Climate Change, Schooling and Child Development: Evidence from Ethiopia *

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Abstract

This study investigates the effects of flooding, a consequence of climate change, on schooling and child labor in Ethiopia by combining a high-quality longitudinal panel of child development and satellite data of flooding. I find that flooding significantly reduces enrollment by 7.8 percentage points, shortens daily school hours by 0.5 hours, and increases child labor by 0.7 hours among Ethiopian boys. These effects are primarily driven by households that take loans to cope with the aftermath of flood shocks. In response to this financial stress, families shift their children from education to child labor to repay the debt. The existing social protection program (PSNP) fails to mitigate these adverse effects. Flooding in childhood significantly reduces math cognition and reading scores by 0.65 standard deviations, and vocabulary performance by 0.99 standard deviations. I examine how the flooding shock affects education choices and the complementarity among health, math, reading, and vocabulary skills, by estimating a child development production function with flood shocks.

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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 attributed to the influence of rainfall on agricultural income, education, and the subsequent investments made in nutrition during early life (Maccini and Yang, 2009; Webb, 2022) as well as mortality (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. The assumption might be violated by the composition change in response or anticipation of shocks, such that the remaining population in areas prone to extreme weather becomes endogenous.

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). Therefore, extreme weather shocks 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).

I use high-quality longitudinal datasets following households and children over 15 years in Ethiopia (Young Lives Ethiopia) from 2002 to 2016. The analysis incorporates controls for individual fixed effects and year fixed effects during estimation. This helps mitigate causal inference issues for estimates using repeated cross-sectional data with weaker assumptions. Furthermore, I merge high-frequency satellite data on flooding with the panel data to validate the results from household survey measures of flooding experience

I examine the impact of flooding on children's education enrolment and time allocation in Ethiopia, such as school dropout and average time allocation of children, including child labor, using the Young Lives dataset which spans from 2002 to 2016. These data include household characteristics, children's characteristics and children's time allocation, covering hours allocated to education, work, leisure, household chores, domestic tasks, and paid work.

I find that flooding shocks have several significant effects on boys in Ethiopia. Flooding significantly 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.

For the mechanism, flooding shocks significantly increase in household loans or credit and a significant rise in illness among both the father and mother of the child. In the heterogeneity analysis, 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.

For cognition outcomes, experiencing flooding in childhood decreased math cognition by 0.65 standard deviations, reduced vocabulary test scores (Peabody Picture Vocabulary Test) by 0.99 standard deviations, and lowered reading scores by 0.65 standard deviations. The results remain significant when use satellite imagery of flooding to validate the robustness of the results from survey measures of flooding.

To understand the mechanism through which flooding affects cognitive development via educational enrollment, and to investigate if there are feedback effects among health, math, vocabulary, and reading skills due to complementarity, the next section examines the impact of flooding through an estimation of the child development production function with flooding shock.

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 documents institutional background and related literature. Section 3 explains data and methods. Section 4 presents the main results and mechanisms. Section 5 explains the heterogeneous effect of flooding by urbanization, household wealth, and access to social protection programs. Section 6 examines the impact of flooding on cognition. Finally, Section 7 concludes.

2 Institutional Background and Related literature

2.1 Child labor in Ethiopia

Child labor in Ethiopia is a pressing issue, with children being exposed to some of the most deplorable forms of exploitation. According to the 2021 report from the US Department of Labor, a distressing 25.3 percent of children between the ages of 5 and 14 in Ethiopia were found to be engaged in child labor. Moreover, children are often made to undertake perilous tasks, such as those associated with traditional weaving. Unfortunately, Ethiopian legislation

does not mandate free basic education or establish a compulsory age for education, leaving children at risk of falling into these exploitative practices. Furthermore, the existing social programs designed to combat child labor have not adequately focused on sectors where child labor is prevalent, notably agriculture and domestic work.

A staggering 76 percent were involved in agriculture, while 21 percent were working in the service sector. The range of activities these children are compelled to undertake is deeply troubling and includes tasks such as planting and harvesting crops like coffee, khat, and sesame, herding livestock (including cattle), and fishing. In the service sector, children are often subjected to domestic work, unpaid household chores such as carrying heavy loads of water and firewood, as well as street-based jobs like shoe shining, weight measurement, assisting taxi drivers, vending, portering, and even begging.

2.2 Household finance in Ethiopia

Household finance in Ethiopia faces challenges related to limited access to formal financial services, vulnerability to shocks, and low financial literacy. Many Ethiopian households, particularly those in rural areas and among low-income populations, have limited access to formal banking services. This lack of access can hinder their ability to save, invest, and access credit. Due to limited access to formal financial institutions, many Ethiopian households rely on informal financial mechanisms.

