On the Way to School: Drought, Enrolment and Commuting Time *

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Abstract

Previous findings often find that rainfall leads to lower education outcomes in developing countries, emphasizing labor market channels: when rainfall raises agricultural wages, the opportunity cost of schooling rises and children substitute into work. This paper shows that commuting to school represents another important mechanism. Using longitudinal data from Ethiopia spanning 2002–2016, which track children's time allocation, cognition tests, and village-level precipitation, I find that moderate drought conditions significantly increase math cognition by 1.28 standard deviations, increase enrollment by 0.37 percentage points, and increase after school study time by 0.38 hours per day, while reducing travel time to school by 0.35 hours. Effects diminish at more extreme drought levels but remain positive, with larger impacts in rural areas. These results suggest that in settings with fragile school access, commuting costs play an important role in shaping the education impact of climate shocks, highlighting transportation infrastructure as a critical margin of resilience.

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1 Introduction

> *"In certain parts of the world, the journey to school is an obstacle course and knowledge is a conquest. Every morning, sometimes at the risk of their lives, heroic children embark on a journey towards knowledge."*
>
> — On the Way to School (2013)[1]

Climate change is contributing to a rise in extreme weather events including droughts (Stott, 2016). An extensive literature has examined how rainfall variation influences human capital formation in developing countries, affecting agricultural income, education, nutritional investments, and mortality outcomes (Maccini and Yang, 2009; Webb, 2022; Burgess et al., 2017; Deschênes and Greenstone, 2011). A popular theoretical explanation focuses on the opportunity cost of schooling through child labor mechanisms. Shah and Steinberg (2017) find that drought exposure is associated with higher educational attainment and school attendance in India. They propose a mechanism whereby when rainfall raises agricultural wages, the opportunity cost of schooling increases and families send children to work instead of school—though they do not directly measure child labor or children's time allocation in their study.

This paper uses high quality longitudinal data on cognition, enrollment, daily activity time spent, including child labor, and village precipitation data. Similar to Shah and Steinberg (2017), I find that moderate and severe drought improves math cognition and educational outcomes after controlling for individual fixed effects. However, I do not find significant effects through the child labor channel when using direct child labor data. Instead of the wage-opportunity cost mechanism, I find that reduced transportation barriers during drought periods appear to be the key explanation for these positive effects.

Specifically, I find that moderate drought conditions significantly increase math cognition by 1.28 standard deviations, increase school enrollment by 0.37 percentage points, and increase study time by 0.38 hours per day. Crucially, moderate drought reduces travel time to school by 21.11 minutes, suggesting that improved road conditions during dry periods facilitate better access to educational facilities. The positive effects are strongest for moder-

[1] Documentary *On the Way to School* (2013, dir. Pascal Plisson). One of the featured children, Jackson, lives in Kenya's Maasai region and walks 15 kilometers across the savannah each morning with his sister to attend school, facing dangers from elephants and other wildlife. The round trip is roughly 30 kilometers per day, taking more than four hours in total. He often holds his sister's hand, comforts her when she gets tired, and encourages her to keep walking. His aspiration is to become a pilot.

ate drought conditions but diminish progressively as drought severity increases, remaining positive even at extreme levels. These results point to a non-linear relationship where mild water scarcity improves transportation infrastructure accessibility, while more severe drought conditions show attenuated but persistent benefits. The transportation channel represents a novel pathway through which climate conditions affect human capital formation, distinct from the wage-opportunity cost mechanisms emphasized in previous literature.

Furthermore, I use an identification strategy that leverages natural variation in drought exposure patterns across the five rounds of Young Lives data collection. Among children in our balanced panel, some experienced severe drought in all five rounds, while others experienced drought in only four out of five rounds. Crucially, among those experiencing four rounds of severe drought, there is variation in the timing of their single non-drought year: some experienced drought relief in Round 1 (early drought relief), while others experienced it in Round 3 (late drought relief). This variation serves as my identification strategy, allowing me to compare children with similar total drought exposure but different timing of relief. Among the 969 children who experienced 4 rounds of severe droughts out of five rounds of survey, 317 (32.71 percent) experienced early drought relief while 652 (67.29 percent) experienced late drought relief, providing substantial statistical power for our analysis. The quasi-random timing of rainfall-driven drought relief, combined with our longitudinal panel structure, enables causal identification of drought effects on child development outcomes.

The event study analysis reveals dynamic patterns in how children respond to drought conditions over time. When children experience relief from severe droughts in round 3, their enrollment significantly decreases compared to the control group (who previously experienced drought relief in round 1), their travel time to school shows an immediate increase, their in-school time and after-school study time both decline, while child labor time shows no significant differences compared to the control group, supporting the transportation mechanism hypothesis. These temporal patterns provide compelling evidence that the transportation channel operates through improved road conditions during drought, enabling better school accessibility that translates into meaningful educational gains.

Understanding heterogeneous effects is crucial for comprehending the full impact of drought on child development. This study examines how drought effects vary across key demographic and geographic dimensions. First, I find no significant differential effects by gender—both boys and girls respond similarly to drought conditions across cognitive, educational, and time allocation outcomes, suggesting the transportation mechanism operates equally regardless of gender.

Second, effects are substantially larger in rural areas. Rural children experience significantly stronger positive effects from moderate drought on cognitive development and school enrollment, consistent with rural areas having more fragile transportation infrastructure that benefits more from reduced flooding during dry periods. Rural households also face greater baseline transportation challenges, making infrastructure improvements during drought particularly valuable for educational access.

Third, Ethiopia's social safety net programs appear ineffective in moderating drought impacts on child outcomes. Neither participation in public work programs nor receipt of direct support transfers significantly alters how children respond to drought conditions. Crucially, when drought relief occurs (return to wet conditions), children experience reduced enrollment, increased commuting time, and decreased school and study time—yet social safety net programs provide no protection against these transportation-related educational disruptions. This suggests existing social protection mechanisms are inadequately designed to address the transportation and infrastructure challenges that drive drought's educational effects. The finding provides compelling evidence that commuting and road access barriers play a bigger role than income shocks and child labor wage effects, as these programs focus on direct financial support rather than addressing transportation infrastructure, highlighting a critical policy gap in Ethiopia's climate adaptation approach.

This paper introduces a novel dimension to the extensive literature on childhood weather shocks and human capital development by examining children's time allocation through transportation and infrastructure mechanisms—a previously underexplored avenue of research. Methodologically, our estimation strategy incorporating individual fixed effects relaxes the assumption often made in prior research that cross-sectional geographic exposure to weather shocks is exogenous to the outcomes of interest.

Previous research demonstrates that rainfall, particularly during childhood, influences height, schooling, and wealth of adult women (Maccini and Yang, 2009), cognitive abilities through increased agricultural income and nutritional investments (Webb, 2022), as well as birthweight (Deschênes et al., 2009) and mortality (Deschênes and Greenstone, 2011; Barreca et al., 2016, 2015; Burgess et al., 2017). However, this literature has primarily focused on agricultural income and nutritional pathways, with limited attention to transportation infrastructure as a mediating mechanism.

This study also contributes to the child labor literature by demonstrating that when child labor rates are already high, weather shocks may operate primarily through alternative channels such as transportation infrastructure rather than labor market adjustments. In Ethiopia's context, where our data show children are already heavily engaged in child labor—averaging 4 hours per day from age 7 onwards—drought shocks do not significantly alter existing work patterns, providing empirical support for this alternative mechanism. This finding adds to the existing literature, which documents that child labor is determined by poverty and economic factors (Basu and Van, 1998; Edmonds and Schady, 2012; Fors, 2012; Bandara et al., 2015), household characteristics (Basu and Van, 1998; Baland and Robinson, 2000; Strauss and Thomas, 1995; Al-Samarrai and Peasgood, 1998), imperfect land and labor markets (Bhalotra and Heady, 2003; Dumas, 2007; Congdon Fors, 2007; Ganglmair, 2005), risk coping mechanisms (Beegle et al., 2006; Ravallion and Chaudhuri, 1997; Morduch, 1999), agriculture shocks (Bandara et al., 2015; Duryea et al., 2007; Baker et al., 2020), relative returns to child labor (Bai and Wang, 2020; Shah and Steinberg, 2017) and policy interventions (Bharadwaj et al., 2020; Basu, 2005; De Hoop et al., 2019; **?**; Skoufias et al., 2001; Edmonds and Shrestha, 2014; De Hoop and Rosati, 2014; De Janvry et al., 2006; Dammert et al., 2018), by highlighting transportation infrastructure as an additional important mechanism.

The findings of this study hold important policy implications. While previous research has established that weather shocks typically have negative impacts on human capital, this paper's findings reveal that moderate drought can actually improve educational outcomes in Ethiopia. This expands conventional approaches to climate adaptation and suggests that in contexts with fragile transportation infrastructure, drought may temporarily reduce commuting barriers and create positive spillovers for education. These results highlight the importance of transportation infrastructure as a critical margin of resilience for sustaining human capital under climate variability, suggesting that infrastructure investments may be as important as traditional child labor interventions.

Notably, transportation infrastructure and road access have received considerably less attention in child labor policy discussions, despite potentially playing a crucial role in determining educational access and child time allocation patterns. Policy discussions on child labor have traditionally focused on cash transfers, direct subsidies, and labor market regulations, with mixed results (Dammert et al., 2018). Some interventions have proven counterproductive: Bharadwaj et al. (2020) found that India's Child Labor Act of 1986 actually increased child employment and decreased wages, while De Hoop et al. (2019) showed that partial education subsidies in the Philippines increased both school attendance and child labor. Successful interventions include Ravallion and Wodon (2000)'s study of Bangladesh's Food Education Program, which increased school enrollment by 19 and 18 percentage points for boys and girls respectively, and conditional cash transfer programs that effectively safeguard enrollment (De Hoop and Rosati, 2014; De Janvry et al., 2006), though these do not prevent parents from increasing child labor during adverse shocks.

The structure of the paper is as follows. Section 2 documents a more detailed literature review. Section 3 explains institutional background, data and methods. Section 4 presents the effects of drought on children's educational, cognitive, and behavioral outcomes in Ethiopia, heterogeneity and robustness check. Section 5 introduces the quasi-experimental design and present the event study results. Section 6 outlines the structural estimation approach. Finally, Section 7 concludes.

2 literature Review

2.1 Weather shocks and human capital

Extensive research explores the impact of precipitation, temperature and windstorms on economic outcomes, emphasizing variations in weather conditions observed over time within specific geographic regions.[2] 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. Shah and Steinberg (2017) find that drought exposure is associated with higher educational attainment and school attendance in India, theoretically proposing that when rainfall raises agricultural wages, the opportunity cost of schooling increases and families send children to work instead of school—though they do not directly measure child labor or children's time allocation in their study.[3]

[2]Temperature-related studies also demonstrate significant effects on human outcomes: Deschênes et al. (2009) finds that extreme heat during pregnancy reduces birth weight in the US; Deschênes and Greenstone (2011) documents non-linear temperature-mortality relationships; Barreca et al. (2016) shows reduced temperature-mortality sensitivity over the 20th century US; Barreca et al. (2015) identifies declining health-mortality relationships; and Burgess et al. (2017) emphasizes temperature-related mortality disparities between rural and urban India through reduced agricultural productivity.

[3]Related research on agricultural productivity and weather includes (Felkner et al., 2009) on weather impacts on crop yields, (Burgess and Donaldson, 2010) on how railroads mitigate agricultural shocks in colonial India,

2.2 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) [4]. 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 (Fors, 2012; Bandara et al., 2015). 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 (Basu and Van, 1998; Baland and Robinson, 2000). Parental education can also impact child labor, as higher-educated parents tend to prioritize their children's education (Strauss and Thomas, 1995; Al-Samarrai and Peasgood, 1998). 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

(Fisher et al., 2012) on climate change impacts on US agriculture, and (Hornbeck, 2012; Deschênes and Greenstone, 2007, 2012) on agricultural land values and revenues.

[4] "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).

