INTERNATIONAL
FOOD POLICY
RESEARCH
INSTITUTE
IFPRI

CGIAR
POLICY
INNOVATIONS

CGIAR
BETTER DIETS
AND NUTRITION

CGIAR
GENDER EQUALITY
AND INCLUSION

CGIAR
CLIMATE
ACTION

IFPRI Discussion Paper 02401

December 2025

Threshold Effects of Extreme Heat on Schooling and Child Labor in Rural Bangladesh

M. Mehrab Bakhtiar
Ridwan Karim

Poverty, Gender, and Inclusion Unit

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), a CGIAR Research Center established in 1975, provides research-based policy solutions to sustainably reduce poverty and end hunger and malnutrition. IFPRI's strategic research aims to foster a climate-resilient and sustainable food supply; promote healthy diets and nutrition for all; build inclusive and efficient markets, trade systems, and food industries; transform agricultural and rural economies; and strengthen institutions and governance. Gender is integrated in all the Institute's work. Partnerships, communications, capacity strengthening, and data and knowledge management are essential components to translate IFPRI's research from action to impact. The Institute's regional and country programs play a critical role in responding to demand for food policy research and in delivering holistic support for country-led development. IFPRI collaborates with partners around the world.

AUTHORS

M. Mehrab Bakhtiar (m.bakhtiar@cgiar.org) is a Research Fellow in the Poverty, Gender, and Inclusion (PGI) Unit of the International Food Policy Research Institute (IFPRI), Washington, DC.

Ridwan Karim (rkarim@wlu.ca) is an Associate Professor in the Department of Economics at Wilfrid Laurier University, Waterloo, Canada.

Notices

[1] IFPRI Discussion Papers contain preliminary material and research results and are circulated in order to stimulate discussion and critical comment. They have not been subject to a formal external review via IFPRI's Publications Review Committee. Any opinions stated herein are those of the author(s) and are not necessarily representative of or endorsed by IFPRI.

[2] The boundaries and names shown and the designations used on the map(s) herein do not imply official endorsement or acceptance by the International Food Policy Research Institute (IFPRI) or its partners and contributors.

[3] Copyright remains with the authors. The authors are free to proceed, without further IFPRI permission, to publish this paper, or any revised version of it, in outlets such as journals, books, and other publications.

Abstract

Identifying threshold effects of extreme heat is key to understanding the true scale of climate-related risks to human capital development. This paper investigates how extreme heat shapes adolescent schooling and labor outcomes in rural Bangladesh, combining household sur-vey data on adolescents with high-resolution temperature records to estimate the effects of prior-year, cumulative, and early-life heat exposure. We identify a precise temperature threshold at 36°C, above which each additional day reduces school attendance by 3.1 percentage points and increases child labor by 2.5 percentage points. Below this threshold, moderate heat (30-36°C) shows minimal single-year effects, though cumulative exposure over three years reveals significant negative impacts, indicating limited household adaptation. Effects are disproportionately concentrated among girls, who shift primarily toward household work rather than wage labor. Three interconnected channels drive these effects: heat-induced income shocks (11% reduction in household income), increased domestic labor demands from heat-related illness, and restrictive gender norms that amplify these impacts by magnifying girls' household responsibilities. Extending the analysis to early-life conditions, exposure during the first 1,000 days also reduces adolescent schooling probability by 3.4-3.8 percentage points, with strongest effects at ages one and two. Boys show slightly larger early-life effects, contrasting with girls' greater vulnerability to contemporaneous exposure, suggesting distinct mechanisms operating through biological development versus gendered household labor allocation. The findings point to both immediate income-mediated responses and long-term developmental pathways, with implications for temperature-triggered social protection, school infrastructure investments, and early-life health interventions.

Keywords: Extreme heat, threshold effects, climate change, adolescent schooling, child labor, Bangladesh

Acknowledgments

We thank Wahid Quabili and seminar and conference participants at the Dhaka Winter Conference in Economics 2025, BRAC University, and the University of Dhaka for their valuable feedback. We would also like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund: https://www.cgiar.org/funders/.

1 Introduction

Understanding how extreme heat shapes human capital formation is critical, particularly in low- and middle-income countries where both schooling and labor outcomes are central to long-run development. Rising temperatures may disrupt learning by reducing children's ability to attend school regularly (Graff Zivin et al. (2018); Goodman et al. (2018)), while at the same time pushing households to reallocate children's time toward labor as a coping strategy (Fruttero et al. (2024); Beegle et al. (2009)). Moreover, the impacts of heat are rarely linear (Deschênes and Greenstone (2011); Burgess et al. (2017)). Threshold effects may emerge, where schooling and labor responses change sharply once temperatures surpass critical points. Identifying and quantifying these thresholds is therefore essential for understanding the true scale of climate risks and for designing effective policy responses.

In this paper, we investigate the impact of extreme heat on adolescent schooling, labor outcomes, and household economic conditions in rural Bangladesh. We combine analyses of short-term, prior-year heat exposure with cumulative and early-life exposure of how high temperatures affect both immediate and longer-term socioeconomic outcomes. The study leverages rich survey data on adolescents (aged 12–16 years), household income, labor allocation, and detailed temperature records, applying both single-threshold and binned empirical strategies to identify the effects of extreme heat.

We find that negative schooling effects consistently emerge above the 36°C threshold and intensify as temperatures rise. Specifically, for all adolescents, each additional day above 36°C in the last year reduces the likelihood that studying is reported as the primary activity and decreases current school attendance, while increasing the likelihood that working is reported as the primary activity and raising dropout rates. These effects are more pronounced for girls, indicating that prior-year heat disproportionately reduces girls' schooling. Boys show similar point estimates, but with greater imprecision and generally non-significant effects. This pattern aligns with broader socioeconomic consequences. Extreme heat above 36°C in the prior year reduces annual household income. Moderate heat (30–36°C) does not produce statistically significant reductions in income, mirroring the non-significant schooling impacts at these temperatures. These results suggest that heat-induced income reductions could serve as a key mechanism driving the loss of schooling, particularly among girls.

We then explore the effects of prior-year heat on labor outcomes, distinguishing between different types of work: paid work, household work, family enterprise work, and farm work. The findings indicate that extreme heat significantly increases the probability of household work, particularly for girls, while effects on boys are smaller. Positive effects on reporting working as the primary activity mirror the reductions in schooling. Other types of work, including family enterprise work and farm work, do not show significant changes. The results also align with self-reported reasons for dropping out of school. For extreme heat, girls are more likely to cite household work and cost-related reasons, while boys show less consistent patterns. These results highlight that reductions in schooling are accompanied by a shift toward household labor.

After establishing the main effects, we examine the underlying mechanisms and moderators. Two interconnected channels directly reduce children's schooling: reduced household income and increased domestic labor demands. Restrictive gender norms moderate these effects, determining which children bear the burden of adjustment. Heat shocks suppress income by lowering labor productivity and increasing illness, tightening liquidity constraints. They also raise the need for household work, prompting families to shift children's time away from school. These pressures are magnified in households with more restrictive views of women's roles, where girls are expected to absorb a larger share of the additional domestic burden. These channels contribute to sizable declines in children's educational investment during periods of extreme heat.

To capture potential household adaptation and lagged effects, we also explore the impacts of cumulative heat exposure over three prior years. The cumulative impacts of extreme heat are generally larger than the effects of the prior year alone, confirming that the consequences of extreme heat persist and households adapt minimally across years. Interestingly, the impacts of cumulative exposure to moderate heat becomes significant and negative in some specifications, suggesting that the initial single-year results may have understated the broader impact of moderate heat on schooling.

Extending the analysis to early-life exposure, we examine whether temperature during the first 1,000 days (in utero through age two) has persistent consequences for schooling and labor outcomes in adolescence. This approach draws on the well-established first 1,000 days hypothesis, which emphasizes the critical role of in utero and early childhood conditions in shaping human capital formation (Heckman (2006); Almond and Currie (2011)). In the Bangladeshi context, Raza et al. (2025) show that extreme heat exposure in early life contributes to childhood stunting, motivating a closer look at adolescent outcomes.

Using date of birth information, we construct temperature thresholds for each individual's first 1,000 days. Mirroring the threshold identified for prior heat exposure, we find that negative effects on schooling emerge from 36°C onwards, with heat exposure at age one consistently showing the strongest negative effects on schooling outcomes. Specifically, each additional day above 36°C in the first 1,000 days lower the probability of reporting being a student as a primary activity in adolescence. Similarly, the probability of reporting working as the primary activity increases from 36°C onwards. The effects on school attendance and dropout mirror the patterns for primary activity. These findings emphasize why extreme heat during early life is consequential: larger temperature exceedances are associated with more severe deficits in schooling-related outcomes. we do not find significant gender differences for the impacts of early life heat exposure. One possible explanation is that early-life exposure operates through a distinct set of mechanisms - such as effects on physical growth, cognitive development, and early health shocks - that may weigh more heavily on boys' schooling trajectories, consistent with evidence of greater male vulnerability to early-life environmental stressors. In contrast, prior-year exposure reflects short-run mechanisms like heightened household labor needs, caregiving responsibilities, and gendered opportunity costs, which tend to constrain girls' schooling more during adolescence.

Across all analyses, the evidence points to two complementary mechanisms. First, prior-year and cumulative heat reduce household income, which in turn likely induces shifts in adolescent time allocation away from schooling toward work. Second, early-life heat exposure appears to affect human capital formation, consistent with the first 1,000 days hypothesis. Restrictive gender norms act as a critical moderator, amplifying heat's negative effects on girls' schooling by determining how household labor burdens are allocated during climate shocks. Together, these findings suggest both immediate income-mediated responses and long-term developmental pathways through which heat affects schooling and labor outcomes. A consistent finding throughout the paper is that girls' schooling outcomes are more sensitive to both prior-year and cumulative heat exposure, while boys show less consistent or smaller effects. For early-life heat exposure, however, boys' schooling outcomes are sometimes slightly more affected than girls', though the patterns are generally weaker than the prior-year effects.

Identifying threshold effects of extreme heat is crucial for understanding its impact on schooling and child labor because the relationship between temperature and these outcomes is rarely linear. Mild or moderate heat may have little to no effect on attendance or work patterns, but once a critical threshold is crossed, the physiological strain, reduced productivity, and competing household demands triggered by extreme heat can cause sharp declines in school participation and shifts toward child labor. Pinpointing these thresholds helps reveal when heat exposure becomes most harmful, enabling policymakers to design targeted interventions such as heat warnings, adjusted school schedules, or social protection measures that activate during the most damaging temperature ranges. Without identifying the exact points at which extreme heat starts to meaningfully disrupt children's education and labor allocation, interventions risk being either too late or unnecessarily costly, and the true scale of climate-related risks to human capital development may remain hidden.

This paper contributes to several intersecting strands of literature. First, it adds to the growing literature on climate shocks and child development, which documents how extreme heat, rainfall, and other weather events affect schooling, labor supply, and health outcomes. Prior studies have shown that high temperatures can reduce cognitive performance and school attendance in the short term (Graff Zivin et al. (2018); Goodman et al. (2018)), and can increase labor supply in response to income shocks (Deryugina and Hsiang (2017)). This paper extends that work by combining short-term and cumulative exposure measures, showing that heat affects both schooling and labor allocation for adolescents in rural Bangladesh, with effects concentrated among girls.

Second, the paper contributes to the literature on child labor and schooling trade-offs. Previous research has documented that children often respond to household income shocks by shifting time away from school toward work (Fruttero et al. (2024); Beegle et al. (2009)). By linking temperature shocks to household labor allocation, this study shows that heat not only reduces school participation but also shapes the type of work adolescents undertake, highlighting the broader economic consequences of environmental stressors.

Third, the study engages with the early-life origins of human capital and the first 1,000 days hypothesis, which emphasizes the critical role of in utero and early childhood conditions in shaping long-term outcomes (Heckman (2006); Almond and Currie (2011)). While much of this literature focuses on nutrition and disease exposure, this paper demonstrates that early-life heat exposure has persistent consequences for schooling and labor outcomes in adolescence, complementing recent evidence on heat-induced stunting in Bangladesh (Raza et al. (2025)). Finally, methodologically, the paper contributes by combining single-threshold and binned approaches to estimate both short-term and cumulative heat effects, allowing for more precise estimation of nonlinearities and heterogeneous effects by gender and type of activity. This approach helps clarify the pathways through which heat impacts both child development and household economics, offering new insights into the long-term socioeconomic costs of climate change in low-income contexts. Overall, the findings bridge the literatures on climate vulnerability, human capital formation, and child labor, emphasizing the gendered and persistent nature of heat impacts on adolescent outcomes.

The rest of the paper is structured as follows. In Section 2, we describe the data sources. Section 3 describes the identification strategy; Section 4 presents the results and their interpretation; and Section 5 concludes.

2 Data

2.1 Schooling and labor data

This paper investigates the impact of extreme heat on adolescent schooling, labor outcomes, and household economic conditions in rural Bangladesh. We define adolescents as individuals aged 12-16 years throughout this analysis. We use data from the Bangladesh Integrated Household Survey (BIHS), a nationally representative panel survey of rural households conducted by the International Food Policy Research Institute (IFPRI). The survey provides detailed household and individual-level information on education, labor, health, and demographics. This survey is merged with high-resolution daily weather data to capture exposure to extreme temperatures during critical periods of child development and adolescence. The combined dataset enables us to track how early life and contemporaneous exposure to heat shocks influence educational outcomes, including school attendance, primary activities, and dropout behavior. In addition, the richness of the survey allows us to examine heterogeneous effects by gender and link these outcomes to labor participation.

Table 1 presents summary statistics for key variables. The average age in the sample is 13.9 years, with similar ages for girls and boys. While most adolescents are primarily students (81%) and currently attending school (82%), about 16% have dropped out. Work is also a significant part of adolescent life: 18% report that their main activity is work, with 10% engaged in paid labor, 16% working in family enterprises, 4% in household work, and 2% on farms.

Gender differences are pronounced and reflect the interaction of schooling patterns, labor demand, and social norms. Girls are more likely than boys to be primarily students (86% vs. 77%) and to be currently attending school (87% vs. 77%), and they are less likely to have dropped out (12% vs. 19%). Boys, in contrast, are more often engaged in paid work (16% vs. 3%) and farm work (3% vs. 0.2%), reflecting their greater participation in market-oriented labor. Girls' work is more likely to take place within the household (8% vs. 0.4%), consistent with gendered divisions of labor in rural settings. These patterns suggest that boys may face stronger pull factors into wage or farm work, while girls face both school and domestic work demands.

2.2 Weather data

We use temperature data from the CPC Global Unified Temperature dataset, provided by the National Oceanic and Atmospheric Administration (NOAA) Physical Sciences Laboratory (PSL)[1]. This dataset offers daily global surface air temperature observations dating back to 1979. It is derived from Global Telecommunication System (GTS) data and is gridded at a spatial resolution of 0.5° × 0.5° (latitude × longitude). The dataset includes both daily minimum and maximum temperatures.

---

[1] Data available at: https://psl.noaa.gov

To estimate local-level temperature conditions, we calculate sub-district-level daily minimum and maximum temperatures by overlaying sub-district administrative boundaries onto the global temperature grid. The temperature data, measured at the location level, indicate that rural areas experience on average 12 days per year with extreme heat above 36°C and 215 days with moderately high temperatures between 30–36°C (Table 1). As illustrated in Figure 1, there has been a clear upward trend in extreme heat accumulation (above 36°C) over the 1997–2018 period. This level of heat exposure could influence both school attendance and labor outcomes, potentially in gender-specific ways if outdoor work or domestic responsibilities respond differently to heat stress.

We obtained monthly precipitation data at the sub-district level from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al. (2015)). On average, sub-districts in my sample received approximately 358.3 centimeters of rainfall over the study period.

3 Empirical methodology

In this section, we outline the empirical strategies for the remainder of the paper. The main empirical strategy estimates the relationship between heat exposure in the prior year and adolescent outcomes in rural Bangladesh using the following specification:

$$Y_{isdmtag} = \beta_0 + \beta_1 HeatExposure_{sdmt} + \boldsymbol{X_{sdmt}}\lambda + \delta_{mt} + \tau_s + \tau_a + \tau_g + \epsilon_{isdmtag} \tag{1}$$

Where $Y_{isdmtag}$ is the outcome for individual i in sub-district s on day d of month m in year t, at age a and gender g. The key regressor, $HeatExposure_{sdmt}$, measures the number of extremely hot days in the sub-district during the previous 365 days before the survey date. "Heat Exposure" is defined flexibly by varying the temperature threshold from 30°C to 40°C, allowing the analysis to capture potential nonlinearities in the heat–outcome relationship. This variation in thresholds helps identify whether the relationship is linear or whether there are sharp increases in impact at certain temperature points (similar to approaches in

Deschênes and Greenstone (2011); Burgess et al. (2017)).

