Extreme Weather, Household Finance, and Schooling: Evidence in Ethiopia *

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Abstract

Prior research has shown the impact of weather shocks on productivity, economic growth, and human capital, encompassing health and education, using cross-sectional data. This paper, based on longitudinal datasets from Ethiopia, finds that flooding significantly influences household finances, children's education enrolment, and child labor. Among Ethiopian boys, flooding shocks significantly reduce enrollment probability by 7.8 percentage points, daily school hours by 0.5 hours, and private leisure by 0.3 hours, while increasing child labor by 0.7 hours (including household chores by 0.2, domestic tasks by 0.3, and paid work by 0.2) and a 0.5 percentage point rise in the probability of severe injury. The result is entirely driven by increased household loans and parental illness following flood shocks among poor households. This underscores climate change's role in exacerbating child inequality by forcing a trade-off between education and child labor as poor families strive to repay household debts after flood shocks. Notably, the existing social protection program (PSNP) fails to mitigate these adverse impacts.

Keywords: child labor, household finance, extreme weather shocks, climate change, human capital

JEL: D14, J13, Q54, J22, J16, J24

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1 Introduction

Climate change is contributing to a rise in extreme weather events (Stott, 2016), impacting agricultural productivity, economic growth (Dell et al., 2014), and various aspects of human capital. Past studies have shown connections between childhood exposure to weather shocks and indicators such as height and schooling (Maccini and Yang, 2009), as well as mortality (bar; Burgess and Michael, 2017; Deschênes and Greenstone, 2011). These investigations have primarily relied on repeated cross-sectional data, assuming that geographic variations in exposure to extreme weather shocks are exogenous.

Utilizing high-quality longitudinal datasets can help mitigate issues related to causal inference (Akabayashi and Psacharopoulos, 1999). Furthermore, there is little evidence on how weather shocks affect children's time allocation, such as hours spent on child labor, particularly in developing countries characterized by prevalent child labor, with children frequently engaged in family farming activities and paid work (ILO, 2020). By hindering human capital development, child labor may disrupt human capital formation by influencing schooling and learning, which can impede the prospects of the child, the family, and ultimately the economy (Akabayashi and Psacharopoulos, 1999; Psacharopoulos, 1997).

In this paper, an investigation is conducted to explore the impact of flooding on children's time allocation in Ethiopia. The analysis incorporates controls for individual fixed effects and year-fixed effects during estimation. The data utilized for this study is derived from the Young Lives dataset, a longitudinal dataset that spans from 2002 to 2016. This dataset offers extensive information on various aspects, including children's time allocation, covering hours allocated to education, work, leisure, household chores, domestic tasks, and paid work.

As a result, the findings indicate that flooding shocks have several significant effects on boys in Ethiopia. Flooding reduces enrollment probability by 7.8 percentage points, daily school hours by 0.5 hours, and private leisure by 0.3 hours. Simultaneously, it increases child labor by 0.7 hours, comprising household chores by 0.2 hours, domestic tasks by 0.3 hours, and paid work by 0.2 hours. Additionally, flooding raises the probability of serious injury

by 0.5 percentage points. Furthermore, flooding shocks are associated with an increase in household loans or credit and a significant rise in illness among both the father and mother of the child. However, there is no significant change in living conditions or food security.

In the heterogeneity analysis, it is observed that the effect is predominantly driven by households that have taken household loans, rural households, and households below the median of a wealth index constructed using a composite measure based on various household assets, housing conditions, and other socio-economic indicators.

Furthermore, the study does not find any evidence that existing safety net programs in Ethiopia, such as the Productive Safety Net Program (PSNP), which provides financial support, food aid, and employment opportunities through public works programs to vulnerable households, effectively mitigate the adverse effects of flooding on children. exposure to extreme hot temperatures during pregnancy leads to lower birth weight in the US.

This paper is closely related to the weather shock literature on human capital (health and education), finding that rainfall, particularly during childhood influences height, schooling, and wealth of adult women (Maccini and Yang, 2009) and cognitive abilities due to increased agricultural income and nutritional investments (Webb, 2022), as well as birthweight (Deschênes et al., 2009) or mortality (bar; Barreca et al., 2015; Burgess and Michael, 2017; Deschênes and Greenstone, 2011). This paper introduces a novel dimension to the link between childhood weather shocks and human capital development by shedding light on the significant impact of these shocks on children's time allocation because of increased household finance loans and parental illness—a previously underexplored avenue of research in this field. In the second part, its estimation strategy, incorporating individual fixed effects, relaxes the assumption often made in prior research that cross-sectional geographic exposure to flooding is exogenous to the outcomes of interest.