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 Dumas (2007); Congdon Fors (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 (Beegle et al., 2006; Bandara et al., 2015). In the absence of formal coping strategies, households employ alternative mechanisms like child labor to smooth consumption when faced with shocks (Ravallion and Chaudhuri, 1997; Morduch, 1999). 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 (Dumas, 2013; Alvi and Dendir, 2011).

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.

3 Data and Institutional Background

3.1 Young Lives Survey

Young Lives Ethiopia is a longitudinal study spanning five rounds of data collection from 2002 to 2016 [5]. The study employs a random sampling approach across two cohorts: 2,000 children aged 6-18 months in 2002 (younger cohort) and 1,000 children aged 7.5-8.5 years (older cohort).

Sampling covers five major regions—Addis Ababa, Oromia, Amhara, SNNPR, and Tigray—representing 96 percent of Ethiopia's population. Districts were strategically selected from economically disadvantaged areas, with 75 percent in high food deficit areas and 25 percent in lower food deficit areas (Outes-Leon and Sanchez, 2008). Three to five districts were selected per region, with peasant associations or kebeles (the lowest administrative level) serving as sentinel sites due to districts being too large. The study ultimately established 20 sentinel sites across all regions, with communities defined according to administrative areas. In practice, Young Lives community boundaries may be smaller, larger, or the same as the

[5] 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.

sentinel site, and may include a whole village or a suburb in a city. The key criterion was finding at least 100 households with 1-year-old children and 50 households with 8-year-old children.

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.

The final sample comprises 60 percent rural and 40 percent urban children, with regional representation of 20 percent each, except Addis Ababa (15 percent) and SNNPR (25 percent). Outes-Leon and Sanchez (2008) shows that Young Lives households were slightly better-off than average Ethiopian households, but held less land, owned less livestock, and were less likely to own a household.

Table 1 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.

The two-cohort design of the Young Lives study is clearly demonstrated in Appendix Table A1, which shows the age distribution within each survey round. This table illustrates how the younger cohort progresses from approximately age 1 in Round 1 to ages 14-15 in Round 5, while the older cohort advances from ages 7-8 in Round 1 to ages 21-22 in Round 5. The clean age progression across rounds confirms the successful longitudinal tracking of the same children over the 14-year study period, providing valuable insights into different developmental stages and life transitions. This design allows us to examine drought effects across crucial developmental periods, from early childhood through adolescence and into early adulthood.

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).

Table 2: Distribution of Observations by Survey Round

Survey Round	**Frequency**	**Percent**
1	2,999	21.14
2	2,892	20.38
3	2,857	20.14
4	2,782	19.61
5	2,659	18.74
Total	14,189	100.00

Notes: This table shows the distribution of observations across the five rounds of data collection in the Young Lives Ethiopia study. Round 1 was conducted in 2002, Round 2 in 2006, Round 3 in 2009, Round 4 in 2013, and Round 5 in 2016. The slight decrease in observations over time reflects natural attrition in the longitudinal study. Total observations: 14,189. Source: Young Lives Ethiopia dataset (2002-2016).

3.2 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. 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, with about 16,200,000 (76 percent) enrolled in primary education. Despite free primary education, 32 percent of children of official primary school ages are out of school. Educational attainment remains low, with approximately 16 percent of youth ages 15-24 having no formal education and 54 percent having attained at most incomplete primary education, meaning that 70 percent of 15-24 year olds have not completed primary education in Ethiopia.

3.3 Education in Ethiopia

Ethiopia's education system operates from September to July, with free primary education for students entering at age 7 (Education Policy and Data Center, 2018). The structure comprises 6 years of primary education (compulsory until age 12), followed by 4 years of lower secondary and 2 years of upper secondary. Despite free primary education, educational access and attainment remain challenging: 32 percent of primary school-age children are out of school, and among youth aged 15-24, approximately 16 percent have no formal education while 54 percent have incomplete primary education—meaning 70 percent have not completed primary education (Education Policy and Data Center, 2018).

In Young Lives, 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.

Given that education is free to attend, it is perhaps unsurprising that enrollment rates are relatively high as shown in Figure 1, which peaks at around 90 percent during primary school ages.

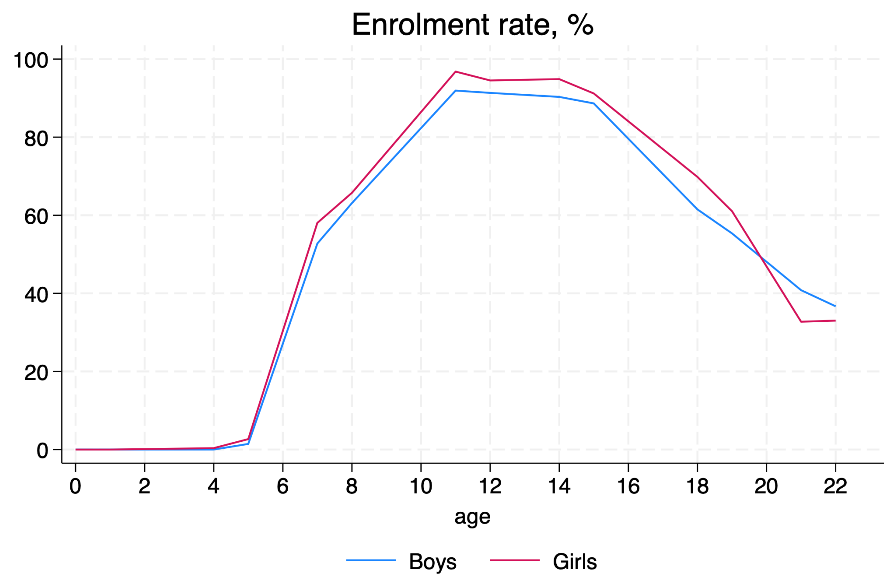

Figure 1: Age profile of enrolment

Notes: This figure shows the age profile of school enrollment for children in the Young Lives Ethiopia study. Source: Young Lives Ethiopia dataset (2002-2016).

Travel time to school is measured in minutes and captures the duration it takes for children to commute from their home to their educational institution. This variable is crucial for understanding the transportation mechanism through which drought conditions may affect educational access. The data is collected through surveys asking households about the typical time required for children to reach school, providing insights into commuting barriers that may vary with weather conditions and infrastructure accessibility.

3.4 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.

According to the same report, a staggering 76 percent of child laborers are involved in agriculture, while 21 percent work 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.

Child Labor Measurement in Young Lives Given this institutional context, measuring child labor accurately is crucial for understanding its prevalence and patterns. In the Young Lives survey, data on children's work activities aged 5 to 17 years is collected through interviews and questionnaires conducted with parents or guardians. 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 normal school day, excluding holidays, festivals, and 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 spend on running household chores, working on household tasks, and working outside the household on paid activities. Running household chores includes work or tasks 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, including 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.

The data reveals concerning patterns consistent with the national statistics. From age 7, children are engaged in child labor for approximately 4 to 5 hours per day, as shown in Figure 2.

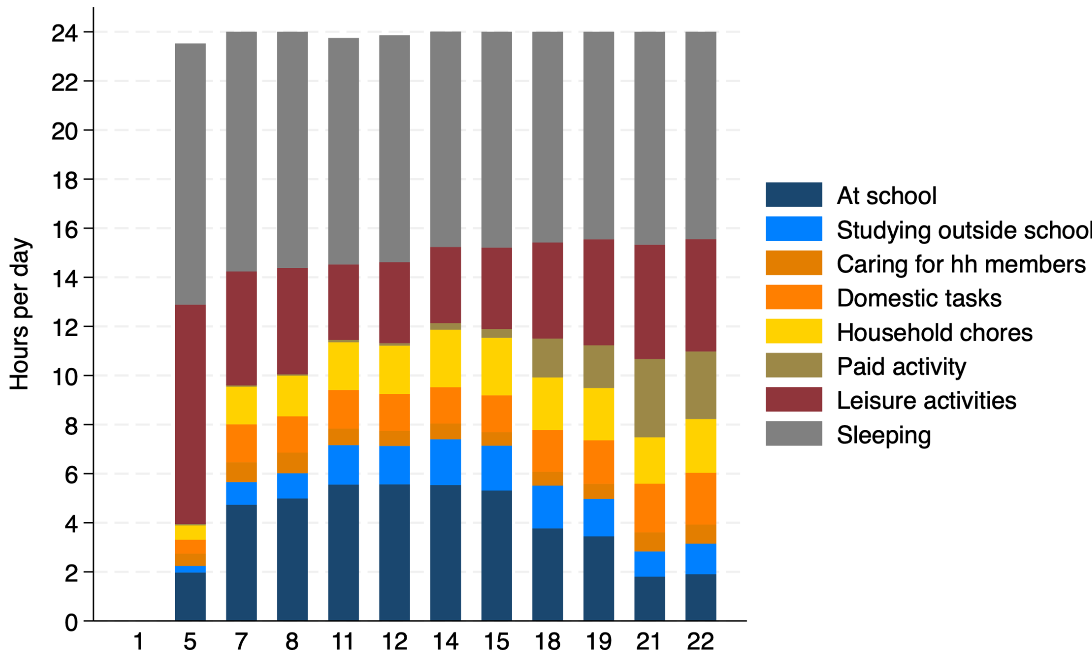

Figure 2: Average Time Allocation of Children in Ethiopia

Notes: This figure shows the time allocation patterns of children across different activities in Ethiopia based on the Young Lives dataset. The allocation includes time spent on education, child labor (household chores, domestic tasks, and paid work), leisure activities, and other daily activities. The Young Lives child's time-allocation information was collected from Round 2 to Round 5 in all countries under the 'time use' section of the questionnaire. The section 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 day, excluding holidays, festivals, days of rest during the weekend, and so on. Source: Young Lives Ethiopia dataset (2002-2016).

3.5 Seasonality and flooding in Ethiopia

Ethiopia experiences distinct seasonal patterns that significantly influence agricultural production and weather-related risks. The country's climate is characterized by three main seasons: Bega (dry season, October–January) with minimal rainfall; Belg (short rainy season, February–May) providing supplementary rainfall for early planting; and Kiremt (primary rainy season, June–September), delivering 50–95 percent of annual precipitation and producing approximately 85 to 95 percent of food crops (Asfaw et al., 2018).

The country faces significant climate variability and vulnerability to both extreme drought and flooding events. Climate change has intensified these challenges, with droughts becoming more frequent and severe, leading to water scarcity and reduced agricultural productivity. Conversely, during heavy rainfall events, particularly in the Kiremt season, substantial risks emerge from flash floods and riverine flooding that can displace communities, damage critical infrastructure, and severely disrupt livelihoods.

3.6 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. Since only Math and PPVT are measured for four rounds while reading is only measured in the last two rounds, I primarily use Math and PPVT as my cognition measures.

3.7 Drought Measurement: Standardised Precipitation Index Construction

To systematically quantify drought conditions experienced by Young Lives communities in Ethiopia, this study employs the Standardised Precipitation Index (SPI) methodology following McQuade and Favara (2024) to construct the standardised precipitation index. The SPI expresses each month's precipitation as the number of standard deviations from the long-run, location-specific mean, after adjusting for the skewed distribution of rainfall.

Data Sources and Community-Level Precipitation Series Monthly precipitation data for Young Lives communities are obtained from McQuade and Favara (2024), who extract location-specific rainfall series from the University of Delaware global gridded climate dataset. This dataset provides monthly precipitation estimates at 0.5° spatial resolution spanning 1901–2017, with community-specific series derived using precise GPS coordinates of each Young Lives village center.