Traditional social networks and community-based insurance mechanisms, which often rely on reciprocity and mutual support, may not have the capacity to provide sufficient assistance to all affected households. Ethiopian households are often vulnerable to various shocks, including natural disasters like droughts and floods, which can have a severe impact on their financial stability. Many households do not have adequate savings or insurance mechanisms to cope with these shocks.

Flooding can affect entire communities or regions simultaneously, straining the capacity of local social networks to provide assistance. When a large portion of the population is affected, the ability to rely on others for support becomes limited.

2.3 Education in Ethiopia

The academic year runs from September to July and education is free at the primary level. Students enter school at age 7 and compulsory (primary) education lasts for six years and

ends at age 12. In Ethiopia, 32 percent of children of official primary school ages are out of school. In Ethiopia, the academic year begins in September and ends in July, and the official primary school entrance age is 7. The system is structured so that the primary school cycle lasts 6 years, lower secondary lasts 4 years, and upper secondary lasts 2 years. Ethiopia has a total of 21,418,000 pupils enrolled in primary and secondary education. Of these pupils, about 16,200,000 (76 percent) are enrolled in primary education. Figure 3 shows the highest level of education reached by youth ages 15-24 in Ethiopia. Although youth in this age group may still be in school and working towards their educational goals, it is notable that approximately 16 percent of youth have no formal education and 54 percent of youth have attained at most incomplete primary education, meaning that in total 70 percent of 15-24 years old have not completed primary education in Ethiopia.

2.4 Seasonality and flooding in Ethiopia

The Kiremt season, which spans from June to August, constitutes the rainy period responsible for producing approximately 85 percent to 95 percent of food crops, as noted in a study by Asfaw et al. (2018). This season is characterized by frequent rainfall and relatively uniform temperatures.

Ethiopian seasons are classified into three: the driest season is called Bega (October to January), Belg (February to May) and the rainy season Kiremt (June to September). Climate change is having significant impacts on Ethiopia, a country in the Horn of Africa. Ethiopia is vulnerable to climate change-induced droughts, which have become more frequent and severe in recent years. These droughts can lead to water scarcity, affecting both agriculture and access to clean drinking water for the population. While droughts are a major concern, Ethiopia also faces the risk of flash floods and riverine flooding during heavy rainfall events. These floods can displace communities, damage infrastructure, and disrupt livelihoods.

2.5 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.

2.6 Child labor

In 2020, the the International Labour Organization (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) [1]. Despite some progress, child labor remains a persistent issue, necessitating effective policy interventions. Dammert et al. (2018) provide extensive literature reviews.

[1] "Child work" and "child labor" are often used interchangeably in the literature, but 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).

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. See appendix B for a literature review in detail.

3 Data and method

3.1 Young Lives Survey

The Young Lives dataset in Ethiopia is a longitudinal dataset that spans five rounds of data collection from 2002 to 2016 [2]. To collect this data, the Young Lives team utilized a 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. 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). Sampling areas cover five major regions: Addis Ababa, Oromia, Amhara, SNNPR, and Tigray, which are home to 96 percent of the country's population. Within each region, sampled districts 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.

Importantly, data collection consistently took place during the dry season, as shown in Table 1. This has significant implications, as many measures derived from inquiries about the children's current activities are specific to the dry season. For example, education enrolment will be dry-season specific.

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,

[2]The data used in this publication come from Young Lives, a 20-year study of childhood poverty and transitions to adulthood in Ethiopia, India, Peru and Vietnam (www.younglives.org.uk). Young Lives is funded by UK aid from the Foreign, Commonwealth & Development Office and a number of further funders. The views expressed here are those of the author(s). They are not necessarily those of Young Lives, the University of Oxford, FCDO, or other funders.

Table 1: Interview months of Young Lives

Month of data collection	Boys	Girls	Total
1	1254	1088	2342
2	554	464	1018
3	69	66	135
4	15	10	25
5	21	26	47
6	1	1	2
8	2	1	3
9	1	1	2
10	1479	1342	2821
11	2063	1903	3966
12	1980	1849	3829
Total	7439	6751	14190

Notes: Seasons in Ethiopia boil down to the dry season (October to May) and wet season (June to September), with the most rain falling in June, July, and August. Source: The Young Lives datasets from round 1 to round 5 from 2002 to 2016 (UK Data Archives).