By demonstrating that extreme weather shocks are also determinants of child labor, this paper also contributes to the child labor literature. This previous literature documents that child labor is determined by poverty and economic factors (Bandara et al., 2015; Basu and

Van, 1998; Edmonds and Schady, 2012; Fors, 2012), household characteristics (Al-Samarrai and Peasgood, 1998; Baland and Robinson, 2000; Basu and Van, 1998; Strauss and Thomas, 1995), imperfect land and labor markets (Bhalotra and Heady, 2003; Congdon Fors, 2007; Dumas, 2007; Ganglmair, 2005), risk coping mechanisms (Beegle et al., 2006; Morduch, 1999; Ravallion and Chaudhuri, 1997), agriculture shocks (Baker et al., 2020; Bandara et al., 2015; Duryea et al., 2007), relative returns to child labor (Bai and Wang, 2020; Shah and Steinberg, 2017) and policy interventions (Basu, 2005; Bharadwaj et al., 2020; Dammert et al., 2018; De Hoop and Rosati, 2014; De Hoop et al., 2019; De Janvry et al., 2006; Edmonds and Shrestha, 2014; Ravallion and Wodon, 2000; Skoufias et al., 2001).

The findings of this study hold important policy implications. While previous research has established the impact of weather shocks on various aspects of human capital and economic growth, this paper's findings emphasize that climate change may exacerbate child inequality, as weather shocks, like flooding, disrupt household finances and contribute to parental illness, subsequently affecting children's time allocation and education negatively among disadvantaged households. Additionally, the study highlights the limitations of the existing social protection program (PSNP) in safeguarding children from the adverse effects of weather shocks, indicating the need for enhanced protective measures.

The structure of the paper is as follows. Section 2.2 documents related literature. Section 3 explains data and methods. Section 4 presents the main results. Finally, Section 6 concludes.

2 Related literature

2.1 Weather shocks and economic outcomes

Extensive research explores the impact of temperature, precipitation, and windstorms on economic outcomes, emphasizing variations in weather conditions observed over time within specific geographic regions. This body of work reveals a diverse array of effects on multiple

economic dimensions, encompassing agricultural and industrial output, labor productivity, energy demand, health, and economic growth, among others. A comprehensive summary of these findings is provided by Dell et al. (2014).

Maccini and Yang (2009) demonstrates that greater early-life rainfall has positive effects on women's outcomes, including increased height, more years of schooling, and improved household wealth, primarily mediated through education using Indonesia Family Life Survey (IFLS). In the same dataset, Webb (2022) finds significant effects of early-life (age 2) weather shocks on adult cognitive abilities, primarily attributed to changes in agricultural income and nutritional investments. Deschênes et al. (2009) exposure to extreme hot temperatures during pregnancy leads to lower birth weight in the US.

Deschênes and Greenstone (2011) uncovers non-linear associations between daily temperatures and annual mortality rates in the US. bar observes a remarkable reduction in the temperature-mortality relationship over the 20th century in the US. Additionally, Barreca et al. (2015) identifies a decline in the health-mortality relationship, with some convergence, but suggests that narrowing the remaining gap may be a slow and challenging process.

In Burgess and Michael (2017), significant temperature-related mortality disparities between rural and urban India are emphasized, as hot days negatively affect rural areas through reduced agricultural productivity and wages, potentially resulting in substantial reductions in rural Indian life expectancy in the context of climate change.

In these studies, (Felkner et al., 2009) examines the impact of weather on crop yield, (Burgess and Donaldson, 2010) investigates how railroads mitigate the effects of agricultural productivity shocks on famine in colonial-era India, (Fisher et al., 2012) focuses on the potential negative impact of climate change on US agriculture, and (Deschênes and Greenstone, 2007, 2012; Hornbeck, 2012) explore various aspects of agricultural land values and revenues.

2.2 The determinants of child labor

"Child work" and "child labor" are often used interchangeably in the literature, but the International Labour Organization (ILO) (ILO, 2020) distinguishes three categories: "children in employment," which encompasses all paid and some unpaid productive activities; "child laborers," which excludes specific forms of child employment.

Another ILO definition characterizes child labor as any work that harms a child's physical, mental, social, or moral development, depriving them of childhood, potential, and dignity. It also hampers their education by denying them access to school, compelling premature departure, or necessitating a burdensome combination of school and excessive labor (ILO, 2023). In 2020, the ILO estimated that 160 million children, or 9.6 percent of the world's 5–17-year-olds, were employed, with 79 million in hazardous conditions (ILO, 2020). Despite some progress, child labor remains a persistent issue, necessitating effective policy interventions. Dammert et al. (2018) provide extensive literature reviews.

Understanding the factors that drive child labor is crucial for effective policy design aimed at its reduction or eradication. Numerous studies have explored these factors, revealing key contributors. Poverty, household characteristics, credit market imperfections, imperfect land and labor markets, and macroeconomic factors have been identified as primary determinants (Bandara et al., 2015; Fors, 2012). For instance, Basu and Van (1998) introduced a seminal model demonstrating how poverty incentivizes child labor in well-functioning labor markets. When adult wages fall below the subsistence threshold, households turn to child labor. Supporting this, Edmonds and Schady (2012) conducted research that reaffirms the poverty-child labor connection. They analyzed a cash transfer program in Ecuador, targeting impoverished families through a lottery system, providing further evidence of the link between poverty and child labor.