The vector $\boldsymbol{X_{sdmt}}$ includes contemporaneous rainfall and other local climate variables to ensure that the estimated effects are not confounded by correlated weather conditions. The inclusion of sub-district fixed effects (τ_s) controls for time-invariant local characteristics such as geography, infrastructure, and long-term economic conditions. Month–year fixed effects (δ_{mt}) absorb national or seasonal shocks (such as crop cycles, festivals, or policy changes) that vary over time but affect all locations equally. Age fixed effects (τ_a) account for systematic differences in outcomes across ages, and ensure that the estimates are identified from within-cohort variation. Gender fixed effects (τ_g) capture average differences between boys and girls. Standard errors are clustered at the sub-district level to allow for arbitrary correlation in the error term within locations over time.

The identifying assumption in this strategy is that, after controlling for rainfall, other contemporaneous climate variables, sub-district fixed effects, month–year fixed effects, age fixed effects, and gender fixed effects, variation in the number of hot days within a sub-district is as good as random with respect to unobserved determinants of the outcome. This approach is similar to empirical designs in the climate–economy literature that exploit high-frequency weather variation within units over time to identify causal effects (e.g., Graff Zivin and Neidell (2014); Hsiang (2016); Dell et al. (2012)). The advantage is that weather shocks are plausibly exogenous to most short-run economic or health behaviors, making the variation in heat exposure a credible source of identification. By varying the temperature threshold from 30°C to 40°C, it also tests whether effects arise only at higher extremes or even at moderately high temperatures, similar to approaches in the climate–health literature (e.g., Deschênes and Greenstone (2011); Burgess et al. (2017); Carleton and Hsiang (2016)).

The single-threshold regressions indicate that effects become statistically significant only when daily temperatures exceed 36°C, pointing to a potential threshold at this level. Building on this, we adopt a complementary specification with two temperature bins, using the following model that separates moderately hot days from very hot days:[2]

---

[2] We avoid using finer bins for two reasons. First, splitting the temperature range into many narrow bins spreads the variation too thin, leaving few days in each bin (for example, very few 37–38°C days), which inflates standard errors and renders coefficients imprecise. Second, temperatures in adjacent bins are often highly correlated (e.g. hot days cluster together) making it difficult to separately identify their effects. This approach is standard in the literature. Coarse temperature bins around physiologically or economically

$$\begin{aligned} Y_{isdmtag} = \beta_0 + \beta_{\geq 36} Days\, Above\, 36^{\circ}_{sdmt} + \beta_{30-36} Days\, Between\, 30 - 36^{\circ}_{sdmt} \\ + \boldsymbol{X_{sdmt}} \lambda + \delta_{mt} + \tau_s + \tau_a + \tau_g + \epsilon_{isdmtag} \end{aligned} \tag{2}$$

Where $Days\, Above\, 36^{\circ}_{sdmt}$ is the number of days in the exposure window where temperatures exceed 36°C, and $30 - 36 Days\, Between\, 30 - 36^{\circ}_{sdmt}$ is the number of days with temperature between 30-36°C. The omitted category is days in the same window with temperature below 30°C. As before, $\boldsymbol{X_{sdmt}}$ includes contemporaneous rainfall and other local weather controls; τ_s, δ_{mt}, τ_a, and τ_g are sub-district, month–year, age, and gender fixed effects respectively; and standard errors are clustered at the sub-district level. $\beta_{\geq 36}$ measures the change in YYY associated with one additional day in the exposure window with temperatures between 30–36°C, relative to a day below 30°C, while β_{30-36} measures the change in YYY from one additional day at or above 36°C, also relative to a day below 30°C. Binning at 30–36°C and $\geq$ 36°C allows us to examine: (i) whether extremely hot days matter, and (ii) how effects intensify once the $\geq$ 36°C threshold is crossed.

4 Results

4.1 Prior year heat exposure on schooling

We begin by estimating the effect of high temperatures on schooling outcomes. Figures 2 - 5 present estimates from the single-threshold specification (equation 1), where the temperature threshold is varied from 30°C to 40°C in one-degree increments. For each of the four schooling outcomes, we plot the estimated coefficients and their 95% confidence intervals separately for all adolescents aged 12–16, for girls only, and for boys only.

For the first outcome, reporting studying as the primary activity, negative effects emerge once daily temperatures exceed 36°C and remain statistically significant for most higher thresholds. The negative effects become progressively larger as temperatures rise. The

---

meaningful thresholds are widely used to capture nonlinear weather effects while preserving precision (e.g., Schlenker and Roberts (2009); Graff Zivin and Neidell (2014); Burke et al. (2015); Carleton and Hsiang (2016)).

estimate at 40°C is negative but imprecisely estimated, likely due to the small number of observations at such extreme temperatures. The pattern for girls closely mirrors that for all adolescents, suggesting that the aggregate effect is driven largely by girls. For boys, the coefficients above 36°C are also negative but not statistically significant.

For the second outcome, reporting working as the primary activity, positive effects appear from 36°C onward. Again, the pattern for girls closely resembles that for the full sample, with statistically significant increases between 36°C and 39°C. For boys, the coefficients above 36°C are positive but remain statistically insignificant.

The third and fourth outcomes provide alternative measures of schooling impacts. For whether the respondents report that they are currently attending school, the results mirror those for studying as the primary activity: negative and significant effects emerge above 36°C, concentrated among girls. For school dropout, the pattern follows that for working as the primary activity: positive and significant effects above 36°C for girls, but no significant effects for boys.

Table 2 reports estimates from the binned specification (equation 2), which separates standardized heat exposure into moderately hot days (30–36°C) and very hot days ($\geq$ 36°C) in the prior year. Because the variables are standardized[3], the coefficients represent the change in the outcome associated with a one standard deviation increase in the number of days in each bin. For all adolescents (Panel A), a one–standard deviation increase in ($\geq$ 36°C) days (equivalent to 17 more days in the prior 365 days) is associated with a 3.1 percentage point decline in the likelihood of reporting studying as the primary activity and a 3.1 percentage point decline in current school attendance, alongside a 2.5 percentage point increase in reporting work as the primary activity. The effect on dropout is positive but not statistically significant. In contrast, a one standard deviation increase in 30–36°C days shows no significant association with any outcome.

The gender-disaggregated results in Panels B and C show that these effects are concen-

---

[3] By standardizing the heat exposure variables, the regression coefficients can be interpreted as the effect of a one standard deviation increase in exposure (rather than a one-day increase). This adjustment has two advantages: i) Comparability across measures of heat: Since the number of days above 36°C is much smaller than the number of days between 30–36°C, their raw scales differ substantially. Standardization makes the measures of heat comparable. ii) Meaningful effect sizes: A "one-day increase" in extreme heat may not be substantively comparable to a "one-day increase" in moderately hot days. But a one standard deviation increase represents a shift of similar magnitude relative to the natural variation in each variable.

trated among girls. For girls, a one standard deviation increase in ($\geq$ 36°C) days corresponds to a 3.9 percentage point decline in studying as the primary activity, a 3.8 percentage point decline in school attendance, and a 3.4 percentage point increase in both reporting work as the primary activity and dropping out. The corresponding estimates for boys are smaller in magnitude and statistically insignificant. Moderately hot days (30–36°C) are not significantly related to any outcome for either gender.

These findings align closely with the single-threshold analysis: negative schooling effects emerge only beyond 36°C, with no detectable impacts at lower heat levels. Standardizing the heat variables allows direct comparison of magnitudes across bins and confirms that the most substantial impacts are linked to very hot days. Taken together, these results suggest that extreme heat primarily affects girls' schooling and labor allocation, reducing the likelihood that their primary activity is studying or that they are attending school, and increasing the likelihood of working or dropping out. Boys show similar point estimates but with greater imprecision, and the effects are generally not statistically significant.

Consistent with these results, we find that extreme heat affects household income in a very similar way. Appendix figure A3 demonstrates similar threshold effects of extreme heat: days above 36°C and beyond in the previous year substantially reduces annual rural household income. In the two-bin regressions presented in Appendix Table A1, a one standard deviation increase in days above 36°C in the prior year lowers total household income by roughly 14.8 thousand BDT and reduces both agricultural and non-agricultural income, whereas moderately hot days (30–36°C) have no statistically significant effect. These results suggest that very hot periods impose tangible economic costs on households, which could in turn constrain resources available for children's education and help explain the observed declines in girls' schooling.

The gender-specific effects are consistent with mechanisms in which extreme heat increases household demands on girls' time, reducing their school attendance and increasing the likelihood of engaging in work. These findings are consistent with well-documented differences in household labor expectations and schooling decisions in rural South Asia. In many rural Bangladeshi households, girls bear a disproportionate share of domestic responsibilities, which may become more time-intensive during hot periods (e.g., caring for siblings indoors, assisting with water collection or food preparation) and crowd out school attendance (Kabeer (2003); Heath and Jayachandran (2016)). At the same time, heat-related disruptions to agricultural or informal labor markets may increase the demand for girls' household contributions, whereas boys' work opportunities in market-oriented activities may not expand as much in extreme heat (Bulte and Lensink (2019)). Parental perceptions of returns to girls' education—often lower than for boys—can also interact with short-term shocks, making girls' schooling more vulnerable to climate-related disruptions (Field and Ambrus (2008); Jensen (2012)). Together, these mechanisms help explain why the observed schooling and labor allocation effects are concentrated among girls.

4.2 Prior year heat exposure on labor

We now examine the effects of heat on child labor, building on the earlier findings that extreme heat reduces girls' schooling and increases the likelihood that work is reported as the primary activity. Table 3 disaggregates labor outcomes to investigate the type of work adolescents engage in during hot periods.

For all adolescents (Panel A), a one standard deviation increase in days above 36°C in the prior year is associated with a 2.2 percentage point increase in household work, while there are no significant effects on working for pay, family enterprise work, or farm labor. Moderately hot days (30–35°C) show no significant associations with any labor outcome.

Gender-disaggregated results indicate that these effects are concentrated among girls. For girls (Panel B), extremely hot days increase household work by 3.6 percentage points, with smaller, statistically insignificant changes in family enterprise work and paid labor. Boys (Panel C) show much smaller magnitudes overall, with only a small but statistically significant increase in household work (0.9 percentage points) and minor, imprecise changes in other labor outcomes.

Figure 6 presents estimates from the single-threshold specification for the probability of an adolescent engaging in household work. The pattern closely mirrors the results for schooling outcomes: the likelihood of household work rises noticeably around 35–36°C and remains statistically significant at higher temperatures. The pattern for girls is nearly identical to that for all adolescents, indicating that the aggregate effect is driven primarily by girls. For boys, the trends are similar, but the estimated magnitudes are much smaller.

These findings complement the earlier schooling results. The reduction in studying and school attendance among girls is accompanied by an increase in domestic labor, suggesting that extreme heat shifts girls' time allocation from education toward household responsibilities. Combined with the prior evidence that very hot days reduce household income, these results imply a potential feedback mechanism: heat shocks depress household earnings, which may increase reliance on children, especially girls, for household work and informal labor, while boys' schooling and labor patterns are less responsive to heat.

Overall, the analysis highlights that extreme heat affects not only schooling but also the composition of child labor, with girls disproportionately absorbing the burden of household work, consistent with observed gendered time allocation patterns in rural Bangladesh.

4.3 Cited reason for dropping out

We next examine the specific reasons households cite for children dropping out of school, using a set of binary dependent variables indicating whether a respondent identifies a particular reason. The sample includes all adolescents, regardless of whether they have actually dropped out, allowing the regressions to capture the broader risks of leaving school for specific reasons associated with heat exposure.

Table 4 reports the effects of standardized heat exposure in the prior year on these cited reasons. For all adolescents (Panel A), extremely hot days (≥ 36°C) increase the likelihood of citing household work (0.7 percentage points) and sickness (0.6 percentage points) as reasons for dropping out, with other reasons remaining largely unaffected. Moderately hot days (30–35°C) are associated with a smaller but statistically significant increase in household work (0.5 percentage points) and a slight decrease in citing family farm work as a reason.

Gender-disaggregated results show that the effects are once again concentrated among girls. For girls (Panel B), each additional standardized day above 36°C raises the probability of citing household work (1.3 percentage points) and sickness (0.6 percentage points) as reasons for dropping out, with other categories largely unaffected. For boys (Panel C), magnitudes are generally smaller and mostly statistically insignificant, with only minor changes in the likelihood of citing family farm work (negative) and schooling costs (positive) for moderately hot days.

These findings align closely with the previous results on schooling and child labor. Earlier analyses showed that extreme heat reduces girls' school attendance and studying as a primary activity while increasing time spent on household work. The current results suggest that these shifts are reflected in households' own reporting of the reasons for dropping out. Household responsibilities and heat-related sickness emerge as important barriers. In conjunction with the earlier finding that very hot days reduce household income, the evidence points towards extreme heat increasing household demands on children.

4.4 Mechanisms, moderators and robustness

In this section, we examine whether extreme heat increases the household's demand for domestic labor and whether this heightened demand helps explain the disproportionately negative effects on girls' schooling. We also investigate the role of restrictive gender norms, assessing whether households with more traditional attitudes toward women's work exhibit stronger gendered responses to heat shocks.

4.4.1 Household demand for domestic labor

Table A2 shows that exposure to extreme temperatures in the prior year meaningfully increases illness among household members. As before, all temperature variables are standardized.. A one–standard deviation increase in the number of days above 36°C in the prior year (equivalent to roughly 17 additional extremely hot days) is associated with a 2.9-percentage-point increase in the probability that someone in the household was sick in the last four weeks. Exposure to moderately hot days (30–36°C) has an even larger association, increasing the likelihood of illness by 4.7 percentage points. Both categories of heat exposure also significantly increase the number of days household members were sick during the prior month. These results show that extreme heat worsens household health and raises the need for care and assistance within the home.

Importantly, Table 1 shows that girls are overwhelmingly responsible for household tasks: 7.5% of girls report household work as their primary activity, compared to just 0.4% of boys.

This sharp gender imbalance implies that any increase in demand for home production, such as the need to care for sick siblings or adults, is likely to fall disproportionately on girls.

Table A4 tests this mechanism directly by interacting heat exposure with an indicator for whether another household member was recently sick. Panel A shows results for all adolescents. Consistent with the earlier findings, a one–standard deviation increase in days above 36°C reduces the likelihood that an adolescent's primary activity is studying by about 3.4 percentage points and reduces current school attendance by a similar amount. The estimates also show increases in work participation, though these are imprecisely estimated. Crucially, the interaction terms reveal that these negative schooling effects are concentrated in households where someone else was sick.

Panels B and C show that this heterogeneity is almost entirely driven by girls. Among girls (Panel B), a one–standard deviation increase in extremely hot days in households with a sick member leads to a 4.0-percentage-point reduction in both studying and current school attendance. These effects are statistically significant and substantially larger than in the pooled sample. In contrast, for boys (Panel C), the interaction effects are small and statistically indistinguishable from zero.

These results are consistent with the mechanism that extreme heat raises household care and domestic work burdens through increased sickness, and girls disproportionately respond by reducing schooling. Because girls already bear the overwhelming majority of household work, additional household labor needs created by heat-related illness fall almost exclusively on them. As a result, their schooling outcomes are more sensitive to heat shocks when the household requires extra care work.

4.4.2 Restrictive gender norms as a moderator

Table A4 examines whether the impact of extreme heat on adolescents' schooling is amplified in households with more restrictive gender norms. The key moderating variable is whether the husband believes that women should not work outside the home - a widely used proxy for low female status and strong adherence to traditional gender roles. If the mechanism is that heat shocks increase the demand for household labor and girls disproportionately supply that labor, then the effects of heat should be stronger precisely in households where girls' labor is most likely to be demanded and investment in girls' human capital is valued the least. Restrictive norms should therefore magnify the schooling impacts of heat.

Panel A of Table A4 shows that, on average, a one–standard deviation increase in the number of extremely hot days in the prior year reduces the likelihood that an adolescent's primary activity is studying by about 2.9 percentage points and lowers current school attendance by a similar amount. However, these effects vary sharply with household gender norms. When the husband does not want women to work outside the home, the interaction term with extremely hot days is large, negative, and statistically significant across outcomes. For instance, the cumulative impact of a one–standard deviation increase in days above 36°C in such households is an 11.1–percentage-point reduction in studying and school attendance. At the same time, the probability of working as the primary activity increases by roughly 10.7 percentage points. These heterogeneous effects suggest that the gender norm environment plays a critical role in shaping how households respond to heat shocks.

Panel B restricts the sample to girls. The results closely mirror the patterns in Panel A: the interaction between restrictive gender norms and extremely hot days yields large and statistically significant declines in both studying and current school attendance. For girls in households where the husband opposes women working outside, a one–standard deviation increase in days above 36°C reduces studying by 8.6 percentage points and lowers current attendance by nearly 9 percentage points.

The magnitude and direction of these effects are consistent with the mechanism that, in households with stricter gender norms, girls are disproportionately expected to substitute into household production when heat raises domestic labor needs (e.g., care for younger siblings, assisting ill members, or helping with tasks made more burdensome due to heat).

Taken together, the evidence points to two direct mechanisms and one key moderator through which extreme heat reduces children's schooling: lower income, higher household labor burdens, and restrictive gender norms. First, heat shocks depress household income through reduced labor productivity and higher illness, tightening short-term liquidity constraints. Second, extreme heat increases the need for domestic labor, forcing families to reallocate children's time toward work. Third, these pressures interact strongly with gender norms: in households with more restrictive views about women's roles, girls are expected to shoulder a disproportionate share of the added domestic burden, leading to larger declines in their schooling. These three channels operate simultaneously, amplifying one another and generating sizable reductions in children's educational investment during periods of extreme heat.

