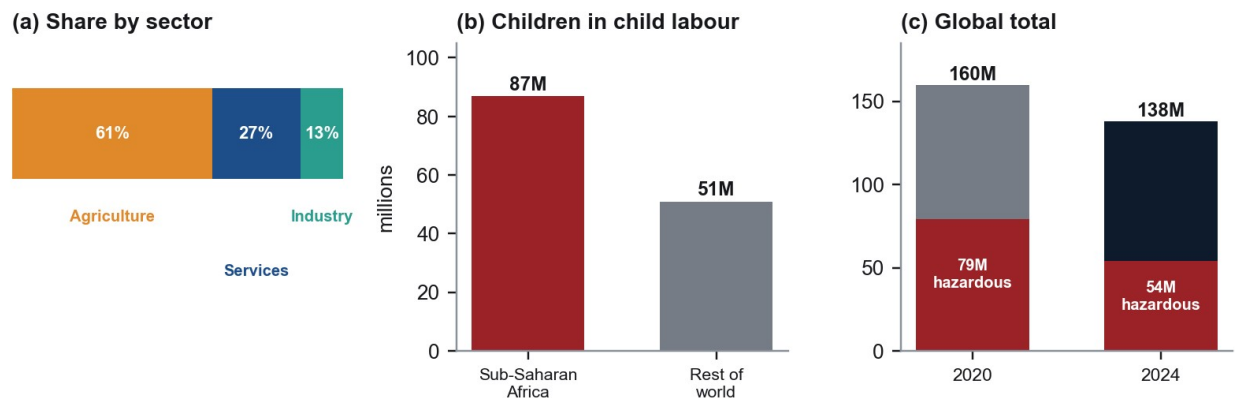


Figure 10. Child labor, 2024. (a) Share of children in child labor by sector. (b) Sub-Saharan Africa and the rest of the world. (c) Global total and hazardous work in 2020 (approximate, derived from the ILO's reported declines) and 2024. Source: ILO and UNICEF (2025), 2024 Global Estimates of Child Labour; the 2020 values are derived from reported reductions of more than 22 million (total) and 25 million (hazardous).

The sectoral structure matters for the argument of this report. Children in child labor are overwhelmingly in agriculture, the sector most exposed to heat, drought and flood. The families that put children to work are the families whose income depends on the weather, which is the link that makes child labor a candidate channel of the trap.

8.2 The cross-country pattern

Figure 11 uses the World Bank's [child-employment indicator](#) for the 97 countries with data to show where child work concentrates. The share of children aged 7 to 14 in employment correlates with the share of national employment in agriculture ($r = 0.65$, $n = 97$) and with the share of people living below \$3 a day

(Spearman $\rho = 0.66$, $n = 93$). Countries with mean annual temperatures above 22 °C have an average child-employment share of 24 percent (61 countries), against 12 percent for cooler ones (36 countries). These data come from household surveys between 2000 and 2016 and are the most recent available, which means that they predate the recent declines recorded by the ILO. They show where child work is concentrated but are not evidence that heat causes it. The raw correlation between child employment and temperature is 0.32 (Pearson), but it falls to 0.14 after controlling for agricultural employment and 0.11 after controlling for extreme poverty ($n = 93$; neither is statistically significant), because hot countries are poorer and more agrarian.

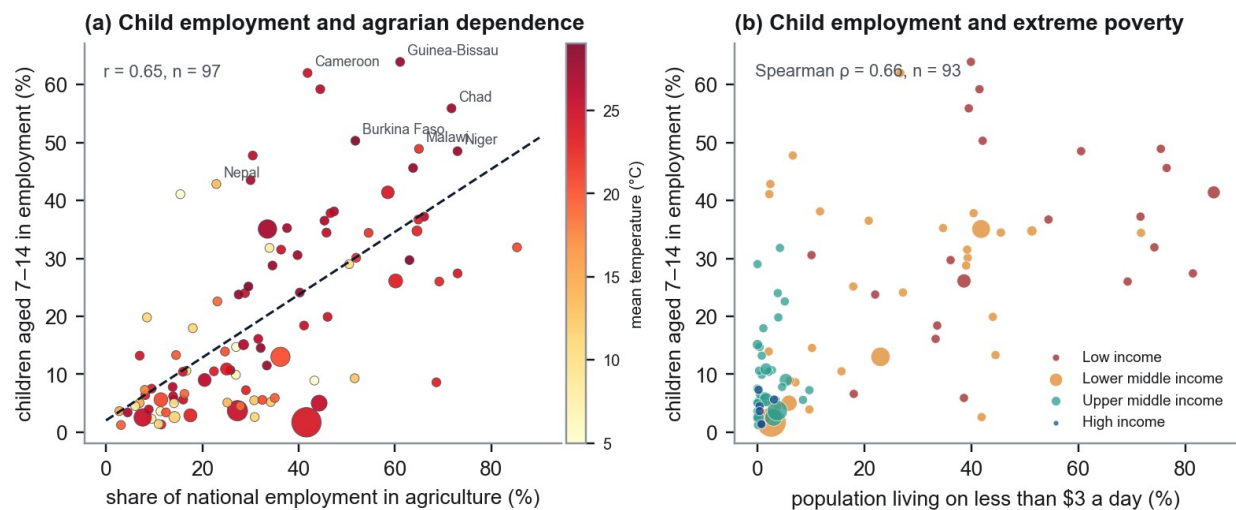


Figure 11. Child employment, agrarian dependence and poverty. (a) Share of children aged 7–14 in employment against the share of employment in agriculture, colored by mean annual temperature, bubble area proportional to population. (b) The same outcome against the share of the population below \$3 a day, colored by income group. Data are latest available surveys, 2000–2016.

Source: H Heuristics analysis of World Bank indicators SL.TLF.0714.ZS, SL.AGR.EMPL.ZS and SI.POV.DDAY; ERA5 temperature via Our World in Data.

8.3 Which way does the response go?

Economic theory does not give a single answer to what a climate shock does to child labor, and the empirical literature reflects that. A shock can push children to work by reducing family income and forcing the household to use all its labor, or pull children to school by reducing the wage they could earn. [Edmonds and Pavcnik \(2005\)](#) concluded in their review that child labor is fundamentally a symptom of poverty, driven by low income and poor institutions. The studies in Table 9 show that the sign depends on the nature of the shock and on whether households can borrow.

Table 9. How child labor and schooling respond to economic and weather shocks

Study	Setting	Shock	Response of children
Beegle et al. 2006	Tanzania	Transitory agricultural income shocks	Child labor used to smooth shocks where households face credit constraints
Duryea et al. 2007	Brazil	Unemployment of the household head	More child employment and less school progression
Kruger 2007	Brazil	Coffee production booms (higher wages)	More child labor and lower school attendance

Study	Setting	Shock	Response of children
Shah and Steinberg 2017	India	Higher rainfall (higher wages)	Children switch from school to work at ages 5–16; early-life human capital rises
Jacoby and Skoufias 1997	India	Seasonal income swings	Attendance falls in lean seasons as self-insurance; little average loss
Edmonds and Schady 2012	Ecuador	Cash transfer (positive shock)	Paid child work falls by 78 percent among families induced to take up the transfer
Corno et al. 2020	Africa, India	Drought	Child marriage rises in Sub-Saharan Africa and falls in India

Summaries follow the abstracts of the cited papers. The studies use different shocks and identification strategies and are not directly comparable.

For heat, which both lowers farm income and reduces adult work capacity, the income effect is likely to dominate in credit-constrained households, but we are not aware of a study that isolates heat as the shock and traces it to child labor in a low-income country. This is the most important gap in the empirical chain. We therefore grade the proposition that climate and pollution shocks raise child labor B/C: strong on mechanism and on income shocks in general, thin on the heat-specific link. The cohort model in Section 12 assumes the income-shock channel and should be read in that light.

8.4 Heat, work and hazard

Heat adds a hazard to child work as well as a cause. Children in agriculture work outdoors, often without protective measures, and 54 million children are in hazardous work according to the ILO. [Kjellstrom et al. \(2016\)](#) showed that heat reduces work capacity at levels already common in the tropics; for children, whose thermoregulation and hydration needs differ from adults, the same exposures carry risks that adult occupational standards do not address. [Graff Zivin and Neidell \(2014\)](#) found that, at higher temperatures, workers in climate-exposed industries reduce their hours; where adults reduce hours in heat, a household under income pressure may compensate with children's labor, though this is an inference rather than a measured result.

8.5 What it costs the child

Child labor is not benign even when combined with schooling. [Beegle, Dehejia and Gatti \(2009\)](#) used Vietnamese panel data and found that children who worked while in school had significantly worse educational outcomes five years later, and a higher probability of wage work as young adults. The interaction with the other channels is direct: a child who is tired, ill from heat or smoke, or absent for work learns less during the days she attends. The link between child labor and the learning-adjusted measures of Section 2 is therefore not only through enrolment but through the quality of the years that remain.

Key point. Child labor is concentrated where farms depend on weather and households lack buffers. Whether climate shocks raise it depends on the shock and on credit. The strongest case is for income-reducing shocks in credit-constrained households, but the heat-specific evidence is thin, and measuring it is a priority.

09

CONSEQUENCES

9. Long-Run Human Capital

9.1 From lost days to lost years

A child's educational career is the sum of three things: how many years she enrolls, how many days she attends in each of them, and how much she learns per day. Each channel in this report reduces one of the three. Heat and pollution reduce learning per day. Disruption and illness reduce days attended. Poverty and child labor reduce years enrolled. Because the three multiply, a modest loss on each compounds. The learning-adjusted years measure used by the [World Bank](#) captures exactly this product, and it is the outcome tracked by the cohort model in Section 12.