Household characteristics, such as parental altruism and education levels, can influence child labor decisions too. While altruistic parents may prioritize education, they may also resort to child labor when faced with credit constraints, poverty, or social norms (Baland

and Robinson, 2000; Basu and Van, 1998). Parental education can also impact child labor, as higher-educated parents tend to prioritize their children's education (Al-Samarrai and Peasgood, 1998; Strauss and Thomas, 1995). Imperfect land and labor markets are also one cause of child labor. For instance, Microeconomic data from developing countries show that children from land-rich households have higher labor force participation but lower school attendance compared to children from land-poor households. This is known as the "wealth paradox," which challenges the assumption that subsistence poverty drives child labor. Bhalotra and Heady (2003) argue that imperfect labor and land markets contribute to this paradox, as land can have both a wealth effect and a substitution effect on child labor. They find that land is positively related to girls' participation in family labor but has no effect on boys' participation. This suggests that land and labor markets are imperfect and significantly contribute to child labor in rural Pakistan, Ghana, Uganda, rural India, and Burkina Faso has shown in Congdon Fors (2007); Dumas (2007); Ganglmair (2005).

Child labor serves as a means of consumption smoothing, allowing households to balance consumption during income fluctuations. Various strategies, such as asset management, borrowing, saving, crop diversification, labor supply adjustments, and formal insurance, can help households achieve this balance. Assets, particularly livestock, can act as a buffer, absorbing transitory income shocks (Bandara et al., 2015; Beegle et al., 2006). In the absence of formal coping strategies, households employ alternative mechanisms like child labor to smooth consumption when faced with shocks (Morduch, 1999; Ravallion and Chaudhuri, 1997). Although these strategies may aid in risk management, they often fall short of achieving Pareto efficiency, as informal insurance can be weak and costly (Morduch, 1999). Labor and credit market imperfections further explain the prevalence of child labor (Alvi and Dendir, 2011; Dumas, 2013).

The literature overall classified shocks as either transitory or permanent. Furthermore, these shocks can be classified as income or non-income shocks, such as the loss of a parent or relatives (Duryea et al., 2007). Numerous studies have demonstrated that natural shocks

have significant implications for the well-being of these children. For example, Bandara et al. (2015) analyzed the effects of income and non-income shocks on child labor in Tanzania using data from two rounds of the Tanzania National Panel Survey. Crop shocks significantly affected overall child labor hours, particularly for boys, with an increase of 7.7 hours per month and a 9.6-hour increase for boys. Girls were more likely to quit school in response to shocks, with a probability of over 70% compared to 50% for boys. Access to credit and assets reduced child labor, with a bank account reducing male child labor by 12 hours. Improved agricultural practices, social safety nets, access to credit, and opportunities for income generation could reduce the adverse effects of transitory shocks on household income and child labor.

In Baker et al. (2020), the authors find that the boll weevil infestation increased educational attainment by 0.24 to 0.36 years for children aged 4 to 9, regardless of race. This shift indicates that the decline in cotton production due to the weevil made education more valuable than child labor, affecting career choices for these children.

In Bai and Wang (2020), the study investigates changes in returns to work affecting household income (income effect) and child labor (price effect). Using the 1991 Indian tariff reform as a natural experiment, they find that lower returns to adult labor-intensive crops reduce schooling due to a negative income effect. Conversely, reduced returns to child labor increase schooling due to a countervailing price effect.

Shah and Steinberg (2017) examine the influence of wages on human capital investment in rural India. They find that positive productivity shocks reduce school enrollment, attendance, and test scores, as children opt for outside work or home production over human capital activities when wages are high. Their study also reveals that early-life positive rainfall shocks increase wages by 2% but decrease math test scores by 2-5% of a standard deviation, school attendance by 2 percentage points, and the likelihood of a child being enrolled by 1 percentage point. These effects are long-lasting, indicating that the opportunity cost of schooling, even for relatively young children, plays a significant role in determining overall

human capital investment.

Since the inception of research on child labor, the identification of effective policy tools has remained one of the vital objectives for scholars in this field. Various policy interventions have been implemented across the globe to address the issue of child labor, with varying levels of success. It is worth noting that some policies have been counterproductive, leading to an increase in child labor instead of a reduction. One study conducted by Bharadwaj et al. (2020) revealed that the enactment of India's Child Labor (Prohibition and Regulation) Act of 1986, which was intended to reduce child labor, did not have the desired impact. In fact, the study found that not only did the policy fail to decrease child labor, it actually led to an increase in child employment and a decrease in child wages following the ban. Basu (2005) research had previously addressed this issue in a theoretical manner. In another example, De Hoop et al. (2019) explores how partial subsidies for child education through a cash transfer program in the Philippines increased school attendance but also child labor, as the subsidy only partially covered school fees. Therefore, examining the issue and its welfare implications is crucial to creating effective policies.

There are also many studies that indicate the success of policies implemented to reduce child labor (Edmonds and Shrestha, 2014; Ravallion and Wodon, 2000; Skoufias et al., 2001). As an example, Ravallion and Wodon (2000) studied the impact of the Food Education Program in Bangladesh, which provides take-home rations to poor households with primary school children. Children must attend 85% of classes per month to receive rations. Using program presence in a child's village as an instrument for participation, they found a reduction in child labor, but education increased by 19 and 18 percentage points for boys and girls, respectively, while the decline in child labor was small in comparison.