4.4.3 Robustness tests

A potential concern with the baseline specification is that the estimated impacts of heat exposure may be confounded by differential trends across sub-districts. For example, some areas may be experiencing improvements in schooling access over time or, conversely, longer-run declines in agricultural income or infrastructure quality that could correlate with rising temperatures. To address this concern, Table A5 augments equation 2 by including sub-district–specific linear time trends, allowing each sub-district to follow its own smooth trajectory over time. This specification absorbs any long-run, location-specific changes in educational investment, local labor demand, or gender norms that could otherwise bias the estimated heat effects. The results are highly consistent with the baseline findings. In Panel A, exposure to hotter days in the prior year—both days above 36°C and moderately hot days (30–36°C)—significantly reduces the probability that an adolescent's primary activity is studying and increases the probability that their primary activity is work. These coefficients remain large in magnitude and precisely estimated even after the inclusion of sub-district trends. For example, a one–standard deviation increase in days above 36°C reduces the likelihood of studying by 5.8 percentage points and increases dropout by 6.2 percentage points. These estimates closely mirror the main-text results, indicating that the heat–schooling relationship is not driven by differential pre-existing trends across regions.

A second concern is that the estimated relationship between heat exposure and schooling might be confounded by unobserved, time-invariant household characteristics. Factors such as parental preferences for education, long-standing gender norms within the household, the household's baseline income level, or persistent differences in household labor allocation could simultaneously influence both children's schooling decisions and where a household chooses to live—and thus the temperatures they experience. To address this, Table A5 re-estimates equation 2 using household fixed effects, comparing siblings within the same household who are interviewed at different times and therefore exposed to different realizations of heat in the preceding year. This specification removes all stable household-level confounders, isolating the impact of short-run variation in heat exposure on schooling outcomes. Panel A shows results for all adolescents. Once household fixed effects are included, the point estimates remain negative for studying and school attendance and positive for work and dropout, but they become smaller and less precisely estimated. This attenuation is unsurprising given the substantial reduction in identifying variation: the estimates now rely solely on within-household, across-interview changes in heat exposure. The direction of the coefficients, however, remains consistent with the main results. Panels B and C present estimates separately for girls and boys. Among girls, the effects of extreme heat remain statistically significant for two outcomes: a one–standard deviation increase in days above 36°C reduces the likelihood that a girl's primary activity is studying by 4.3 percentage points and increases the probability that her primary activity is working by 3.6 percentage points. The estimated impact on dropout is also positive and marginally significant. These results indicate that even within the same household, girls interviewed after a hotter prior year are more likely to reallocate time away from schooling and toward domestic work, consistent with the mechanism that heat increases household labor demands disproportionately borne by girls. For boys, by contrast, the coefficients are small and statistically indistinguishable from zero across all outcomes. This suggests that within-household reallocation of children's time in response to heat shocks falls almost entirely on girls, not boys—reinforcing the strong gender asymmetries observed in the main results. Overall, the household fixed effects specification provides a stringent test of the causal interpretation. Despite reduced power, the results for girls remain directionally consistent, demonstrating that the main findings are not driven by unobserved, time-invariant household characteristics.

Finally, table A7 re-estimates equation 2 using narrower 2-degree temperature bins: 31–32°C, 33–34°C, 35–36°C, 37–38°C, and above 38°C. This provides a more fine-grained characterization of how different intensities of heat affect adolescents' schooling and work decisions. Although imprecisely estimated, the direction of the effects is consistent with the baseline findings: extremely hot days decrease studying and school attendance while increasing work and dropout.

4.5 Persistent and cumulative impacts

We next examine the impacts of heat exposure over a longer horizon by augmenting equation 2 with temperature measures from two and three years prior to the survey date. The specification becomes:

$$
\begin{aligned}
Y_{isdmtag} = \beta_0 &+ \beta_1 Days\,Above\,36^\circ\,1\,Year\,Prior_{sdmt} + \beta_2 Days\,Above\,36^\circ\,2\,Years\,Prior_{sdmt} \\
&+ \beta_3 Days\,Above\,36^\circ\,3\,Years\,Prior_{sdmt} + \beta_4 Days\,Between\,30to36^\circ\,1\,Year\,Prior_{sdmt} \\
&+ \beta_5 Days\,Between\,30to36^\circ\,2\,Years\,Prior_{sdmt} + \beta_6 Days\,Between\,30to36^\circ\,3\,Years\,Prior_{sdmt} \\
&+ \boldsymbol{X_{sdmt}}\lambda + \delta_{mt} + \tau_s + \tau_a + \tau_g + \epsilon_{isdmtag}
\end{aligned} \tag{3}
$$

This approach serves two purposes. First, estimates based solely on prior-year heat may understate the true effect if temperature shocks persist beyond a single year; including additional lagged measures helps mitigate this bias. Ignoring such dynamic effects implicitly assumes that impacts fully decay after one year, potentially underestimating the cumulative consequences of heat. Second, incorporating earlier years' exposure allows for more accurate estimation of longer-run effects. For instance, the sum of the coefficients β_1 through β_3 captures the total impact of one additional day above 36°C over the three preceding years.

4.5.1 Cumulative impacts of heat exposure on schooling and labor

Table 5 reports the effects of lagged and cumulative heat exposure on schooling outcomes for all adolescents. The results indicate that the impacts of extreme heat ($\geq$ 36°C) are primarily driven by exposure in the prior year, with coefficients for heat two and three years prior generally small and statistically insignificant. This suggests that the adverse effects of extreme heat on schooling are concentrated in the short term, rather than persisting strongly over multiple years.

However, when considering the cumulative impact over three years, the total effects of both extreme heat and moderately hot days (30–36°C) are larger than the estimates for the prior year alone, indicating limited adaptation and accumulated impacts. The total effects are reported in the bottom four rows of the table, alongside the estimated standard errors of the estimated impact. Notably, the cumulative impacts of moderately hot days, which were not statistically significant in the single-year regressions, become significant once combined across multiple years. This suggests that the first set of prior-year results may have understated the true effects of moderate heat on schooling.

Specifically, a one–standard deviation increase in cumulative days $\geq$ 36°C over the past three years reduces the probability that an adolescent reports studying as their primary activity by 5.2 percentage points and lowers school attendance by 5.3 percentage points, while increasing the likelihood of working or dropping out by roughly 4–4.5 percentage points. Similarly, cumulative moderate heat reduces studying and attendance and increases work and dropout by 5–5.6 percentage points. These findings highlight that repeated exposure to high temperatures—both extreme and moderate—has meaningful and persistent effects on adolescent schooling in rural Bangladesh, reinforcing the earlier results that girls' education is particularly vulnerable to heat shocks. We report the cumulative effects separately for boys and girls in Appendix Tables A8 and A9, which again show that the overall impacts are largely driven by reductions in girls' schooling and are primarily associated with prior-year heat exposure.

Table 6 examines the effects of lagged and cumulative heat exposure on adolescents' labor outcomes. The estimated effects of prior-year or cumulative extreme heat ($\geq$ 36°C) on work are generally small and statistically insignificant. Lagged effects from two and three years prior are small and imprecise across all outcomes, suggesting that labor responses to heat are more dispersed and less immediate than schooling responses. Overall, these findings indicate that while extreme heat strongly affects schooling, particularly for girls, the corresponding changes in child labor are more modest and concentrated in certain categories. Much of the heat-driven increase in work observed in prior-year single-threshold regressions is captured primarily by household work among girls, whereas cumulative labor adjustments are smaller and less consistent across work types.

4.6 Impacts of early life heat exposure

A growing body of evidence highlights the critical importance of early life environmental conditions for human capital formation. The "first 1,000 days" hypothesis posits that the period from conception to approximately two years of age is a window of heightened vulnerability, during which environmental shocks can have disproportionately large and potentially irreversible effects on physical growth, cognitive development, and long-term health (Victora et al. (2022); Black et al. (2016)). Exposure to adverse conditions during this formative period can permanently alter developmental trajectories, with downstream consequences for schooling, labor market participation, and lifetime earnings.

In the context of climate change, high temperatures represent a growing early life risk factor. Heat can adversely affect fetal and infant development through multiple pathways, including maternal heat stress, increased risk of infection, and reduced food security. Recent work in Bangladesh by Raza et al. (2025) provides compelling evidence that extreme heat exposure during the first 1,000 days significantly increases the risk of childhood stunting. Using detailed temperature and anthropometric data, the authors show that cumulative exposure to high temperatures in early life is associated with substantial deficits in height-for-age, highlighting the susceptibility of child growth to climatic conditions in this critical developmental window.

We independently verify this pattern using my dataset. In appendix Figure A4, we plot the coefficients from single-threshold regressions of various anthropometric indicators—height-for-age z-scores (HAZ), weight-for-age z-scores (WAZ), weight-for-height z-scores (WHZ), and BMI z-scores—on heat exposure during the first 1,000 days. The results show a consistent pattern: from 35°C onwards, anthropometric outcomes become progressively worse, and the severity of the deficits rising as temperatures climb.

These findings motivate the next part of the analysis: if early life heat exposure can impair physical growth, it may also have lasting effects on later-life outcomes, including schooling attainment and labor market engagement. Given the potential for these impacts to compound over the life course, identifying such long-run consequences is critical for understanding the full human capital costs of climate change.

4.6.1 Early life heat exposure on schooling and labor

Building on the evidence that the first 1,000 days of life are a critical developmental window, we examine whether extreme heat during this period leaves lasting marks on adolescents' schooling and labor outcomes. Using each individual's date of birth, we construct measures of the number of days in the first 1,000 days of life exceeding specific temperature thresholds, and estimate "single-threshold" regressions for thresholds between 30°C and 40°C. Figures 7 - 10 presents estimates from the single-threshold specification linking heat exposure during the first 1,000 days of life to later-life schooling outcomes for adolescents aged 12–16. For each individual, temperature thresholds were constructed based on date of birth. These figures plot the coefficients and 95% confidence intervals separately for all adolescents aged 12–16, girls only, and boys only.

For the likelihood of reporting studying as the primary activity, negative effects emerge from around 36°C onward and remain statistically significant at higher thresholds. These patterns are very similar to the results for prior-year heat exposure discussed earlier in the paper, underscoring that extreme heat matters substantially in this context. These findings are consistent across genders, though the magnitude of the effect is slightly larger for boys, contrasting with results from prior-year heat exposure where girls were more adversely affected.

For reporting working as the primary activity, positive and statistically significant effects also emerge from 36°C onward - a pattern that once again closely mirrors the prior-year heat exposure results. Again, no substantive gender differences are evident, although the point estimates are marginally larger for boys. The estimated effects for school attendance and dropout reinforce these patterns. Attendance (figure 9) declines in a manner that mirrors the studying outcome, while dropout (figure 10) increases in line with the working outcome. In each case, the onset of significant effects occurs at roughly the same temperature threshold of 36°C.

Taken together, these results suggest that high heat exposure in the critical early-life window has lasting consequences for educational engagement, with the onset of impacts occurring at similar temperature thresholds across different outcome measures. These findings are consistent with the biological and developmental pathways identified in the literature, and with my own anthropometric evidence showing progressive deterioration in child growth outcomes above 35°C.

Tables 7 breaks down the effects of early life heat exposure during the first 1,000 days into three distinct exposure windows: in utero, age one, and age two for the full sample of adolescents. Exposure to days above 36°C during ages one and two is consistently associated with lower likelihoods of being a student or currently attending school, and higher likelihoods of working or having dropped out. The largest and most statistically significant effects are observed for exposure at age one, where one standard deviation increase in hot days above 36°C is associated with a 3.4 percentage point decrease in the likelihood of being a student, a 3.8 point decrease in school attendance, and corresponding increases in working and dropout. Heat exposure in age two also has similar impacts but with lower magnitudes. In utero exposure shows no statistically significant effects for the full sample.

Appendix tables A12 and A13 provide the results separately for girls and boys, respectively. For girls, coefficients are generally smaller and mostly statistically insignificant, with the only notable effect being a marginal increase in dropout associated with hot days at age one. In contrast, boys exhibit much stronger and more consistent negative impacts. Exposure above 36°C during ages one and two is linked to substantial reductions in being a student (3.8–4.3 points) and school attendance (4.1–4.9 points), alongside corresponding increases in working and dropout probabilities. For boys, even moderately hot days (30–36°C) at age two have large and significant negative schooling effects. This stands in contrast to the findings from prior-year heat exposure, where the negative schooling effects were driven largely by girls. One possible explanation is that early-life exposure captures a different set of mechanisms - likely related to physical growth, cognitive development, and early-life health shocks - that may have a stronger effect on boys' schooling trajectories (consistent with some literature showing higher male vulnerability to early-life environmental stressors). By contrast, prior-year exposure likely operates through short-run mechanisms such as increased household labor demands, caregiving burdens, and gendered opportunity costs, which disproportionately affect girls in adolescence. Thus, while girls are more vulnerable to contemporaneous heat shocks due to socio-cultural factors, boys may bear a heavier long-run penalty from early-life heat exposure.

Table 8 provides the impacts of early life heat on labor outcomes for all adolescents. Early-life heat exposure has modest effects on adolescent labor outcomes, with age-two exposure above 36°C significantly increasing the likelihood of household work. Effects for other types of work and for other ages are generally small and statistically insignificant. When disaggregating by gender (appendix tables A14 and A15), patterns differ: for girls, age-two exposure above 36°C increases household work, while moderate heat at age one slightly raises the probability of paid work. For boys, age-one and age-two heat exposure reduces household work but increases farm labor, and in-utero exposure slightly lowers farm work participation. These findings contrast with the prior-year results where labor shifts were more pronounced for girls. This suggests that early-life heat may shape later labor participation through long-run health and developmental pathways that differ by gender, rather than the short-run household labor reallocation channels driving the contemporaneous effects.

Overall, these results indicate that heat exposure during early childhood, particularly during the first two years of life, has lasting adverse effects on schooling outcomes.

5 Conclusion

This paper examines how extreme heat affects adolescent human capital formation in rural Bangladesh, combining analyses of short-term, cumulative, and early-life heat exposure. We identify a temperature threshold at 36°C, above which negative impacts on schooling intensify sharply. Each additional day above this threshold reduces studying as a primary activity by 3.1 percentage points and school attendance by 3.1 percentage points, while increasing working by 2.5 percentage points. These effects are highly nonlinear—moderate heat (30-36°C) shows minimal single-year impacts, though cumulative exposure over three years reveals significant negative effects. The precision of this threshold enables targeted policy responses that would be impossible under assumptions of linear climate-outcome relationships, allowing interventions to concentrate resources on the specific temperature ranges when harm intensifies most.

The evidence points to two complementary mechanisms through which heat disrupts human capital formation. First, prior-year and cumulative heat exposure operates through immediate income-mediated responses. Extreme heat reduces annual household income by approximately 14,800 BDT (11% of mean income), forcing households to reallocate children's time from schooling toward productive and household work. Second, early-life heat exposure during the first 1,000 days affects long-term human capital formation through developmental pathways. Each additional day above 36°C during ages one and two reduces adolescent schooling probability by 3.4-3.8 percentage points, with effects persisting a decade after exposure. These findings suggest both immediate household optimization responses to income shocks and permanent developmental impacts that alter educational trajectories. The limited adaptation we observe—with cumulative effects matching or exceeding the sum of single-year effects—indicates that rural Bangladeshi households lack the resources or opportunities to adjust effectively despite repeated exposure.

Gender differences in heat impacts are substantial and vary by exposure timing. For prior-year and cumulative exposure, girls experience larger effects, with a one standard deviation increase in days above 36°C reducing girls' studying by 3.9 percentage points while boys show statistically insignificant effects. Girls shift primarily toward household work (3.6 percentage point increase), reflecting the interaction of heat-induced income shocks, increased domestic labor demands from illness, and restrictive gender norms. In households where husbands oppose women working outside the home, extreme heat reduces girls' schooling by an additional 8.6 percentage points compared to more egalitarian households. For early-life exposure, boys show slightly larger effects, likely reflecting biological vulnerability to early environmental stressors versus gendered household labor allocation during adolescence.

The findings suggest several policy interventions. Temperature-triggered social protection programs—conditional cash transfers or agricultural insurance that activate when temperatures exceed 36°C—could stabilize household finances during heat shocks and prevent destructive coping strategies. School infrastructure investments in cooling systems and adjusted calendars during extreme heat months would directly reduce heat exposure during learning hours. Given girls' disproportionate burden, gender-targeted interventions including labor-saving household technologies and community childcare programs could reduce the domestic labor demands that pull girls from school. Early-life protection through community cooling centers for pregnant women and enhanced maternal-child health services during hot seasons would address the developmental pathway. The cost-benefit case appears strong: current costs include 11% income losses plus permanent human capital damage, while the threshold nature of impacts allows efficient targeting of interventions to high-risk periods.