The cohort model gives a sense of the compounding. For a stylized poor, credit-constrained rural household cohort, the mean learning-adjusted schooling at age 18 is 6.3 years in today's climate. It falls to 5.8 years with 0.5 °C of additional global warming, 5.4 with 1.0 °C and 4.5 with 2.0 °C. Years actually spent in school fall less, from 10.5 to 8.3 years, because the learning rate and attendance are also falling. The point is that a loss of one enrolled year is not a loss of one effective year: the children who stay are learning less, and the children who leave are learning nothing.

9.2 What the loss is worth

The standard way to price lost schooling is the Mincerian return. [Psacharopoulos and Patrinos \(2018\)](#) put the average private return at about 9 percent per year of schooling, and [Hanushek and Woessmann \(2008\)](#) showed that returns attach to cognitive skills rather than to time in school. Applying a 9 percent return to learning-adjusted years, the model's lifetime income index for the cohort falls by 4 percent at +0.5 °C, 7 percent at +1.0 °C and 14 percent at +2.0 °C, relative to the cohort schooled in today's climate. These are averages across the cohort; the loss is concentrated in the children who leave school and who earn the least.

The calculation understates the cost for three reasons. It prices schooling only through private earnings, not through health, fertility, civic participation or the education of the next generation. It ignores the effect of early-life damage, which lowers the starting point of learning (Section 4.4). And it applies to the cohort the loss in effective years, without considering the likelihood that the loss in cognitive skills from lead or malnutrition is not recoverable by later schooling. For all three reasons the figures should be read as the order of magnitude of the *schooling* channel rather than of the total human-capital loss.

9.3 Education as adaptive capacity

Education does more than raise income. [Lutz, Muttarak and Striessnig \(2014\)](#) argued in *Science* that universal education is key to enhanced climate adaptation, because educated people are better informed about risks, better able to respond to warnings, and more economically resilient. [Muttarak and Lutz \(2014\)](#)

reviewed the evidence on education and vulnerability to natural disasters and concluded that education is a key factor in reducing vulnerability. If this is right, as we judge it to be (grade B), then the loss of schooling is not only a loss of future income but a loss of the capacity to withstand the next shock. That is the feedback in the red arrow of Figure 2. Children who learn less become adults who are less able to adapt, and their children are born into households with thinner buffers.

9.4 The next generation

The evidence on early-life origins (Section 2.3) implies that the loss does not end with the cohort. A mother's education affects the health and nutrition of her children, and a poorer household's lower buffer raises its vulnerability to the next shock. [Almond, Currie and Duque \(2018\)](#) found that relatively mild shocks in early life can have substantial negative effects and that effects vary with household resources. We model this with a single parameter: the learning quality of a child's schooling rises with the parent's learning-adjusted years, with an elasticity of 0.35. The parameter is an assumption in the plausible range of intergenerational persistence in schooling, not an estimate for any country. Its effect, shown in Section 12, is to raise the long-run share of children below the trap threshold by about a quarter relative to the single-generation loss in the warmest scenario.

9.5 An order-of-magnitude illustration

To give a sense of scale without claiming a forecast, consider the 30 countries with the highest Trap Exposure Index scores (Section 11), which together hold about 443 million children under 15, or 22 percent of the world's children. If the cohort model's trap shares applied to their children, the model's increase from 6 percent today to 18 percent at +1.0 °C would put about 53 million additional children below the trap threshold, and the increase to 30 percent at +2.0 °C about 106 million. The model is calibrated to a stylized high-exposure household and not to the average child in these countries, so the application overstates the share if many children live in less exposed or better-buffered households. The figures show what is at stake in the assumptions rather than what will happen.

Key point. Lost schooling is persistent, costly and passes to the next generation. Each of these three features turns what looks like a transitory climate episode into a durable change in the human capital of a region.

10

FEEDBACK AND COUPLING

10. The Trap as a System

10.1 Coupling between channels

The channels in Sections 4 to 8 are not independent. Figure 12 maps the strength of the causal links between ten elements of the system: three hazards, three household and child conditions, and four educational outcomes. Scores run from 0 (no documented link) to 3 (strong and well evidenced), based on the studies reviewed in this report and H Heuristics' judgement where evidence is thin. The matrix has 36 links out of 90 possible, a density of 40 percent, of which 14 are rated strong. Heat is the strongest driver of the system, with a total out-strength of 13: it acts on income, health, learning, attendance and, indirectly, child labor. The most-driven element is attendance and continuity, with an in-strength of 14, because it is the point at which hazards, health, income and child labor all converge.

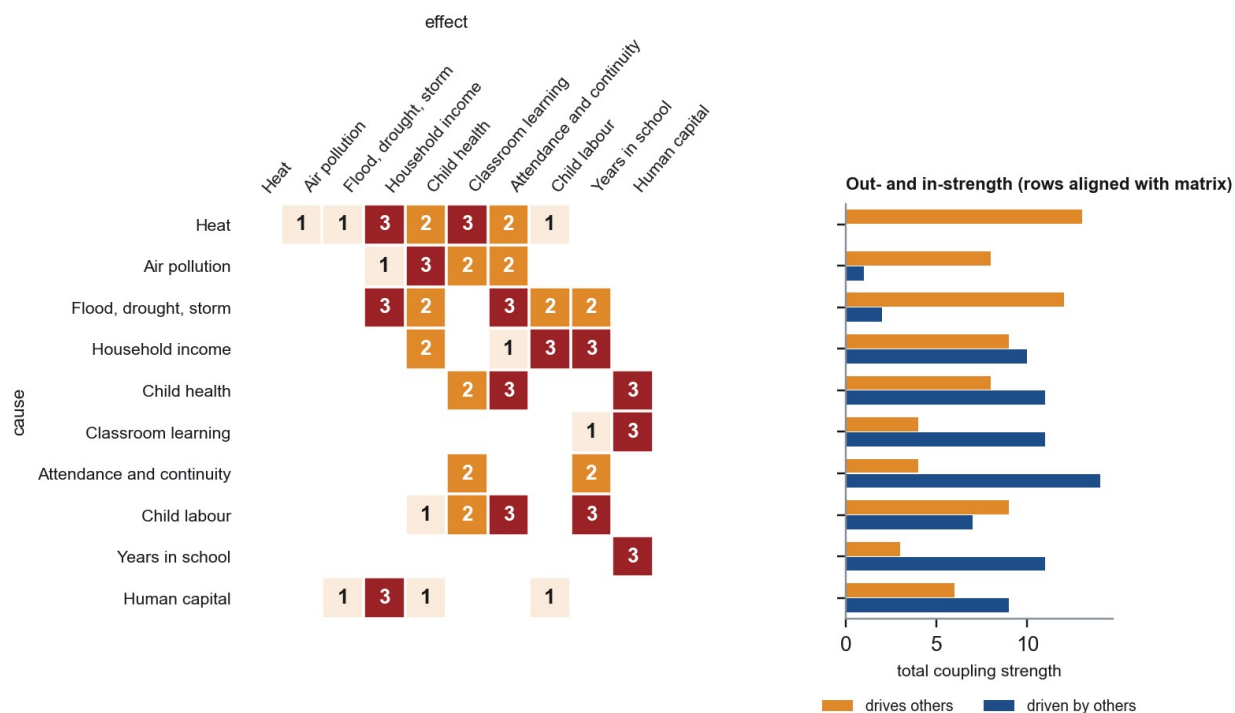


Figure 12. Coupling matrix of the trap. Rows are causes and columns are effects; cell values give the strength of the documented link, from 1 (weak or indirect) to 3 (strong and well evidenced). The bars show total out-strength (how strongly an element drives the others) and in-strength (how strongly it is driven), aligned with the rows of the matrix.

Source: H Heuristics assessment based on the studies cited in Sections 4 to 9. Scores are expert judgements and not estimates (grade D for the scores; grades for individual links are in Table 4).

The structure shows why single-channel interventions disappoint. An intervention that cools classrooms acts on one link out of many; the child it protects still faces the household income shock, the illness and the closure. A cash transfer acts on the household-income node, which drives child labor, years in school and health, and therefore has more downstream reach. The matrix cannot rank interventions on its own, but it indicates where leverage lies, a point that the cohort model then tests quantitatively.

10.2 Feedback loops

A trap requires feedback, and Figure 13 sets out the four reinforcing loops and two balancing loops identified in the evidence. R1, the poverty–withdrawal loop, is the core: a shock lowers income, income loss removes the child from school, and lost schooling reduces both future income and the buffer for the next shock. R2 links heat and learning to income and then back to the capacity to cool schools and homes. R3 links pollution to child illness, lost learning and poorer adult health, which leaves families less able to afford clean fuels. R4 operates at the level of the state: repeated disasters absorb public budgets and neglect schools, which weakens resilience. The two balancing loops, B1 social protection and B2 educated adaptation, show where the system can be turned. The evidence for B1 is the strongest (Section 7.5), and the evidence for B2 is the most consequential in the long run.