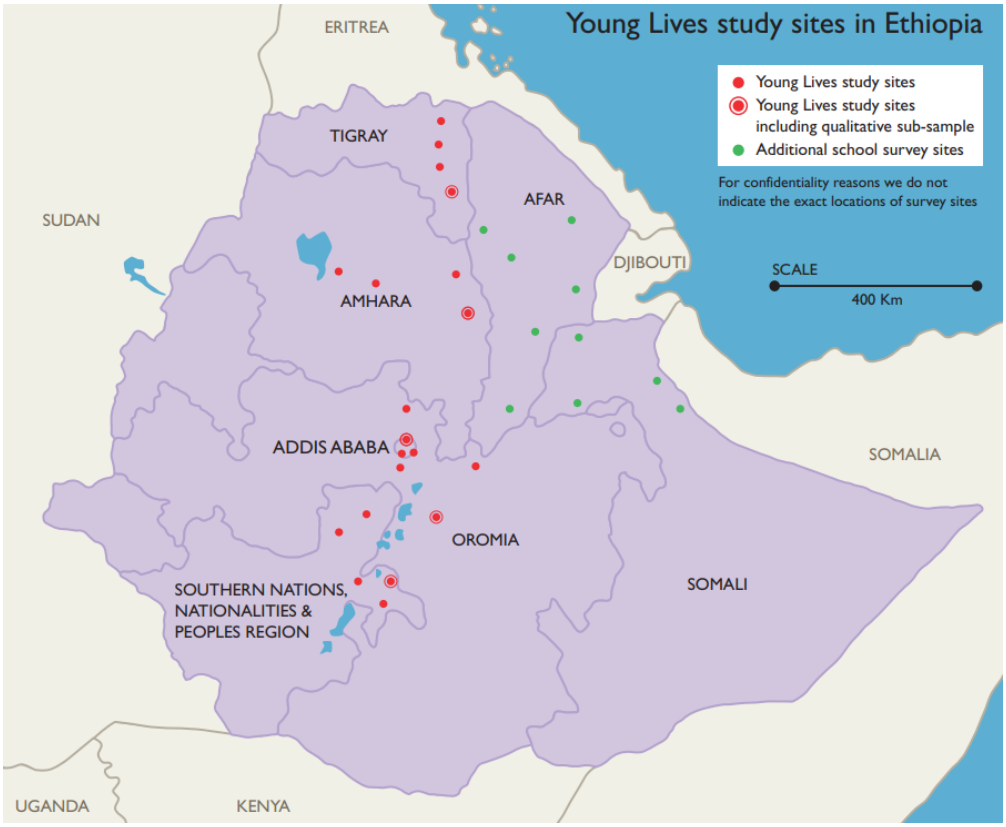
De Hoop and Rosati (2014) study extensively reviews the literature on cash transfer policies and their impact on child labor. Likewise, De Janvry et al. (2006) have constructed a household decision model and validated its predictions with a panel dataset from Mexico's Progresa program. The empirical evidence reveals a significant level of state dependence on

school enrollment, with conditional cash transfers proving effective in safeguarding enrollment. However, such transfers do not deter parents from increasing child labor in response to adverse shocks.

3 Data and method

3.1 Young Lives Survey

The Young Lives dataset in Vietnam is a longitudinal dataset that spans five rounds of data collection from 2002 to 2016. To collect this data, the Young Lives team utilized a sentinel site surveillance system, employing a multi-stage, purposive, and random sampling approach to select two cohorts of children. The younger cohort consists of 2,000 children aged between 6 and 18 months in 2002, while the older cohort comprises 1,000 children aged 7.5 and 8.5 years. There are 20 sentinel sites in total, as shown in 1. This sampling methodology involved randomizing households within each study site, with the selection of these sites based on predetermined criteria. Notably, in the Ethiopian context, sentinel sites were chosen to ensure representation of the country's cultural and geographic diversity, urban and rural differences, and alignment with the project's pro-poor focus (Outes-Leon and Sanchez, 2008). These sites cover five major regions: Addis Ababa, Oromia, Amhara, SNNPR, and Tigray, which are home to 96 percent of the country's population. These sites were chosen based on the criteria of being in economically disadvantaged areas, with 75 percent in high food deficit districts and 25 percent in lower food deficit districts within each region. Rural children make up 60 percent of the sample, while 40 percent come from urban areas. Each region contributes 20 percent of the total sample, except for Addis Ababa (15 percent) and SNNPR (25 percent). The selection of sentinel sites within regions considered population density, food deficits, and input from regional policymakers and stakeholders. In each sentinel site, a random sample of 100 households was surveyed. If there is more than one eligible child in the household, the one chosen is randomized.



[a]

Figure 1: Young Lives 20 sites in Ethiopia

[a]Source: Outes-Leon and Sanchez (2008)

The dataset includes various measures of children's well-being and development, such as physical health, cognitive development, educational attainment, and social and emotional well-being. The dataset also includes information on children's time use, such as time spent on education, work, leisure, and household chores. Additionally, the dataset captures information on children's families, including parental education, income, occupation, and household characteristics, as well as community-level data such as access to basic services, infrastructure, and social programs. Flooding is measured as a binary response of the household to the question "Have you experienced any flooding since the previous round?".

Table 1 shows the summary statistics of Young Lives in 2006 and 2016 for Ethiopia and Vietnam.