Climate change poses a fundamental threat to human capital accumulation in developing countries. Rising temperatures systematically undermine educational investments, particularly for girls who face compounding pressures from income shocks, household labor demands, and restrictive norms. Early-life heat exposure generates permanent deficits that constrain opportunities into adulthood. Bangladesh's rapid warming—with extreme heat days increasing substantially over 1997-2018—makes interventions increasingly urgent. Without coordinated action across social protection, education, health, and gender equality domains, warming temperatures will exacerbate inequality and create intergenerational poverty traps. Protecting children's human capital during extreme heat is not merely climate adaptation—it is fundamental to sustaining development progress and ensuring equitable opportunity as the planet warms. The precise threshold effects we identify enable cost-effective policy design, but action must be immediate given accelerating climate trends and the irreversibility of human capital losses during critical developmental periods.

References

Almond, Douglas and Janet Currie, “Killing me softly: The fetal origins hypothesis,” *Journal of economic perspectives*, 2011, *25* (3), 153–172.

Beegle, Kathleen, Rajeev Dehejia, and Roberta Gatti, “Why should we care about child labor?: The education, labor market, and health consequences of child labor,” *Journal of Human Resources*, 2009, *44* (4), 871–889.

Black, Maureen M, Susan P Walker, Lia CH Fernald, Christopher T Andersen, Ann M DiGirolamo, Chunling Lu, Dana C McCoy, Günther Fink, Yusra R Shawar, Jeremy Shiffman et al., “Advancing Early Childhood Development: From Science to Scale 1: Early childhood development coming of age: Science through the life course,” *Lancet (London, England)*, 2016, *389* (10064), 77.

Bulte, Erwin and Robert Lensink, “Women’s empowerment and domestic abuse: Experimental evidence from Vietnam,” *European economic review*, 2019, *115*, 172–191.

Burgess, Robin, Olivier Deschenes, Dave Donaldson, and Michael Greenstone, “Weather, climate change and death in India,” *University of Chicago*, 2017, pp. 577–617.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel, “Global non-linear effect of temperature on economic production,” *Nature*, 2015, *527* (7577), 235–239.

Carleton, Tamma A and Solomon M Hsiang, “Social and economic impacts of climate,” *Science*, 2016, *353* (6304), aad9837.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, “Temperature shocks and economic growth: Evidence from the last half century,” *American Economic Journal: Macroeconomics*, 2012, *4* (3), 66–95.

Deryugina, Tatyana and Solomon Hsiang, “The marginal product of climate,” Technical Report, National Bureau of Economic Research 2017.

Deschênes, Olivier and Michael Greenstone, "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US," *American Economic Journal: Applied Economics*, 2011, *3* (4), 152–185.

Field, Erica and Attila Ambrus, "Early marriage, age of menarche, and female schooling attainment in Bangladesh," *Journal of political Economy*, 2008, *116* (5), 881–930.

Fruttero, Anna, Daniel Halim, Chiara Broccolini, Bernardo Coelho, Horace Gninafon, and Noël Muller, "Gendered impacts of climate change: evidence from weather shocks," *Environmental Research: Climate*, 2024, *3* (4), 045018.

Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, James Rowland, Laura Harrison, Andrew Hoell et al., "The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes," *Scientific data*, 2015, *2* (1), 1–21.

Goodman, Joshua, Michael Hurwitz, Jisung Park, and Jonathan Smith, "Heat and learning," Technical Report, National Bureau of Economic Research 2018.

Heath, Rachel and Seema Jayachandran, "The causes and consequences of increased female education and labor force participation in developing countries," Technical Report, National Bureau of Economic Research 2016.

Heckman, James J, "Skill formation and the economics of investing in disadvantaged children," *Science*, 2006, *312* (5782), 1900–1902.

Hsiang, Solomon, "Climate econometrics," *Annual Review of Resource Economics*, 2016, *8* (1), 43–75.

Jensen, Robert, "Do labor market opportunities affect young women's work and family decisions? Experimental evidence from India," *The Quarterly Journal of Economics*, 2012, *127* (2), 753–792.

Kabeer, Naila, *Gender Mainstreaming in Poverty Eradication and the Millennium Development Goals: A handbook for policy-makers and other stakeholders*, Commonwealth Secretariat, 2003.

Raza, Wameq Azfar, Farzana Misha, Syed Shahadat Hossain, Jahida Gulshan, Bazlur Rashid, Sheikh Mohammad Sayem, Souvik Ghosal Aranya, and Deepika Chaudhery, "Extreme heat exposure in the first 1000 days: Implications for childhood stunting in Bangladesh," *Public Health*, 2025, *241*, 83–88.

Schlenker, Wolfram and Michael J Roberts, "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of sciences*, 2009, *106* (37), 15594–15598.

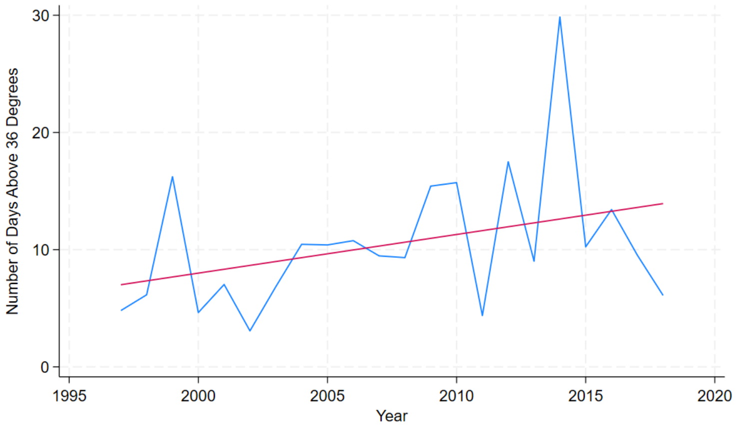
Victora, Cesar G, Fernando P Hartwig, Luis P Vidaletti, Reynaldo Martorell, Clive Osmond, Linda M Richter, Aryeh D Stein, Aluisio JD Barros, Linda S Adair, Fernando C Barros et al., "Effects of early-life poverty on health and human capital in children and adolescents: analyses of national surveys and birth cohort studies in LMICs," *The Lancet*, 2022, *399* (10336), 1741–1752.

Zivin, Joshua Graff and Matthew Neidell, "Temperature and the allocation of time: Implications for climate change," *Journal of Labor Economics*, 2014, *32* (1), 1–26.

_ , Solomon M Hsiang, and Matthew Neidell, "Temperature and human capital in the short and long run," *Journal of the Association of Environmental and Resource Economists*, 2018, *5* (1), 77–105.

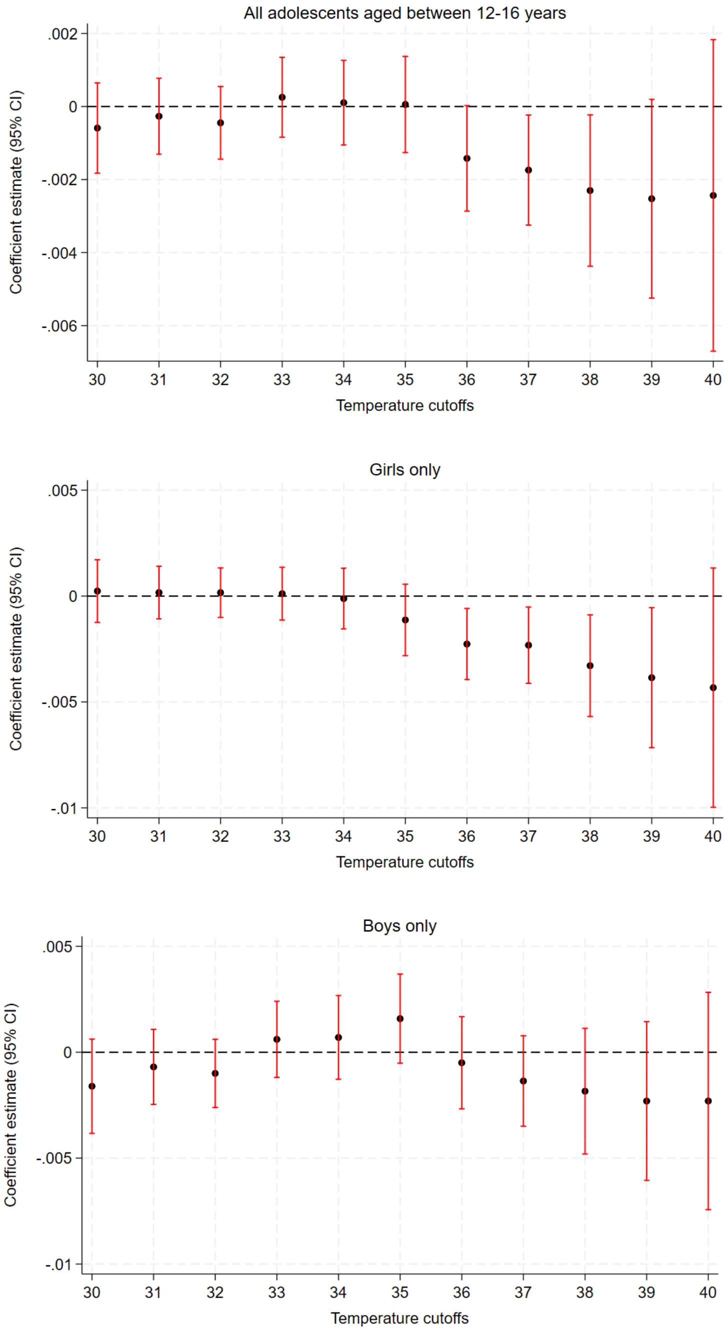
6 Figures and Tables

Figure 1: Sub-district level historical trends in number of days above 36°C



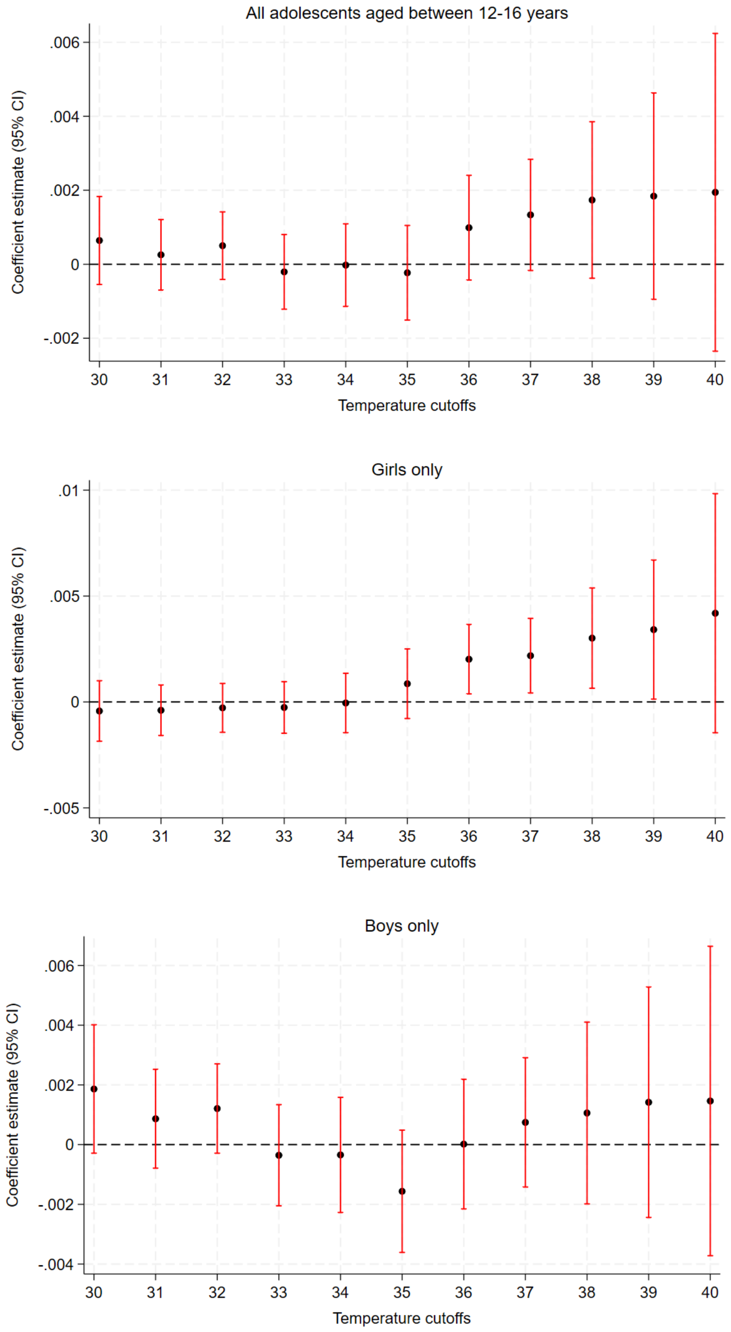
The figure plots average number of days above 36°C for all rural sub-districts in Bangladesh over the years from 1997 to 2018. Source: Authors' calculations based on CPC Global Unified Temperature dataset (NOAA Physical Sciences Laboratory).

Figure 2: Heat exposure and likelihood of reporting studying as the primary activity



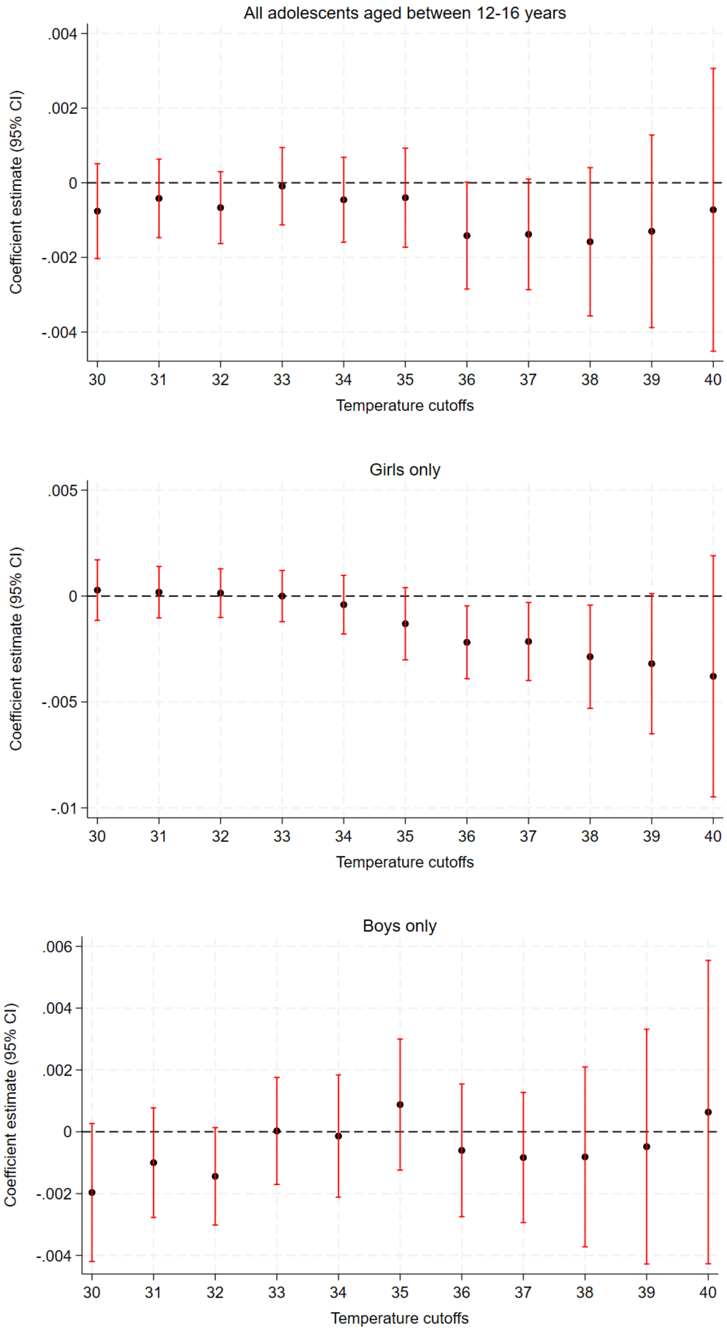
These figures show how an additional day above each temperature threshold (x-axis) in the past 365 days affects the probability of reporting that being student is the primary activity of the respondent in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure 3: Heat exposure and likelihood of reporting working as the primary activity