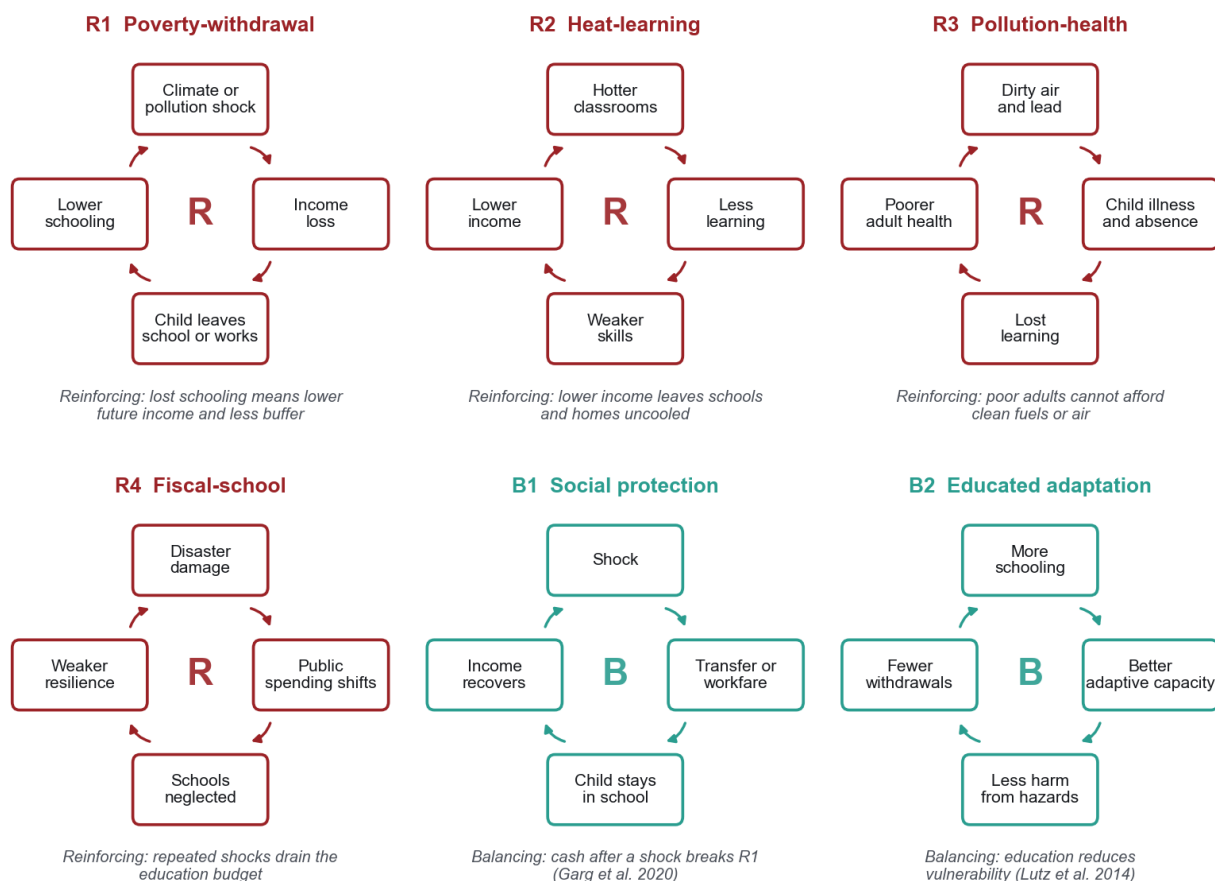


Figure 13. Reinforcing (R) and balancing (B) loops in the trap. R1 to R4 sustain the trap; B1 and B2 are the main mechanisms by which it can be broken. Arrows show the direction of influence around each loop.

Source: H Heuristics; B1 draws on Garg et al. (2020) and B2 on Lutz et al. (2014).

R4 is the least studied of the loops. The Pakistan floods of 2022 destroyed or damaged nearly 27,000 schools in a country that already had tens of millions of children out of school (Section 6), and the rebuilding competes with other post-disaster needs. We are not aware of a systematic cross-country estimate of how much public education spending is displaced by disaster response. The loop is plausible, but it is a hypothesis (grade C), and testing it with budget data is a research priority.

10.3 Thresholds and irreversibility

The loops explain why the trap can be sharp. When shocks are rare relative to the time a household needs to rebuild its buffer, the household recovers between them and the system is stable. When shocks arrive faster than recovery, buffers are never rebuilt and each new shock finds the household weaker. The change from one regime to the other occurs over a narrow range of shock frequency, which makes the system prone to threshold behavior. The same logic appears in the H Heuristics analysis of [cascading risk](#), in which repeated shocks erode the capacity to recover. For education, the threshold has a particular feature: schooling is time-bound. A year of early learning missed at age seven cannot be fully reclaimed at age seventeen, because [dynamic complementarity](#) means later learning builds on earlier learning, and a cohort passes through the age window once.

Section 12 tests this directly. In the model, the share of children falling below the trap threshold rises from near zero to more than half across the plausible range of shock frequency and buffer size, and the warming scenarios move a thin-buffer household toward the steep part of the surface.

10.4 Leverage points

Reading the loops together suggests where intervention yields the most. Raising household buffers breaks R1 and weakens R2 and R3. Maintaining continuity limits the in-strength of the attendance node. Cooling and clean air improve the classroom and the child's health, with most of the benefit going to learning per day. And mitigation, by reducing the frequency and severity of heat and pollution, lowers the hazard side of every loop at once. These do not substitute for one another; their effects add and in some cases multiply, as the portfolio analysis in Section 13 shows.

Key point. The trap is a system, not a sequence. Heat is the strongest driver, attendance is where the channels converge, and household income is the node whose protection reaches furthest.

11

HOTSPOTS

11. The Geography of the Trap

11.1 A Trap Exposure Index

To locate the places where the channels overlap, we construct a simple Trap Exposure Index for countries with more than one million people and at least four of five component indicators. The components are heat (mean annual temperature, 1991–2020, from ERA5), air pollution (population-weighted PM2.5, [World Bank](#)), extreme poverty (share of the population below \$3 a day, [World Bank](#)), learning deficit (the inverse of [learning-adjusted years of schooling](#)) and child share (population aged 0–14 as a share of the total, [UN](#)). Each is converted to a percentile rank, and the index is the mean of available ranks scaled from 0 to 100. The index covers 150 countries. It is a screening device and not a risk model: it measures overlap of conditions, not the probability of any outcome.

Two robustness checks suggest the ranking is stable. Dropping each component in turn leaves the ranking highly correlated with the baseline (the lowest Spearman correlation is 0.98), and replacing mean temperature with the warming since 1951–1980 gives a correlation of 0.92.

11.2 Where the overlap is greatest

Figure 14 shows the 20 highest-scoring countries and the contribution of each component. The top five are Niger, Chad, Mali, Central African Republic, Burkina Faso. Eighteen of the top 20 are in Sub-Saharan Africa. The pattern is a belt across the Sahel and Central Africa where mean temperatures are near 27 °C, extreme poverty is common, learning-adjusted schooling is below three years in several countries, and children under 15 make up more than 40 percent of the population. The 30 countries in the top fifth of the index together hold about 443 million children under 15, 22 percent of the world’s total.

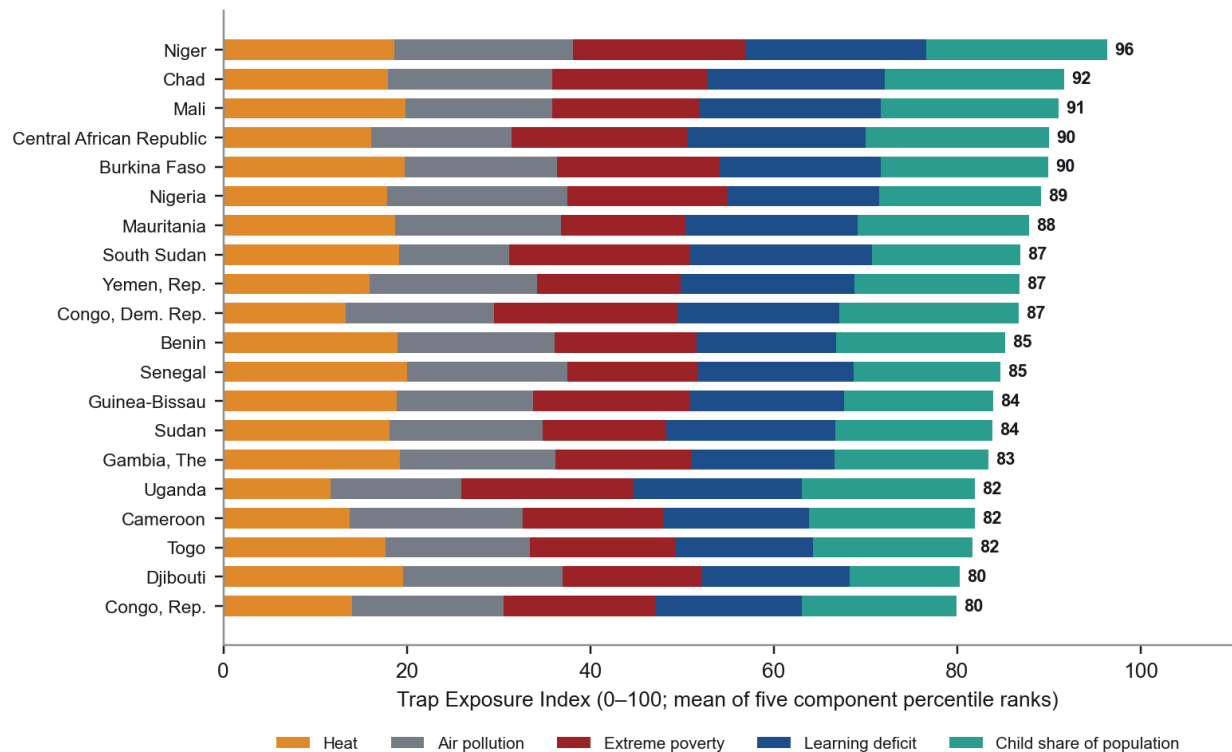


Figure 14. The Trap Exposure Index: the 20 highest-scoring countries. Each bar is the mean of five component percentile ranks (0 to 100); segments show each component's contribution, and the number is the index value. Countries with more than one million people and at least four of five components are included.

Source: H Heuristics analysis of World Bank indicators (PM2.5, poverty at \$3 a day, learning-adjusted years of schooling, population shares), ERA5 mean temperature via Our World in Data and UN World Population Prospects.