Statistical Distribution Modeling Following McKee et al. (1993) and McQuade and Favara (2024), monthly precipitation totals are modeled using a two-parameter gamma distribution, which is particularly suitable for non-negative, right-skewed rainfall data. For precipitation $x > 0$, the probability density function is specified as:

$$g(x; \alpha, \beta) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta},$$

where $\alpha > 0$ is the shape parameter, $\beta > 0$ the scale parameter, and $\Gamma(\alpha)$ the gamma function. Parameters $(\hat{\alpha}, \hat{\beta})$ are estimated by maximum likelihood. In cases where convergence fails, we use Thom's (1958) moment-based approximation:

$$A = \ln(\bar{x}) - \frac{1}{n}\sum_{i=1}^{n} \ln(x_i), \quad \hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right), \quad \hat{\beta} = \frac{\bar{x}}{\hat{\alpha}},$$

with $\bar{x}$ denoting the sample mean over n observations.

Treatment of Zero Precipitation Values Because months with zero rainfall are common, I employ a mixed distribution that incorporates the empirical probability of zero precipitation:

$$H(x) = q + (1 - q)G(x),$$

where $q = P(x = 0)$ and $G(x)$ is the cumulative distribution function (CDF) of the fitted gamma distribution.

Standardization to Normal Distribution The cumulative probability $H(x)$ is transformed into a standard normal variate Z using the Abramowitz–Stegun approximation (Abramowitz and Stegun, 1964). Define

$$t = \begin{cases} \sqrt{\ln\left(\frac{1}{H(x)^2}\right)}, & 0 < H(x) \leq 0.5, \\ \sqrt{\ln\left(\frac{1}{(1-H(x))^2}\right)}, & 0.5 < H(x) < 1, \end{cases}$$

and constants

$$c_0 = 2.515517, \quad c_1 = 0.802853, \quad c_2 = 0.010328, \quad d_1 = 1.432788, \quad d_2 = 0.189269, \quad d_3 = 0.001308.$$

Then

$$SPI = \begin{cases} -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & 0 < H(x) \leq 0.5, \\ \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & 0.5 < H(x) < 1. \end{cases}$$

Drought Classification and Data Integration The procedure is implemented in `Stata` by defining an `SPI` program and applying it separately to each (COMMID, MONTH) group using the user-written command `runby`. This produces an approximately standard normal SPI time series for each village-month observation. Negative SPI values indicate drier-than-normal conditions, while positive values indicate wetter-than-normal conditions.

Following McKee et al. (1993); Lloyd-Hughes and Saunders (2002); McQuade and Favara (2024), drought severity categories are defined based on SPI thresholds: moderate drought corresponds to SPI ≤ -1.0, severe drought to SPI ≤ -1.5, and extreme drought to SPI ≤ -2.0. These standardized thresholds allow for consistent drought identification across different villages and time periods, accounting for local precipitation patterns and seasonality. The resulting drought indicators are subsequently merged with the Young Lives dataset using temporal and geographic identifiers to create binary drought exposure variables for each survey round.

3.8 Empirical Specification

To estimate the effects of drought on child development outcomes, I employ the following fixed effects specification:

$$Y_{ict} = \alpha + \beta \text{Drought}_{ct} + \theta_i + \varepsilon_{ict} \tag{1}$$

where Y_{ict} represents the outcome of interest for child i in community c at time t. Drought_{ct} is a binary indicator for drought conditions, estimated separately for moderate (SPI ≤ -1.0), severe (SPI ≤ -1.5), and extreme (SPI ≤ -2.0) drought thresholds in separate regressions. θ_i represents individual fixed effects that control for all time-invariant child-specific characteristics, and ε_{ict} is the error term clustered at the community level to account for spatial correlation in weather patterns and unobserved community characteristics.

The individual fixed effects specification is crucial as it eliminates potential confounding from time-invariant child, household, and community characteristics that might be correlated with both drought exposure and child outcomes. The coefficient β captures the causal effect of drought exposure on child development outcomes, identified through within-child variation in drought exposure across survey rounds. By estimating separate regressions for each drought severity level, I can examine how the magnitude and significance of drought effects vary with drought intensity. This approach also provides robustness evidence that my results are not sensitive to how drought is defined, as consistent patterns emerge across different drought severity thresholds.

4 The Effects of Droughts

This section presents the empirical analysis of drought effects on children's educational, cognitive, and behavioral outcomes in Ethiopia. Using the Standardised Precipitation Index (SPI) to precisely measure drought severity, I examine how different levels of drought conditions—moderate (SPI $\leq$ -1.0), severe (SPI $\leq$ -1.5), and extreme (SPI $\leq$ -2.0)—affect multiple dimensions of child development. The analysis proceeds as follows: I first examine drought effects on cognitive development, then school enrollment patterns, followed by detailed time allocation analysis across different activities. I subsequently investigate health outcomes and conclude with heterogeneous effects by gender, urban versus rural contexts, and policy interactions with Ethiopia's direct support programs, providing comprehensive insights into how different groups respond to drought conditions under varying institutional settings.

4.1 Drought Effects on Cognition

Table 3: Effects of Drought on Cognitive Outcomes: Overall and by Gender

Panel A: Math Scores									
	All			Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moderate drought (SPI ≤ -1.0)	1.27***			1.26***			1.28***		
	(0.01)			(0.01)			(0.13)		
Severe drought (SPI ≤ -1.5)		1.26***			1.19***			1.32***	
		(0.11)			(0.12)			(0.11)	
Extreme drought (SPI ≤ -2.0)			0.51			0.50			0.52
			(0.31)			(0.30)			(0.33)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6572	6572	6572	3414	3414	3414	3158	3158	3158
Panel B: PPVT Scores									
	All			Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moderate drought (SPI ≤ -1.0)	0.90***			1.02***			0.76***		
	(0.01)			(0.02)			(0.23)		
Severe drought (SPI ≤ -1.5)		0.45			0.46			0.44	
		(0.48)			(0.55)			(0.38)	
Extreme drought (SPI ≤ -2.0)			0.27			0.26			0.30
			(0.51)			(0.49)			(0.54)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7088	7088	7088	3761	3761	3761	3327	3327	3327

Notes: This table shows regression results examining the effects of drought on cognitive outcomes for all children and by gender. Panel A presents results for Math scores and Panel B presents results for PPVT scores. Columns (1)-(3) present results for all children, columns (4)-(6) present results for boys, and columns (7)-(9) present results for girls. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3 demonstrates that drought conditions have significant effects on children's cognitive development across both Math and PPVT outcomes. The overall results show that moderate drought conditions (SPI ≤ -1.0) are associated with substantial improvements in Math scores, with an increase of 1.27 points, and improvements in PPVT vocabulary scores of 0.90 points. However, the effects become less pronounced or statistically insignificant as drought severity increases to severe (SPI ≤ -1.5) or extreme (SPI ≤ -2.0) levels. The gender-specific results reveal interesting patterns: boys show very similar effects to the overall sample for both Math and PPVT outcomes across all drought severity levels. For girls, the Math effects appear similar in magnitude but with larger standard errors, particularly for moderate drought conditions, while PPVT effects are somewhat smaller than for boys. These findings suggest that drought's positive cognitive effects operate similarly for both genders, supporting the hypothesis that improved transportation access during drought periods benefits all children regardless of gender.

4.2 Drought Effects on School Enrollment and Time Allocation

Table 4 presents the comprehensive effects of different drought severity levels on school enrollment and time allocation for all children and by gender. Panel A shows that drought has positive effects on enrollment, with moderate drought (SPI ≤ -1.0) increasing enrollment probability by 0.37 percentage points. As drought severity increases, the effects become more precisely estimated: severe drought (SPI ≤ -1.5) increases enrollment by 0.24 percentage points, while extreme drought (SPI ≤ -2.0) shows the strongest and most statistically significant effect with an increase of 0.14 percentage points.

Panel B examines how drought conditions affect children's commuting time to school, providing crucial insights into the transportation mechanism. The results show that drought conditions are significantly associated with reduced travel time to school: moderate drought reduces commuting time by 21.12 minutes, severe drought by 24.35 minutes, and extreme drought by 9.23 minutes.

Panels C and D examine time allocation to educational activities. Panel C shows that moderate drought significantly increases study time by 0.38 hours per day for all children, with boys showing a larger increase (0.48 hours) compared to girls (0.18 hours). Panel D demonstrates that drought conditions also increase time spent in school, with moderate drought leading to 2.44 additional hours of school time, though this effect is more pronounced for boys (2.60 hours) than girls (2.25 hours).

The gender-specific results across all panels reveal that boys and girls respond similarly to drought conditions, with no significant differential effects by gender, suggesting the transportation mechanism operates equally regardless of gender. These findings support the transportation mechanism hypothesis, suggesting that when drought reduces road flooding and improves transportation infrastructure accessibility, children can reach school more easily, spend less time commuting, and dedicate more time to educational activities, which translates into higher enrollment rates and better educational access.

Understanding drought's impact on health outcomes is particularly important because, as shown by Attanasio et al. (2020) using Young Lives data in India, human capital has two relevant dimensions that may reinforce each other in development: cognition and health. Following Cunha et al. (2010) and Attanasio et al. (2020), child development can be expressed

Table 4: Effects of Drought on School Enrollment and Time Allocation: Overall and by Gender

Panel A: School Enrollment									
	All			Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moderate drought (SPI ≤ -1.0)	0.37*			0.38**			0.36		
	(0.19)			(0.16)			(0.22)		
Severe drought (SPI ≤ -1.5)		0.23**			0.21*			0.25**	
		(0.11)			(0.10)			(0.11)	
Extreme drought (SPI ≤ -2.0)			0.14**			0.14**			0.13**
			(0.05)			(0.05)			(0.05)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11419	11419	11419	6003	6003	6003	5416	5416	5416
Panel B: Travel Time to School (minutes)									
	All			Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moderate drought (SPI ≤ -1.0)	-21.12***			-21.12***			-15.28***		
	(0.01)			(0.01)			(3.08)		
Severe drought (SPI ≤ -1.5)		-24.35***			-24.92***			-23.76***	
		(7.89)			(8.13)			(8.02)	
Extreme drought (SPI ≤ -2.0)			-9.23*			-9.24*			-9.21*
			(4.47)			(4.57)			(4.49)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8229	8229	8229	4267	4267	4267	3962	3962	3962
Panel C: Study Time (hours per day)									
	All			Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moderate drought (SPI ≤ -1.0)	0.38***			0.48***			0.18***		
	(0.00)			(0.00)			(0.009)		
Severe drought (SPI ≤ -1.5)		0.27***			0.31***			0.24***	
		(0.06)			(0.08)			(0.05)	
Extreme drought (SPI ≤ -2.0)			0.24			0.28*			0.19
			(0.16)			(0.16)			(0.16)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8154	8154	8154	4286	4286	4286	3868	3868	3868
Panel D: School Time (hours per day)									
	All			Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moderate drought (SPI ≤ -1.0)	2.44			2.60*			2.25		
	(1.61)			(1.41)			(1.85)		
Severe drought (SPI ≤ -1.5)		1.28*			1.29*			1.27	
		(0.75)			(0.72)			(0.80)	
Extreme drought (SPI ≤ -2.0)			0.87**			0.92**			0.81**
			(0.36)			(0.37)			(0.36)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11009	11009	11009	5782	5782	5782	5227	5227	5227

Notes: This table shows regression results examining the effects of drought on school enrollment and time allocation for all children and by gender. Panel A presents results for school enrollment, Panel B for travel time to school (in minutes), Panel C for study time (hours per day), and Panel D for school time (hours per day). Columns (1)-(3) present results for all children, columns (4)-(6) present results for boys, and columns (7)-(9) present results for girls. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

as $H_a = H\left(\theta_a^c, \theta_a^h\right)$, where cognition ($\theta_a^c$) and health ($\theta_a^h$) evolve through dynamic production functions that allow for complementarity between these dimensions. However, our results reveal that drought has minimal effects on health outcomes, suggesting this potential source of reinforcement between health and cognitive development is less of a concern in our Ethiopian context.

As shown in Table 4, moderate drought significantly increases study time by 0.38 hours and school attendance time, indicating that drought conditions may facilitate greater educational engagement. Importantly, our analysis of time allocation to child labor activities (work, household chores, and domestic tasks) and health outcomes (injury rates and health problems) shows no significant effects of drought conditions (detailed results are presented in Appendix Table A3). This finding suggests that drought conditions may lead to changes in children's activity patterns that reduce exposure to injury risks, but the effects are not statistically significant.