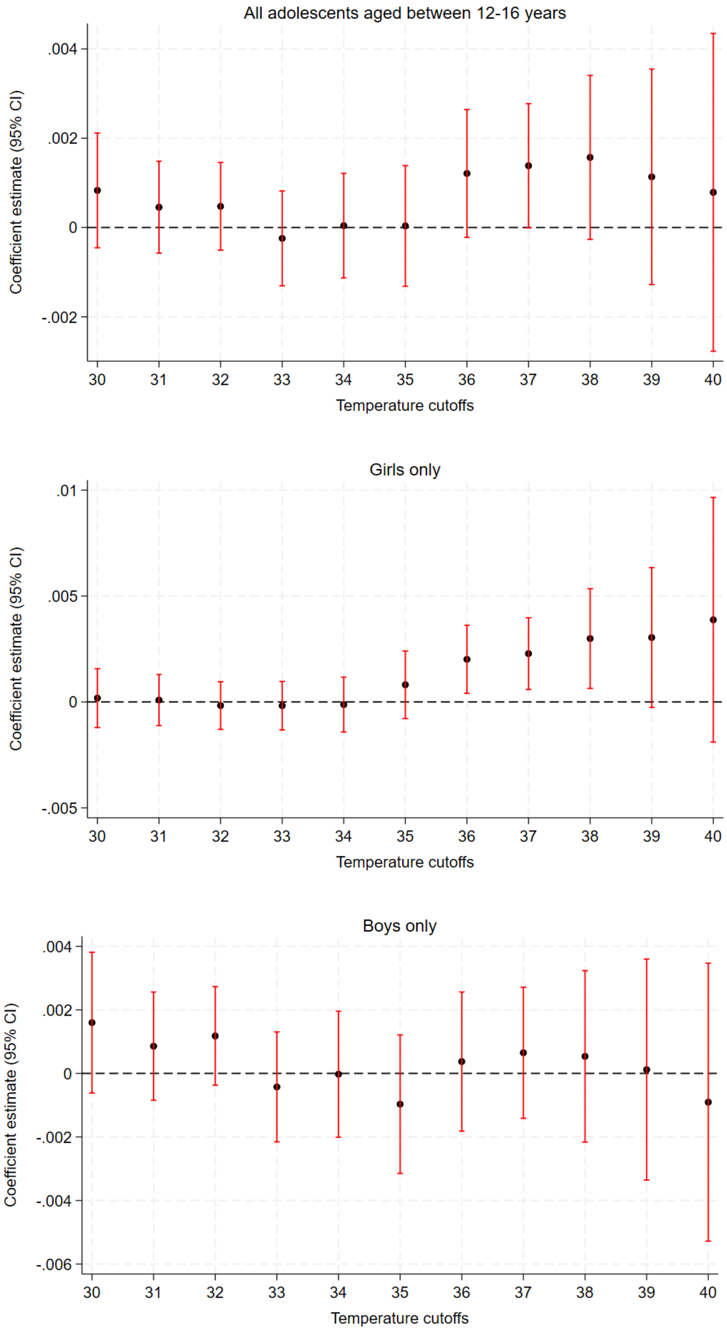
These figures show how an additional day above each temperature threshold (x-axis) in the past 365 days affects the probability of reporting that working is the primary activity of the respondent in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure 4: Heat exposure and likelihood of attending school



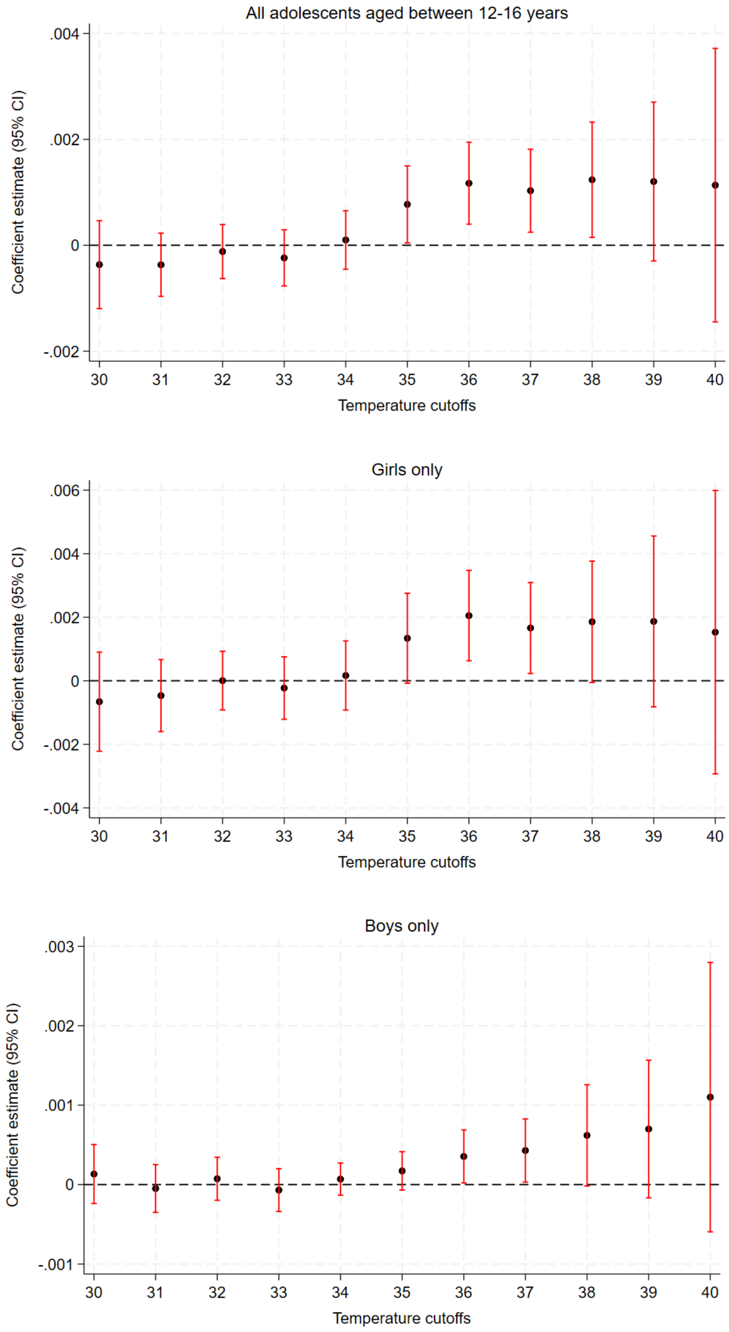
These figures show how an additional day above each temperature threshold (x-axis) in the past 365 days affects the probability of attending school in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure 5: Heat exposure and likelihood of dropping out



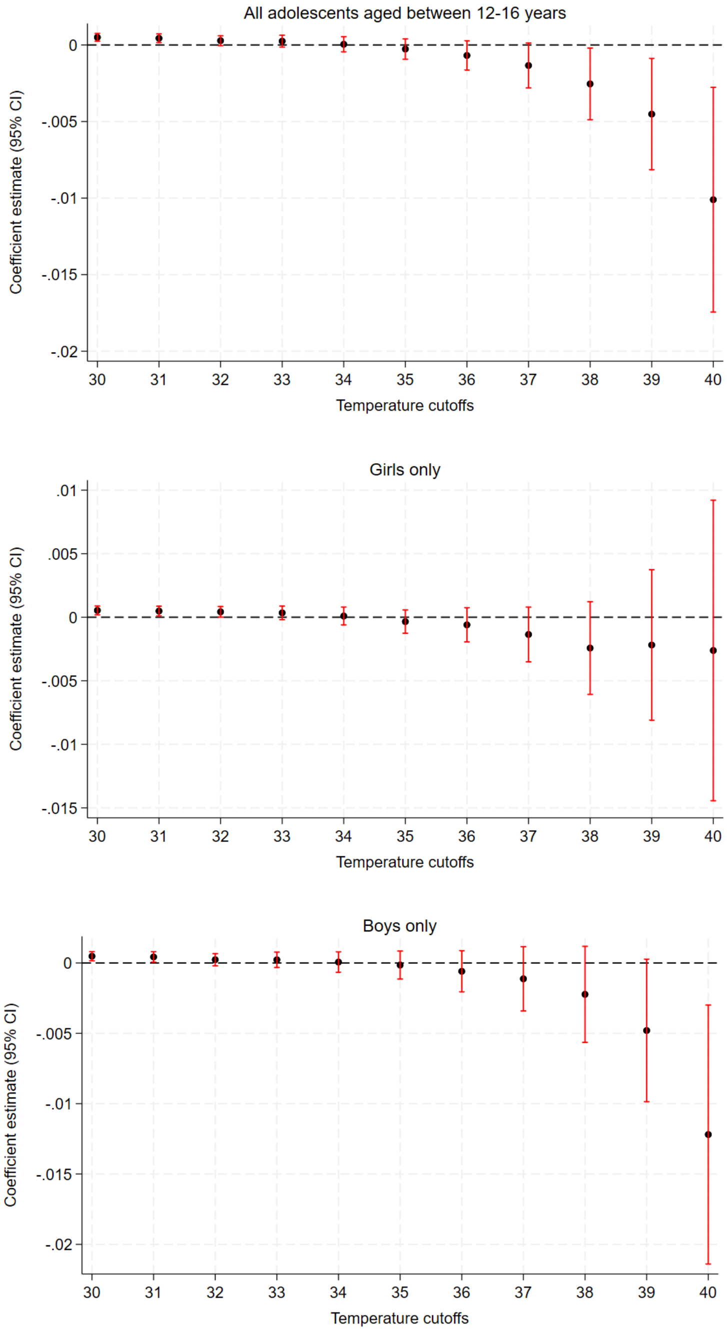
These figures show how an additional day above each temperature threshold (x-axis) in the past 365 days affects the probability of dropping out of school in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure 6: Heat exposure and likelihood of working within household



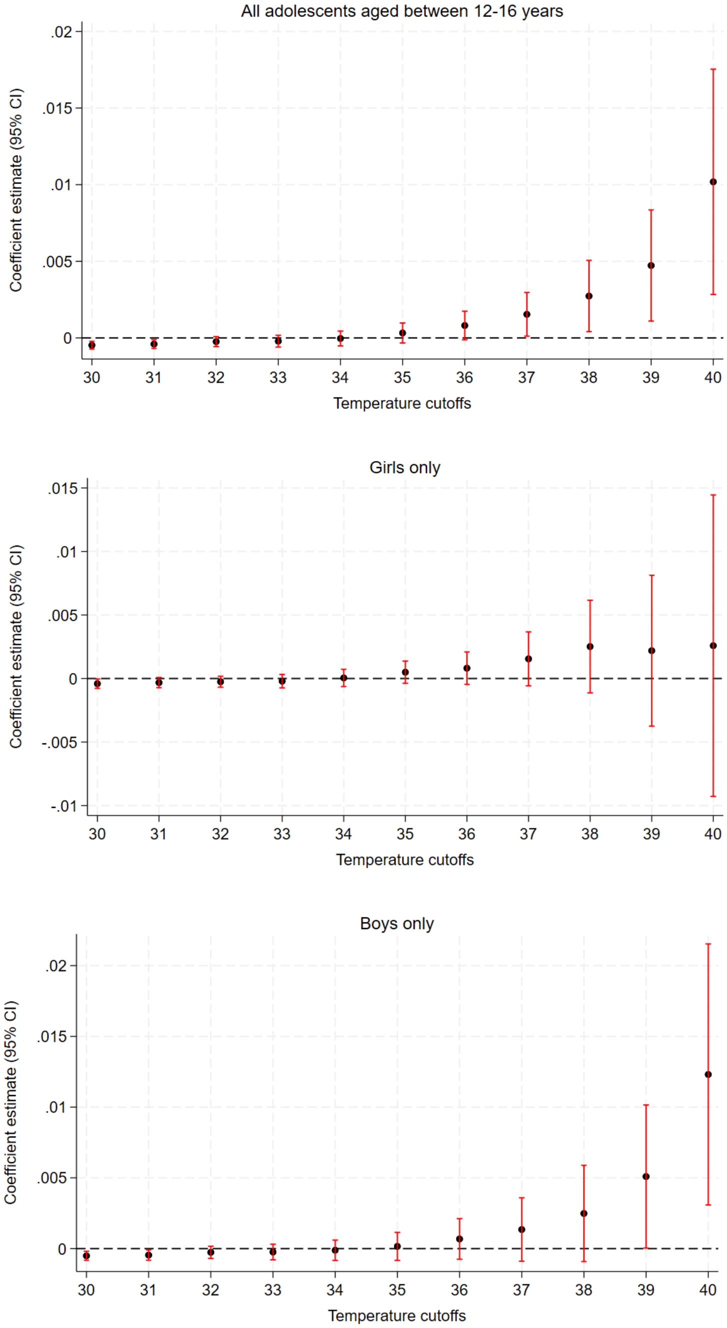
These figures show how an additional day above each temperature threshold (x-axis) in the past 365 days affects the probability of working within household in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure 7: Early life heat exposure and likelihood of reporting studying as the primary activity



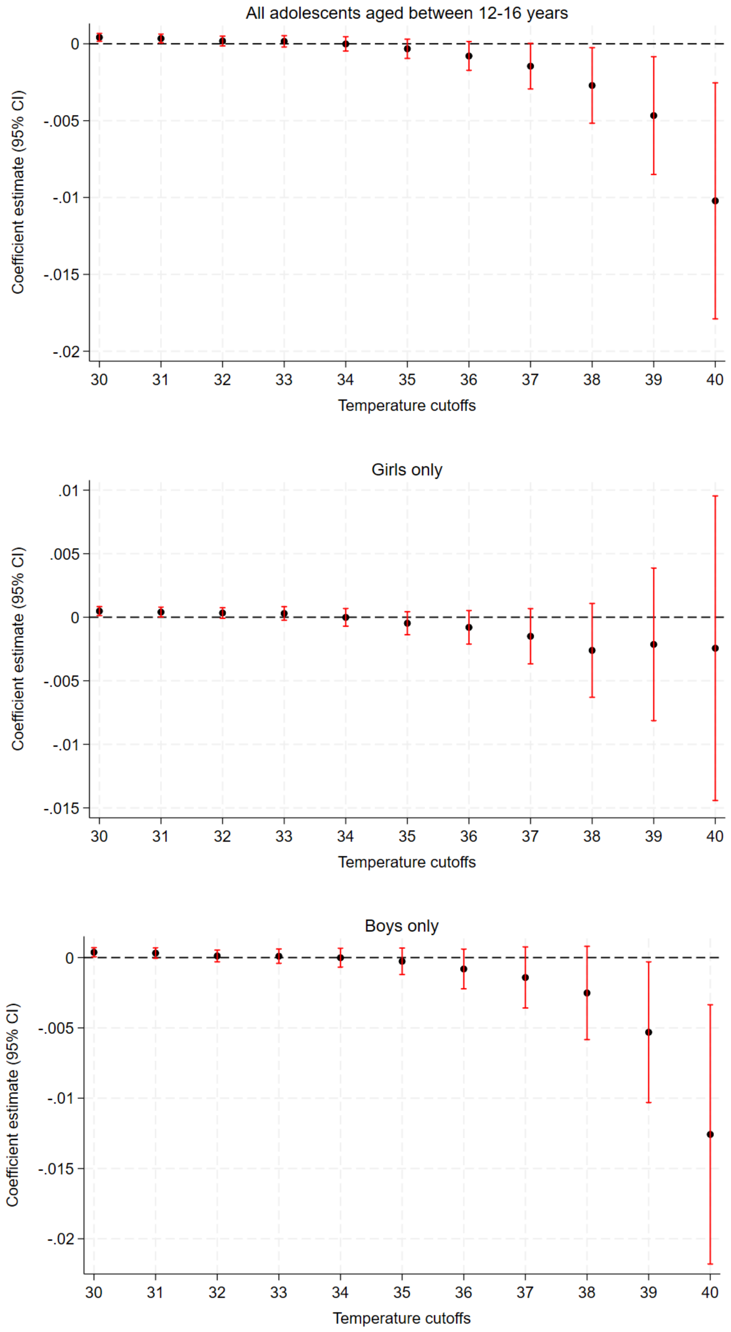
These figures show how an additional day above each temperature threshold (x-axis) in the first 100 days of life affects the probability of reporting that being student is the primary activity of the respondent in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure 8: Early life heat exposure and likelihood of reporting working as the primary activity



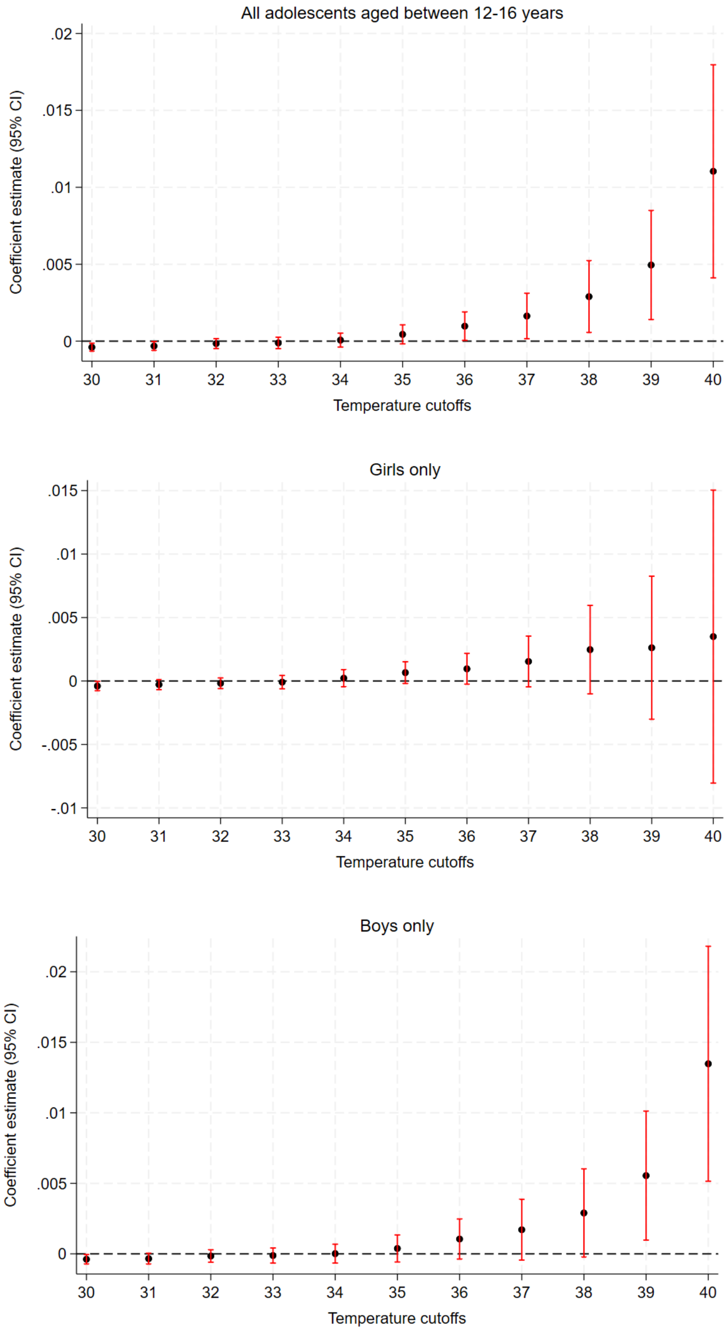
These figures show how an additional day above each temperature threshold (x-axis) in the first 100 days of life affects the probability of reporting that working is the primary activity of the respondent in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure 9: Early life heat exposure and likelihood of attending school