Table 10. The 15 highest-scoring countries on the Trap Exposure Index

Country	Region	Index	Mean temp. (°C)	PM2.5 (µg/m³)	Below \$3/day (%)	LAYS (years)	Aged 0–14 (%)	Children 0–14 (M)
Niger	SSA	96	27.5	65	60	2.7	46	12.9
Chad	SSA	92	27.1	43	40	2.8	46	9.7
Mali	SSA	91	28.7	36	36	2.6	46	11.5
Central African Republic	SSA	90	25.8	33	72	2.7	49	2.7
Burkina Faso	SSA	90	28.6	37	42	4.5	41	9.9
Nigeria	SSA	89	27.1	66	42	5.0	41	96.2
Mauritania	SSA	88	27.5	47	10	4.2	42	2.3
South Sudan	SSA	87	27.7	24	76	2.5	38	4.6
Yemen, Rep.	MENA-AP	87	25.8	47	33	4.2	41	17.1
Congo, Dem. Rep.	SSA	87	24.1	36	85	4.5	46	51.8
Benin	SSA	85	27.6	40	27	5.7	41	6.1
Senegal	SSA	85	28.7	42	18	4.8	38	7.1

Country	Region	Index	Mean temp. (°C)	PM2.5 (µg/m³)	Below \$3/day (%)	LAYS (years)	Aged 0–14 (%)	Children 0–14 (M)
Guinea-Bissau	SSA	84	27.5	32	40	—	38	0.9
Sudan	SSA	84	27.2	38	10	4.3	40	20.8
Gambia, The	SSA	83	27.8	38	22	5.4	40	1.1

SSA = Sub-Saharan Africa; MENA-AP = Middle East, North Africa, Afghanistan and Pakistan; LAYS = learning-adjusted years of schooling. Survey years differ by country; poverty and LAYS values are the most recent available, and Guinea-Bissau and Djibouti lack LAYS values.

11.3 Regional profiles

Table 11 aggregates the index by World Bank region with population weights. Sub-Saharan Africa scores highest, with the highest poverty (45.5 percent below \$3 a day), the lowest learning-adjusted schooling (4.8 years) and the largest child population of any region. South Asia has the highest air pollution (a population-weighted mean of 55 µg/m³) and a large child population, and its extreme-poverty rate at the \$3 line is low (2.9 percent), which is why the index understates its exposure: it is a region where the heat, the air and the scale of the school-age population are extreme, but where household buffers are probably somewhat stronger than in the Sahel. The Middle East, North Africa, Afghanistan and Pakistan group combines high pollution, high temperatures and, in several countries, conflict that the index does not measure.

Table 11. Trap Exposure Index by region (population-weighted)

Region	Countries	Children 0–14 (M)	Mean temp. (°C)	PM2.5 (µg/m³)	Below \$3/day (%)	LAYS (years)	Index
Sub-Saharan Africa	42	523	24.7	36	45.5	4.8	80
Middle East, North Africa, Afghanistan, Pakistan	21	261	21.1	46	11.5	6.1	66
South Asia	4	416	24.1	55	2.9	7.0	64
Latin America & Caribbean	21	145	22.2	18	4.4	8.1	48
East Asia & Pacific	16	410	13.2	28	1.4	9.1	35
Europe & Central Asia	44	157	8.3	14	0.5	10.4	23
North America	2	65	8.1	7	1.0	10.7	22

Regions follow the World Bank's current classification. Averages are population-weighted across countries included in the index (more than one million people, at least four of five components).

Table 12. Selected countries on the Trap Exposure Index

Country	Rank of 150	Index	Mean temp. (°C)	PM2.5 (µg/m³)	Below \$3/day (%)	LAYS (years)	Children 0–14 (M)
Niger	1	96	27.5	65	60	2.7	13
Nigeria	6	89	27.1	66	42	5.0	96
Congo, Dem. Rep.	10	87	24.1	36	85	4.5	52
Ethiopia	28	75	23.4	24	39	4.3	53
Pakistan	31	75	20.4	58	23	5.1	93

Country	Rank of 150	Index	Mean temp. (°C)	PM2.5 (µg/m³)	Below \$3/day (%)	LAYS (years)	Children 0–14 (M)
India	53	64	24.2	54	3	7.1	354
Bangladesh	35	73	25.4	69	6	6.0	49
Yemen, Rep.	9	87	25.8	47	33	4.2	17

Pakistan and Bangladesh, whose exposure to floods, cyclones and extreme heat is among the world's highest (Section 6), rank in the middle of the index because it does not measure these hazards.

The selected countries in Table 12 illustrate how the index reads. Niger ranks first, combining a mean temperature of 27.5 °C, extreme poverty of 60 percent, learning-adjusted schooling of 2.7 years and a population that is 46 percent children. Nigeria ranks sixth and holds about 96 million children under 15, which makes it the country where the most children live in conditions of high overlap. The Democratic Republic of the Congo combines low learning with the highest poverty share in the table. India ranks lower, at 53, because its extreme-poverty rate at the \$3 line is low, but it holds about 354 million children under 15 and is exposed to some of the highest heat and PM2.5 levels in the world, so the number of children affected is large even where the rate is lower.

11.4 What the index leaves out

- **Extreme heat and humidity.** Mean temperature is a coarse proxy for the number of days when learning and work are impaired. A country with a moderate mean can have severe heat peaks.
- **Floods, storms and drought.** Small island states, river deltas and coastal South Asia face high flood and storm risk that is not captured, and the index understates their exposure.
- **Conflict and displacement.** Several of the highest-scoring countries also suffer conflict, which compounds every channel.
- **Household buffers.** The index uses national poverty rates as a proxy for buffers. Within countries, rural, informal and female-headed households have much thinner buffers than the averages suggest.
- **Within-country variation.** National averages hide the extremes; the places with the worst overlap are often subnational.

Key point. The overlap of heat, poor air, poverty and a young population is greatest in a belt from the Sahel to Central Africa, but the largest absolute numbers of children exposed are in South Asia and Nigeria. Different parts of the map call for different policies: buffers in the Sahel, air and heat protection in South Asia.

12

SCENARIOS AND THRESHOLDS

12. Modelling the Trap

12.1 Purpose and structure

The empirical chain of this report ends in a quantity that no study has measured directly: how climate and pollution shocks, acting through households, change the distribution of effective schooling in a cohort. To explore it, we built a simple cohort model. The model follows a cohort of households through twelve school grades, from ages 6 to 17. In each year a household may be hit by an income shock, whose probability rises with global warming. The household first draws on its buffer, a stock of savings and assets expressed as a share of annual income. If the shock exceeds the buffer, the uncovered gap raises the probability that the child is withdrawn from school. A withdrawn child may return in a later year if the household recovers. A child who is in school gains a year of schooling, scaled by a learning quality factor that falls when classrooms are hot, when closures and absence rise, and when the parent's own learning was low. The outcome is learning-adjusted years of schooling by age 18, and a child with fewer than 3.5 effective years is classed as below the trap threshold.

The model is a stylized representation of a poor, credit-constrained, agrarian household and not of any particular country. Its baseline, a mean of 6.3 learning-adjusted years and about 10.5 enrolled years, is close to the lower-middle-income average in our country panel (6.5 learning-adjusted years and 11.0 expected years of schooling), and is deliberately above the low-income average of 4.3. Table 13 lists the parameters and their basis. Only two have a direct empirical anchor (the heat effect from Park et al. and the return to schooling from Psacharopoulos and Patrinos); the remainder are assumptions chosen to produce plausible baseline behavior, and their effects are explored in the sensitivity analysis.

Table 13. Cohort model: parameters and their basis

Parameter	Value	Basis
Households per scenario	60,000–100,000	Monte Carlo; fixed seeds
Grades	12 (ages 6–17)	Standard primary and secondary cycle
Shock probability today	0.20 per year	Assumption (grade D); range 0.15–0.25 tested
Added shock probability per °C	+0.10 per year	Assumption; consistent with rising frequency of heat and flood episodes; range 0.05–0.15 tested
Mean income loss in a shock	22% of annual income	Assumption; gamma-distributed; range 15–30% tested
Median household buffer	12% of annual income	Assumption; lognormal, rising with income; range 8–16% tested
Withdrawal response (ϕ)	2.2 per unit of uncovered loss	Assumption: each 10% of income uncovered raises withdrawal by 22 points; range 1.5–3.0 tested
Re-entry rate	0.30 per year	Assumption; range 0.20–0.40 tested

Parameter	Value	Basis
Learning quality	0.62 of benchmark	Calibrated so baseline learning-adjusted schooling is near the lower-middle-income average
Heat effect on learning	1% per °F, reduced by share cooled	Park et al. (2020) ; 15% of classrooms assumed cooled
Local warming over land	1.4 × global	Land warms faster than the global mean; range 1.2–1.6 tested
Closure days	4 per year plus 3 per °C	Assumption (grade D); informed by UNICEF’s 2024 snapshot
Pollution absence	3 days per year	Assumption within the range implied by absence studies; range 1–6 tested
Return to schooling	9% per year	Psacharopoulos and Patrinos (2018)
Intergenerational transmission	0.35	Assumption within the plausible range of schooling persistence
Trap threshold	< 3.5 learning-adjusted years	Defined for this report as roughly half the baseline cohort mean

The model has no climate-specific calibration. It is a laboratory for the mechanisms of Sections 4 to 10. The equations are in Appendix A.

12.2 Results: effective schooling falls faster than enrolment

Figure 15 shows the main results. In today’s climate, 6 percent of children fall below the trap threshold. With 0.5 °C of additional warming, the share is 9 percent; with 1.0 °C, 18 percent; and with 2.0 °C, 30 percent. The cumulative distribution in panel (a) shows that warming shifts the whole distribution to the left and thickens its lower tail. Mean learning-adjusted schooling falls from 6.3 to 4.5 years at +2.0 °C, and the average number of years a child spends out of school after first enrolling rises from 1.5 to 3.7. The response is nonlinear: the share trapped triples between today’s climate and +1.0 °C (from 6 to 18 percent), and rises by a further 12 points by +2.0 °C. These scenarios are modest relative to some projections of end-of-century warming.