As children age in Ethiopia, school enrollment rates experience notable growth, with 86

Table 1: Summary Statistics of Children in Young Lives Ethiopia

	2002 Mean	2006 Mean	2009 Mean	2013 Mean
Child characteristics				
age	2.97	7.18	10.16	14.04
	(3.15)	(3.16)	(3.17)	(3.12)
Female	0.47	0.47	0.47	0.46
	(0.50)	(0.50)	(0.50)	(0.50)
Child's weight (kg)	11.22	20.02	26.40	35.94
	(5.58)	(7.60)	(10.46)	(11.63)
Child's height (cm)	84.40	114.71	130.76	147.83
	(22.28)	(18.18)	(17.47)	(13.46)
Enrolment	0.15	0.28	0.73	0.86
	(0.35)	(0.45)	(0.45)	(0.35)
School	.	3.19	5.07	5.08
	(.)	(3.22)	(2.42)	(2.35)
Hours/day spend in household chores	.	1.23	1.91	1.91
	(.)	(1.53)	(1.46)	(1.49)
Hours/day spent in domestic tasks	.	0.95	1.53	1.74
	(.)	(1.81)	(2.18)	(2.36)
Hours/day spent in paid work	.	0.06	0.13	0.43
	(.)	(0.57)	(0.90)	(1.81)
Household characteristics				
Rural residence	0.66	0.66	0.66	0.66
	(0.48)	(0.47)	(0.47)	(0.47)
Mother's age	29.34	33.41	36.41	40.31
	(7.10)	(7.05)	(7.09)	(7.06)
Father's age	38.58	42.54	45.44	49.10
	(9.46)	(9.54)	(9.50)	(9.35)
household size	5.98	6.27	6.34	5.90
	(2.17)	(2.06)	(2.00)	(1.97)
Household wealth	0.22	0.30	0.35	0.39
	(0.18)	(0.19)	(0.18)	(0.17)
N	2364	2259	2228	2167

Notes: Wealth Index is a composite index measuring households' access to services such as water and sanitation, their ownership of consumer durables such as refrigerators, and the quality of floor, roof, and wall materials in their dwelling. The standard deviation is in the parentheses. Source: The Young Lives datasets (UK Data Archives).

percent of children in Young Lives survey attending school in 2013 compared to the earlier age. Furthermore, household size remains relatively stable over time, with an average of around 6 members, while household wealth displays a gradual improvement, with the mean

wealth index rising from 0.22 in 2002 to 0.39 in 2013. The gender balance in the cohort remains relatively consistent over the years. In 2002, approximately 47 percent of the cohort consisted of females, and this proportion remained stable, with 46 percent of females in 2013. This suggests a relatively even distribution of gender within the cohort throughout the observed years in Ethiopia.

3.2 Estimation strategy

I use a two-way fixed effect estimation following,

$$Y_{idt} = \alpha + \beta A_{dt} + \gamma_i + \tau_t + \epsilon_{idt} \tag{1}$$

where A_{dt} is the house of department d at year t, and Y_{it} is the outcome of interest, such as whether child i is currently enrolled at year t. This specification includes year-fixed effects and individual-fixed effects. Standard errors are clustered at the level of sentinel sites, because the number of clusters in the sample is a very small fraction of the number of clusters in the population of interests (Abadie et al., 2023).

4 Results

4.1 The impact of flooding shocks on enrolment and child labor

As shown in Table 2, the impact of flooding shocks in Ethiopia exhibits significant gender disparities. Specifically, among boys, flooding significantly reduces education enrollment by 7.8 percentage points. Furthermore, at the intensive margin, it has reduced the average daily school hours by 0.48 hours. Flooding has also resulted in a noteworthy increase in child labor among boys, with an additional 0.72 hours dedicated to such activities. Moreover, boys have experienced a decrease in leisure time, with a reduction of 0.33 hours in daily play. In addition to these effects, flooding has led to a significant increase of 0.5 percentage

points in the occurrence of serious injuries among boys. As presented in Table 3, flooding simultaneously increases child labor by 0.7 hours, encompassing household chores by 0.2 hours, domestic tasks by 0.3 hours, and paid work by 0.2 hours.

Notably, these outcomes do not appear to be linked to school closures or direct harm from flooding itself, as girls in Ethiopia have not encountered any similar effects, as demonstrated in panel B of Table 2. Furthermore, the effects of flooding shocks are not directly attributed to changes in living conditions. As demonstrated in Table 2, there is no observable impact of flooding on the wealth index, which is a composite measure assessing households' access to services like water and sanitation, ownership of consumer durables such as refrigerators, and the quality of floor, roof, and wall materials in their dwellings.

Furthermore, as shown in Table A1, there is no statistically significant difference in most covariates between female and male sample, except that boys live in households with significantly more food security than households with girls.

