On the Way to School: Rainfall, Commuting Time, and Cognitive Development*

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Abstract

Previous research shows that rainfall shocks reduce education outcomes in developing countries. A common explanation is the child labor mechanism: when rainfall raises agricultural wages, the opportunity cost of schooling increases and children substitute into work. This paper highlights commuting as another mechanism. Using longitudinal data from Ethiopia on children's time allocation, cognitive scores, and village-level precipitation, I document non-linear effects: excessive rainfall increases commuting time and reduces enrollment, but only where schools are connected by dirt roads rather than gravel roads. The cognition gap between communities where schools are connected by gravel versus dirt roads widens when rainfall deviations from normal. Exploiting the school calendar, I show that commuting disruptions occur primarily when excessive rainfall coincides with term time. Moderate droughts, by contrast, raise enrollment, increase after-school study time, and reduce travel time to school, with stronger effects in rural areas. Long commutes not only reduce the time available for study but may also lower learning efficiency through fatigue. To separate these channels, I estimate a cognition production function with time inputs in which commuting affects both the quantity and quality of studying hours. These findings underscore the importance of infrastructure in protecting child development under climate change.

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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 excessive rainfall and droughts (Stott, 2016). An extensive literature has examined how rainfall variation influences human capital formation in developing countries, affecting agricultural income, education, nutrition, and mortality (Maccini and Yang, 2009; Webb, 2022; Burgess et al., 2017; Deschênes and Greenstone, 2011). Shah and Steinberg (2017) find that drought exposure in India increases math scores and school attainment, arguing that reduced agricultural productivity lowers the incentive for child labor.

First of all, this paper documents non-linear effects: excessive rainfall increases commuting time and reduces enrollment, but only if roads to school are dirt roads instead of gravel roads. The cognition gap between communities where schools are connected by gravel versus dirt roads widens when rainfall deviates from normal. Furthermore, I explore the variation in deviation of rainfall around school calendar to shows the robustness check that commuting impact is driven by school-term rainfall deviation. So it is a placebo test as we are happy that it is not driven by break school term rainfall deviation we shouldn't find anything if our commuting story is true.

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),

[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 one day.

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.

This paper highlights another mechanism through which weather conditions also affect education: road infrastructure and commuting to school. Using high-quality longitudinal data from Ethiopia (2002–2016), I document that in community survey, 45.3 percent of children must travel on dry-weather roads to reach school—roads that become impassable during heavy rains and flooding. The vast majority (90.7 percent) walk to school, with average round-trip commutes of 44.2 minutes. Nearly one-fifth of children spend more than an hour commuting daily, representing a substantial burden on time and energy available for learning.

This transportation mechanism is particularly important in the Ethiopian context given children's already constrained time budgets. As demonstrated in the empirical analysis below, children in Ethiopia are heavily engaged in child labor activities, averaging 4 hours per day from age 7 onwards, while spending approximately 5 hours in school. This intensive time allocation across competing activities makes additional commuting time particularly costly, as it further reduces the limited time available for educational activities and potentially exacerbates existing constraints on human capital development. The data show that children in this sample are engaged in work with considerable intensity, both in terms of duration across the year and the number of days worked per week. On average, children report working about 10 months per year, with roughly two-thirds (66.5%) employed for the full 12 months, indicating that year-round child labor is the norm rather than the exception. Work intensity within each week is also high: children average about 4.4 days of work per week, and nearly 45% report working 6–7 days per week, while another 30% work 3–5 days. Only a small minority work less than two days weekly or for a few scattered months. Taken together, the evidence suggests that most working children are not engaged in short-term or occasional labor but are instead contributing on a regular and sustained basis, often comparable to full-time adult employment.

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 moderate 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.

To understand the underlying mechanisms more deeply, I estimate a cognition production function with children's time inputs as key determinants of learning outcomes. The quantitative model decomposes how commuting time affects cognitive development through two distinct channels: a time budget channel and a learning efficiency channel. The time budget channel operates through direct substitution—longer commutes reduce time available for studying and in-school learning. The learning efficiency channel captures how extended commuting affects the productivity of educational time through fatigue, stress, and reduced concentration. Children who undertake lengthy walks to school, particularly on difficult terrain or unsafe roads, may arrive exhausted and less able to absorb instruction effectively. By explicitly modeling both channels, the structural approach provides a more complete understanding of how transportation barriers translate into educational disadvantages and quantifies the relative importance of each mechanism in determining cognitive outcomes.

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.