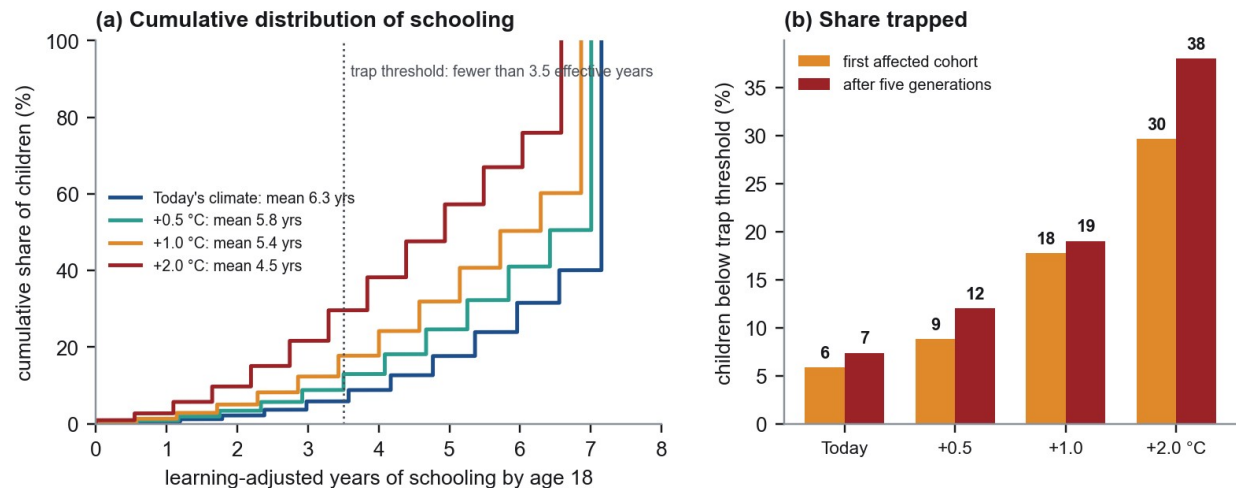


Figure 15. Original calculation: the cohort model of schooling under compounding shocks. (a) Cumulative distribution of learning-adjusted years of schooling at age 18 in today's climate and with +0.5, +1.0 and +2.0 °C of further global warming; the dotted line marks the trap threshold of 3.5 effective years. (b) Share of children below the threshold in the first cohort exposed and after five generations with intergenerational transmission.

Source: H Heuristics cohort model (Appendix A); 100,000 households per scenario. Illustrative; parameters are assumptions as listed in Table 13.

12.3 Thresholds: the nonlinear map

The sharpest feature of the model is its threshold behavior. Figure 16 maps the share of children below the trap threshold across a grid of shock probability and median household buffer. Over the grid the share ranges from near zero to 61 percent. For households with large buffers, even a high shock frequency leaves most children in school, because the buffer absorbs the loss. For households with thin buffers, the trap share climbs steeply once the annual shock probability passes about 0.3 to 0.4. The positions marked for today and the two warming scenarios show that the climate shift moves a typical thin-buffer household from a flat region of the map toward a steep one. This is the quantitative form of the UNICEF analyst's observation that families cope with one or two shocks but become severely strained after three or more.

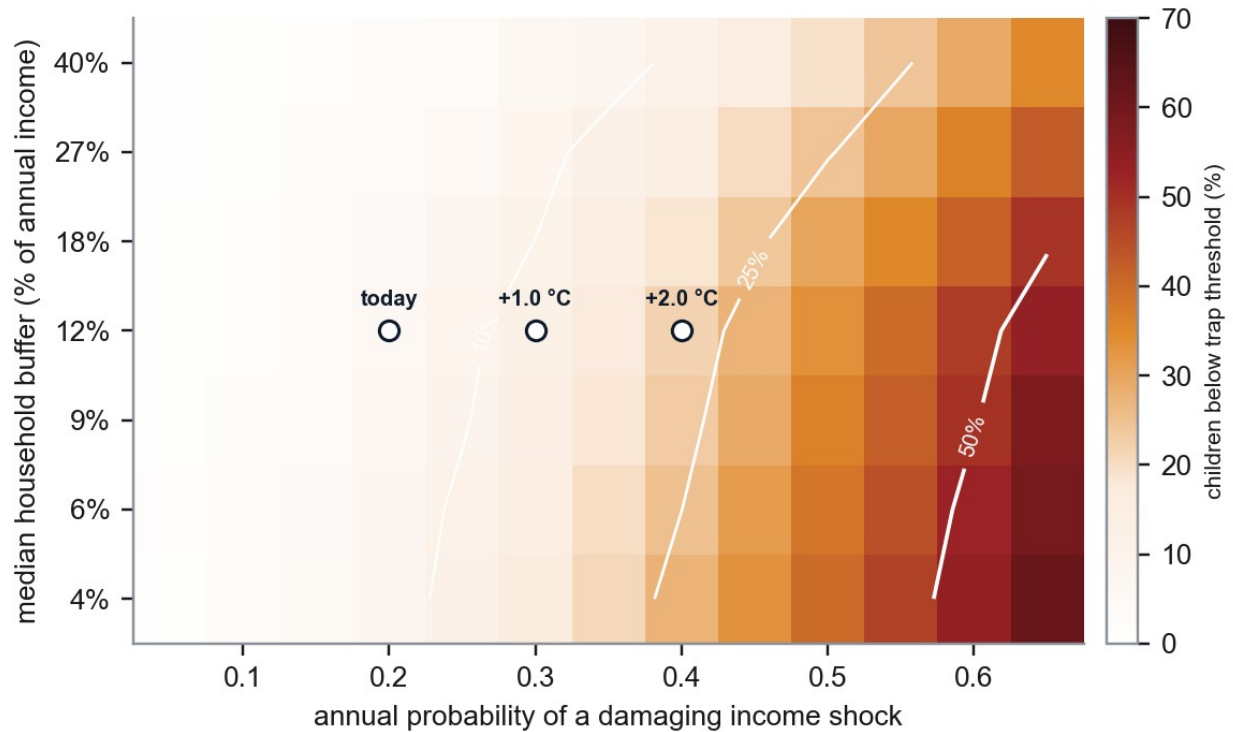


Figure 16. Threshold map. Share of children below the trap threshold by annual probability of a damaging income shock (horizontal) and median household buffer as a share of annual income (vertical). White contours mark 10, 25 and 50 percent; the circles mark the model's central household in today's climate and with +1.0 and +2.0 °C of warming.

Source: H Heuristics cohort model; 15,000 households per grid cell; all other parameters at central values.

12.4 The intergenerational ratchet

The model's final mechanism links generations: a child's learning quality rises with her parent's learning-adjusted schooling. Figure 17 shows its effect. Without intergenerational transmission (dotted lines), the share trapped is the same in every generation, because each generation faces the same climate. With transmission, the share rises in the first two or three generations and then stabilizes at a higher level. At +2.0 °C the share trapped is 30 percent in the first cohort and 38 percent after five generations, against 30 percent without transmission; mean schooling falls to 4.0 years against 4.5. The ratchet is a modest amplification and not a runaway: in this model, a lasting loss is created by the climate and then carried forward by the family, but it stabilizes. A model with stronger transmission, for example through the early-life channels of Section 9, would show a larger ratchet.

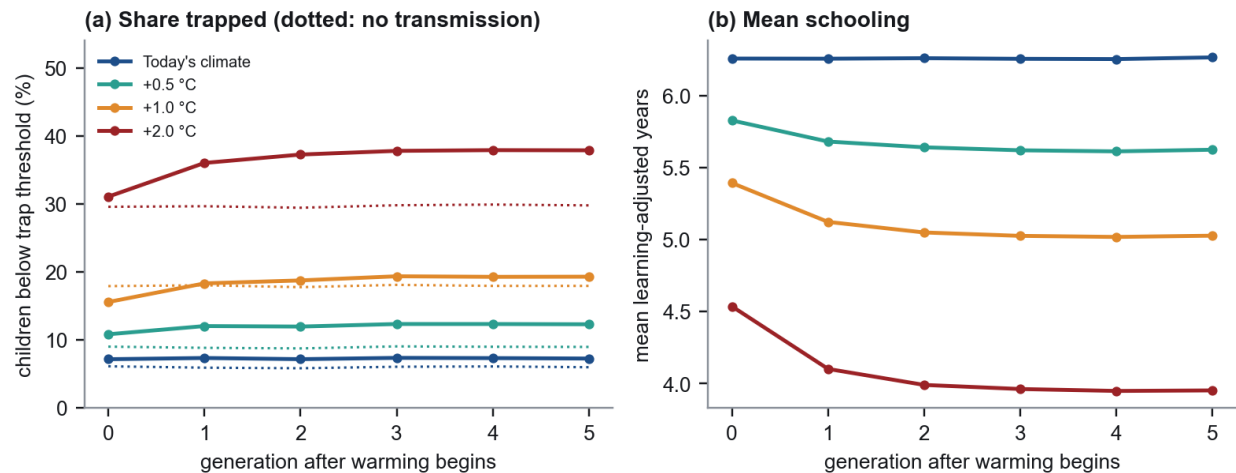


Figure 17. Intergenerational transmission. (a) Share of children below the trap threshold by generation after warming begins, with (solid) and without (dotted) transmission of learning quality from parent to child. (b) Mean learning-adjusted years by generation with transmission.

Source: H Heuristics cohort model; 60,000 lineages per scenario; transmission elasticity 0.35.

12.5 Sensitivity: what drives the result

Figure 18 varies ten parameters one at a time around the central case of +1.0 °C, where the share trapped is 18 percent. The parameters that matter most are those that govern the *household* response: the severity of shocks (a range of 15 to 30 percent of income changes the share trapped by between –8.0 and +8.2 percentage points), the rate at which withdrawn children re-enter school, the frequency of shocks and the strength of the withdrawal response. The parameters that govern the *classroom* have much smaller effects on the trap share: the share of classrooms cooled, pollution-related absence and climate closures change it by less than half a point, though they change mean learning-adjusted schooling by 0.02 to 0.1 years. In other words, in the model the trap is made by the household decision, and the classroom conditions change how much each child learns but do not decide which children leave.