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 2 shows the summary statistics of Young Lives in 2006 and 2016 for Ethiopia. As children age in Ethiopia, school enrollment rates experience notable growth, with 86 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 has remained 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 Variables

Flooding The flood measure in the Young Lives study is a binary variable that assesses whether a household has experienced flooding in their locality during a specified period. Researchers collect this information through interviews and questionnaires conducted with

Table 2: 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).

parents or guardians of the children in the study. Households are asked whether they have encountered flooding in their area, and their responses are used to categorize them as either

"exposed to flooding" if they have experienced flooding or "not exposed to flooding" if they have not.

Enrolment Enrollment is measured through survey data collected from participants and households. Researchers gather information on whether children of school age are currently enrolled in any formal educational institution, such as a school or a preschool. This data is collected through interviews and questionnaires conducted with parents or guardians of the children. The binary variable takes the value of 1 if a child is currently enrolled in a formal educational institution (such as a school or preschool) and 0 if the child is not enrolled.

Child labor To measure if children aged 5 to 17 years are engaged in any form of work, this data is collected through interviews and questionnaires conducted with parents or guardians of the children. The survey asks the amount of time (in hours) a child spends on eight activities during a typical day, where a typical day is defined as a weekday or a normal school days, excluding holidays, festivals, days of rest during the weekend. The surveys inquire about the type of work children are involved in, the number of hours they spend working, and whether the work is paid or unpaid. I define child labor as the number of hours children spent on running household chores, working on household tasks, and working outside the household on paid activities. Running household chores includes work or task done to help at home such as fetching water, firewood, cleaning, cooking, washing, shopping and so on; excludes caring for others. Working on household tasks includes the amount of work inside the household that generates income, this includes farming, cattle herding, shepherding, and other family business. Working outside the household on paid activities includes the amount of time doing paid work including travel time to and from work.

Additionally, the surveys may capture details about the nature of the work, such as whether it involves household chores, agricultural activities, or other forms of labor.

Household Loans or Credit This variable captures whether the household has taken loans or credit since the last round of the survey. Respondents are asked questions related to their household's financial situation, including whether they have borrowed money or taken credit for various purposes, such as income generation, consumption, or dealing with emergencies. The variable is typically binary, with "1" indicating that the household has taken loans or credit and "0" indicating otherwise.

Severe Injury of Children This variable aims to capture instances where children in the household have experienced significant injuries that required medical attention, hospitalization or resulted in long-term impairment. Household respondents are asked about any such injuries that have occurred to children in the household during a specified reference