This paper also contributes to the literature on rural road access in developing countries. Existing studies have shown that rural roads influence agricultural productivity, crop diversification, migration, land values, and poverty reduction (Asher and Novosad, 2020; Shamdasani, 2021; Shrestha, 2020; Aggarwal, 2021; Aggarwal et al., 2022; Gebresilasse, 2023; Wondemu and Weiss, 2012; Nakamura et al., 2020; Kebede, 2024). In Ethiopia, recent evidence highlights complementarities between rural roads and agricultural extension programs (Gebresilasse, 2023), as well as large welfare gains from the Universal Rural Road Access Program (URRAP) (Kebede, 2024). By focusing on schooling and cognition, my paper extends this literature to human capital formation, emphasizing that infrastructure resilience—specifically whether schools are connected by gravel or dirt roads—conditions the extent to which rainfall shocks disrupt educational outcomes.

Finally, this paper contributes to the literature on child development and cognition in developing countries. A large body of work has documented the importance of early-life investments for cognitive and non-cognitive skills, often emphasizing the role of parental inputs, home environments, and early interventions (Attanasio et al., 2015, 2020a; Attanasio and Rubio-Codina, 2015). My paper complements this literature by showing how external factors—specifically climate shocks interacting with road infrastructure—affect children's ability to attend school and study effectively, thereby influencing cognitive outcomes. This highlights that investments in infrastructure resilience may be as important as household- or policy-driven interventions in sustaining child development under climate change.

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 4.5 presents the effects of drought on children's educational, cognitive, and behavioral outcomes in Ethiopia, heterogeneity and robustness check. Section **??** introduces the quasi-experimental design and present the event study results. Section 5 outlines the structural estimation approach. Finally, Section 6 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).

This paper demonstrates a nonlinear relationship between rainfall and educational outcomes, mediated by transportation infrastructure. I find that excessive rainfall significantly reduce enrolment and increases school commuting times, particularly for children in communities where schools are connected by dirt roads rather than gravel roads. These transportation disruptions translate into lower mathematics test scores. Conversely, during drought periods (below-normal rainfall), commuting times are shorter and more stable, leading to improved math scores, especially for those with poor road access to school. These findings highlight that transportation costs are a critical channel through which weather shocks affect human capital accumulation in Ethiopia, with basic infrastructure like gravel roads to schools providing significant resilience.

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

[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.

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]

2.2 Cognition and human capital in developing countries

This paper also contributes to the literature on cognition and human capital formation in developing countries. A large body of work emphasizes that cognitive skills acquired during childhood are strong predictors of later-life schooling, labor market performance, and health outcomes. A central theme in this literature is that early-life investments, parental inputs, and household resources are critical for the development of cognitive skills, particularly in environments where poverty and market imperfections limit opportunities for children. Attanasio et al. (2020b) show that parental investments are central to human capital accumulation in India, while Attanasio et al. (2017) document how poverty constrains human capital growth in Ethiopia and Peru. Other studies demonstrate that differences in parental behavior and home environments account for much of the variation in cognitive outcomes across households, underscoring the role of family decisions in shaping long-run inequality.

A complementary strand of research has evaluated targeted interventions aimed at stimulating child development. Evidence from randomized controlled trials in Colombia and other low-income settings highlights the effectiveness of early childhood investments and parenting programs in improving cognitive and non-cognitive skills (Attanasio et al., 2015, 2020a; Attanasio and Rubio-Codina, 2015). These studies show that relatively small changes in parental engagement, learning environments, and nutritional inputs can generate substantial gains in children's cognitive trajectories. More broadly, this body of work highlights the malleability of cognitive skills early in life

[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, (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.

and the high returns to timely interventions.

2.3 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

[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).

force participation but lower school attendance compared to children from land-poor households. This is known as the "wealth paradox," which challenges the assumption that subsistence poverty drives child labor. Bhalotra and Heady (2003) argue that imperfect labor and land markets contribute to this paradox, as land can have both a wealth effect and a substitution effect on child labor. They find that land is positively related to girls' participation in family labor but has no effect on boys' participation. This suggests that land and labor markets are imperfect and significantly contribute to child labor in rural Pakistan, Ghana, Uganda, rural India, and Burkina Faso has shown in 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.

2.4 Rural road access

This paper is also related to the literature on road infrastructure and development. A large body of work highlights the importance of transport networks for facilitating the movement of goods, people, and ideas, and for reducing trade costs (Ali et al., 2015; Atkin and Donaldson, 2015). Much of this literature has examined the expansion of highways and railroads in emerging economies such as China, India, Turkey, and the United States (Faber, 2014; Ghani et al., 2016; Donaldson, 2018; Coşar and Demir, 2016; Allen and Arkolakis, 2014, 2022).