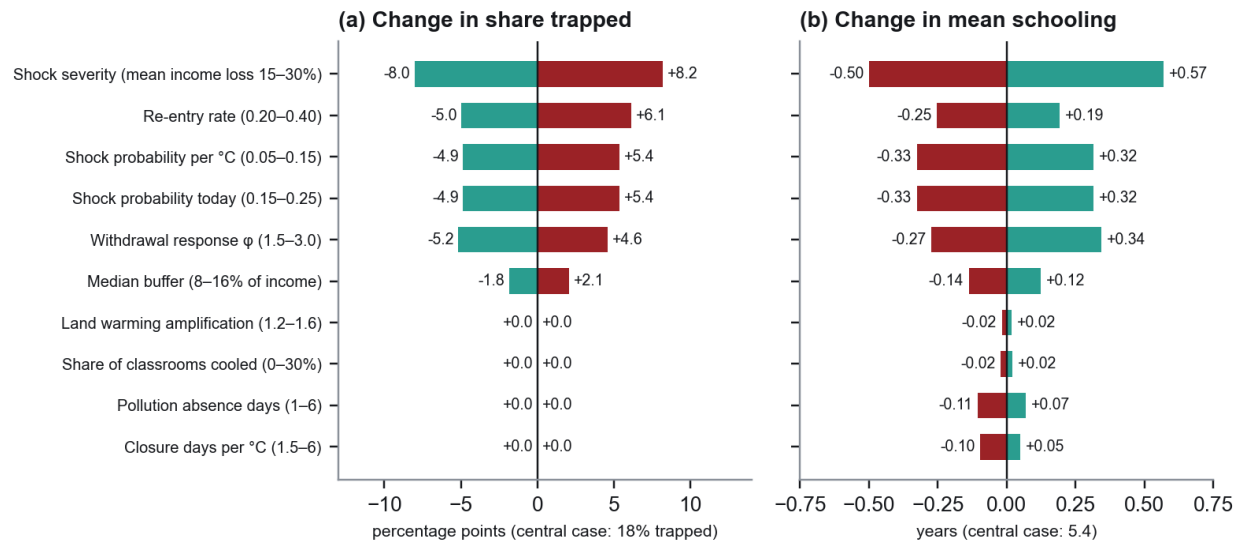


Figure 18. Sensitivity analysis around the central case. All parameters are varied one at a time with global warming held at +1.0 °C. (a) Change in the share of children below the trap threshold, in percentage points, when each parameter is moved to the low and high ends of its range (teal and red show the direction of the change). (b) Change in mean learning-adjusted years. Parameters are ranked by their effect on the trap share.

Source: H Heuristics cohort model; 60,000 households per run; ranges in Table 13.

12.6 Limitations

- **The sign of the child-labor response.** The model assumes the liquidity channel: income loss raises withdrawal. As Section 8 shows, shocks that raise children's wages can have the opposite effect. The results hold for income-reducing shocks such as crop failure and illness, not for wage booms.
- **Parameters are assumptions.** Most are plausible and tested over a range, but none is estimated from data on climate shocks and schooling in a specific country. The model identifies mechanisms and relative magnitudes; it should not be used to forecast.
- **Independence of shocks.** Shocks are independent across years and households. In reality, climate shocks are spatially correlated, which undermines informal risk-sharing among neighbors and would make the trap worse.
- **No adaptation or migration.** The model does not allow households to change crops, migrate or invest in cooling in response to the shocks, nor governments to build schools and safety nets.
- **Pollution and health are thin.** Pollution enters only as absence days. Cognitive, prenatal and lead effects, and the effect of illness on household income, are not modelled, so the contribution of pollution is a lower bound.
- **Mincer extrapolation.** The 9 percent return is applied to learning-adjusted years and assumed to hold in the shifted distribution.

Key point. The cohort model says that in a world of rising shocks the trap is determined by the buffer. Cooling schools and cleaning the air improve the quality of each child's year, but keeping the child in the school is a household income problem.

13

POLICY PORTFOLIO

13. Breaking the Trap

13.1 Three lines of defense and one root cause

The system view of Section 10 and the model of Section 12 point to a portfolio with three lines of defense and one action at the root. The first line protects the **household**, so that a shock does not turn into a decision to withdraw a child. The second protects the **classroom**, so that a child who is in school learns as much as possible. The third protects **continuity**, so that closures, damage and absence are short and followed by catch-up. The root action is **mitigation**: cutting emissions and local pollution lowers the hazard side of every loop at once, and nothing in the first three lines substitutes for it. Figure 19 sets out a sequence of actions across three time horizons.

	NOW to 2028	2028 to 2035	2035 to 2050
Protect the household	<ul style="list-style-type: none"> • Adaptive cash transfers that pay out automatically after a heat, flood or drought trigger • Workfare and school-linked transfers for the poorest households • Index insurance and savings for smallholders 	<ul style="list-style-type: none"> • Shock-responsive social registries in all high-exposure countries • Child-labour monitoring linked to climate alerts 	<ul style="list-style-type: none"> • Social protection that covers the informal rural majority
Protect the classroom	<ul style="list-style-type: none"> • Heat protocols: shaded play, water, shifted hours, early closure rules • Passive cooling retrofits for the hottest schools • Clean cooking and clean fuels in feeder households 	<ul style="list-style-type: none"> • Solar-powered cooling and ventilation in schools • Air-quality alerts and indoor air filtration near smoke sources 	<ul style="list-style-type: none"> • Climate-resilient school design standards
Protect continuity	<ul style="list-style-type: none"> • Flexible calendars and hot-season break timing • Catch-up learning and structured pedagogy after closures • Data on every climate-related closure 	<ul style="list-style-type: none"> • Rebuild-to-resilient programmes for storm and flood damage • Learning-recovery funds that trigger with disaster declarations 	<ul style="list-style-type: none"> • Education-system continuity planning as a national standard

Figure 19. A portfolio for breaking the trap. Actions are grouped by line of defense and sequenced over three horizons. The first horizon contains measures that can be started with existing institutions; later horizons build the systems that make protection automatic.

Source: H Heuristics, drawing on the evidence in Sections 4 to 12.

13.2 The evidence for each line

Household protection. The evidence is strongest here. Workfare reduced the effect of heat on test scores in India ([Garg et al., 2020](#)). A small cash transfer cut paid child work by 78 percent among compliers in Ecuador ([Edmonds and Schady, 2012](#)). In Malawi, unconditional transfers to adolescent girls lowered pregnancy and marriage among those who left school, while conditional transfers kept more girls in school ([Baird et al., 2011](#)). The implication is that design matters: transfers should be timed to arrive when the shock occurs, and conditions should be set with attention to who they exclude.

Classroom protection. [Park et al. \(2020\)](#) found that school air conditioning largely offsets heat’s effect on learning, and the dose-response calculation of Section 4 shows that cooling 60 percent of classrooms rather than 15 percent cuts the cumulative loss of learning-days by more than half. In poor countries cooling should start with passive measures (shade, ventilation, roof color and insulation, timetable changes) and with power, which in many places will be solar. Clean air at school and at home, through clean cooking, filtration and alerts, protects attendance and cognition, though the evidence on its effect on learning in low-income countries is thin.

Continuity. The pandemic evidence of Section 6 shows that learning lost to closure is not automatically recovered and that income shocks drive permanent dropout ([Azevedo et al., 2021](#)). The structured-pedagogy evidence shows that catch-up can be delivered at scale: [Banerjee et al. \(2017\)](#) describe the integration of Teaching at the Right Level into Indian government schools. The missing element is a trigger that connects a disaster declaration to funded catch-up.

Education as adaptation. [Lutz et al. \(2014\)](#) argue that universal education is among the most effective forms of climate adaptation, because educated people are better able to prepare for and recover from hazards. If so, protecting schooling today is itself an investment in the capacity to bear the climate of the future, and the education budget belongs in the climate-adaptation conversation.

13.3 What the model says about the portfolio

Figure 20 compares four interventions at +1.0 °C of additional warming, where the share trapped after five generations is 19 percent with no new action, against 7 percent in today’s climate. Adaptive cash transfers, defined as a payment of 10 percent of annual income after a shock, reduce the share trapped to 7 percent, raise mean learning-adjusted schooling from 5.03 to 6.04 years, and raise the lifetime income index by 7.7 percent. Cooling 60 percent of classrooms, cutting pollution absence to one day, and halving climate closures, taken singly, each reduce the share trapped by about one point and add 0.1 to 0.2 learning-adjusted years. The four combined bring the share trapped to 6 percent and add about 1.5 learning-adjusted years, with a lifetime income gain of 11.4 percent.