Table 2: The effect of flood shocks on children's outcomes

	(1) Household wealth	(2) Enrolment	(3) Child labor	(4) Serious injury
Panel A: Boys				
Flooding	0.006	-0.078***	0.715***	0.051**
	(0.005)	(0.026)	(0.135)	(0.019)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	4699	4650	4434	4682
Panel B: Girls				
Flooding	0.013	-0.001	0.063	0.004
	(0.008)	(0.050)	(0.179)	(0.015)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	4031	3949	3762	4017

Notes: Wealth Index is a composite index measuring households' access to services such as water and sanitation, their ownership of consumer durables such as refrigerators, and the quality of floor, roof, and wall materials in their dwelling. Enrolment is a binary indicator if the child is currently enrolled. Child labor is a sum of hours per day spent in household chores, domestic tasks including farming, and family business, and spent in paid activities. Source: The Young Lives datasets (UK Data Archives), Standard errors in parentheses clustered at department level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: The effect of flooding shocks on children's time allocation

	(1) Child labor	(2) Household chores	(3) Domestic Tasks	(4) Paid work	(5) Play	(6) School
Panel A: Boys						
Flooding	0.715***	0.213**	0.294***	0.208**	-0.329**	-0.477***
	(0.135)	(0.095)	(0.095)	(0.074)	(0.128)	(0.160)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4434	4434	4434	4434	4435	4435
Panel B: Girls						
Flooding	0.063	0.059	-0.077	0.076	0.128	-0.078
	(0.179)	(0.084)	(0.073)	(0.109)	(0.160)	(0.248)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3762	3766	3762	3762	3765	3765

Notes: Child labor is a sum over hours per day spent in household chores, domestic tasks including farming, and family business, and spent in paid activities. Serious injury is a binary indicator if the child has had serious injury since last interview. Source: The Young Lives datasets (UK Data Archives), Standard errors in parentheses clustered at department level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2 Mechanism: household loans and parental illness

Subsequently, I investigate the underlying mechanism behind the shift from education to child labor among boys in Ethiopia in response to flood shocks. As presented in Table 4, this shift does not appear to be primarily triggered by a decrease in food security following flooding shocks. However, a notable increase is observed in household loans and credits. The incidence of flooding significantly elevates the probability of households obtaining loans or credit by 10 percentage points. Additionally, there is a significant increase in the likelihood of fathers experiencing illness after flooding shocks, with a similar effect observed for mothers as well.

Table 4: The effect of flooding shocks on food security, household finance, and parental illness

	(1) Food insecurity	(2) Household loan	(3) Illness of father	(4) Illness of mother
Panel A: Boys				
Flooding	0.043	0.108**	0.080***	0.098**
	(0.053)	(0.042)	(0.015)	(0.034)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	2812	2310	4704	4704
Panel B: Girls				
Flooding	0.043	0.190***	0.076	0.069*
	(0.076)	(0.054)	(0.059)	(0.036)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	2506	1945	4039	4039

Notes: Food insecurity is a binary indicator if household sometimes or frequently do not eat enough in the last 12 months. Household loan is a binary indicator if household has taken loans or credit in the last 12 months. Illness of parents is a binary indicator if she/he is ill. Source: The Young Lives datasets (UK Data Archives), Standard errors in parentheses clustered at department level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Heterogneity

To verify the channel that the increase in child labor is a coping mechanism for households to pay back debts following flooding in the presence of parents being ill. I do the heterogeneity analysis by splitting the sample by household loan takers and non-takers.

Furthermore, I investigate by heterogeneity if the effect is primarily driven by

5.1 Household loan, wealth and urbanization

The heterogeneity analysis in Table 5 reveals that the impact of flooding on child outcome is primarily attributed to households that have acquired loans in response to flooding shocks. Furthermore, this effect is predominantly observed within rural households and those with wealth levels below the median. These findings imply that climate change, marked by escalating extreme weather events, has exacerbated inequality among children in developing countries where child labor is widespread. Appendix table A2 and A3 shows heterogeneity

in the time allocation of children and the mechanism respectively.

5.2 Social protection

The question is whether social protection programs, such as Ethiopia's Productive Safety Net Program (PSNP), could mitigate the adverse effects of flooding on child outcomes. PSNP is a national program designed to address chronic food insecurity and short-term shocks, particularly droughts, and it targets a population vulnerable to climate-related events. These programs typically provide financial assistance to affected households, which can help families manage the economic losses resulting from flooding. As a result, families may be less likely to rely on child labor to repay household loans incurred due to flood shocks.

As indicated in Tables 6, the safety net program appears ineffective in mitigating the impact of flooding shocks, particularly in terms of the shift away from education enrollment toward child labor. Notably, this effect remains significant for households with at least one member benefiting from the PSNP-Public Works Programme.

One reason is that PSNP public works is to support employment instead of as a buffer for transitory shock households experience, that could be why there is no effect. The most relevant program should be the PSNP direct support program. However, unfortunately, the Young Lives datasets only contain 95 children from households with at least one member benefiting from the PSNP Direct Support Programme. The sample size may be too small to have reliable causal inference.