In contrast, the effects of rural roads—which directly affect the daily lives of agrarian households—are less well understood. Evidence from India shows that rural road construction facilitated exit from agriculture with limited income gains (Asher and Novosad, 2020), but also encouraged crop diversification, technology adoption, and labor demand (Shamdasani, 2021). Road access in Nepal increased agricultural land values (Shrestha, 2020), while studies from India and Tanzania document improved healthcare utilization and technology adoption (Aggarwal, 2021; Aggarwal et al., 2022).

In Ethiopia, Gebresilasse (2023) highlights complementarities between rural roads and agricultural extension programs, while Wondemu and Weiss (2012) and Nakamura et al. (2020) show that road investments reduce poverty and strengthen resilience. Most recently, Kebede (2024) documents substantial welfare gains from Ethiopia's Universal Rural Road Access Program (URRAP), finding that new rural roads increased agricultural incomes by 13% through crop price adjustments and land reallocation.

Relative to this literature, my paper emphasizes a novel dimension: the interaction between rainfall shocks and road quality in shaping educational outcomes. Whereas existing studies focus on market integration, agricultural productivity, or land values, I show that infrastructure resilience—specifically, whether schools are connected by gravel or dirt roads—conditions how climate shocks translate into children's time allocation, enrollment, and cognition.

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 sentinel site, and may include a whole

[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.

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.

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.

3.2 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. 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, educational access and attainment remain challenging: 32 percent of primary school-age children

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).

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).

I document that 45.3 percent of children in Young Lives communities must travel on dry weather roads to reach school—infrastructure that becomes impassable during heavy rains and flooding. This finding reveals the critical role of transportation barriers in educational access, as the overwhelming majority (90.7 percent) of children walk to school, facing average commute times of 44.2 minutes per day, with some children enduring daily commutes of up to 6 hours in a particular village.

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.

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).

Figure 4 illustrates the alignment of Ethiopia's academic calendar with seasonal rainfall and temperature patterns. The figure demonstrates how the country's education system, operating from September to July, intersects with distinct seasonal variations in precipitation and temperature. The two academic semesters are clearly marked: Semester 1 runs from September through December, coinciding with the transition from the primary rainy season (Kiremt) to the dry season (Bega), while Semester 2 spans January through June, covering the dry season and the short rainy season (Belg). This seasonal alignment has important implications for educational access, particularly regarding transportation infrastructure and commuting conditions that

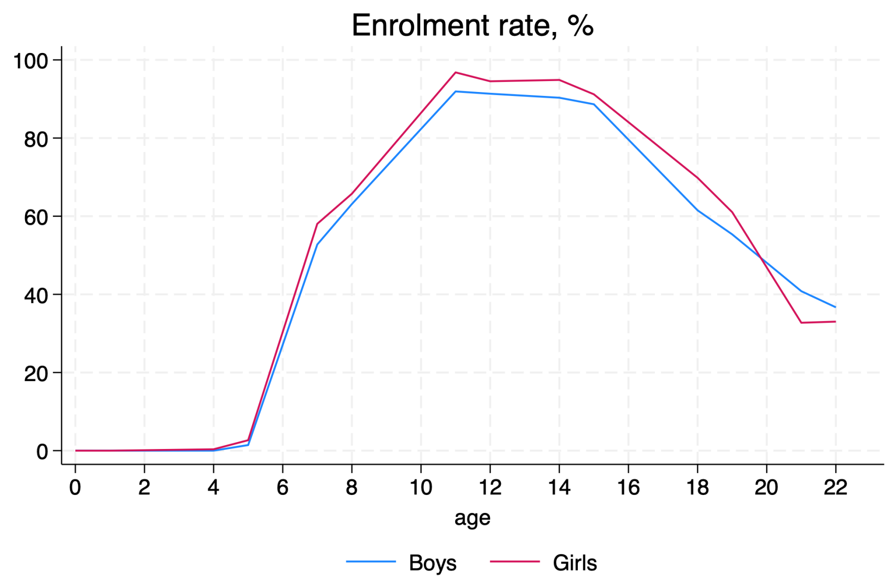


Figure 1: Age profile of enrolment

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).

affect children's ability to attend school regularly.

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.

3.3 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.