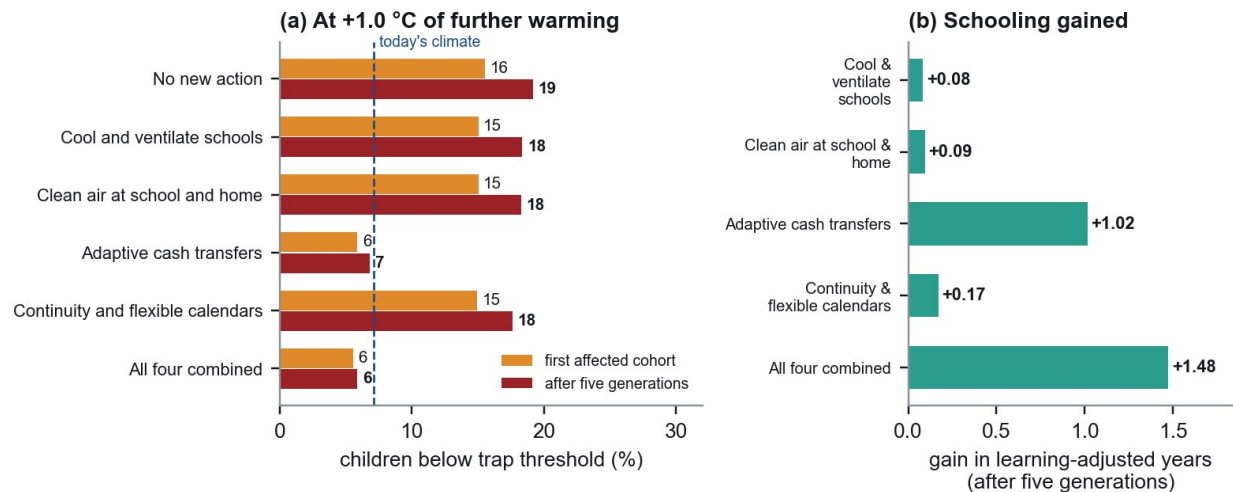


Figure 20. Original calculation: comparing four interventions under further warming. Global warming is held at +1.0 °C above the mid-2020s level. (a) Share of children below the trap threshold in the first cohort (orange) and after five generations (red) under no new action, four single interventions and all four combined; the dashed line marks the long-run share in today's climate. (b) Gain in mean learning-adjusted years after five generations relative to no new action.

Source: H Heuristics cohort model; 60,000 lineages per run. Cooling raises the classrooms cooled to 60%; clean air cuts pollution absence to 1 day; transfers pay 10% of income after a shock; continuity halves closure days.

Three cautions apply. First, the model captures the interventions' effects on schooling through learning rate, attendance and household income only; it omits the health, comfort and wellbeing benefits of cooling and clean air, which are important in themselves and which the evidence on cognition and absence suggests would also raise learning. Second, the strong showing of transfers rests on the model's assumption that the household income shock is the cause of withdrawal, which Section 8 shows is supported for income-reducing shocks but not uniformly. Third, the interventions are not rivals. In the model, the classroom measures change how much each child learns and the transfer changes who stays in school, and the combination is better than any single element.

13.4 A rough benefit–cost calculation

A payment of 10 percent of annual income to every household in a shock year, at a shock probability of 0.30, costs an expected 3 percent of annual household income per year. Over twelve school years, discounted at 5 percent, the expected cost is about 28 percent of one year's household income. The model's lifetime income gain of 7.7 percent, applied over a forty-year working life starting at age 18 and discounted at the same rate, is worth about 114 percent of a year's income at the start of schooling. The ratio is about 4 to 1 on income alone. The figure is stylized: it assumes transfers reach every household, ignores administration costs and leakage, and counts only private earnings. Targeting the poorest households would reduce the cost and raise the ratio, and counting health, intergenerational and adaptive benefits would raise it further. It is meant to show that the order of magnitude is favorable and not to be used as an appraisal.

Table 14. The policy portfolio: channels, evidence and modelled effect at +1.0 °C

Intervention	Channel addressed	Evidence base	Grade	Model effect: share trapped (long run); schooling gain
Adaptive cash transfers and workfare	Household buffer	Garg 2020 ; Edmonds and Schady 2012 ; Baird 2011	A/B	19% → 7%; +1.01 years
Cooling and ventilating schools	Classroom (learning per day)	Park 2020	A	19% → 18%; +0.08 years
Clean air at school and home	Health, absence, cognition	Currie 2009 ; Ebenstein 2016	B	19% → 18%; +0.09 years (lower bound)
Continuity and structured catch-up	Disruption	Banerjee 2017 ; Azevedo 2021	B	19% → 18%; +0.17 years
All four combined	All	As above	–	19% → 6%; +1.47 years
Mitigation at source (+2.0 → +1.0 °C)	All hazards	WMO ; Section 3	A	38% → 19%
Education as adaptation	Long-run capacity	Lutz 2014	B	Not modelled

Model effects are for the first and fifth generations in the central stylized cohort and are illustrative. The mitigation row compares the long-run share trapped at +2.0 and +1.0 °C of additional warming.

The last row of Table 14 is the most significant. Holding additional warming to 1.0 °C instead of 2.0 °C reduces the long-run share of children trapped by about half, from 38 percent to 19 percent in the model, an effect larger than any single adaptation measure and comparable to the combined package. Adaptation protects against the harm; mitigation reduces the harm to be protected against, and the two should be pursued together. The H Heuristics study of [the heat trap](#) examines the demographic and survivability dimensions of the same exposure.

13.5 Targeting and equity

The trap falls unevenly, and the portfolio should be targeted accordingly. Rural and agrarian households carry the highest exposure and the thinnest buffers. Girls face a particular risk of early marriage after income shocks in some regions ([Corno et al., 2020](#)), and the design of transfers can either reduce or exacerbate this, as the Malawi results show. Children in informal and displaced settings are often outside the systems that deliver transfers and school services. And the children who work in hazardous agriculture need heat protection and removal from the worst forms of work, not only a transfer. Targeting by exposure, such as the hotspot analysis of Section 11, can be combined with targeting by household vulnerability so that the limited resources go first to the places where the overlap is greatest.

Key point. The most cost-effective protection of schooling in a warming world is to protect the household income that keeps the child in school, supported by cool, clean-air classrooms and by a plan for the days when schools close. And the most powerful lever overall is to limit the warming itself.

14

IMPLEMENTATION

14. Financing, Measurement and Governance

14.1 What is not measured cannot be managed

The sections above repeatedly ran into the same obstacle: the data needed to see the trap do not exist, or exist only in fragments. Climate-related school closures are not systematically recorded; UNICEF reconstructed its 2024 figure from official sources, UN reports and media, and the UK analysis in Section 6 notes that neither the government nor local councils publish official data on closures. Child-labor surveys are conducted infrequently, and the country data used in Section 8 date from 2000 to 2016. Classroom temperatures, school cooling status and air quality at schools are almost never monitored. Table 15 proposes a core set of indicators, which we call *Trap Watch*, that could be built from existing surveys and administrative systems at low cost.

Table 15. Trap Watch: a proposed core indicator set

Indicator	What it measures	Existing source	Main gap
Climate closure days per pupil	School days lost to heat, flood, storm, smoke or fire	UNICEF snapshot ; ministries	No systematic national reporting
Classroom heat exceedance	Days with indoor temperature above a heat-stress threshold	None at scale	No monitoring; low-cost loggers could fill it
School electricity and cooling	Share of schools with power and with cooling	UNESCO ; education management information systems	Cooling status rarely recorded
Air quality at schools	PM2.5 at or near schools	State of Global Air (national modelled)	No school-level data
Child blood lead	Share of children above 5 µg/dL	UNICEF and Pure Earth	Sparse surveys
Child labor in exposed districts	Prevalence by district and season	ILO ; household surveys	Infrequent; not linked to climate data
Post-shock dropout	Withdrawal in the year after a hazard	Administrative enrolment data	Rarely linked to shock events
Learning after disruption	Assessment results in affected areas	National and citizen-led assessments	No post-disaster protocol
Social protection coverage in exposed areas	Share of poorest households with shock-responsive cover	World Bank and ILO programme data	Coverage of informal rural workers
Education budget execution after disasters	Share of education spending protected in disaster years	Public finance data	No standard tracking

A proposed set for national and international monitoring; none is yet a standard indicator.

14.2 Financing

The financing logic follows from the cohort model. The expected annual cost of an adaptive transfer is small relative to the household's income because it is paid only after shocks, and the benefits accrue over a lifetime. The question is who pays and how the money arrives when it is needed. Four mechanisms stand out as a basis for work, each of which is a proposal and not a tested policy (grade D). The first is shock-responsive social protection, in which existing cash transfer and workfare programmes are designed to scale up automatically on a trigger such as a heat index, a rainfall threshold or a disaster declaration. The second is pre-arranged contingent finance, including parametric insurance and contingent credit lines, so that governments do not have to find money after a disaster. The third is an education-protection rule under which the education budget and a catch-up fund are ring-fenced in disaster years. The fourth is the use of adaptation and loss-and-damage funds for measures that protect schooling, such as school cooling and education-linked transfers, which are not always classified as adaptation. We have not found a reliable global tabulation of how much climate finance reaches education or how much education aid addresses climate risk, which is itself an indication of the gap.

14.3 Governance

Breaking the trap requires coordination among ministries that rarely work together: education, social protection, health, energy, environment and finance. The responsibilities are specific. Education ministries run heat and air-quality protocols, school design standards and catch-up programmes. Social protection ministries run registries and trigger-based payments. Energy ministries electrify schools and clean-cooking households. Health ministries address lead, nutrition and heat illness. Finance ministries hold contingent finance. Local authorities and school communities carry out the protocols, because the decision to close a school or shift its hours is made at school level, and they need clear guidance and permission.

We propose four national commitments as a basis for discussion, each measurable with the Trap Watch indicators. Every country should report climate-related school closures annually. Every school in a high-exposure district should have a heat and air-quality protocol and a plan for continuity. Every child in a high-exposure district whose household is in the poorest two quintiles should be covered by shock-responsive social protection. And every disaster declaration should trigger a funded catch-up plan for the affected students. These are not targets derived from the evidence; they are proposals consistent with it.

14.4 A research agenda

1. Estimate the effect of heat on learning and attendance in low-income, un-cooled schools, especially in Sub-Saharan Africa.
2. Trace heat, drought and flood shocks to child labor and dropout in low-income settings, separating income and wage effects.
3. Measure the joint effect of heat and particulate or smoke exposure on cognition and attendance, and quantify the displacement of education spending after disasters (loop R4).
4. Evaluate trigger-based transfers and catch-up funds at scale, with outcomes in schooling and learning, and test a registry of climate-related school closures in planning.

5. Study lead exposure in school electrification and cooling programmes, and estimate intergenerational transmission in climate-exposed households.