4.3 Heterogeneous Effects of Drought by Gender

This subsection examines the differential effects of drought across gender, providing insights into how boys and girls respond differently to drought conditions across various outcomes including cognitive development, educational enrollment, time allocation, and health.

Importantly, our analysis reveals that drought conditions have no significant effects on children's time allocation to child labor activities (work, household chores, and domestic tasks) or on health outcomes including injury rates and long-term health problems (detailed results are presented in Appendix Table A3). This finding is particularly noteworthy as it suggests that the positive educational and cognitive effects of drought operate through transportation mechanisms rather than through reductions in competing activities or health improvements.

Tables 3 and 4 reveal important heterogeneous effects of drought conditions across multiple domains of child development. Table 3 demonstrates that drought impacts on cognitive outcomes operate similarly for boys and girls, with both groups showing substantial improvements in Math and PPVT scores during moderate drought conditions. The gender-specific patterns show boys have very similar effects to the overall sample, while girls show comparable magnitudes but with somewhat larger standard errors. The enrollment and time allocation results in Table 4 show that boys and girls respond similarly to drought conditions, with no significant differential effects by gender, suggesting the transportation mechanism operates equally regardless of gender.

As discussed above and detailed in Appendix Table A3, drought conditions show no significant effects on children's time allocation to child labor activities or health outcomes. The appendix table reveals that while there are some gender-specific patterns in the point estimates, none of the effects on work activities, household chores, domestic tasks, injury rates, or health problems reach statistical significance across any drought severity level. These null findings are important as they demonstrate that the positive educational and cognitive effects of drought operate primarily through the transportation mechanism rather than through reductions in competing activities or health improvements.

These results demonstrate that drought impacts show interesting patterns across gender dimensions. While cognition, enrollment, and commuting effects operate similarly for boys and girls (supporting the transportation mechanism hypothesis), time allocation patterns and health outcomes exhibit more substantial gender differences. The similarity in cognitive, enrollment, and transportation effects suggests that the core mechanisms through which drought influences child development—particularly through improved transportation access—operate equally regardless of gender. However, the differential patterns in time allocation and health outcomes indicate that cultural norms, household responsibilities, and safety considerations may still create gender-specific responses in some domains. Understanding these nuanced patterns is crucial for designing targeted policy interventions that address both the common mechanisms and the gender-specific vulnerabilities during drought periods.

4.4 Heterogeneous Effects of Drought by Urban/Rural Location

This subsection examines the differential effects of drought across urban and rural areas, providing insights into how children in different geographic settings respond to drought conditions across various outcomes including cognitive development, educational enrollment, time allocation, and transportation.

Table 5: Urban/Rural-Specific Effects of Drought on Cognitive Outcomes

	Math			PPVT(vocabulary)		
	(1)	(2)	(3)	(4)	(5)	(6)
Moderate drought	-0.21			0.26		
	(0.55)			(0.28)		
Rural · Moderate drought	1.49**			0.64**		
	(0.55)			(0.29)		
Severe drought		0.59***			-0.32***	
		(0.02)			(0.06)	
Rural · Severe drought		0.74***			1.19***	
		(0.03)			(0.08)	
Extreme drought			0.24			0.64
			(0.58)			(0.93)
Rural · Extreme drought			0.36			-0.64
			(0.68)			(1.06)
Rural area	-1.47***	-0.70	-0.38	-1.31***	-1.86***	-0.38
	(0.01)	(0.52)	(0.64)	(0.27)	(0.54)	(0.81)
N	6572	6572	6572	7088	7088	7088

Standard errors in parentheses

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

Notes: This table shows regression results examining the differential effects of drought on cognitive outcomes by urban/rural location. Panel A presents results for urban areas and Panel B presents results for rural areas. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Urban/Rural-Specific Effects of Drought on Study Time and Travel Time to School

	Study time (hours per day)			Travel time to school (minutes)		
	(1)	(2)	(3)	(4)	(5)	(6)
Moderate drought	0.47			-16.54***		
	(0.34)			(2.07)		
Rural · Moderate drought	-0.09			-4.65**		
	(0.35)			(2.14)		
Severe drought		0.12**			-4.20***	
		(0.05)			(0.50)	
Rural · Severe drought		0.17**			-22.67**	
		(0.08)			(8.32)	
Extreme drought			0.36			-1.76
			(0.40)			(1.82)
Rural · Extreme drought			-0.17			-11.19
			(0.42)			(6.55)
Rural area	-0.37***	-0.62*	-0.43	2.74	19.42**	8.19
	(0.01)	(0.30)	(0.36)	(2.00)	(8.82)	(6.34)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8154	8154	8154	8229	8229	8229

Notes: This table shows regression results examining the differential effects of drought on time allocated to studying (hours per day) and travel time to school (minutes) by urban/rural location. Columns (1)-(3) present results for study time and columns (4)-(6) present results for travel time to school. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tables 5 and 6 reveal important heterogeneous effects of drought conditions across urban and rural contexts. Table 5 demonstrates that drought impacts on cognitive outcomes vary significantly between urban and rural areas, with differential effects on both Math and PPVT scores across different drought severity levels.

The time allocation and transportation patterns also exhibit substantial urban-rural differences. Table 6 shows how drought affects both study time and travel time to school differently in urban versus rural settings, reflecting the different economic structures, infrastructure, and agricultural dependencies between these areas. The differential effects on both time allocation and transportation are particularly important given the different infrastructure quality and transportation options available in each setting.

These results demonstrate that drought impacts vary significantly between urban and rural areas, with differential effects on cognitive outcomes, educational enrollment, time allocation patterns, and transportation costs. Understanding these geographic differences is crucial for designing location-specific policy interventions that address the particular vulnerabilities and opportunities in each context during drought periods. Rural areas, with their greater agricultural dependence, may experience different drought effects compared to urban areas where economic activities are more diversified and infrastructure may be more resilient to weather shocks.

PSNP Public Works Program: I also examined the differential effects of drought by PSNP Public Works participation status, analyzing how households participating in Ethiopia's public works component of the Productive Safety Net Program respond differently to drought conditions. The results for PSNP Public Works are very similar to those presented below for PSNP Direct Support, showing no significant differential impacts of drought across program participation status. Neither the Public Works component nor the Direct Support component of PSNP significantly alters how children respond to drought conditions across cognitive, educational, and time allocation outcomes. For brevity, the detailed PSNP Public Works results are presented in Appendix A.2, and I focus the main text discussion on the Direct Support component which yields comparable findings.

4.5 Heterogeneous Effects of Drought by PSNP Participation - Direct Support

This subsection examines the differential effects of drought across households participating in the Direct Support component of Ethiopia's Productive Safety Net Program (PSNP) versus non-participating households. The PSNP Direct Support component provides targeted assistance to households that are unable to participate in public works activities due to labor constraints, typically including households with elderly members, pregnant or lactating women, or those caring for young children or disabled family members.

Understanding how drought effects vary by PSNP Direct Support participation is crucial for policy design, as it reveals whether this targeted social protection mechanism effectively buffers the most vulnerable households from climate shocks. The Direct Support component serves households that are often among the most vulnerable to economic and climate-related shocks, making the analysis of its protective effects particularly important for understanding the comprehensive impact of Ethiopia's social safety net system. The detailed heterogeneous effects by PSNP-Public Works participation are presented in Appendix A.2.

Table 7: PSNP Direct Support-Specific Effects of Drought on School Enrollment

	Enrolment		
	(1)	(2)	(3)
Moderate drought	0.62^{***}		
	(0.01)		
PSNP-DS · Moderate drought	0.08^{**}		
	(0.03)		
Severe drought		0.66^{***}	
		(0.09)	
PSNP-DS · Severe drought		0.14	
		(0.10)	
Extreme drought			0.25^{**}
			(0.11)
PSNP-DS · Extreme drought			-0.16
			(0.11)
PSNP-Direct Support household	-0.04^{***}	-0.11	0.15^{*}
	(0.00)	(0.09)	(0.07)
N	5038	5038	5038

Standard errors in parentheses

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

Notes: This table shows regression results examining the differential effects of drought on school enrollment by PSNP-Direct Support participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP Direct Support-participating households. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: PSNP Direct Support-Specific Effects of Drought on Cognitive Outcomes

	Math			PPVT(vocabulary)		
	(1)	(2)	(3)	(4)	(5)	(6)
Moderate drought	1.61***			2.24***		
	(0.02)			(0.01)		
PSNP-DS · Moderate drought	0.65***			0.61***		
	(0.12)			(0.11)		
Severe drought		1.55***			1.72***	
		(0.11)			(0.55)	
PSNP-DS · Severe drought		0.39			1.16*	
		(0.24)			(0.61)	
Extreme drought			0.62			0.48
			(0.37)			(0.44)
PSNP-DS · Extreme drought			-0.69*			-0.48
			(0.34)			(0.43)
PSNP-Direct Support household	-0.51***	-0.26	0.60***	-0.53***	-1.04*	0.46*
	(0.02)	(0.20)	(0.17)	(0.01)	(0.54)	(0.25)
N	4905	4905	4905	4142	4142	4142

Standard errors in parentheses

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

Notes: This table shows regression results examining the differential effects of drought on Math and PPVT cognitive outcomes by PSNP-Direct Support participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP Direct Support-participating households. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: PSNP Direct Support-Specific Effects of Drought on Study and School Time

	Study time			School time		
	(1)	(2)	(3)	(4)	(5)	(6)
Moderate drought	0.68***			2.83***		
	(0.01)			(0.03)		
PSNP-DS · Moderate drought	-0.14			0.67***		
	(0.10)			(0.20)		
Severe drought		0.83***			3.41***	
		(0.08)			(0.54)	
PSNP-DS · Severe drought		0.33			0.76	
		(0.45)			(0.62)	
Extreme drought			0.52***			1.32**
			(0.16)			(0.56)
PSNP-DS · Extreme drought			-0.53*			-0.88
			(0.29)			(0.60)
PSNP-Direct Support household	0.39***	-0.08	0.58***	-0.47***	-0.61	0.81**
	(0.01)	(0.39)	(0.19)	(0.02)	(0.56)	(0.37)
N	5026	5026	5026	5039	5039	5039

Standard errors in parentheses

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

Notes: This table shows regression results examining the differential effects of drought on time allocated to studying and attending school by PSNP-Direct Support participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP Direct Support-participating households. The regression includes individual fixed effects and village fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: PSNP Direct Support-Specific Effects of Drought on Travel Time to School

	Travel time to school (minutes)		
	(1)	(2)	(3)
Moderate drought	-28.49***		
	(0.32)		
PSNP-DS · Moderate drought	3.88		
	(2.34)		
Severe drought		-32.37***	
		(9.29)	
PSNP-DS · Severe drought		-22.31	
		(23.78)	
Extreme drought			-14.02**
			(5.89)
PSNP-DS · Extreme drought			7.53
			(8.57)
PSNP-Direct Support household	-5.39***	20.77	-7.02
	(0.18)	(23.12)	(6.67)
N	4738	4738	4738

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows regression results examining the differential effects of drought on travel time to school by PSNP-Direct Support participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP Direct Support-participating households. The regression includes individual fixed effects and village fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tables 7, 8, 9, and 10 reveal important heterogeneous effects of drought conditions across PSNP Direct Support participation status. The tables present coefficients for non-PSNP households (baseline effects) and interaction terms that capture the additional effects for households participating in the PSNP Direct Support program.

Table 7 demonstrates how drought impacts on school enrollment vary significantly between PSNP Direct Support-participating and non-participating households. The interaction terms reveal whether the targeted assistance provided by Direct Support effectively buffers children from drought-induced disruptions to schooling, particularly important given that Direct Support households often face additional vulnerabilities due to labor constraints.