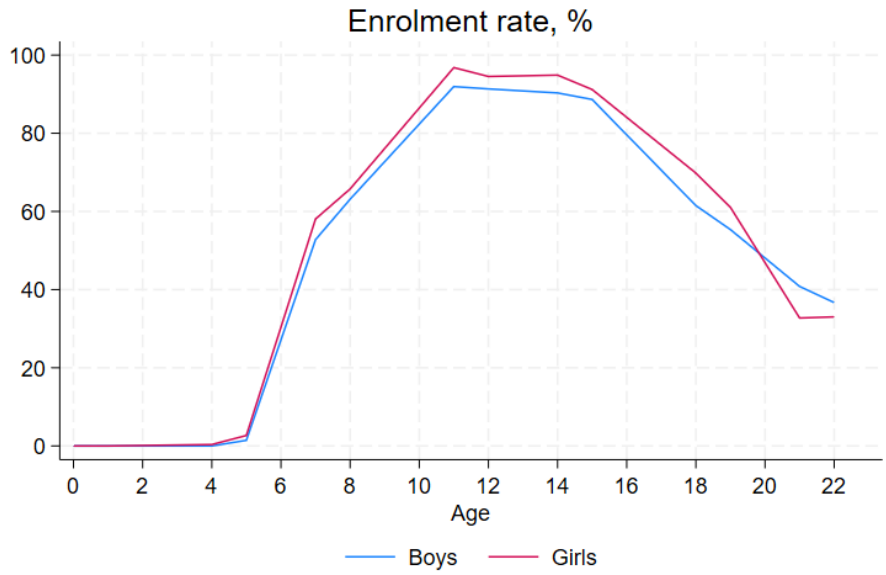


Figure 1: Age profile of enrolment

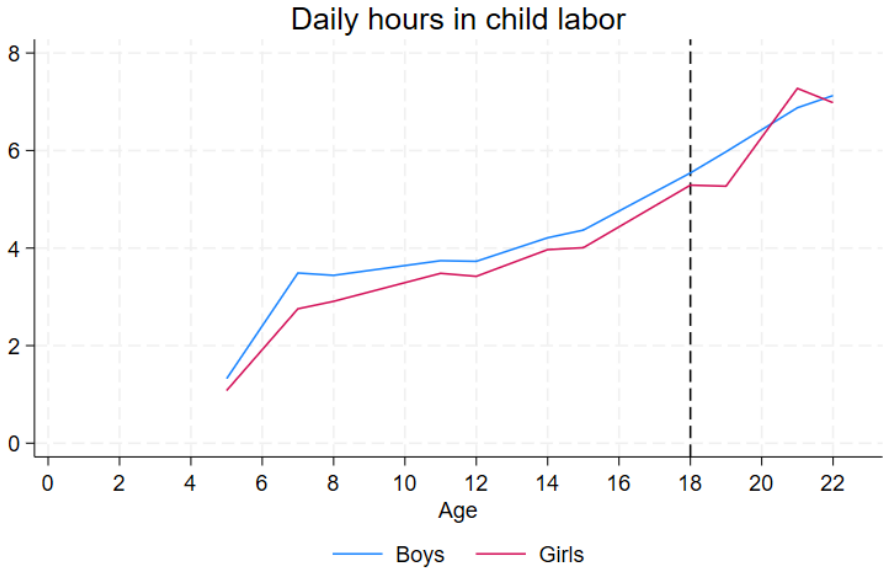


Figure 2: Age profile of child labor

period. The variable is coded as "1" if a severe injury event has occurred for a child within the household during that period; otherwise, it is coded as "0."

Household wealth The wealth index is a comprehensive measure that incorporates multiple household indicators, including ownership of assets like televisions and refrigerators,

housing conditions such as flooring and roofing materials, and access to essential services like sanitation and clean water. Researchers assign specific weights to these indicators based on their relevance in reflecting a household's socioeconomic status. By summing up the weighted values of these indicators, a composite score is generated for each household. This score allows for the ranking of households by their relative wealth, where higher scores correspond to higher socioeconomic status, and lower scores indicate lower wealth levels.

Cognition In the Young Lives study in Ethiopia, cognitive abilities are assessed using three primary measures to capture the breadth of cognitive development among children. The first measure is the Peabody Picture Vocabulary Test (PPVT), which evaluates receptive vocabulary skills and verbal reasoning abilities by requiring children to match words with corresponding pictures, serving as an indicator of verbal intelligence and language development. The second measure is the mathematics score, derived from assessments that test the child's understanding of basic mathematical concepts, numerical operations, and problem-solving skills, reflecting their quantitative reasoning abilities. Lastly, the reading score is determined through tests that measure the ability to recognize letters, read words and sentences, and understand written passages, indicating the child's proficiency in reading and comprehension.

3.3 Satellite data of flooding

I use the Tellman et al. (2021)'s daily satellite flooding data in this study. The satellite flood maps provided by Tellman et al. (2021) are derived from the analysis of 12,719 NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) images spanning the period from 2000 to 2018. These maps offer daily satellite imagery at a 250-meter resolution.

However, Young Lives data cannot share location data due to our confidentiality agreements. Therefore, the flooding data of the satellite is measured at the region level.

3.4 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

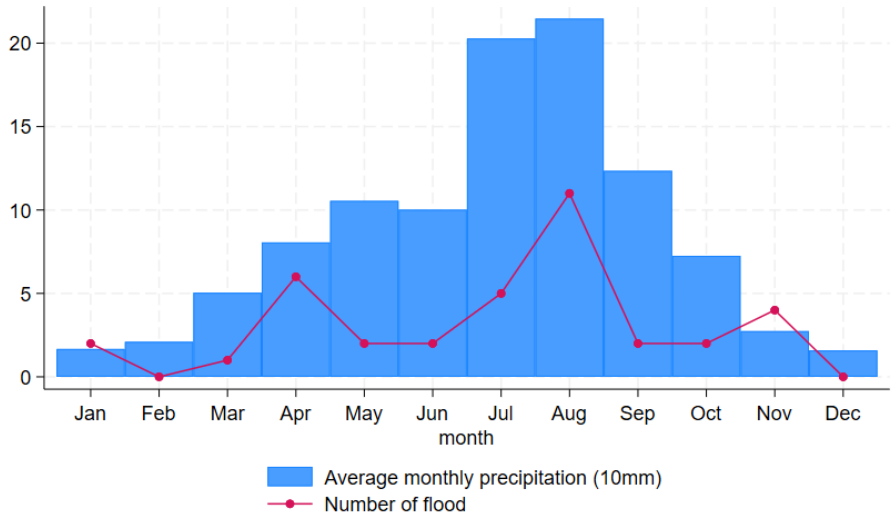


Figure 3: Precipitation and flooding from 2001 to 2017 in Addis Ababa, Oromia, Amhara, SNNPR, and Tigray