These figures show how an additional day above each temperature threshold (x-axis) in the first 100 days of life affects the probability of attending school in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure 10: Early life heat exposure and likelihood of dropping out



These figures show how an additional day above each temperature threshold (x-axis) in the first 100 days of life affects the probability of dropping out of school in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, age, and gender fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Table 1: Summary Table

Variable	Mean	Standard Deviation	Observations	Minimum	Maximum
A. All adolescents: Age 12-16 Years					
Age	13.850	1.394	8748	12.000	16.000
Primary activity: student	0.814	0.389	8748	0.000	1.000
Primary activity: works	0.180	0.384	8748	0.000	1.000
Currently attending school	0.818	0.386	8748	0.000	1.000
Dropped out	0.155	0.362	8748	0.000	1.000
Works for pay	0.095	0.293	8748	0.000	1.000
Works in Household	0.039	0.193	8748	0.000	1.000
Works in family enterprise	0.161	0.368	8748	0.000	1.000
Works in farm	0.017	0.129	8748	0.000	1.000
B. Girls					
Age	13.830	1.386	4294	12.000	16.000
Primary activity: student	0.861	0.346	4294	0.000	1.000
Primary activity: works	0.134	0.340	4294	0.000	1.000
Currently attending school	0.866	0.341	4294	0.000	1.000
Dropped out	0.117	0.321	4294	0.000	1.000
Works for pay	0.030	0.171	4294	0.000	1.000
Works in Household	0.075	0.263	4294	0.000	1.000
Works in family enterprise	0.158	0.365	4294	0.000	1.000
Works in farm	0.002	0.043	4294	0.000	1.000
C. Boys					
Age	13.870	1.402	4454	12.000	16.000
Primary activity: student	0.768	0.422	4454	0.000	1.000
Primary activity: works	0.225	0.418	4454	0.000	1.000
Currently attending school	0.772	0.420	4454	0.000	1.000
Dropped out	0.192	0.394	4454	0.000	1.000
Works for pay	0.157	0.364	4454	0.000	1.000
Works in Household	0.004	0.065	4454	0.000	1.000
Works in family enterprise	0.163	0.370	4454	0.000	1.000
Works in farm	0.031	0.174	4454	0.000	1.000
D. Temperature Variables					
Days: Temperature above 36 °C	12.391	17.170	281	0.000	75.000
Days: Temperature between 30-36 °C	215.278	33.100	281	9.000	257.000

Table 2: Prior year heat exposure on schooling

	Primary activity: student (1)	Primary activity: works (2)	Currently attending school (3)	Dropped out (4)
Panel A: All adolescents				
Days above 36°C	-0.0310**	0.0245*	-0.0314**	0.0163
	(0.0146)	(0.0142)	(0.0142)	(0.0152)
Days between 30-36°C	-0.0107	0.0113	-0.0110	0.000354
	(0.0111)	(0.0103)	(0.0111)	(0.0120)
Observations	8747	8747	8747	8747
Mean of Dep Variable	0.814	0.180	0.818	0.155
Panel B: Girls only				
Days above 36°C	-0.0386**	0.0337*	-0.0376**	0.0335*
	(0.0187)	(0.0181)	(0.0189)	(0.0178)
Days between 30-36°C	-0.00147	0.000507	-0.00251	0.000378
	(0.0145)	(0.0141)	(0.0142)	(0.0135)
Observations	4294	4294	4294	4294
Mean of Dep Variable	0.861	0.134	0.866	0.117
Panel C: Boys only				
Days above 36°C	-0.0230	0.0168	-0.0226	0.00419
	(0.0226)	(0.0227)	(0.0219)	(0.0231)
Days between 30-36°C	-0.0222	0.0240	-0.0202	0.00653
	(0.0208)	(0.0202)	(0.0210)	(0.0206)
Observations	4453	4453	4453	4453
Mean of Dep Variable	0.768	0.225	0.772	0.192

*All regressions in Panel A include month-year, sub-district, age, and gender fixed effects. All regressions in Panel B and C include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table 3: Prior year heat exposure on labor outcomes

	Worked for pay	Household work	Family enterprise work	Worked in farms
	(1)	(2)	(3)	(4)
Panel A: All adolescents				
Days above 36°C	0.00367	0.0222**	0.0222	-0.000657
	(0.0128)	(0.00865)	(0.0217)	(0.00543)
Days between 30-36°C	0.00557	0.00493	0.00739	0.00360
	(0.0105)	(0.00674)	(0.0133)	(0.00349)
Observations	8747	8747	8747	8747
Mean of Dep Variable	0.0947	0.0388	0.161	0.0168
Panel B: Girls only				
Days above 36°C	-0.00145	0.0363**	0.0275	0.00160
	(0.00915)	(0.0160)	(0.0254)	(0.00205)
Days between 30-36°C	-0.00547	0.00517	-0.000660	-0.000169
	(0.00736)	(0.0125)	(0.0170)	(0.000442)
Observations	4294	4294	4294	4294
Mean of Dep Variable	0.0303	0.0745	0.158	0.00186
Panel C: Boys only				
Days above 36°C	0.0189	0.00937**	0.0112	-0.00245
	(0.0219)	(0.00372)	(0.0303)	(0.0111)
Days between 30-36°C	0.0256	0.00528*	0.0123	0.00520
	(0.0179)	(0.00317)	(0.0216)	(0.00746)
Observations	4453	4453	4453	4453
Mean of Dep Variable	0.157	0.00427	0.163	0.0312

*All regressions in Panel A include month-year, sub-district, age, and gender fixed effects. All regressions in Panel B and C include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table 4: Prior year heat on cited reason for dropping out

	Household work (1)	Family farm work (2)	Work outside of home (3)	Sickness (4)	Schooling too expensive (5)	Other reasons (6)
			Panel A: All adolescents			
Days above 36°C: 1 year prior	0.00726**	-0.00333	-0.00309	0.00635**	0.00954	-0.000466
	(0.00321)	(0.00367)	(0.00501)	(0.00288)	(0.0113)	(0.0120)
Days between 30-36°C: 1 year prior	0.00528**	-0.00907**	-0.00255	0.00131	0.0126	-0.00725
	(0.00258)	(0.00412)	(0.00481)	(0.00207)	(0.00867)	(0.00836)
Observations	8747	8747	8747	8747	8747	8747
Mean of Dep Variable	0.00846	0.00823	0.0149	0.00400	0.0550	0.0647
			Panel B: Girls only			
Days above 36°C: 1 year prior	0.0134**	0.000396	0.00134	0.00616**	0.00599	0.00622
	(0.00558)	(0.00287)	(0.00229)	(0.00293)	(0.0118)	(0.0150)
Days between 30-36°C: 1 year prior	0.00732	-0.000516	0.00188	0.00360	-0.00279	-0.00912
	(0.00466)	(0.00324)	(0.00177)	(0.00227)	(0.00969)	(0.0118)
Observations	4294	4294	4294	4294	4294	4294
Mean of Dep Variable	0.00908	0.00233	0.00210	0.00303	0.0452	0.0552
			Panel B: Boys only			
Days above 36°C: 1 year prior	0.00385	-0.00749	-0.00686	0.00680	0.0139	-0.00602
	(0.00489)	(0.00724)	(0.00956)	(0.00479)	(0.0166)	(0.0188)
Days between 30-36°C: 1 year prior	0.00395	-0.0172**	-0.00387	-0.00114	0.0279**	-0.00310
	(0.00364)	(0.00776)	(0.01000)	(0.00360)	(0.0131)	(0.0114)
Observations	4453	4453	4453	4453	4453	4453
Mean of Dep Variable	0.00786	0.0139	0.0272	0.00494	0.0645	0.0739

*All regressions in Panel A include month-year, sub-district, age, and gender fixed effects. All regressions in Panel B and C include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table 5: Lagged and cumulative heat exposure on schooling: All adolescents

	Primary activity: student (1)	Primary activity: works (2)	Currently attending school (3)	Dropped out (4)
Days above 36°C: 1 year prior	-0.0387**	0.0328*	-0.0421**	0.0371*
	(0.0184)	(0.0177)	(0.0182)	(0.0190)
Days above 36°C: 2 years prior	-0.00299	0.00272	0.00000930	0.00332
	(0.0189)	(0.0188)	(0.0187)	(0.0190)
Days above 36°C: 3 years prior	-0.0107	0.00861	-0.0110	0.00245
	(0.0192)	(0.0190)	(0.0188)	(0.0195)
Days between 30-36°C: 1 year prior	-0.0216	0.0233	-0.0291	0.0357
	(0.0226)	(0.0217)	(0.0228)	(0.0233)
Days between 30-36°C: 2 years prior	-0.0226	0.0244	-0.0108	0.0185
	(0.0223)	(0.0221)	(0.0213)	(0.0221)
Days between 30-36°C: 3 years prior	-0.0195	0.00669	-0.0154	0.00221
	(0.0296)	(0.0289)	(0.0284)	(0.0288)
Observations	8747	8747	8747	8747
Mean of Dep Variable	0.814	0.180	0.818	0.155
Cumulative impact of days above 36°C	-0.0524**	0.0441**	-0.0531**	0.0428*
S.E.	(0.0212)	(0.0201)	(0.0214)	(0.0227)
Cumulative impact of days between 30-36°C	-0.0638**	0.0544**	-0.0553**	0.0564**
S.E.	(0.0272)	(0.0270)	(0.0270)	(0.0278)

*All regressions in include month-year, sub-district, age, and gender fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table 6: Lagged and cumulative heat exposure on labor outcomes: All adolescents

	Worked for pay (1)	Household work (2)	Family enterprise work (3)	Worked in farms (4)
Days above 36°C: 1 year prior	0.0196	0.0161	0.0133	-0.00241
	(0.0170)	(0.0117)	(0.0254)	(0.00703)
Days above 36°C: 2 years prior	-0.0110	-0.00139	-0.00257	0.00221
	(0.0172)	(0.0107)	(0.0255)	(0.00776)
Days above 36°C: 3 years prior	0.0167	-0.00150	-0.0213	-0.00533
	(0.0193)	(0.0115)	(0.0285)	(0.00702)
Days between 30-36°C: 1 year prior	0.0259	-0.00377	-0.0162	0.00286
	(0.0219)	(0.0142)	(0.0300)	(0.00984)
Days between 30-36°C: 2 years prior	0.00272	0.00677	0.00369	-0.00123
	(0.0195)	(0.0123)	(0.0321)	(0.00783)
Days between 30-36°C: 3 years prior	0.0314	-0.0109	0.0125	-0.0161
	(0.0288)	(0.0191)	(0.0455)	(0.0110)
Observations	8747	8747	8747	8747
Mean of Dep Variable	0.0947	0.0388	0.161	0.0168
Cumulative impact of days above 36°C	0.0253	0.0132	-0.0106	-0.00553
S.E.	(0.0193)	(0.0140)	(0.0366)	(0.00755)
Cumulative impact of days between 30-36°C	0.0600**	-0.00790	-0.0000139	-0.0145
S.E.	(0.0267)	(0.0193)	(0.0472)	(0.00981)

*All regressions in include month-year, sub-district, age, and gender fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table 7: Early life heat exposure on schooling: All adolescents

	Primary activity: student (1)	Primary activity: works (2)	Currently attending school (3)	Dropped out (4)
Days above 36°C: Age two	-0.0229*	0.0247*	-0.0243*	0.0288**
	(0.0134)	(0.0130)	(0.0137)	(0.0126)
Days above 36°C: Age one	-0.0337**	0.0329**	-0.0375***	0.0395***
	(0.0134)	(0.0137)	(0.0139)	(0.0121)
Days above 36°C: In Utero	-0.00402	0.00558	-0.00281	0.0125
	(0.0102)	(0.0101)	(0.0104)	(0.00939)
Days between 30-36°C: Age two	-0.0247	0.0243	-0.0240	0.0284*
	(0.0166)	(0.0162)	(0.0168)	(0.0165)
Days between 30-36°C: Age one	0.00187	-0.00118	0.00136	0.00418
	(0.0189)	(0.0183)	(0.0196)	(0.0186)
Days between 30-36°C: In Utero	-0.00219	0.00132	-0.00558	0.0245***
	(0.0112)	(0.0108)	(0.0116)	(0.00873)
Observations	5697	5697	5697	5697
Mean of Dep Variable	0.852	0.142	0.854	0.127

*All regressions include month-year, sub-district, age, and gender fixed effects. All regressions control for prior year heat exposure variables. All temperature regressors are standardized Robust standard errors (in parentheses) clustered at the sub-district level. . * 10%, ** 5%, *** 1% significance levels.*

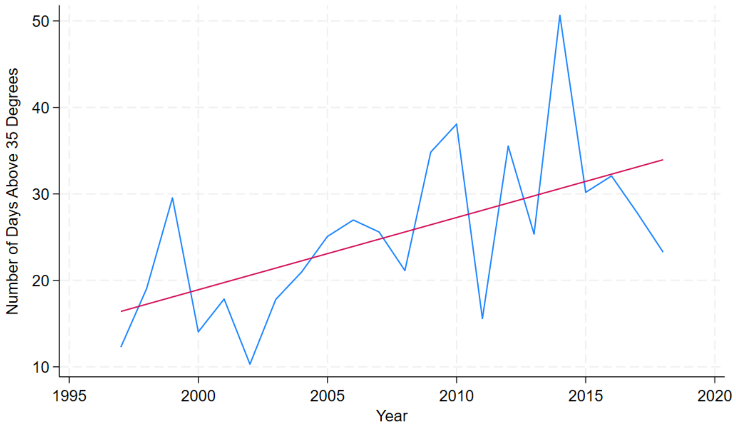
Table 8: Early life heat exposure on labor outcomes: All adolescents

	Worked for pay	Household work	Family enterprise work	Worked in farms
	(1)	(2)	(3)	(4)
Days above 36°C: Age two	0.00946	0.0135**	-0.000958	0.00100
	(0.00942)	(0.00624)	(0.0143)	(0.00377)
Days above 36°C: Age one	0.00206	0.00230	-0.00524	0.00664
	(0.0102)	(0.00557)	(0.0132)	(0.00522)
Days above 36°C: In Utero	0.00460	-0.000734	0.0122	-0.00455
	(0.00752)	(0.00300)	(0.00991)	(0.00305)
Days between 30-36°C: Age two	0.0168	0.00273	0.00956	-0.00122
	(0.0126)	(0.00611)	(0.0168)	(0.00559)
Days between 30-36°C: Age one	0.00554	-0.00574	-0.0240	0.000177
	(0.0129)	(0.00842)	(0.0178)	(0.00662)
Days between 30-36°C: In Utero	-0.00148	0.00104	0.00543	-0.00437
	(0.00947)	(0.00452)	(0.00898)	(0.00507)
Observations	5697	5697	5697	5697
Mean of Dep Variable	0.0795	0.0246	0.185	0.0128

*All regressions include month-year, sub-district, age, and gender fixed effects. All regressions control for prior year heat exposure variables. All temperature regressors are standardized Robust standard errors (in parentheses) clustered at the sub-district level. . * 10%, ** 5%, *** 1% significance levels.*