Table 5: The effect on wealth, educational enrolment, child labor hours and probability of serious injury

	(1) Wealth index	(2) Enrolment	(3) Child labor	(4) Serious injury
Panel A: household loan taker				
Flooding	0.010	-0.160**	1.581***	-0.009
	(0.014)	(0.067)	(0.467)	(0.049)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	1506	1496	1492	1495
Panel B: Not household loan taker				
Flooding	0.002	0.035	0.385	0.041
	(0.021)	(0.081)	(0.443)	(0.161)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	802	797	794	796
Panel C: Household wealth index above mediian				
Flooding	0.018**	-0.072	0.771*	0.073*
	(0.007)	(0.050)	(0.406)	(0.042)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	2553	2522	2450	2540
Panel D: Household wealth index below median				
Flooding	0.010*	-0.061***	0.768***	0.046**
	(0.005)	(0.021)	(0.161)	(0.017)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	2146	2123	1980	2137
Panel E: Urban				
Flooding	-0.019	-0.012	0.453	0.172**
	(0.025)	(0.098)	(0.529)	(0.070)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	1536	1509	1449	1529
Panel F: Rural				
Flooding	0.013**	-0.071**	0.725***	0.034*
	(0.005)	(0.027)	(0.145)	(0.018)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	3163	3141	2985	3153

Notes: Wealth Index is a composite index measuring households' access to services such as water and sanitation, their ownership of consumer durables such as refrigerators, and the quality of floor, roof, and wall materials in their dwelling. Enrolment is a binary indicator if the child is currently enrolled. Child labor is a sum of hours per day spent in household chores, domestic tasks including farming, and family business, and spent in paid activities. Source: The Young Lives datasets (UK Data Archives), Standard errors in parentheses clustered at department level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: The effect on wealth, educational enrolment, child labor hours and probability of serious injury

	(1) Wealth index	(2) Enrolment	(3) Child labor	(4) Serious injury
Panel A: Households in PSNP - Public Work (PW) Program				
Flooding	-0.006	-0.116	1.039***	0.117
	(0.013)	(0.091)	(0.265)	(0.068)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	702	697	696	698
Panel B: Households NOT in PSNP - Public Work Program				
Flooding	0.009	-0.091	0.684**	0.074*
	(0.007)	(0.059)	(0.308)	(0.036)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	2795	2770	2778	2781
Panel C: Households in PSNP - Direct Support (DS) Program				
Flooding	0.068	-0.736***	4.017***	-0.045
	(0.051)	(0.217)	(1.239)	(0.151)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	146	147	147	147
Panel D: Households NOT in PSNP - Direct Support Program				
Flooding	0.004	-0.099*	0.747***	0.069*
	(0.006)	(0.049)	(0.243)	(0.034)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	3350	3319	3326	3331
Panel E: Households either in PW or DS program				
Flooding	0.008	-0.149*	0.993***	0.097
	(0.016)	(0.081)	(0.282)	(0.064)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	793	789	788	790
Panel F: Households neither in PW nor DS program				
Flooding	0.005	-0.085	0.712**	0.073*
	(0.007)	(0.059)	(0.297)	(0.038)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	2703	2677	2685	2688

Notes: Wealth Index is a composite index measuring households' access to services such as water and sanitation, their ownership of consumer durables such as refrigerators, and the quality of floor, roof, and wall materials in their dwelling. Enrolment is a binary indicator if the child is currently enrolled. Child labor is a sum of hours per day spent in household chores, domestic tasks including farming, and family business, and spent in paid activities. Source: The Young Lives datasets (UK Data Archives), Standard errors in parentheses clustered at department level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

In summary, this study has delved into the multifaceted effects of extreme weather events, specifically flooding, on child labor, education, and household finances in Ethiopia. By leveraging longitudinal data from 2002 to 2016, this research provides more robust causal insights compared to cross-sectional studies.

The results demonstrate that flooding significantly harms boys in Ethiopia. It reduces their school enrollment, cuts down their daily school hours, and diminishes their leisure time. Simultaneously, it increases their engagement in child labor, including household chores, domestic tasks, and paid work, while also elevating the risk of serious injuries. These adverse impacts are particularly pronounced in households with existing loans, rural settings, and lower socio-economic status, highlighting the vulnerability of disadvantaged children to weather shocks.

Moreover, the study underscores the limitations of the current social protection program, the Productive Safety Net Program (PSNP), in shielding children from the negative effects of flooding. This emphasizes the urgency of more targeted policies to address climate change's impact on child well-being, especially in vulnerable communities.

In conclusion, this research emphasizes the significance of considering child labor and education within the context of climate change and extreme weather events. As these events become more frequent and severe, addressing these challenges becomes increasingly critical. Efforts to enhance resilience and protect the most vulnerable, particularly children, should be central to climate adaptation and mitigation strategies. This study adds to the growing body of evidence illustrating the intricate links between climate change, household dynamics, and child well-being, offering valuable insights for policymakers and stakeholders working towards a more sustainable and equitable future.