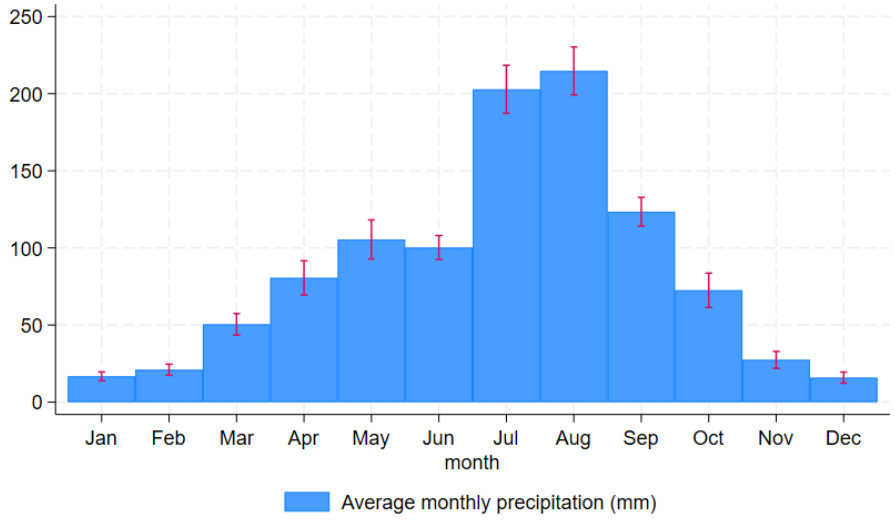


Figure 4: Precipitation and flooding from 2001 to 2017 in Addis Ababa, Oromia, Amhara, SNNPR, and Tigray

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 3, 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 4, 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 3. Furthermore, the effects of flooding shocks are not directly attributed to changes in living conditions. As demonstrated in Table 3, 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.

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 5, 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 3: 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 4: 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.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: 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 if the effects depend on family wealth, urbanization, and social protection programs.

5.1 Household loan, wealth and urbanization

The heterogeneity analysis in Table 6 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 7, 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

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: 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 7: 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.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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.

6 Impact of flooding on cognition

This section examines the impact of flooding on cognition. First I present the results from the reduced form specification.

6.1 Reduced form effects

Besides the survey measure of flooding experience, I use satellite imagery of flooding to validate the robustness of the results. The survey measure of flooding is assessed at the household level. It may be endogenous to family factors that influence household choices in education and the cognitive development of children.

Table 8 presents the results. Experiencing flooding in childhood decreased math cognition by 0.65 standard deviations, reduced vocabulary test scores (Peabody Picture Vocabulary Test) by 0.99 standard deviations, and lowered reading scores by 0.65 standard deviations. When we utilize the flooding measure derived from satellite imagery at a regional level, the effect remains significant, but the magnitude is halved.

Table 8: The effect of childhood flooding on cognition

	(1) Math	(2) Math	(3) Vocabulary	(4) Vocabulary	(5) Reading	(6) Reading
Flood (survey)	-0.65***		-0.99***		-0.62***	
	(0.08)		(0.07)		(0.12)	
Flood (satellite)		-0.36***		-0.52***		-0.30*
		(0.11)		(0.10)		(0.17)
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2870	2870	2532	2532	2199	2199

Notes: Math score is standardised. Vocabulary score is from The Peabody Picture of Vocabulary Test, and is standardised. The reading item required children to read three letters, a word, and a sentence. Children were scored 1 if they could read the sentence, 0.66 if they could read the word, 0.33 if they could read the letters, and 0 if they could not read anything or did not respond * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This may be due to the fact that regional measures of flooding are less accurate than

household-level measures. However, it could also be attributed to the likelihood that household-level flooding is more prone to endogeneity, resulting in an upward bias in the estimated negative impact of flooding on cognition.

To understand the mechanism through which flooding affects cognitive development via educational enrollment, and to investigate if there are feedback effects among math, vocabulary, and reading skills due to complementarity, the next section examines the impact of flooding through an estimation of the child development production function with flooding shock.

6.2 Structural estimation (work in progress)

In this section we examine the dynamic effect of flooding on the evolution of child development (cognition and health) in Ethiopia allowing for feedback effects and complementarity among health, educational enrolment and cognition to influence each other. To do so, I incorporate flood shocks into the seminal work of Cunha and Heckman (2007), Cunha et al. (2010), and Attanasio et al. (2020).