Table 8 shows differential effects on cognitive outcomes (Math and PPVT scores) across

PSNP Direct Support participation status, indicating whether the direct cash transfers and assistance provided by this component help maintain or improve children's cognitive development during drought periods. These results are crucial for understanding whether targeted social protection programs can mitigate the human capital costs of climate shocks among the most vulnerable households.

Table 9 examines whether Direct Support households are better able to maintain children's educational time investments during droughts, providing insights into how PSNP Direct Support participation alters family educational decisions during drought periods.

Table 10 examines differential effects on school transportation costs and accessibility, which is particularly relevant given that Direct Support households may face greater transportation barriers due to their limited labor capacity and economic constraints. Understanding how drought affects commuting time differently for these vulnerable households provides insights into access barriers and potential intervention points.

These findings provide important evidence for the effectiveness of the Direct Support component of Ethiopia's largest social safety net program in protecting children from climate-related shocks. The results inform policy discussions about the design and targeting of social protection programs for the most vulnerable populations in climate-vulnerable countries, demonstrating whether existing targeted safety nets adequately buffer households with limited labor capacity from drought impacts or whether additional interventions are needed to protect child development outcomes during climate emergencies. The comparison between Direct Support and Public Works effects (analyzed in the previous subsection) offers insights into how different components of comprehensive social protection systems can address diverse vulnerability profiles within climate-affected populations.

5 Quasi-experimental design

Our identification exploits the fact that some children in the panel are exposed to droughts in every survey round except one. This creates a natural "event" when a child experiences a non-drought year within an otherwise persistent drought environment. We treat the timing of this non-drought year as quasi-random, since SPI-defined droughts are driven by exogenous rainfall shocks. We then compare children whose single non-drought occurs early (e.g., in Round 1) to those whose single non-drought occurs later (e.g., Round 3), holding child fixed effects constant. This event-style design allows us to trace out the dynamic response of outcomes before, during, and after the non-drought shock, while differencing out time-invariant heterogeneity at the child level.

To maintain a balanced panel for this analysis, I focus on children who appear in all five survey rounds. The distribution of observations by number of rounds shows that the vast majority of children (91.88 percent, or 13,030 observations) are present in all five rounds, while smaller proportions appear in four rounds (5.75 percent), three rounds (1.29 percent), two rounds (0.35 percent), or only one round (0.73 percent). This high retention rate in the balanced panel ensures that my quasi-experimental identification strategy can rely on consistent longitudinal tracking of the same children across the full study period, strengthening the validity of my within-child comparisons over time.

Within that balanced panel, the distribution of drought exposure across children reveals substantial variation that enables our quasi-experimental identification strategy.

Number of Droughts	**Frequency**	**Percent**	**Cumulative**
0	6	0.23	0.23
1	36	1.38	1.61
2	71	2.72	4.34
3	184	7.06	11.40
4	1,218	46.74	58.14
5	1,091	41.86	100.00
Total	**2,606**	**100.00**	

Table 11: Distribution of Drought Exposure in Balanced Panel

Table 11 reveals several important patterns in drought exposure that support our identification strategy. Most notably, a substantial proportion of children (41.86 percent) experience drought in all five survey rounds, while 46.74 percent experience drought in four out of five rounds, meaning that nearly 89 percent of children in our balanced panel experience drought conditions in at least four of the five survey rounds.

Crucially for our empirical strategy, identification of drought effects using individual fixed effects relies exclusively on within-child variation in drought exposure across survey rounds. This means that children who experience the same drought exposure in all five rounds—specifically, the 6 children (0.23 percent) who never experience drought and the 1,091 children (41.86 percent) who experience drought in every round—do not contribute to identifying the treatment effects. Our identification comes primarily from the 1,509 children (57.91 percent) who experience temporal variation in drought exposure: 36 children with 1 drought year, 71 with 2 drought years, 184 with 3 drought years, and most importantly, 1,218 children (46.74 percent) with 4 drought years who provide substantial identifying variation through the timing of their single non-drought year.

The timing of the single non-drought year among the 4-drought children provides particularly clean identification. Among the 969 children for whom I have complete round information, 317 children (32.71 percent) experienced their non-drought year in Round 1, while 652 children (67.29 percent) experienced their non-drought year in Round 3. This temporal variation allows me to compare children who are otherwise similar in total drought exposure but differ in the timing of drought relief, providing a natural experiment to identify the dynamic effects of drought conditions on child development outcomes.

This distribution is particularly advantageous for our quasi-experimental design, as it provides a large sample of children who experience drought in all but one survey round (those with 4 droughts), enabling us to exploit variation in the timing of the single non-drought year. The percentage of children with very low drought exposure (0-3 droughts, comprising 11.40 percent of the sample) reflects some geographic variation in drought exposure during our study period, while still providing useful variation for robustness checks.

The concentration of children in the 4-5 drought categories ensures sufficient statistical power for our event study analysis, where we compare children whose single non-drought year occurs at different points in time. This variation in drought timing, combined with the high retention rate in the balanced panel, strengthens the validity of my quasi-experimental identification strategy by allowing me to trace dynamic responses to drought relief while controlling for time-invariant child characteristics through individual fixed effects.

I visualize this by plotting mean outcomes (e.g., enrolment, school time, commuting, cognition, and time use) over survey rounds for the two groups, with confidence intervals and vertical reference lines marking the timing of the non-drought shock. The design ensures that identification comes from comparing otherwise similar children whose exposure to a single non-drought year differs in timing, rather than from cross-sectional differences in drought intensity.

5.1 Event Study Results

Our event study analysis compares children who experienced different timing of drought relief within the subset of children who experienced drought in four out of five survey rounds. The treatment group consists of children who did not experience drought in Round 3 (experiencing drought relief later in the study period), while the control group consists of children who did not experience drought in Round 1 (experiencing drought relief early in the study period). This design allows us to identify the dynamic effects of drought relief timing on child development outcomes.

The empirical specification for the event study analysis follows a standard event study framework with individual and time fixed effects. For each outcome variable, we estimate the following regression:

$$Y_{ict} = \alpha + \beta_1 \text{Event1}_{ict} + \beta_3 \text{Event3}_{ict} + \beta_4 \text{Event4}_{ict} + \beta_5 \text{Event5}_{ict} + \gamma_t + \theta_i + \varepsilon_{ict} \quad (2)$$

where Y_{ict} represents the outcome of interest (such as school enrollment) for child i in community c at time t. The event time indicators Event1_{ict}, Event3_{ict}, Event4_{ict}, and Event5_{ict} capture the timing relative to each child's single non-drought year, with Round 2 serving as the omitted reference period. The specification includes time fixed effects γ_t to control for common time trends across all children, and individual fixed effects θ_i to eliminate time-invariant child-specific heterogeneity. Standard errors are clustered at the community level to account for spatial correlation in weather patterns and local economic conditions. This specification allows us to trace the dynamic response of child outcomes before, during, and after the drought relief event, providing insights into both immediate and persistent effects of improved weather conditions on child development. This analysis investigates the effect of experiencing a period with no drought on children's school enrolment. Using a balanced panel of children observed across multiple survey rounds, we construct an event-time framework that aligns all children around the round in which they first experience the absence of drought. Children who never experience a no-drought round serve as the comparison group, while children who do experience one are treated as "eventually treated." By creating event-time dummies (e.g., two rounds before, at the event, and several rounds after), we compare enrolment outcomes relative to the pre-event baseline.

The regression absorbs child fixed effects, which control for time-invariant differences across children, and round fixed effects, which control for common shocks such as policy changes or seasonal patterns. Standard errors are clustered at the community level to allow for correlation in unobserved shocks within villages or communities. This ensures that our inference is robust to within-community correlations.

Figures 3 through 10 present the event study results across multiple domains of child development and time allocation. The blue lines represent the control group (no drought in Round 1), while the red dashed lines represent the treatment group (no drought in Round

3). The vertical reference lines mark the timing of the non-drought shock for each group, allowing us to trace the dynamic response patterns before, during, and after drought relief.

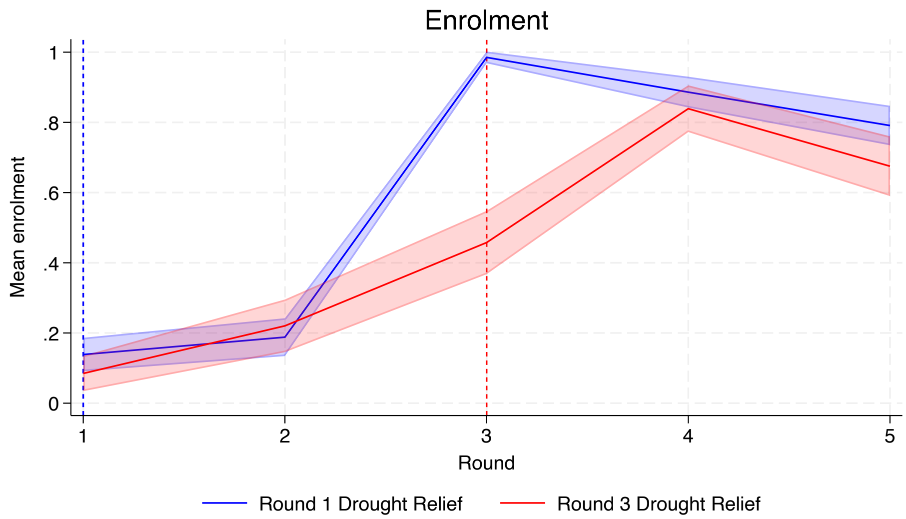

Figure 3: Event Study: School Enrollment

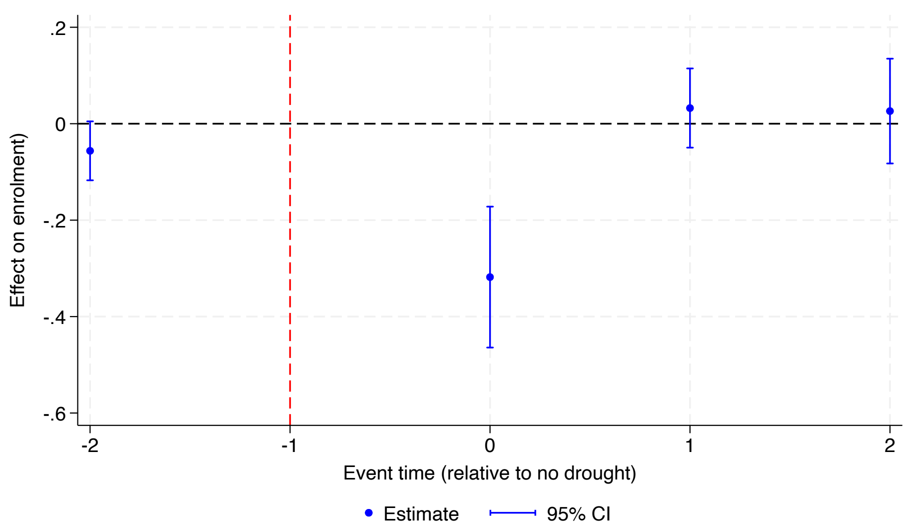

Figure 4: Event study: school enrolment

Notes: This figure shows the event study analysis of drought effects on school enrollment. The analysis compares children who experienced different timing of drought relief using individual and time fixed effects regression with clustered standard errors. Source: Young Lives Ethiopia dataset (2002-2016).