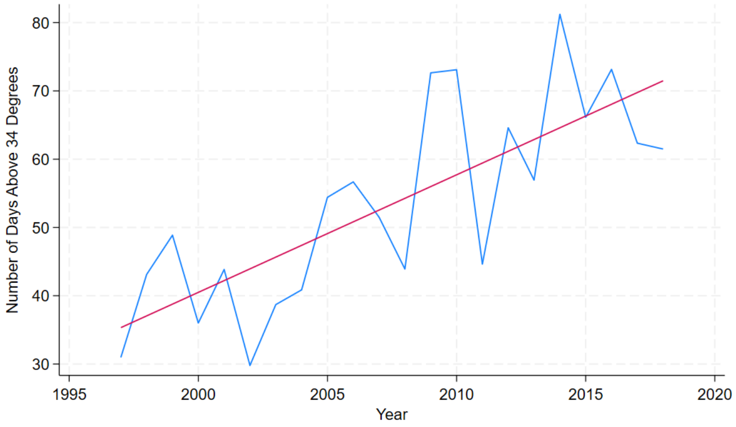
7 Additional Figures and Tables

Figure A1: Sub-district level historical trends in number of days above 36°C



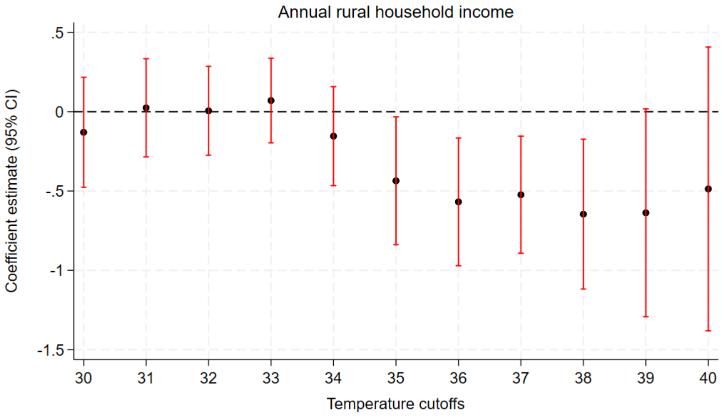
The figure plots average number of days above 36°C. The sample includes all rural sub-districts in Bangladesh over the years from 1997 to 2018

Figure A2: Sub-district level historical trends in number of days above 34°C



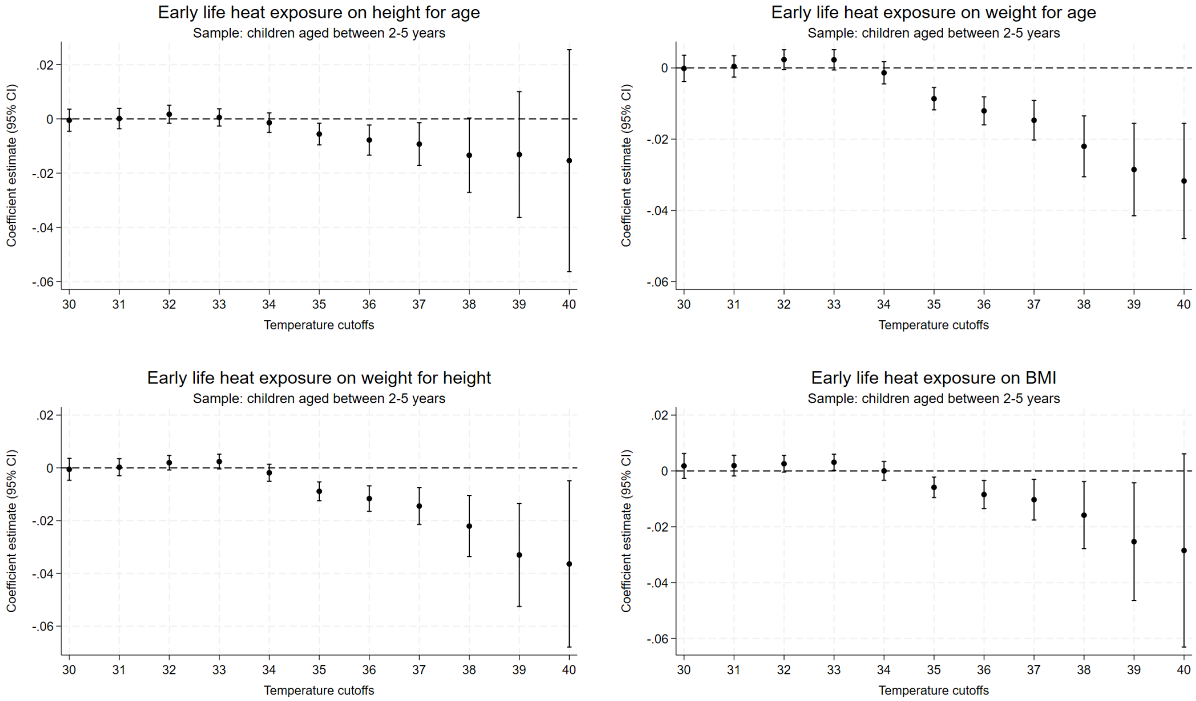
The figure plots average number of days above 34°C. The sample includes all rural sub-districts in Bangladesh over the years from 1997 to 2018

Figure A3: Heat exposure and annual household income



This figure show how an additional day above each temperature threshold (x-axis) in the past 365 days affects rural household income in the same year. Each point estimate comes from a separate regression that includes month-year, sub-district, and household fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Figure A4: Heat exposure and child anthropometric outcomes



These figures show how an additional day above each temperature threshold (x-axis) in the first 1000 days of life affects childrens' anthropometric outcomes. Each point estimate comes from a separate regression that includes month-year, sub-district, and household fixed effects. Markers represent the point estimates, and the error bars show the 95% confidence intervals, with standard errors clustered at the sub-district level.

Table A1: Prior year heat exposure on household annual income (in 1,000 BDT)

	Total income		Total non-agricultural income		Total agricultural income	
	(1)	(2)	(3)	(4)	(5)	(6)
Days above 36°C: 1 year prior	-14.83***	-11.08***	-10.08***	-7.756**	-4.749*	-3.322
	(4.486)	(4.172)	(3.721)	(3.461)	(2.427)	(2.385)
Days between 30-36°C: 1 year prior	-3.311	-2.260	-1.882	-2.271	-1.429	0.0111
	(3.042)	(2.797)	(2.690)	(2.399)	(1.610)	(1.552)
Observations	14661	13855	14661	13855	14661	13855
Mean of Dep Variable	101.1	102.1	68.42	68.33	32.73	33.73
Household fixed effects	No	Yes	No	Yes	No	Yes

*All regressions include month-year, and sub-district fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A2: Prior year heat exposure on illness (all household members)

	Sick in the last four weeks	Days sick in the last four weeks
	(1)	(2)
Days above 36°C: 1 year prior	0.0285***	0.236*
	(0.00685)	(0.134)
Days between 30-36°C: 1 year prior	0.0474***	1.445***
	(0.00499)	(0.0978)
Observations	74425	74425
Mean of Dep Variable	0.398	5.727

*All regressions include month-year, sub-district, age, and gender fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A3: Prior year heat exposure and household member sickness on schooling

	Primary activity: student	Primary activity: works	Currently attending school	Dropped out
	(1)	(2)	(3)	(4)
Panel A: All adolescents				
Days above 36°C: 1 year prior	-0.0335**	0.0257*	-0.0338**	0.0166
	(0.0158)	(0.0154)	(0.0152)	(0.0161)
Days between 30-36°C: 1 year prior	-0.00617	0.000931	-0.00526	-0.00238
	(0.0162)	(0.0159)	(0.0162)	(0.0158)
Someone else in HH was sicks X Days above 36°C: 1 year prior	0.00413	-0.00332	0.00399	-0.000751
	(0.00962)	(0.00954)	(0.00978)	(0.00868)
Someone else in HH was sick X Days between 30-36°C: 1 year prior	-0.00471	0.0111	-0.00592	0.00285
	(0.0152)	(0.0147)	(0.0152)	(0.0126)
Someone else in HH was sick	-0.00831	0.00869	-0.0112	0.00622
	(0.0116)	(0.0114)	(0.0116)	(0.0108)
Observations	8747	8747	8747	8747
Mean of Dep Variable	0.814	0.180	0.818	0.155
Cumulative impact of days between 30-35°C if someone else in HH was sick	-0.0109	0.0121	-0.0112	0.000462
S.E.	(0.0114)	(0.0106)	(0.0114)	(0.0122)
Cumulative impact of days above 36°C if someone else in HH was sick	-0.0294	0.0224**	-0.0298**	0.0159
S.E.	(0.0148)	(0.0145)	(0.0145)	(0.0156)
Panel B: Girls only				
Days above 36°C: 1 year prior	-0.0336	0.0300	-0.0316	0.0342*
	(0.0207)	(0.0202)	(0.0206)	(0.0199)
Days between 30-36°C: 1 year prior	0.0105	-0.0144	0.0103	-0.00689
	(0.0215)	(0.0212)	(0.0213)	(0.0220)
Someone else in HH was sick X Days between 30-36°C: 1 year prior	-0.0133	0.0166	-0.0143	0.00778
	(0.0221)	(0.0199)	(0.0222)	(0.0205)
Someone else in HH was sicks X Days above 36°C: 1 year prior	-0.00629	0.00368	-0.00752	-0.00122
	(0.0128)	(0.0123)	(0.0128)	(0.0117)
Someone else in HH was sick	-0.0246*	0.0210	-0.0236*	0.0245*
	(0.0143)	(0.0136)	(0.0140)	(0.0129)
Observations	4294	4294	4294	4294
Mean of Dep Variable	0.861	0.134	0.866	0.117
Cumulative impact of days between 30-35°C if someone else in HH was sick	-0.00281	0.00226	-0.00401	0.000895
S.E.	(0.0153)	(0.0144)	(0.0150)	(0.0138)
Cumulative impact of days above 36°C if someone else in HH was sick	-0.0399**	0.0337*	-0.0391**	0.0330*
S.E.	(0.0187)	(0.0183)	(0.0190)	(0.0182)
Panel C: Boys only				
Days above 36°C: 1 year prior	-0.0309	0.0196	-0.0312	-0.000132
	(0.0257)	(0.0258)	(0.0247)	(0.0253)
Days between 30-36°C: 1 year prior	-0.0238	0.0181	-0.0211	0.00562
	(0.0265)	(0.0275)	(0.0265)	(0.0274)
Someone else in HH was sick X Days between 30-36°C: 1 year prior	0.00153	0.00645	0.000947	0.00158
	(0.0138)	(0.0151)	(0.0137)	(0.0146)
Someone else in HH was sicks X Days above 36°C: 1 year prior	0.0117	-0.00558	0.0125	0.00560
	(0.0158)	(0.0154)	(0.0160)	(0.0144)
Someone else in HH was sick	0.0158	-0.0113	0.0101	-0.0198
	(0.0175)	(0.0172)	(0.0176)	(0.0166)
Observations	4453	4453	4453	4453
Mean of Dep Variable	0.768	0.225	0.772	0.192
Cumulative impact of days between 30-35°C if someone else in HH was sick	-0.0222	0.0245	-0.0201	0.00720
S.E.	(0.0207)	(0.0201)	(0.0209)	(0.0205)
Cumulative impact of days above 36°C if someone else in HH was sick	-0.0192	0.0141	-0.0186	0.00547
S.E.	(0.0232)	(0.0233)	(0.0227)	(0.0241)

*All regressions in Panel A include month-year, sub-district, age, and gender fixed effects. All regressions in Panel B and C include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A4: Prior year heat exposure and status of woman on schooling

	Primary activity: student (1)	Primary activity: works (2)	Currently attending school (3)	Dropped out (4)
Panel A: All adolescents				
Days above 36°C: 1 year prior	-0.0291**	0.0226	-0.0296**	0.0148
	(0.0145)	(0.0141)	(0.0141)	(0.0152)
Days between 30-36°C: 1 year prior	-0.0109	0.0114	-0.0111	0.000391
	(0.0110)	(0.0103)	(0.0111)	(0.0120)
Husband does not want woman to work outside X Days above 36°C: 1 year	-0.0823*	0.0843**	-0.0818*	0.0618*
	(0.0418)	(0.0423)	(0.0420)	(0.0370)
Husband does not want woman to work outside X Days between 30-36°C: 1	-0.0326	0.0378	-0.0189	0.0330
	(0.0563)	(0.0558)	(0.0558)	(0.0548)
Husband does not want woman to work outside	-0.0271	0.0356	-0.0160	0.0439
	(0.0505)	(0.0503)	(0.0495)	(0.0468)
Observations	8747	8747	8747	8747
Mean of Dep Variable	0.814	0.180	0.818	0.155
Cumulative impact of days between 30-35°C if husband does not want woman to work outside	-0.0435	0.0493	-0.0300	0.0334
S.E.	(0.0563)	(0.0559)	(0.0558)	(0.0545)
Cumulative impact of days above 36°C if husband does not want woman to work outside	-0.111**	0.107**	-0.111**	0.0766**
S.E.	(0.0436)	(0.0439)	(0.0437)	(0.0383)
Panel B: Girls only				
Days above 36°C: 1 year prior	-0.0371*	0.0321	-0.0359*	0.0323
	(0.0208)	(0.0205)	(0.0205)	(0.0197)
Days between 30-36°C: 1 year prior	-0.00224	0.00132	-0.00330	0.00106
	(0.0147)	(0.0144)	(0.0145)	(0.0139)
Husband does not want woman to work outside X Days above 36°C: 1 year	-0.0493	0.0513	-0.0539	0.0334
	(0.0395)	(0.0388)	(0.0389)	(0.0373)
Husband does not want woman to work outside X Days between 30-36°C: 1	0.00618	0.00368	0.0209	-0.0275
	(0.0572)	(0.0563)	(0.0564)	(0.0541)
Husband does not want woman to work outside	-0.0923**	0.107**	-0.0749*	0.105**
	(0.0449)	(0.0441)	(0.0442)	(0.0424)
Observations	4294	4294	4294	4294
Mean of Dep Variable	0.861	0.134	0.866	0.117
Cumulative impact of days between 30-35°C if husband does not want woman to work outside	0.00394	0.00500	0.0176	-0.0265
S.E.	(0.0592)	(0.0582)	(0.0583)	(0.0559)
Cumulative impact of days above 36°C if husband does not want woman to work outside	-0.0864**	0.0835**	-0.0898**	0.0657
S.E.	(0.0438)	(0.0430)	(0.0431)	(0.0414)
Panel C: Boys only				
Days above 36°C: 1 year prior	-0.0220	0.0157	-0.0217	0.00354
	(0.0225)	(0.0225)	(0.0218)	(0.0231)
Days between 30-36°C: 1 year prior	-0.0213	0.0231	-0.0193	0.00541
	(0.0209)	(0.0202)	(0.0210)	(0.0207)
Husband does not want woman to work outside X Days above 36°C: 1 year	-0.163***	0.168***	-0.164***	0.130**
	(0.0576)	(0.0600)	(0.0579)	(0.0509)
Husband does not want woman to work outside X Days between 30-36°C: 1	-0.190	0.198	-0.193	0.241
	(0.144)	(0.145)	(0.144)	(0.147)
Husband does not want woman to work outside	0.126*	-0.122*	0.129**	-0.0817
	(0.0658)	(0.0662)	(0.0653)	(0.0604)
Observations	4453	4453	4453	4453
Mean of Dep Variable	0.768	0.225	0.772	0.192
Cumulative impact of days between 30-35°C if husband does not want woman to work outside	-0.211	0.221	-0.212	0.247*
S.E.	(0.145)	(0.146)	(0.145)	(0.147)
Cumulative impact of days above 36°C if husband does not want woman to work outside	-0.185***	0.183***	-0.185***	0.134**
S.E.	(0.0597)	(0.0623)	(0.0601)	(0.0524)

*All regressions in Panel A include month-year, sub-district, age, and gender fixed effects. All regressions in Panel B and C include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A5: Prior year heat exposure on schooling: with sub-district-specific linear time trends

	Primary activity: student	Primary activity: works	Currently attending school	Dropped out
	(1)	(2)	(3)	(4)
Panel A: All adolescents				
Days above 36°C: 1 year prior	-0.0577***	0.0554***	-0.0480**	0.0616***
	(0.0174)	(0.0159)	(0.0195)	(0.0178)
Days between 30-36°C: 1 year prior	-0.0935***	0.0910***	-0.0825***	0.1000***
	(0.0224)	(0.0206)	(0.0255)	(0.0231)
Observations	8747	8747	8747	8747
Mean of Dep Variable	0.814	0.180	0.818	0.155
Panel B: Girls only				
Days above 36°C: 1 year prior	-0.0494**	0.0492**	-0.0351	0.0425**
	(0.0212)	(0.0205)	(0.0220)	(0.0198)
Days between 30-36°C: 1 year prior	-0.0599**	0.0566**	-0.0406	0.0404
	(0.0289)	(0.0286)	(0.0308)	(0.0278)
Observations	4281	4281	4281	4281
Mean of Dep Variable	0.861	0.134	0.866	0.117
Panel C: Boys only				
Days above 36°C: 1 year prior	-0.0948***	0.0902***	-0.0887**	0.112***
	(0.0326)	(0.0312)	(0.0347)	(0.0343)
Days between 30-36°C: 1 year prior	-0.148***	0.145***	-0.147***	0.185***
	(0.0393)	(0.0369)	(0.0428)	(0.0417)
Observations	4439	4439	4439	4439
Mean of Dep Variable	0.768	0.225	0.772	0.192

*All regressions in Panel A include month-year, sub-district, age, and gender fixed effects. All regressions in Panel B and C include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A6: Prior year heat exposure on schooling: with household fixed effects