6.2.1 Production function set up

Similar to Attanasio et al. (2020) who use Young Lives data in India, I assume that human capital has two relevant dimensions, cognition, and health.

$$H_a = H\left(\theta_a^c, \theta_a^h\right) \tag{2}$$

I follow Cunha et al. (2010) and Attanasio et al. (2020) to express the evolution of cognition and health by a series of dynamic production functions over stages (t) of childhood.

$$\begin{aligned} \theta_{c,t+1} &= G\left(\theta_{ct}, \theta_{ht}, \theta_{mt}, \theta_{dt}, X_t\right) \\ \theta_{h,t+1} &= F\left(\theta_{ct}, \theta_{ht}, \theta_{mt}, \theta_{dt}, X_t\right) \end{aligned} \tag{3}$$

Both child cognition θ_c and health θ_h in the period depend on the last period cognition, last period health, current material investment θ_m (such as books at home and deworming medication), and education enrolment decision θ_d during the period, as well as covariates X_t including household and individual characteristics such as parental education, household wealth, gender, and birth order. The production functions define how cognition, health, material investment, and enrolment interact in the dynamic structure. I group the child

development period by 3 stages including 0 to 5, 6 to 11, and 12 to 18 due to the sampling collection year interval of Young Lives. I denote the child's stage by t. Following Cunha et al. (2010), I assume a CES function. Therefore, I have that

$$\begin{aligned}\theta_{c,t+1} &= [\delta_{ct}(\theta_{ct})^{\rho_t} + \delta_{ht}(\theta_{ht})^{\rho_t} + \delta_{mt}(\theta_{mt})^{\rho_t} + \delta_{dt}(\theta_{dt})^{\rho_t}]^{\frac{1}{\rho_t}} A_{ct} \\ \theta_{h,t+1} &= [\alpha_{ct}\,(\theta_{ct})^{\zeta_t} + \alpha_{ht}\,(\theta_{ht})^{\zeta_t} + \alpha_{mt}\,(\theta_{mt})^{\zeta_t} + \alpha_{dt}\,(\theta_{dt})^{\zeta_t}]^{\frac{1}{\zeta_t}} A_{ht}\end{aligned} \tag{4}$$

The parameters of the production function all vary with age t. The parameters ρ_t and ζ_t determine the elasticity of substitution between the various inputs in the cognition and health production function, respectively. The α_ts and the δ_ts sum to one, respectively, within each period and where

$$\begin{aligned}A_{ct} &= \exp\left(d_{0t} + d'_{Xt}X_t + u_{ct}\right) \\ A_{ht} &= \exp\left(g_{0t} + g'_{Xt}X_t + u_{ht}\right)\end{aligned} \tag{5}$$

Characteristics X_t include time-varying family wealth as well as time-invariant variables such as gender, birth order, parental year of schooling, and parental ages when the child was born.

6.2.2 Investment for children

In a utility maximization of parental choices such as Del Boca et al. (2014) , the assumption is that parents have perfect information on the child production function, which is against evidence such as Cunha et al. (2013). Therefore, I follow Attanasio et al. (2020) to estimate a reduced form investment equation that includes time-varying family wealth as well as time-invariant variables such as gender, birth order, parental year of schooling, and parental ages when the child was born. In addition, I include current period cognition, and the health of the child, to allow for feedback effect. However, the endogeneity problem arises as unobservable reasons may drive both parental investments and correlate with shocks in the child quality production functions.

Furthermore, the enrolment investment is also a reduced form equation that includes parental education, gender of the child, current period cognition, and health of the child. This is because Young Lives does not collect the value of loans taken by the family but only a binary indicator if the households have taken credit or loans. Therefore, I am not able to use a utility maximization framework where flooding increases the amount of borrowing in the budget set of the family.

6.2.3 Control for the endogeneity of education enrolment

Identification requires instruments that are relevant for enrolment but are excluded from the child quality production function. As flooding incidence significantly predicts enrolment as shown in the initial analysis, I use hydrological features, such as the slope of the riverbed, as instruments for educational choices, conditional on family wealth, gender of the child, birth order and parental education and age when the child is born.