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A Appendix A. Tables

Appendix Table A1: Gender differences in summary statistics and two-sample t-test unpaired data with unequal variances

	(1)		(2)		(3)
	mean	sd	mean	sd	b
Age	10.248	3.199	10.060	3.139	0.188
Female	0.000	0.000	1.000	0.000	-1.000
Child's weight (kg)	26.392	9.879	26.418	11.082	-0.027
Child's height (cm)	131.185	17.934	130.271	16.919	0.914
Serious injury	0.111	0.314	0.068	0.252	0.043***
Enrolment	0.711	0.453	0.742	0.438	-0.031
School (hours/day)	4.987	2.466	5.167	2.357	-0.181
Child labor (hours/day)	3.876	2.619	3.224	2.041	
Household chores (hours/day)	1.458	1.231	2.437	1.522	-0.979***
Domestic tasks (hours/day)	2.249	2.486	0.698	1.372	1.551***
Paid work (hours/day)	0.169	1.021	0.087	0.731	0.082*
Rural residence	0.674	0.469	0.648	0.478	0.026
Mother's age	36.531	7.071	36.276	7.109	0.255
Father's age	45.578	9.536	45.273	9.458	0.305
Household size	6.341	1.968	6.341	2.027	-0.000
Wealth index	0.355	0.182	0.348	0.179	0.006
PSNP - Public Work	0.283	0.450	0.262	0.440	0.021
PSNP - Direct Support	0.034	0.183	0.032	0.176	0.003
Households owns land	0.927	0.261	0.909	0.288	0.018
Household own the house	0.757	0.429	0.742	0.438	0.015
Food insecurity	0.346	0.476	0.411	0.492	-0.065**
Observations	1189		1039		2228

Notes: Two-sample t-test unpaired data with unequal variances. Source: The Young Lives datasets (UK Data Archives), Standard errors in parentheses clustered at department level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Child labor is a sum of hours per day spent in household chores, domestic tasks including farming, and family business, and spent in paid activities. Enrolment is a binary indicator if the child is currently enrolled. Serious injury is a binary indicator if the child has had a serious injury since last interview. Wealth Index is a composite index measuring households' access to services such as water and sanitation, their ownership of consumer durables such as refrigerators, and the quality of floor, roof, and wall materials in their dwelling.

Appendix Table A2: The effect of flooding shocks on children's time allocation

	(1) Child labor	(2) Household chores	(3) Domestic tasks	(4) Paid work	(5) Play	(6) School
Panel A: household loan taker						
Flooding	1.581***	0.276	1.179***	0.126	-0.396	-0.818**
	(0.467)	(0.246)	(0.283)	(0.363)	(0.310)	(0.333)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1492	1492	1492	1492	1492	1492
Panel B: Not household loan taker						
Flooding	0.385	0.017	0.991	-0.623	-0.189	-0.173
	(0.443)	(0.305)	(0.827)	(0.685)	(0.424)	(0.481)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	794	794	794	794	794	794
Panel C: Household wealth index above mediian						
Flooding	0.771*	-0.086	0.519	0.337	-0.034	-0.718**
	(0.406)	(0.196)	(0.344)	(0.236)	(0.266)	(0.259)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2450	2450	2450	2450	2450	2450
Panel D: Household wealth index below median						
Flooding	0.768***	0.319**	0.280*	0.168*	-0.536**	-0.286
	(0.161)	(0.125)	(0.154)	(0.087)	(0.214)	(0.205)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1980	1980	1980	1980	1981	1981
Panel E: Urban						
Flooding	0.453	-0.599***	0.752	0.300**	-0.492	0.026
	(0.529)	(0.122)	(0.396)	(0.121)	(0.570)	(0.410)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1449	1449	1449	1449	1449	1449
Panel F: Rural						
Flooding	0.725***	0.242**	0.302**	0.182**	-0.437**	-0.305*
	(0.145)	(0.091)	(0.111)	(0.080)	(0.154)	(0.161)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2985	2985	2985	2985	2986	2986

Notes: Child labor is a sum over hours per day spent in household chores, domestic tasks including farming, and family business, and spent in paid activities. Serious injury is a binary indicator if the child has had serious injury since last interview. Source: The Young Lives datasets (UK Data Archives), Standard errors in parentheses clustered at department level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A3: The effect of flooding shocks on food security, household finance, and parental illness

	(1) Food insecurity	(2) Household loan	(3) Illness of father	(4) Illness of mother
Panel A: household loan taker				
Flooding	0.054	0.000	0.000	0.091***
	(0.107)	(.)	(0.032)	(0.027)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	1050	1506	1506	1506
Panel B: Not household loan taker				
Flooding	-0.168	0.000	-0.120	0.172
	(0.179)	(.)	(0.081)	(0.142)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	573	804	804	804
Panel C: Household wealth index above mediian				
Flooding	-0.059	0.189***	0.034	0.031
	(0.048)	(0.063)	(0.031)	(0.040)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	1566	1466	2553	2553
Panel D: Household wealth index below median				
Flooding	-0.001	0.022	0.096***	0.132***
	(0.075)	(0.060)	(0.020)	(0.023)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	1245	842	2146	2146
Panel E: Urban				
Flooding	-0.170	-0.012	0.051**	-0.050
	(0.238)	(0.026)	(0.017)	(0.125)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	908	750	1538	1538
Panel F: Rural				
Flooding	0.058	0.106*	0.070***	0.095**
	(0.054)	(0.051)	(0.017)	(0.033)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	1904	1560	3166	3166

Notes: Food insecurity is a binary indicator if household sometimes or frequently do not eat enough in the last 12 months. Household loan is a binary indicator if household has taken loans or credit in the last 12 months. Illness of parents is a binary indicator if she/he is ill. Source: The Young Lives datasets (UK Data Archives), Standard errors in parentheses clustered at department level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$