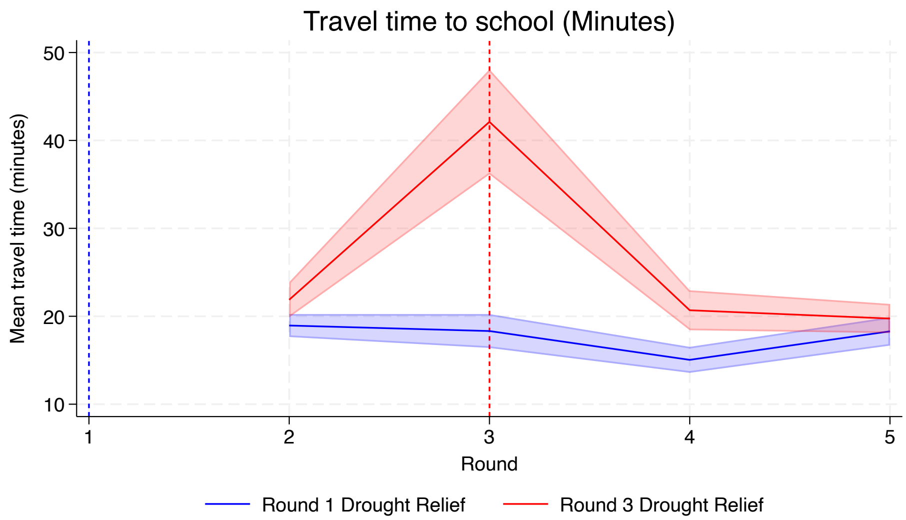

Figure 5: Event Study: Travel Time to School

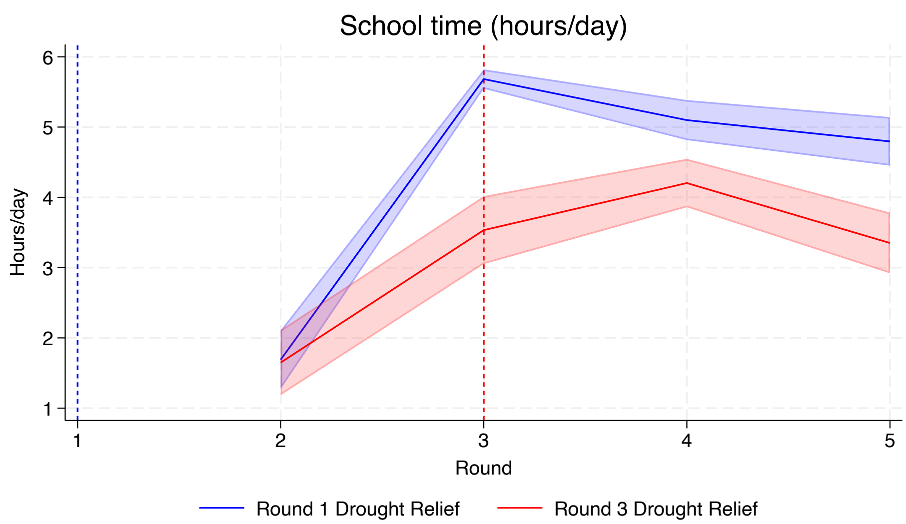

Figure 6: Event Study: School Time

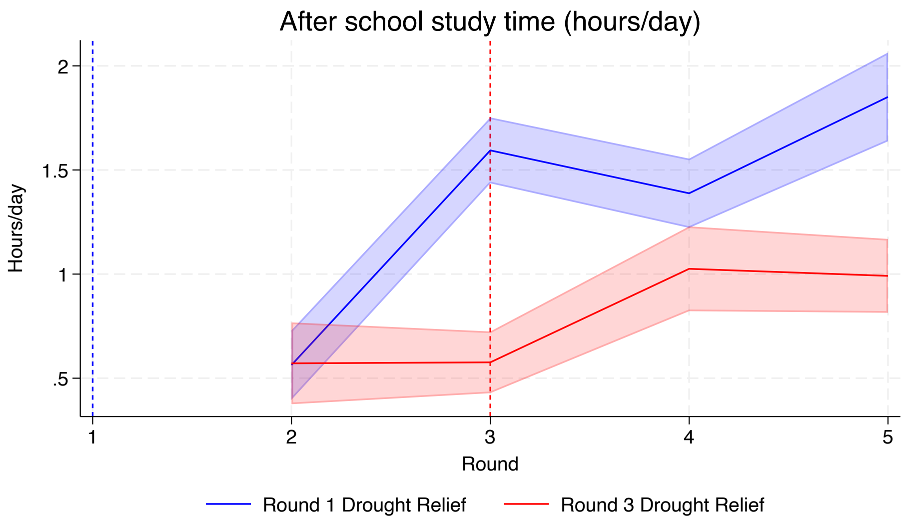

Figure 7: Event Study: Study Time

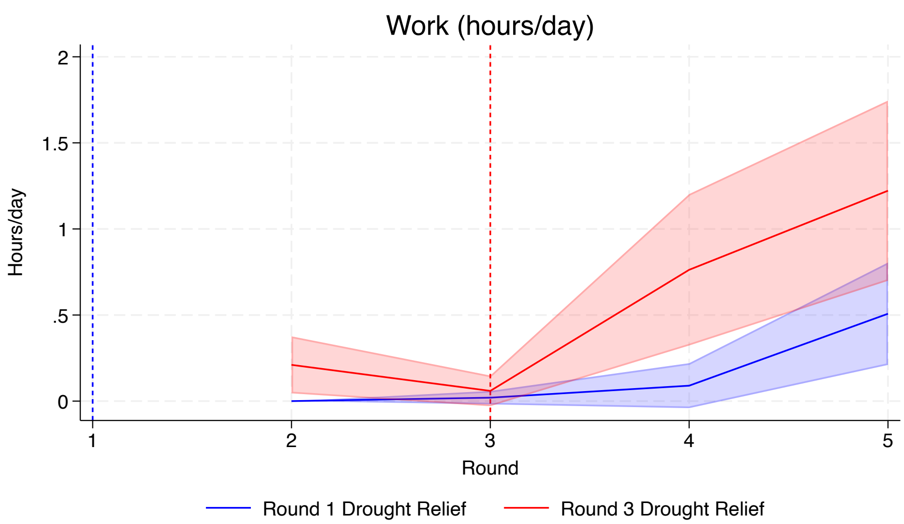

Figure 8: Event Study: Work Time

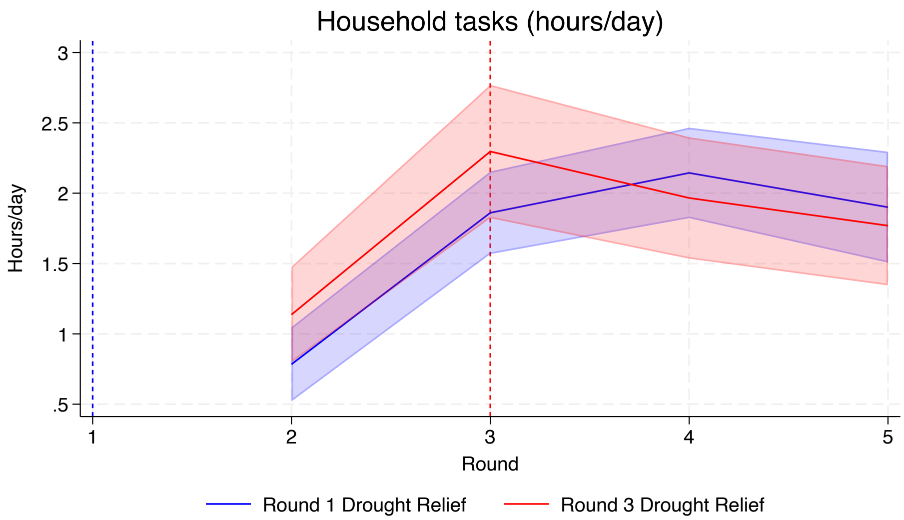

Figure 9: Event Study: Domestic Task Time

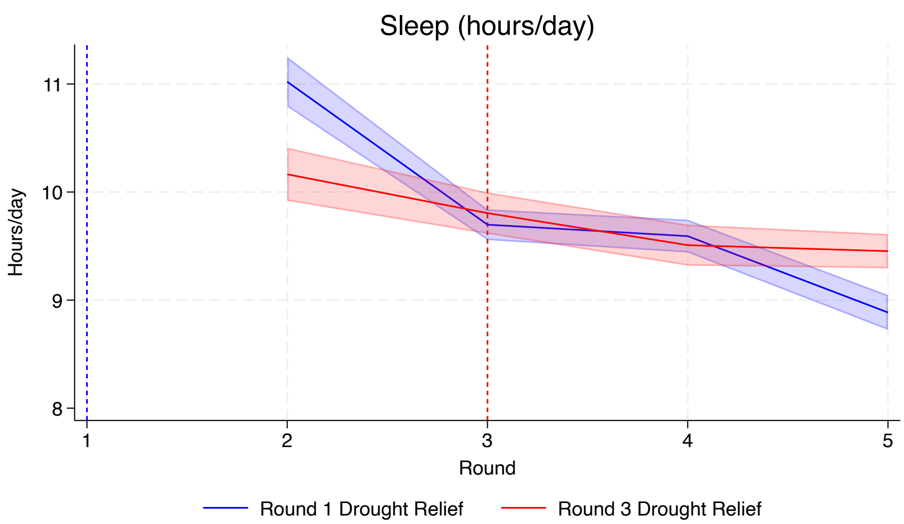

Figure 10: Event Study: Sleep Time

The event study results reveal several important patterns in how the timing of drought relief affects child development outcomes.

Figure 3 shows the effects of drought relief timing on school enrollment. The patterns demonstrate that children who experience drought relief in Round 3 show distinct enrollment responses compared to those who experience relief in Round 1, with the Round 3 drought relief group showing improved enrollment rates following their non-drought year.

Figure 5 provides evidence for one of the key mechanisms through which drought affects educational outcomes. The reduction in travel time to school following drought relief suggests that improved road conditions and reduced transportation barriers play an important role in facilitating educational access during non-drought periods. This commuting effect represents a key non-wage mechanism through which drought influences child development outcomes.

Figure 6 demonstrates that children who experience drought relief in Round 3 show a substantial increase in school time precisely when they experience the non-drought year, with the effect persisting through subsequent rounds. This pattern suggests that drought relief has immediate positive effects on educational participation that are maintained over time.

Figure 7 complements the school time results by showing similar patterns for time spent studying at home. The Round 3 drought relief group shows increased study time following their non-drought year, indicating that the educational benefits of drought relief extend beyond formal school attendance to include home-based learning activities.

Importantly, the labor allocation patterns reveal minimal effects on child labor activities. Figure 8 shows no significant changes in children's work activities following drought relief timing, suggesting that drought effects operate primarily through transportation and educational access mechanisms rather than through child labor adjustments. Similarly, Figure 9 demonstrates minimal effects on domestic tasks, indicating that the positive educational effects of drought relief occur without substantial reallocation from household responsibilities.

Figure 10 reveals that drought relief also affects children's sleep patterns and overall well-being. The Round 3 drought relief group shows improvements in sleep time following their non-drought year, suggesting that the benefits of improved weather conditions extend to basic health and welfare outcomes.

These event study results provide strong evidence that the timing of drought relief matters for child development outcomes. The clear divergence in trajectories between the Round 1 and Round 3 drought relief groups at their respective drought relief periods, combined with the persistence of effects in subsequent rounds, supports our identification strategy and demonstrates that drought conditions have dynamic, lasting effects on multiple dimensions of child welfare and development.

6 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).

6.0.1 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.

$$H_a = H\left(\theta_a^c, \theta_a^h\right) \tag{3}$$

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.

$$\begin{aligned}\theta_{c,t+1} &= G\left(\theta_{ct}, \theta_{ht}, \theta_{mt}, \theta_{dt}, X_t\right) \\ \theta_{h,t+1} &= F\left(\theta_{ct}, \theta_{ht}, \theta_{mt}, \theta_{dt}, X_t\right)\end{aligned} \tag{4}$$

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

$$\begin{aligned}\theta_{c,t+1} &= \left[\delta_{ct}(\theta_{ct})^{\rho_t} + \delta_{ht}(\theta_{ht})^{\rho_t} + \delta_{mt}(\theta_{mt})^{\rho_t} + \delta_{dt}(\theta_{dt})^{\rho_t}\right]^{\frac{1}{\rho_t}} A_{ct} \\ \theta_{h,t+1} &= \left[\alpha_{ct}\left(\theta_{ct}\right)^{\zeta_t} + \alpha_{ht}\left(\theta_{ht}\right)^{\zeta_t} + \alpha_{mt}\left(\theta_{mt}\right)^{\zeta_t} + \alpha_{dt}\left(\theta_{dt}\right)^{\zeta_t}\right]^{\frac{1}{\zeta_t}} A_{ht}\end{aligned} \tag{5}$$

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

$$
\begin{aligned}
A_{ct} &= \exp\left(d_{0t} + d'_{X_t} X_t + u_{ct}\right) \\
A_{ht} &= \exp\left(g_{0t} + g'_{X_t} X_t + u_{ht}\right)
\end{aligned} \tag{6}
$$

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.