	Primary activity: student	Primary activity: works	Currently attending school	Dropped out
	(1)	(2)	(3)	(4)
		Panel A: All adolescents		
Days above 36°C: 1 year prior	-0.0181	0.0121	-0.0176	0.00697
	(0.0159)	(0.0156)	(0.0155)	(0.0169)
Days between 30-36°C: 1 year prior	-0.000555	0.00426	-0.000760	-0.00666
	(0.0140)	(0.0126)	(0.0138)	(0.0159)
Observations	7069	7069	7069	7069
Mean of Dep Variable	0.815	0.178	0.819	0.155
		Panel B: Girls only		
Days above 36°C: 1 year prior	-0.0432**	0.0356*	-0.0327	0.0352*
	(0.0210)	(0.0211)	(0.0206)	(0.0203)
Days between 30-36°C: 1 year prior	-0.00212	0.000656	-0.00307	0.00223
	(0.0178)	(0.0177)	(0.0175)	(0.0179)
Observations	2784	2784	2784	2784
Mean of Dep Variable	0.882	0.114	0.885	0.100
		Panel C: Boys only		
Days above 36°C: 1 year prior	0.0101	-0.0145	0.00647	-0.0190
	(0.0274)	(0.0272)	(0.0276)	(0.0262)
Days between 30-36°C: 1 year prior	0.0145	-0.00935	0.0171	-0.0275
	(0.0274)	(0.0258)	(0.0272)	(0.0239)
Observations	2958	2958	2958	2958
Mean of Dep Variable	0.765	0.228	0.769	0.197

*All regressions in Panel A include month-year, sub-district, age, and gender fixed effects. All regressions in Panel B and C include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A7: Prior year heat exposure on schooling: with finer temperature bins

	Primary activity: student (1)	Primary activity: works (2)	Currently attending school (3)	Dropped out (4)
Panel A: All adolescents				
Days between 31-32°C: 1 year prior	-0.000707	0.000674	-0.000674	0.000614
	(0.000546)	(0.000532)	(0.000535)	(0.000564)
Days between 33-34°C: 1 year prior	-0.000332	0.000374	-0.000316	-0.0000893
	(0.000411)	(0.000396)	(0.000397)	(0.000420)
Days between 35-36°C: 1 year prior	0.00000242	-0.000108	-0.000282	-0.000342
	(0.000682)	(0.000668)	(0.000687)	(0.000696)
Days between 37-38°C: 1 year prior	-0.00131	0.00129	-0.00159	0.00153
	(0.00142)	(0.00146)	(0.00139)	(0.00139)
Days above 38°C: 1 year prior	-0.00615	0.00385	-0.00504	0.000322
	(0.00391)	(0.00408)	(0.00399)	(0.00378)
Observations	8747	8747	8747	8747
Mean of Dep Variable	0.814	0.180	0.818	0.155
Panel B: Girls only				
Days between 31-32°C: 1 year prior	-0.0000291	-0.0000331	-0.0000472	0.000283
	(0.000760)	(0.000730)	(0.000745)	(0.000701)
Days between 33-34°C: 1 year prior	0.0000335	-0.0000765	-0.0000328	-0.000192
	(0.000558)	(0.000561)	(0.000540)	(0.000505)
Days between 35-36°C: 1 year prior	-0.000541	0.000201	-0.000819	-0.0000346
	(0.000964)	(0.000927)	(0.000969)	(0.000900)
Days between 37-38°C: 1 year prior	-0.00116	0.00147	-0.00138	0.00223
	(0.00185)	(0.00186)	(0.00190)	(0.00169)
Days above 38°C: 1 year prior	-0.00865**	0.00565	-0.00774*	0.00244
	(0.00416)	(0.00405)	(0.00430)	(0.00384)
Observations	4294	4294	4294	4294
Mean of Dep Variable	0.861	0.134	0.866	0.117
Panel C: Boys only				
Days between 31-32°C: 1 year prior	-0.00145	0.00141	-0.00130	0.00118
	(0.00100)	(0.000991)	(0.000959)	(0.00101)
Days between 33-34°C: 1 year prior	-0.000656	0.000753	-0.000539	0.0000832
	(0.000735)	(0.000721)	(0.000724)	(0.000695)
Days between 35-36°C: 1 year prior	0.000920	-0.000700	0.000709	-0.000637
	(0.00105)	(0.00104)	(0.00105)	(0.00110)
Days between 37-38°C: 1 year prior	-0.000810	0.000503	-0.00109	0.000488
	(0.00221)	(0.00224)	(0.00207)	(0.00218)
Days above 38°C: 1 year prior	-0.00449	0.00322	-0.00279	-0.0000710
	(0.00665)	(0.00682)	(0.00652)	(0.00651)
Observations	4453	4453	4453	4453
Mean of Dep Variable	0.768	0.225	0.772	0.192

*All regressions in Panel A include month-year, sub-district, age, and gender fixed effects. All regressions in Panel B and C include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A8: Lagged and cumulative heat exposure on schooling: Girls only

	Primary activity: student (1)	Primary activity: works (2)	Currently attending school (3)	Dropped out (4)
Days above 36°C: 1 year prior	-0.0426*	0.0353	-0.0418*	0.0552**
	(0.0227)	(0.0222)	(0.0228)	(0.0225)
Days above 36°C: 2 years prior	0.0184	-0.0222	0.00998	-0.0230
	(0.0232)	(0.0237)	(0.0236)	(0.0222)
Days above 36°C: 3 years prior	-0.0163	0.0161	-0.00496	0.0161
	(0.0253)	(0.0252)	(0.0253)	(0.0233)
Days between 30-36°C: 1 year prior	-0.0136	0.00858	-0.0169	0.0422
	(0.0263)	(0.0258)	(0.0260)	(0.0257)
Days between 30-36°C: 2 years prior	-0.0337	0.0313	-0.0298	0.0293
	(0.0283)	(0.0284)	(0.0287)	(0.0260)
Days between 30-36°C: 3 years prior	0.0159	-0.0227	0.0323	-0.0172
	(0.0404)	(0.0407)	(0.0387)	(0.0360)
Observations	4294	4294	4294	4294
Mean of Dep Variable	0.861	0.134	0.866	0.117
Cumulative impact of days between 30-36°C	-0.0315	0.0172	-0.0144	0.0543
S.E.	0.0366	0.0362	0.0358	0.0354
Cumulative impact of days above 36°C	-0.0405	0.0292	-0.0368	0.0483
S.E.	0.0277	0.0270	0.0273	0.0267

*All regressions include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A9: Lagged and cumulative heat exposure on schooling: Boys only

	Primary activity: student (1)	Primary activity: works (2)	Currently attending school (3)	Dropped out (4)
Days above 36°C: 1 year prior	-0.0381	0.0350	-0.0442	0.0267
	(0.0287)	(0.0276)	(0.0282)	(0.0285)
Days above 36°C: 2 years prior	-0.0230	0.0243	-0.00885	0.0309
	(0.0286)	(0.0281)	(0.0282)	(0.0293)
Days above 36°C: 3 years prior	0.00246	-0.00509	-0.0109	-0.0242
	(0.0331)	(0.0322)	(0.0323)	(0.0337)
Days between 30-36°C: 1 year prior	-0.0389	0.0464	-0.0501	0.0419
	(0.0376)	(0.0368)	(0.0381)	(0.0369)
Days between 30-36°C: 2 years prior	-0.0128	0.0184	0.00717	0.0119
	(0.0331)	(0.0322)	(0.0310)	(0.0341)
Days between 30-36°C: 3 years prior	-0.0474	0.0299	-0.0596	0.00570
	(0.0559)	(0.0544)	(0.0546)	(0.0538)
Observations	4453	4453	4453	4453
Mean of Dep Variable	0.768	0.225	0.772	0.192
Cumulative impact of days between 30-36°C	-0.0991	0.0946	-0.103	0.0595
S.E.	0.0518	0.0507	0.0521	0.0495
Cumulative impact of days above 36°C	-0.0586	0.0542	-0.0639	0.0334
S.E.	0.0358	0.0344	0.0362	0.0353

*All regressions include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A10: Lagged and cumulative heat exposure on labor outcomes: Girls only

	Worked for pay	Household work	Family enterprise work	Worked in farms
	(1)	(2)	(3)	(4)
Days above 36°C: 1 year prior	0.0106	0.0261	-0.00349	0.00359
	(0.0135)	(0.0215)	(0.0299)	(0.00325)
Days above 36°C: 2 years prior	-0.0247	-0.00173	0.00156	-0.000548
	(0.0160)	(0.0205)	(0.0337)	(0.00255)
Days above 36°C: 3 years prior	0.0219	0.00304	-0.00582	-0.00240
	(0.0152)	(0.0211)	(0.0328)	(0.00234)
Days between 30-36°C: 1 year prior	0.0155	-0.0108	-0.0632*	0.00389
	(0.0196)	(0.0264)	(0.0366)	(0.00476)
Days between 30-36°C: 2 years prior	0.000897	0.0271	-0.0165	-0.000714
	(0.0171)	(0.0238)	(0.0410)	(0.00275)
Days between 30-36°C: 3 years prior	0.0162	-0.0347	0.0783	-0.00666*
	(0.0212)	(0.0350)	(0.0546)	(0.00348)
Observations	4294	4294	4294	4294
Mean of Dep Variable	0.0303	0.0745	0.158	0.00186
Cumulative impact of days between 30-36°C	0.0326	-0.0184	-0.00146	-0.00348
S.E.	0.0196	0.0363	0.0575	0.00236
Cumulative impact of days above 36°C	0.00780	0.0274	-0.00774	0.000648
S.E.	0.0148	0.0259	0.0434	0.00269

*All regressions include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A11: Lagged and cumulative heat exposure on labor outcomes: Boys only

	Worked for pay	Household work	Family enterprise work	Worked in farms
	(1)	(2)	(3)	(4)
Days above 36°C: 1 year prior	0.0381	0.00827*	0.0237	-0.00570
	(0.0279)	(0.00495)	(0.0333)	(0.0132)
Days above 36°C: 2 years prior	-0.00565	0.00423	0.00162	0.00252
	(0.0298)	(0.00492)	(0.0312)	(0.0153)
Days above 36°C: 3 years prior	0.0109	-0.00278	-0.0504	-0.0112
	(0.0333)	(0.00577)	(0.0371)	(0.0142)
Days between 30-36°C: 1 year prior	0.0485	0.00212	0.0278	0.00419
	(0.0345)	(0.00662)	(0.0411)	(0.0173)
Days between 30-36°C: 2 years prior	-0.00562	-0.00669	0.0240	-0.000276
	(0.0348)	(0.00671)	(0.0390)	(0.0153)
Days between 30-36°C: 3 years prior	0.0415	0.0204*	-0.0606	-0.0322
	(0.0515)	(0.0113)	(0.0617)	(0.0222)
Observations	4453	4453	4453	4453
Mean of Dep Variable	0.157	0.00427	0.163	0.0312
Cumulative impact of days between 30-36°C	0.0843	0.0158	-0.00876	-0.0283
S.E.	0.0481	0.0108	0.0687	0.0206
Cumulative impact of days above 36°C	0.0434	0.00973	-0.0251	-0.0144
S.E.	0.0337	0.00730	0.0491	0.0165

*All regressions include month-year, sub-district, and age fixed effects. Robust standard errors (in parentheses) clustered at the sub-district level. All temperature regressors are standardized. * 10%, ** 5%, *** 1% significance levels.*

Table A12: Early life heat exposure on schooling: Girls only

	Primary activity: student	Primary activity: works	Currently attending school	Dropped out
	(1)	(2)	(3)	(4)
Days above 36°C: Age two	-0.00157	0.00819	0.00135	0.00877
	(0.0205)	(0.0201)	(0.0208)	(0.0194)
Days above 36°C: Age one	-0.0182	0.0192	-0.0189	0.0293*
	(0.0176)	(0.0180)	(0.0174)	(0.0164)
Days above 36°C: In Utero	0.00185	0.0000519	0.00103	0.00713
	(0.0136)	(0.0135)	(0.0134)	(0.0127)
Days between 30-36°C: Age two	0.0158	-0.00537	0.0186	-0.00228
	(0.0207)	(0.0197)	(0.0203)	(0.0179)
Days between 30-36°C: Age one	0.0188	-0.0157	0.0228	-0.00706
	(0.0267)	(0.0265)	(0.0264)	(0.0247)
Days between 30-36°C: In Utero	0.0114	-0.0105	0.0136	0.000965
	(0.0167)	(0.0166)	(0.0168)	(0.0147)
Observations	2469	2469	2469	2469
Mean of Dep Variable	0.901	0.0944	0.905	0.0859

*All regressions include month-year, sub-district, and age fixed effects. All regressions control for prior year heat exposure variables. All temperature regressors are standardized Robust standard errors (in parentheses) clustered at the sub-district level. . * 10%, ** 5%, *** 1% significance levels.*

Table A13: Early life heat exposure on schooling: Boys only

	Primary activity: student (1)	Primary activity: works (2)	Currently attending school (3)	Dropped out (4)
Days above 36°C: Age two	-0.0381*	0.0358*	-0.0410**	0.0484***
	(0.0194)	(0.0184)	(0.0197)	(0.0173)
Days above 36°C: Age one	-0.0429**	0.0423**	-0.0485**	0.0454***
	(0.0191)	(0.0189)	(0.0199)	(0.0171)
Days above 36°C: In Utero	-0.00536	0.00709	-0.00434	0.0171
	(0.0151)	(0.0147)	(0.0153)	(0.0134)
Days between 30-36°C: Age two	-0.0566**	0.0481**	-0.0555**	0.0518**
	(0.0246)	(0.0239)	(0.0250)	(0.0240)
Days between 30-36°C: Age one	-0.0113	0.0107	-0.0140	0.0165
	(0.0287)	(0.0266)	(0.0299)	(0.0268)
Days between 30-36°C: In Utero	-0.0131	0.0108	-0.0176	0.0373***
	(0.0153)	(0.0144)	(0.0159)	(0.0121)
Observations	3219	3219	3219	3219
Mean of Dep Variable	0.815	0.178	0.816	0.159

*All regressions include month-year, sub-district, and age fixed effects. All regressions control for prior year heat exposure variables. All temperature regressors are standardized Robust standard errors (in parentheses) clustered at the sub-district level. . * 10%, ** 5%, *** 1% significance levels.*

Table A14: Early life heat exposure on labor outcomes: Girls only

	Worked for pay (1)	Household work (2)	Family enterprise work (3)	Worked in farms (4)
Days above 36°C: Age two	-0.000403	0.0297**	0.0103	-0.00163
	(0.00786)	(0.0150)	(0.0236)	(0.00219)
Days above 36°C: Age one	-0.00439	0.0144	-0.0145	-0.00157
	(0.00822)	(0.0140)	(0.0200)	(0.00134)
Days above 36°C: In Utero	0.00644	-0.00587	0.0170	0.00174
	(0.00737)	(0.00786)	(0.0174)	(0.00162)
Days between 30-36°C: Age two	0.00352	0.0155	-0.0228	0.00172
	(0.00914)	(0.0144)	(0.0251)	(0.00184)
Days between 30-36°C: Age one	0.0133*	0.000552	-0.0249	-0.000166
	(0.00790)	(0.0199)	(0.0275)	(0.00125)
Days between 30-36°C: In Utero	-0.00305	0.00287	0.0184	-0.000382
	(0.00900)	(0.0130)	(0.0164)	(0.000636)
Observations	2469	2469	2469	2469
Mean of Dep Variable	0.0166	0.0502	0.205	0.000810

*All regressions include month-year, sub-district, and age fixed effects. All regressions control for prior year heat exposure variables. All temperature regressors are standardized Robust standard errors (in parentheses) clustered at the sub-district level. . * 10%, ** 5%, *** 1% significance levels.*

Table A15: Early life heat exposure on labor outcomes: Boys only

	Worked for pay	Household work	Family enterprise work	Worked in farms
	(1)	(2)	(3)	(4)
Days above 36°C: Age two	0.0214	0.00500	-0.000923	0.00545
	(0.0157)	(0.00352)	(0.0193)	(0.00711)
Days above 36°C: Age one	0.0000159	-0.00707**	-0.00128	0.0130*
	(0.0156)	(0.00325)	(0.0182)	(0.00788)
Days above 36°C: In Utero	0.00176	0.000269	0.00650	-0.00917*
	(0.0111)	(0.00141)	(0.0130)	(0.00488)
Days between 30-36°C: Age two	0.0270	-0.00112	0.0326	-0.00225
	(0.0214)	(0.00369)	(0.0256)	(0.00988)
Days between 30-36°C: Age one	0.00363	-0.00739*	-0.0298	-0.00344
	(0.0222)	(0.00432)	(0.0271)	(0.0122)
Days between 30-36°C: In Utero	0.00219	-0.00153	0.00250	-0.00471
	(0.0133)	(0.00346)	(0.0127)	(0.00748)
Observations	3219	3219	3219	3219
Mean of Dep Variable	0.128	0.00466	0.171	0.0221

*All regressions include month-year, sub-district, and age fixed effects. All regressions control for prior year heat exposure variables. All temperature regressors are standardized Robust standard errors (in parentheses) clustered at the sub-district level. . * 10%, ** 5%, *** 1% significance levels.*

ALL IFPRI DISCUSSION PAPERS

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org