15

CONCLUSION

15. Conclusion

15.1 What the evidence supports

The central claim of this report is that heat, polluted air and climate disasters form a system that works against children’s schooling, and that the system is strongest where households have the thinnest buffers. The evidence supports it in parts. It is strong that heat lowers learning and that air pollution, lead and early-life heat lower cognition and later outcomes (Sections 4 and 5). It is strong that climate hazards now disrupt schooling for hundreds of millions of students, mainly in poorer countries, and that disruption has lasting costs when it is combined with an income shock (Section 6). It is strong that cash transfers and workfare protect schooling and reduce child labor (Section 7). It is thinner on the specific link between heat and child labor in low-income countries (Section 8), and thinnest on the joint effects of heat, smoke and poverty acting on the same child. The cohort model of Section 12 shows that if the household channel operates as the evidence on income shocks suggests, the effect of warming on the share of children who accumulate too little schooling is large and nonlinear, and that it is carried to the next generation.

Five propositions were stated in Section 1. P1, that heat and pollution lower learning, holds (grade A/B). P2, that climate hazards are a major and growing cause of school disruption, concentrated in poorer regions, holds (B). P3, that shocks raise child labor and withdrawal where households lack buffers, holds for income-reducing shocks and is uncertain for heat in particular (B/C). P4, that lost schooling is persistent and intergenerational, holds (A/B). P5, that protecting household income is the most powerful single lever, is supported by the model and by the evidence on transfers but depends on assumptions the model cannot test (C).

15.2 Four things to do now

- 1. Protect household income when shocks hit.** Make cash transfers and workfare shock-responsive, with triggers tied to heat, rainfall and disaster declarations, and prioritize the 30 or so countries where the overlap of heat, poor air, poverty and young populations is greatest.
- 2. Make classrooms safe to learn in.** Adopt heat and air-quality protocols everywhere, start with passive cooling and ventilation, and electrify and cool schools with solar power while managing battery lead.
- 3. Plan for the days when schools close.** Fund catch-up learning automatically after disasters, adopt flexible calendars, and record every climate closure.
- 4. Cut the hazard at its source.** Limit warming and local air pollution. In the cohort model, holding additional warming to 1.0 °C instead of 2.0 °C roughly halves the long-run share of children below the trap threshold.

15.3 The larger point

The polycrisis is usually described in terms of systems: energy, food, finance, ecosystems and governance. Its human meaning is found in the lives of children. A child who learns less, leaves school earlier or begins work sooner is the point at which climate change, pollution and poverty are converted into a permanent loss. The same conversion works in reverse. A child who stays in school, learns in a cool classroom, breathes clean air and grows up in a household protected from the next shock becomes an adult who can adapt, earn and protect her own children. The Climate–Pollution–Education Trap is not a prediction. It is a description of what happens when the buffers fail, and an argument for rebuilding them before the next hot season begins.

Final verdict. The decisive question for the human capital of the twenty-first century is not whether the climate will warm, but whether the households and schools that stand between a hazard and a child will be protected in time. That is a choice, and it is cheaper to make before the shocks than after them.

Appendix A. Methods and Model Specification

A.1 Cohort model

The model simulates N households (60,000 to 100,000 per scenario), each with one child who passes through $G = 12$ grades. Let ΔT be additional global warming above the mid-2020s level (about 1.4°C above 1850–1900), and let local school-year warming be $\Delta T_{\text{loc}} = 1.4 \Delta T$. The annual probability of a damaging income shock is

$$\lambda(\Delta T) = \lambda_0 + \lambda_1 \Delta T, \quad \lambda_0 = 0.20, \quad \lambda_1 = 0.10 \text{ per } ^\circ\text{C} \quad (\text{A1})$$

In each school year a household draws an income shock S_t , equal to zero with probability $1 - \lambda$ and otherwise gamma-distributed with shape 2 and mean 0.22 of annual income, truncated at 1. The household has a buffer B_t , initially lognormal, $B_0 = b y^\gamma e^{\sigma z}$, where $b = 0.12$ is the median buffer as a share of annual income, y is the household's relative income, $\gamma = 0.6$, $\sigma = 0.9$ and z is standard normal. The uncovered gap and the update are

$$G_t = \max(S_t - B_t, 0), \quad B_{t+1} = \max(B_t - S_t, 0) + (\rho/2) \cdot 1[\text{no shock}], \quad \rho = 0.05 \quad (\text{A2})$$

A child enrolled in year t is withdrawn with probability $\min(1, \phi G_t)$, with $\phi = 2.2$. A withdrawn child re-enters with probability 0.30 in any year in which the household's gap is zero. When transfers are active, S_t is reduced by the transfer amount in shock years before the gap is calculated. Learning per enrolled year is

$$e = q \cdot (1 - d/180) \cdot (1 - h) \cdot m, \quad d = d_0 + d_1 \Delta T + a(1 + 0.1 \Delta T) \quad (\text{A3})$$

where $q = 0.62$ is baseline learning quality, d is the number of school days lost per year to closures ($d_0 = 4$, $d_1 = 3$ per $^\circ\text{C}$) and pollution-related absence ($a = 3$ days), $h = 0.01 \times 1.8 \times \Delta T_{\text{loc}} \times (1 - c)$ is the heat penalty from Park et al. (2020) converted from $^\circ\text{F}$ to $^\circ\text{C}$, with c the share of classrooms effectively cooled (0.15 in the central case), and $m = \text{clip}(1 + \theta(L_p/L_{\text{ref}} - 1), 0.4, 1.6)$ transmits learning quality from the parent's learning-adjusted years L_p ($\theta = 0.35$, $L_{\text{ref}} = 6.26$). Learning-adjusted years by age 18 are $L = e \times$ (years enrolled). A child with $L < 3.5$ is below the trap threshold. The lifetime income index is the cohort mean of

$$I = \exp(0.09 L) \quad (\text{A4})$$

For the intergenerational runs, the first generation's parents are drawn from a baseline cohort in today's climate with $\theta = 0$. In each later generation the household's relative income is $\exp(0.09 L_p + 0.35 \epsilon)$, with ϵ standard normal, and the child's learning quality follows equation A3. Each lineage keeps its index across generations. The threshold map (Figure 16) varies λ_0 and b over a grid with 15,000 households per cell. The sensitivity analysis (Figure 18) varies one parameter at a time at $\Delta T = 1.0$ with 60,000 households per run and a fixed random seed. Results are deterministic given the seeds; the code is available from H Heuristics on request.

A.2 Trap Exposure Index

The index uses five components for countries with more than one million people: mean annual 2 m temperature 1991–2020 (ERA5 via Our World in Data); population-weighted PM2.5 (World Bank EN.ATM.PM25.MC.M3, 2023); share of the population below \$3 a day (SI.POV.DDAY, latest year from 2000); learning-adjusted years of schooling (HD.HCI.LAYS, latest year); and the share of the population aged 0–14 (SP.POP.0014.TO.ZS). Each is converted to a percentile rank across the sample (inverted for learning-adjusted years), and the index is the mean of available ranks multiplied by 100. Countries with fewer than four of five components are excluded. The number of children under 15 is population (SP.POP.TOTL) times the child share. Robustness was tested by dropping each component (minimum Spearman correlation with the baseline 0.98) and by replacing mean temperature with warming since 1951–1980 (correlation 0.92).

A.3 Data sources and vintages

Table 16. Data sources used in the original analysis

Data	Source	Vintage
Country indicators (poverty, PM2.5, schooling, population, power, cooking, child employment)	World Bank World Development Indicators via the API	Downloaded October 2026; latest year per country
Country temperature	ERA5 monthly 2 m temperature via Our World in Data , Copernicus Climate Change Service	1940–2026 (2026 partial)
Global temperature anomaly	Our World in Data extract of HadCRUT5	1850–2026
Population by age and income group	UN World Population Prospects 2024 via Our World in Data	1950–2100, medium variant
Child labor, school disruption, exposure counts	ILO and UNICEF ; UNICEF ; UNESCO	2020–2026 publications
Air-pollution deaths	Health Effects Institute State of Global Air	2025 edition, 2023 data

Country-year values differ by indicator. Child-employment data are the oldest, with survey years from 2000 to 2016.

Appendix B. Notes on Evidence, Limitations and Interpretation

- **Peer-reviewed sources** are cited by DOI and were checked against the registered titles in the Crossref registry. Where a first-named paper did not resolve, it was replaced or removed. A widely cited 2024 estimate of the economic commitment of climate change was not used because the journal retracted it in December 2025.
- **News and agency sources** are cited for events of 2024 to 2026 for which no peer-reviewed analysis exists yet. They are indicative. The UK and Indian heat and school-closure figures in particular are news-based estimates, and the UNICEF 2026 figures were read from press releases and coverage of the launch rather than from the full report.
- **Cross-country correlations** are descriptive. They cannot separate the effects of heat and pollution from those of income, agrarian structure, institutions and conflict.
- **The cohort model** is illustrative. Its assumptions are stated in Section 12, and the results that depend on them are the qualitative ones: the household decision is the pivot, the response is nonlinear, and the effect carries across generations.
- **The coupling matrix** is an expert judgement derived from the literature and should be treated as a hypothesis for testing.
- **Dates.** This report reflects sources available to October 2026. Several figures, including the UNICEF 2026 exposure estimates and the 2026 school closures, are recent and may be revised.

References

The list below gives full details for every peer-reviewed source cited by DOI in the text, generated from the DOI registry metadata and checked against registered titles. Reports and data from international agencies, including the World Bank, UNICEF, UNESCO, the ILO, the WMO, the WHO, the Health Effects Institute and the UN Population Division, and news sources for the 2024 to 2026 events, are linked in the text where they are used and are not repeated here. The *Lancet Countdown on health and climate change* (2025) is listed with the peer-reviewed literature.

H Heuristics sources

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