6.0.2 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.

6.0.3 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.

$$\begin{aligned}\ln\theta_{mt} &= \gamma_0 + \gamma_{ct}\ln\theta_{ct} + \gamma_{ht}\ln\theta_{ht} + \gamma'_{X_t}X_t + \gamma'_{pt}\ln p_{mt} + v_t \\ \theta_{dt} &= \eta_0 + \eta_{ct}\ln\theta_{ct} + \eta_{ht}\ln\theta_{ht} + \eta'_{X_t}X_t + \eta'_{pt} + \beta F_{jt} + v_t\end{aligned} \tag{7}$$

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

$$\begin{aligned}E\left(u_{ct} \mid Q_t, Z_t\right) &= \kappa_c v_t \\ E\left(u_{ht} \mid Q_t, Z_t\right) &= \kappa_h v_t\end{aligned} \tag{8}$$

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.

6.0.4 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:

$$m_{jkt} = a_{jkt} + \lambda_{jkt}\ln\left(\theta_{kt}\right) + \epsilon_{jkt} \tag{9}$$

In a matrix form:

$$M = \mathbf{A} + \Lambda\ln\theta + \Sigma\varepsilon \tag{10}$$

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.

$$F_\theta = \tau\Phi\left(\mu_A, \Omega_A\right) + (1-\tau)\Phi\left(\mu_B, \Omega_B\right) \tag{11}$$

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:

$$F_M = \tau\Phi\left(\Pi_A, \Psi_A\right) + (1-\tau)\Phi\left(\Pi_B, \Psi_B\right) \tag{12}$$

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:

$$F_{\theta,X} = \tau\Phi\left(\mu_A^{\theta,X}, \Omega_A^{\theta,X}\right) + (1-\tau)\Phi\left(\mu_B^{\theta,X}, \Omega_B^{\theta,X}\right) \tag{13}$$

6.0.5 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:

$$\tau\mu_{A,t=0} + (1 - \tau)\mu_{B,t=0} = 0 \tag{14}$$

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.

References

Milton Abramowitz and Irene A. Stegun, editors. *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*. Number 55 in National Bureau of Standards Applied Mathematics Series. U.S. Government Printing Office, Washington, D.C., 1964.

Samer Al-Samarrai and Tessa Peasgood. Educational attainments and household characteristics in tanzania. *Economics of education review*, 17(4):395–417, 1998.

Eskander Alvi and Seife Dendir. Weathering the storms: Credit receipt and child labor in the aftermath of the great floods (1998) in bangladesh. *World development*, 39(8):1398–1409, 2011.

Amogne Asfaw, Belay Simane, Ali Hassen, and Amare Bantider. Variability and time series trend analysis of rainfall and temperature in northcentral ethiopia: A case study in woleka sub-basin. *Weather and climate extremes*, 19:29–41, 2018.

Orazio Attanasio, Costas Meghir, and Emily Nix. Human capital development and parental investment in india. *The Review of Economic Studies*, 87(6):2511–2541, 2020.

Jie Bai and Yukun Wang. Returns to work, child labor and schooling: The income vs. price effects. *Journal of Development Economics*, 145:102466, 2020. ISSN 0304-3878.

Richard B. Baker, John Blanchette, and Katherine Eriksson. Long-run impacts of agricultural shocks on educational attainment: Evidence from the boll weevil. *The Journal of Economic History*, 80(1):136–174, 2020.

Jean-Marie Baland and James A Robinson. Is child labor inefficient? *Journal of political economy*, 108(4):663–679, 2000.

Amarakoon Bandara, Rajeev Dehejia, and Shaheen Lavie-Rouse. The impact of income and non-income shocks on child labor: Evidence from a panel survey of tanzania. *World development*, 67:218–237, 2015.

Alan Barreca, Karen Clay, Olivier Deschênes, Michael Greenstone, and Joseph S Shapiro. Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900–2004. *American Economic Review*, 105(5):247–251, 2015.

Alan Barreca, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro. Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1):105–159, 2016.

Kaushik Basu. Child labor and the law: Notes on possible pathologies. *Economics Letters*, 87(2):169–174, 2005.

Kaushik Basu and Pham Hoang Van. The economics of child labor. *American economic review*, pages 412–427, 1998.

Kathleen Beegle, Rajeev H Dehejia, and Roberta Gatti. Child labor and agricultural shocks. *Journal of Development economics*, 81(1):80–96, 2006.

Sonia Bhalotra and Christopher Heady. Child farm labor: The wealth paradox. *The World Bank Economic Review*, 17(2):197–227, 2003.

Prashant Bharadwaj, Leah K Lakdawala, and Nicholas Li. Perverse consequences of well intentioned regulation: Evidence from india's child labor ban. *Journal of the European Economic Association*, 18(3):1158–1195, 2020.

Robin Burgess and Dave Donaldson. Can openness mitigate the effects of weather shocks? evidence from india's famine era. *American Economic Review*, 100(2):449–453, 2010.

Robin Burgess, Olivier Deschenes, Dave Donaldson, and Michael Greenstone. Weather, climate change and death in india. Working Paper, 2017.

Heather Congdon Fors. The determinants of rural child labor: an application to india. *rapport nr.: Working Papers in Economics 256*, 2007.

Flavio Cunha and James Heckman. The technology of skill formation. *American economic review*, 97(2):31–47, 2007.

Flavio Cunha, James J Heckman, and Susanne M Schennach. Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3):883–931, 2010.

Flávio Cunha, Irma Elo, and Jennifer Culhane. Eliciting maternal expectations about the technology of cognitive skill formation. Technical report, National Bureau of Economic Research, 2013.

Ana C Dammert, Jacobus De Hoop, Eric Mvukiyehe, and Furio C Rosati. Effects of public policy on child labor: Current knowledge, gaps, and implications for program design. *World development*, 110:104–123, 2018.

Jacobus De Hoop and Furio C Rosati. Cash transfers and child labor. *The World Bank Research Observer*, 29(2):202–234, 2014.

Jacobus De Hoop, Jed Friedman, Eeshani Kandpal, and Furio C Rosati. Child schooling and child work in the presence of a partial education subsidy. *Journal of Human Resources*, 54(2):503–531, 2019.

Alain De Janvry, Frederico Finan, Elisabeth Sadoulet, and Renos Vakis. Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks? *Journal of development economics*, 79(2):349–373, 2006.

Daniela Del Boca, Christopher Flinn, and Matthew Wiswall. Household choices and child development. *Review of Economic Studies*, 81(1):137–185, 2014.

Melissa Dell, Benjamin F Jones, and Benjamin A Olken. What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature*, 52(3):740–798, 2014.

Olivier Deschênes and Michael Greenstone. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review*, 97(1):354–385, 2007.

Olivier Deschênes and Michael Greenstone. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: reply. *American Economic Review*, 102(7):3761–3773, 2012.

Olivier Deschênes, Michael Greenstone, and Jonathan Guryan. Climate change and birth weight. *American Economic Review*, 99(2):211–217, 2009.

Olivier Deschênes and Michael Greenstone. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics*, 3(4):152–85, October 2011. doi: 10.1257/app.3.4.152. URL https://www.aeaweb.org/articles?id=10.1257/app.3.4.152.

Christelle Dumas. Why do parents make their children work? a test of the poverty hypothesis in rural areas of burkina faso. *Oxford economic papers*, 59(2):301–329, 2007.

Christelle Dumas. Market imperfections and child labor. *World development*, 42:127–142, 2013.

Suzanne Duryea, David Lam, and Deborah Levison. Effects of economic shocks on children's employment and schooling in brazil. *Journal of development economics*, 84(1):188–214, 2007.

Eric V Edmonds and Norbert Schady. Poverty alleviation and child labor. *American Economic Journal: Economic Policy*, 4(4):100–124, 2012.

Eric V Edmonds and Maheshwor Shrestha. You get what you pay for: Schooling incentives and child labor. *Journal of development economics*, 111:196–211, 2014.

Education Policy and Data Center. Ethiopia: National education profile (2018 update), 2018. URL https://www.epdc.org/sites/default/files/documents/EPDC_NEP_2018_Ethiopia.pdf. Compiles UIS (2015–2017) and DHS 2016 data.

John Felkner, Kamilya Tazhibayeva, and Robert Townsend. Impact of climate change on rice production in thailand. *American Economic Review*, 99(2):205–210, 2009.

Anthony C Fisher, W Michael Hanemann, Michael J Roberts, and Wolfram Schlenker. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment. *American Economic Review*, 102(7):3749–3760, 2012.

Heather Congdon Fors. Child labour: A review of recent theory and evidence with policy implications. *Journal of Economic Surveys*, 26(4):570–593, 2012.

Bernhard Ganglmair. A note on the effects of income and property on child labor in rural uganda. *Unpublished manuscript, University of Bonn*, 2005.

Richard Hornbeck. The enduring impact of the american dust bowl: Short-and long-run adjustments to environmental catastrophe. *American Economic Review*, 102(4):1477–1507, 2012.

ILO. Child labour: Global estimates 2020, trends and the road forward. Technical report, International Labour Office, 2020.

ILO. Child labour facts and figures, 2023. URL https://www.ilo.org/ipec/facts/lang--en/index.htm. Accessed April 8, 2023.

Benjamin Lloyd-Hughes and Mark A. Saunders. A drought climatology for europe. *International Journal of Climatology*, 22(13):1571–1592, 2002. doi: 10.1002/joc.846.

Sharon Maccini and Dean Yang. Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, 99(3):1006–26, June 2009. doi: 10.1257/aer.99.3.1006. URL https://www.aeaweb.org/articles?id=10.1257/aer.99.3.1006.

Thomas B. McKee, Nolan J. Doesken, and John Kleist. The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, pages 179–184, Anaheim, CA, 1993. American Meteorological Society.

Gerald McQuade and Marta Favara. Identifying climate shocks in young lives communities: estimating weather conditions using a global gridded time series. 2024.

Jonathan Morduch. Between the state and the market: Can informal insurance patch the safety net? *The World Bank Research Observer*, 14(2):187–207, 1999.

Ingo Outes-Leon and Alan Sanchez. An assessment of the young lives sampling approach in ethiopia. 2008.

Martin Ravallion and Shubham Chaudhuri. Risk and insurance in village india: Comment. *Econometrica: Journal of the Econometric Society*, pages 171–184, 1997.

Martin Ravallion and Quentin Wodon. Does child labour displace schooling? evidence on behavioural responses to an enrollment subsidy. *The economic journal*, 110(462):158–175, 2000.

Manisha Shah and Bryce Millett Steinberg. Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, 125 (2):527–561, 2017.

Emmanuel Skoufias, Susan W Parker, Jere R Behrman, and Carola Pessino. Conditional cash transfers and their impact on child work and schooling: Evidence from the progresa program in mexico [with comments]. *Economia*, 2(1):45–96, 2001.

Peter Stott. How climate change affects extreme weather events. *Science*, 352(6293):1517–1518, 2016.

John Strauss and Duncan Thomas. Human resources: Empirical modeling of household and family decisions. *Handbook of development economics*, 3:1883–2023, 1995.

Duncan Webb. Critical periods in cognitive and socioemotional development: Evidence from weather shocks in indonesia. *Working Paper*, 2022.

A Appendix

A.1 Young Lives Ethiopia

The Young Lives Ethiopia dataset is a longitudinal panel study covering five waves of data collection from 2002 to 2016. The dataset includes comprehensive information on children's development, household characteristics, and community-level measures across Ethiopia's major regions. Child survey. hosuehold survey. community level surveys.