Notice that the enrolment decision θ_{dt} will now depend on the flooding incidence F_{jt}) at area j in year t.

$$\begin{aligned} \ln \theta_{mt} =& \gamma_0 + \gamma_{ct} \ln \theta_{ct} + \gamma_{ht} \ln \theta_{ht} + \gamma'_{Xt} X_t + \gamma'_{pt} \ln p_{mt} + v_t \\ \theta_{dt} =& \eta_0 + \eta_{ct} \ln \theta_{ct} + \eta_{ht} \ln \theta_{ht} + \eta'_{Xt} X_t + \eta'_{pt} + \beta F_{jt} + v_t \end{aligned} \tag{6}$$

With the instruments, I use a control function approach, similar to Attanasio et al. (2020 b). Specifically, assume that

$$\begin{aligned} E\left(u_{ct} \mid Q_t, Z_t\right) &= \kappa_c v_t \\ E\left(u_{ht} \mid Q_t, Z_t\right) &= \kappa_h v_t \end{aligned} \tag{7}$$

Where Q_t is the full set of variables in the production functions including parental investments, and Z_t is the instruments. The control function procedure is to include the estimated residual from the investment equation as regressors. Assuming that investments are exogenous amounts to impose. These are testable hypotheses to check empirically.

For material investment, the instrument variables are the set of local prices of products for educational purpose or health, such as the price of books and price of deworming medicine.

For educational enrolment investment, the instrumental variables will the the set of hydrological features including slope, watershed shape, and stream gradient.

6.2.4 Latent factor models and the measurement system

Except for the enrolment indicator, all the other measures such as child cognition, child health, and after-school investment are inherently latent (Cunha et al., 2010). Directing using proxies without correcting for measurement error would lead to biases with unknown directions because of the nonlinearity of the production function.

I start by assuming a semi-log relationship between the measures and latent variables:

$$m_{jkt} = a_{jkt} + \lambda_{jkt} \ln(\theta_{kt}) + \epsilon_{jkt} \tag{8}$$

In a matrix form:

$$M = \mathbf{A} + \Lambda \ln \theta + \Sigma\varepsilon \tag{9}$$

Here m_{jkt} denotes the jth measurements related to the kth latent variable in time t, and λ_{jkt} is the corresponding factor loading accompanied with the measurement error ϵ_{jkt}.

The joint distribution of the log latent factors is assumed to be a mixture of Gaussian. The departure from normality is necessary Attanasio et al. (2020) as assuming normality would restrict the production functions to be Cobb-Douglas (linear in logs) with the substitution elasticity equal to 1. For computational simplicity I assume there are only two underlying clusters, though generalizing to the case of more clusters is straightforward.

$$F_\theta = \tau\Phi(\mu_A, \Omega_A) + (1-\tau)\Phi(\mu_B, \Omega_B) \tag{10}$$

where τ is the mixture weights, namely the probability that each realised observation is from the first normal distribution.

The factor that all θ are unobservable and the assumed above semi-log relationship between measurements and latent variables give rise to the mixture Gaussian distribution for the measurements system:

$$F_M = \tau\Phi(\Pi_A, \Psi_A) + (1-\tau)\Phi(\Pi_B, \Psi_B) \tag{11}$$

where

$$\Psi_A = \Lambda^T \Omega_A \Lambda + \Sigma; \quad \Psi_B = \Lambda^T \Omega_B \Lambda + \Sigma$$
$$\Pi_A = \mathbf{A} + \Lambda\mu_A; \quad \Pi_B = \mathbf{A} + \Lambda\mu_B$$

Finally, besides the latent variables in our model, there are also additional variables used in the production functions and as the instruments in the time investment functions. These variables are observable and I treat them as error-free measures so that they appear both in the measurement system and the latent variable system, which then means an augmented system of mixture Gaussian:

$$F_{\theta,X} = \tau\Phi\left(\mu_A^{\theta,X}, \Omega_A^{\theta,X}\right) + (1-\tau)\Phi\left(\mu_B^{\theta,X}, \Omega_B^{\theta,X}\right) \tag{12}$$

6.2.5 Estimation

Following to Attanasio et al. (2020), the estimation scheme consist of three steps:

(i) Use the expectation-maximization (EM) algorithm to estimate all the parameters that characterise the mixture Gaussian measurement system: the weights τ, the mean vectors Π_A, Π_B and the covariance matrices Ψ_A, Ψ_B. There is a closed-form solution in both the E step and M step in each iteration thanks to the Gaussian assumption. In each iteration, the temporarily obtained parameters should be taken carefully to prevent an ill-conditioned matrix in the next round.

(ii) Recover the parameters needed to characterize the joint distribution of latent variables θ: the shift vector $\mathbf{A}$, factor loading matrix Λ, measurement error matrix Σ, the mean vectors μ_A, μ_B and the covariance matrices Ω_A, Ω_B from the parameters obtained in (i). Here four restrictions are imposed to reduce the degrees of freedom:

1. Assumption that the measurement error is mutually independent so that Σ is a diagonal matrix.

2. Assumption that each measurement links to only one underlying factor, so only the corresponding factor loading is non-zero. Besides, I impose normalization following Cunha et al. (2010) and Attanasio et al. (2020). For child cognition, normalize the loading on standardised math test to one. Child health is normalized on the z scores of height. Material inputs are normalized on the number of books at home. In practice, we assign the above measurement as the first measurement for the associated factor.