Table A2 presents the age distribution of children across all observations in the Young Lives Ethiopia panel dataset. The distribution reflects the longitudinal nature of the study, with children aged from infancy to young adulthood. The dataset captures two distinct cohorts: a younger cohort initially aged 6-18 months and an older cohort initially aged 7.5-8.5 years at the start of the study. The age distribution shows the natural progression of these cohorts through the five waves of data collection, with peak observations at ages representing key developmental stages including early childhood (ages 1, 5, 8), pre-adolescence (ages 11-12), and adolescence (ages 14-15).

The twenty study sites in Ethiopia were selected in 2001 following a three-stage process based on the national administrative structures. First, the regions where the study would take place were selected, then the woredas (districts) within each region, and then a kebele (the lowest level of administrative) within each woreda as a sentinel site. Finally 100 young children and 50 older children were randomly selected within the chosen sites. The panel structure of the Young Lives study is illustrated in Table 2, which shows the distribution of observations across the five survey rounds. Round 1 was conducted in 2002, followed by Round 2 in 2006, Round 3 in 2009, Round 4 in 2013, and Round 5 in 2016. The table reveals a relatively balanced distribution across rounds, with a slight decline from 2,999 observations in Round 1 to 2,659 observations in Round 5, reflecting natural attrition that is typical in longitudinal studies. This attrition rate of approximately 11

The two-cohort design of the study is clearly demonstrated in Table A1, which shows the age distribution within each survey round. This table illustrates how the younger cohort progresses from approximately age 1 in Round 1 to ages 14-15 in Round 5, while the older cohort advances from ages 7-8 in Round 1 to ages 21-22 in Round 5. The clean age progression across rounds confirms the successful longitudinal tracking of the same children over the 14-year study period, providing valuable insights into different developmental stages and life transitions.

Figure 2 provides crucial context for understanding children's daily activities and time allocation patterns in Ethiopia. This visualization shows how children distribute their time across different activities including education, various forms of child labor (household chores, domestic tasks, and paid work), leisure activities, and other daily responsibilities. The time allocation patterns revealed in this figure help contextualize the findings from our main analysis regarding how flooding shocks affect the trade-offs between schooling and child labor among Ethiopian children.

Appendix Table A1: Age Distribution by Survey Round: Two Cohort Structure

	Round 1 (2002)		**Round 2 (2006)**		**Round 3 (2009)**		**Round 4 (2013)**		**Round 5 (2016)**	
Age	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**
1	1,061	51.48								
5			1,328	57.54						
7	611	29.65			630	22.14				
8	389	18.87			1,241	43.62				
11			419	18.15	1	0.04	618	22.33		
12			561	24.31			1,251	45.21		
14					433	15.22			660	25.27
15					540	18.98			1,144	43.80
18							369	13.34		
19							529	19.12		
21									364	13.94
22									444	17.00
Total	2,061	100.00	2,308	100.00	2,845	100.00	2,767	100.00	2,612	100.00

Notes: This table demonstrates the two-cohort design of the Young Lives Ethiopia study. The younger cohort started at approximately age 1 in Round 1 (2002) and progressed to age 14-15 by Round 5 (2016). The older cohort started at ages 7-8 in Round 1 and reached ages 21-22 by Round 5. The clear age progression across rounds shows the longitudinal tracking of the same children over 14 years. Source: Young Lives Ethiopia dataset (2002-2016).

Appendix Table A2: Distribution of Children by Age in Young Lives Ethiopia

Age	**Frequency**	**Percent**
0	938	6.64
1	1,061	7.51
4	576	4.07
5	1,328	9.40
6	8	0.06
7	1,241	8.78
8	1,630	11.53
9	11	0.08
11	1,038	7.34
12	1,812	12.82
13	1	0.01
14	1,093	7.73
15	1,684	11.91
16	2	0.01
17	1	0.01
18	369	2.61
19	529	3.74
20	3	0.02
21	364	2.58
22	444	3.14
23	2	0.01
Total	14,135	100.00

Notes: This table shows the age distribution of all child observations across the five waves of the Young Lives Ethiopia panel dataset. The dataset includes children from two cohorts: a younger cohort initially aged 6-18 months and an older cohort initially aged 7.5-8.5 years. Total observations: 14,135. Source: Young Lives Ethiopia dataset (2002-2016).

Appendix Table A3: Effects of Drought on Time Allocation and Health Outcomes: Overall and by Gender

Panel A: Overall Effects					
	Time Allocation			Health Outcomes	
	Work	Chores	Tasks	Child injury	Health problem
	(1)	(2)	(3)	(4)	(5)
Severe drought (SPI ≤ -1.5)	0.04	-0.21	-0.14	-0.05	-0.06
	(0.06)	(0.16)	(0.18)	(0.04)	(0.04)
Individual FE	Yes	Yes	Yes	Yes	Yes
N	8150	8156	8150	8743	7111
Panel B: Boys					
	Time Allocation			Health Outcomes	
	Work	Chores	Tasks	Child injury	Health problem
	(1)	(2)	(3)	(4)	(5)

A.2 PSNP Public Works Program Results

This subsection presents the detailed results for the differential effects of drought across households participating in Ethiopia's Productive Safety Net Program (PSNP) Public Works component versus non-participating households. The PSNP is Ethiopia's largest national social safety net program, designed to respond to both chronic food insecurity and shorter-term shocks, particularly droughts. The program targets highly climate-vulnerable populations and offers a practical model of how social safety nets can simultaneously meet social protection needs while reducing disaster and climate-related risks.

Understanding how drought effects vary by PSNP participation is crucial for policy design, as it reveals whether existing social protection mechanisms effectively buffer vulnerable households from climate shocks or whether additional interventions are needed. The PSNP-Public Works component provides employment opportunities and income support to participating households, which may alter how families respond to drought conditions in terms of children's educational participation, time allocation, and overall well-being.

Appendix Table A4: PSNP Public Works-Specific Effects of Drought on School Enrollment

	Enrolment		
	(1)	(2)	(3)
Moderate drought	0.58***		
	(0.02)		
PSNP · Moderate drought	0.05*		
	(0.02)		
Severe drought		0.66***	
		(0.11)	
PSNP · Severe drought		0.01	
		(0.11)	
Extreme drought			0.26**
			(0.11)
PSNP · Extreme drought			-0.06
			(0.15)
PSNP-Public Works household	-0.04**	0.01	0.03
	(0.02)	(0.12)	(0.10)
N	5039	5039	5039

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows regression results examining the differential effects of drought on school enrollment by PSNP-Public Works participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP-participating households. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A5: PSNP Public Works-Specific Effects of Drought on Cognitive Outcomes

	Math			PPVT(vocabulary)		
	(1)	(2)	(3)	(4)	(5)	(6)
Moderate drought	1.71***			2.33***		
	(0.04)			(0.04)		
PSNP · Moderate drought	-0.23***			-0.22***		
	(0.07)			(0.06)		
Severe drought		1.55***			1.26**	
		(0.14)			(0.47)	
PSNP · Severe drought		-0.09			0.86*	
		(0.16)			(0.46)	
Extreme drought			0.70*			0.49
			(0.37)			(0.46)
PSNP · Extreme drought			-0.50			-0.17
			(0.50)			(0.67)
PSNP-Public Works household	-0.53***	-0.64***	-0.47	-0.46***	-1.52***	-0.63
	(0.07)	(0.17)	(0.30)	(0.04)	(0.52)	(0.43)
N	4906	4906	4906	4143	4143	4143

Standard errors in parentheses

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

Notes: This table shows regression results examining the differential effects of drought on Math and PPVT cognitive outcomes by PSNP-Public Works participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP-participating households. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A6: PSNP Public Works-Specific Effects of Drought on Study and School Time

	Study time			School time		
	(1)	(2)	(3)	(4)	(5)	(6)
Moderate drought	0.65***			2.84***		
	(0.03)			(0.09)		
PSNP · Moderate drought	0.01			-0.04		
	(0.05)			(0.14)		
Severe drought		0.88***			3.50***	
		(0.07)			(0.65)	
PSNP · Severe drought		-0.25**			-0.42	
		(0.11)			(0.68)	
Extreme drought			0.59***			1.39**
			(0.17)			(0.61)
PSNP · Extreme drought			-0.39*			-0.47
			(0.20)			(0.79)
PSNP-Public Works household	-0.27***	-0.01	-0.01	-0.07	0.38	0.16
	(0.05)	(0.12)	(0.15)	(0.10)	(0.71)	(0.50)
N	5027	5027	5027	5040	5040	5040

Standard errors in parentheses

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

Notes: This table shows regression results examining the differential effects of drought on time allocated to studying and attending school by PSNP-Public Works participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP-participating households. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A7: PSNP Public Works-Specific Effects of Drought on Travel Time to School

	Travel time to school (minutes)		
	(1)	(2)	(3)
Moderate drought	-31.06***		
	(1.32)		
PSNP · Moderate drought	3.51*		
	(1.97)		
Severe drought		-33.61***	
		(10.33)	
PSNP · Severe drought		4.50	
		(9.36)	
Extreme drought			-14.82**
			(6.72)
PSNP · Extreme drought			4.46
			(8.56)
PSNP-Public Works household	-4.07**	-5.52	-2.80
	(1.54)	(9.16)	(5.28)
N	4739	4739	4739

Standard errors in parentheses

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

Notes: This table shows regression results examining the differential effects of drought on travel time to school by PSNP-Public Works participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP-participating households. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A8: PSNP Public Works-Specific Effects of Drought on Work, Chores, and Tasks

	Work			Chores			Tasks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moderate drought	0.16***			0.23***			-1.40***		
	(0.02)			(0.06)			(0.05)		
PSNP · Moderate drought	0.20***			-0.26**			1.42***		
	(0.05)			(0.10)			(0.10)		
Severe drought		0.17***			0.31**			-0.06	
		(0.02)			(0.13)			(0.16)	
PSNP · Severe drought		0.08			-0.21			0.13	
		(0.11)			(0.16)			(0.19)	
Extreme drought			0.11*			0.29**			-0.20
			(0.05)			(0.11)			(0.14)
PSNP · Extreme drought			-0.01			-0.14			0.14
			(0.09)			(0.11)			(0.20)
PSNP-Public Works household	-0.40***	-0.28*	-0.20	-0.04	-0.09	-0.20	-1.36***	-0.07	-0.05
	(0.05)	(0.16)	(0.12)	(0.10)	(0.19)	(0.17)	(0.12)	(0.20)	(0.21)
N	5026	5026	5026	5029	5029	5029	5026	5026	5026

Standard errors in parentheses

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

Notes: This table shows regression results examining the differential effects of drought on time allocated to work, household chores, and domestic tasks by PSNP-Public Works participation status. The coefficients on drought variables represent the effects for non-PSNP households (baseline), while the interaction terms show the additional effects for PSNP-participating households. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Tables A4, A5, A6, A7, and A8 reveal important heterogeneous effects of drought conditions across PSNP Public Works participation status. The tables present coefficients for non-PSNP households (baseline effects) and interaction terms that capture the additional effects for households participating in the PSNP-Public Works program.

The results demonstrate that PSNP Public Works participation does not significantly alter how children respond to drought conditions across cognitive, educational, and time allocation outcomes. The interaction terms are generally small and statistically insignificant, indicating that the social safety net provided by PSNP Public Works does not effectively buffer children from drought impacts differently than non-participating households. These findings are consistent with the results for PSNP Direct Support presented in the main text, suggesting that Ethiopia's existing social protection mechanisms are inadequately designed to address the transportation and infrastructure challenges that drive drought's educational effects.

These findings provide evidence that Ethiopia's largest social safety net program has limited effectiveness in protecting children from climate-related shocks through either the Public Works or Direct Support components. The results inform policy discussions about the need for redesigned social protection programs in climate-vulnerable countries that address transportation infrastructure and access barriers rather than focusing solely on income support.