3. The assumption that the growth of the measurement is due only to the growth of the associated latent variables. This, together with the normalisation of loading to the first measurement for each latent variable, imposes a restriction on the constant vector $\mathbf{A}$ that the elements in A corresponding to each first measurement are unchanged dynamically, so we only need to pin down their values in the first period.

4. The normalisation that the weighted mean of the latent variables in the first period is zero:

$$\tau\mu_{A,t=0} + (1-\tau)\mu_{B,t=0} = 0 \tag{13}$$

This helps us to identify elements in $\mathbf{A}$ for all measurements in the first period, which

are mathematically the empirical average of the measurements. Together with the restrictions above I can identify all the rest elements in $\mathbf{A}$ as well as the loading λ and means μ_A, μ_B.

(iii) With the joint distribution in hand, I draw a synthetic dataset to estimate the parameters of interest in the dynamic system of equations, i.e. the production functions at different stages, using the control function approach with hydrological features, such as the slope of the river bed as instruments.

7 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.

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: Measures of flooding risks

The flood occurs when the capacity of the channel fills and the water flows out of the channel. Ethiopia has nine main river basins; the drainage schemes start from the centrally located upland and formulate their manner downwards to the outlying lowland. Mainly for the duration of the training period (June–September), foremost permanent rivers, and their frequent tributaries form the country's drainage systems bringing their peak discharge (Desalegn and Mulu, 2021). Flash flooding depends on various factors, including the topography of the river system, flow phenomena, land cover, and the spilling of the main river and its tributaries (Lin, 1999; Ologunorisa and Adeyemo, 2005).

The topography of a river system refers to the physical characteristics of the land, such as its elevation, slope, and terrain. In the context of flooding, the topography plays a crucial role in how water flows and accumulates. Areas with low elevation or flat terrain are more susceptible to flooding.

Land cover refers to the types of vegetation and land use in a particular area. Different land cover types, such as forests, grasslands, urban areas, or agricultural fields, can affect how water is absorbed or runs off the land. Changes in land cover, such as deforestation or urbanization, can impact flooding patterns.

Flow phenomena refer to the behavior of water within the river system. This can include factors such as the speed of the water, the volume of water flowing, and how water moves through the landscape. Understanding flow phenomena is essential for predicting and managing floods.

Tributaries can cause flooding to overflow their banks. This often happens during periods of heavy rainfall, snowmelt, or when there is an excessive inflow of water into the river system. The overflow can inundate nearby areas and cause flooding.

For flood management literature, the Digital Elevation Model (DEM) is essential. ArcGIS is used to important Parameters for flood vulnerability such as drainage density, digital elevation model, land use/land cover, soil type, rainfall, and slope.

For example, Desalegn and Mulu (2021) calculates the slopes in Ethiopia from a 20-meter contour interval characteristic rank which was digitized from the Digital Elevation Model scale with additional modification within the GIS environment. The smaller slope value was flatter topography and, likewise, the upper slope values were the steeper topography.

B Appendix: Related Literature

B.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.

B.2 Child labor

In 2020, the the International Labour Organization (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) [3]. 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.

[3] "Child work" and "child labor" are often used interchangeably in the literature, but 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).

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.

C Appendix A. Tables

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.

C.1 Dynamic effects

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

	Boys (1)		Girls (2)		Difference (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.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A4: The effect on wealth, educational enrolment, child labor hours and probability of serious injury

	(1) Household wealth	(2) Enrolment	(3) Child labor	(4) Serious injury
Panel A: Boys				
Flooding	0.005	-0.114*	0.681***	0.088**
	(0.007)	(0.055)	(0.227)	(0.032)
L.Flooding	-0.004	-0.032	0.125	0.029
	(0.005)	(0.040)	(0.121)	(0.021)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	3483	3454	3460	3465
Panel B: Girls				
Flooding	0.020**	-0.074	0.287	0.019
	(0.009)	(0.087)	(0.279)	(0.031)
L.Flooding	0.005	-0.070*	0.092	0.003
	(0.008)	(0.040)	(0.156)	(0.023)
year FE	Yes	Yes	Yes	Yes
individual FE	Yes	Yes	Yes	Yes
N	2967	2897	2945	2946

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$