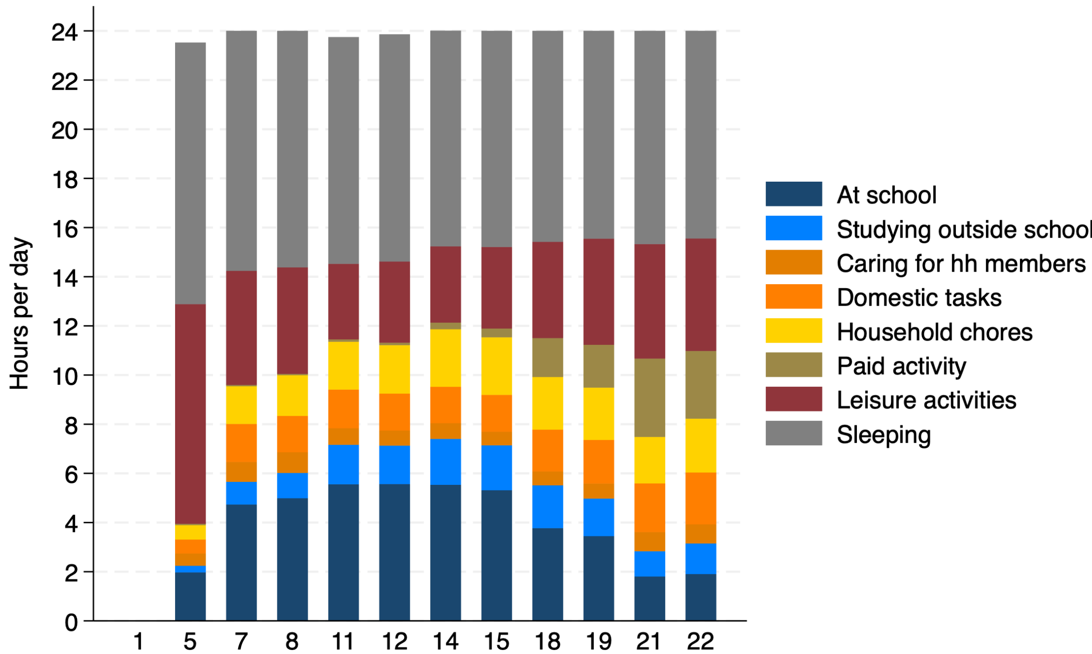


Figure 2: Average Time Allocation of Children in Ethiopia

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).

3.4 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.

3.5 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:

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

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

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

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

$$SPI = \begin{cases} -(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}), & 0 < H(x) \le 0.5, \\ (t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}), & 0.5 < H(x) < 1. \end{cases}$$

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.

4 Empirical results

This section presents empirical evidence on how rainfall variation affects children's educational outcomes in Ethiopia through transportation infrastructure mechanisms. The analysis proceeds in four stages: First, I examine nonlinear rainfall relationships and infrastructure moderation effects. Second, I test robustness by distinguishing school-term from break-term rainfall impacts. Third, I employ an event study design exploiting quasi-random weather transitions. Fourth, I examine drought effects and alternative mechanisms. These findings provide both reduced-form evidence for the transportation channel and identification variation for structural estimation of the cognition production function.

4.1 Nonlinear Impact of Rainfall and Road Infrastructure

I begin the empirical analysis by systematically examining the relationship between precipitation deviations and children's educational outcomes. By analyzing the full spectrum of rainfall variation—from drought to excessive precipitation—I provide foundational evidence for the transportation mechanism that underlies the main results presented in subsequent sections.

This analysis is crucial for several interconnected reasons. First, it demonstrates how road infrastructure moderates the relationship between weather shocks and educational access, providing direct evidence that commuting costs vary systematically with rainfall patterns. this nonlinear analysis provides essential inputs for the structural estimation of the cognition production function presented later, as it identifies the key relationships between weather, commuting time, and educational outcomes that inform the structural model's parameters.

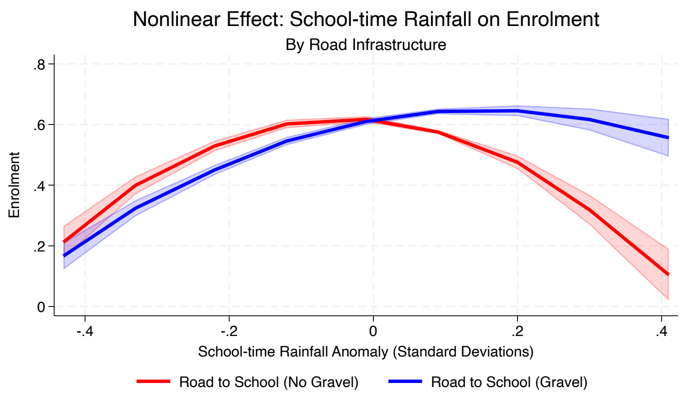
To construct the nonlinear relationships shown in Figure 3, I estimate separate quadratic regressions, separately for communities where schools are accessible via gravel roads versus dirt roads while controlling for individual fixed effects and village fixed effects. The specification is:

$$Y_{ict} = \alpha + \beta_1 R_{ct} + \beta_2 R_{ct}^2 + \theta_i + \gamma_c + \varepsilon_{ict} \tag{1}$$

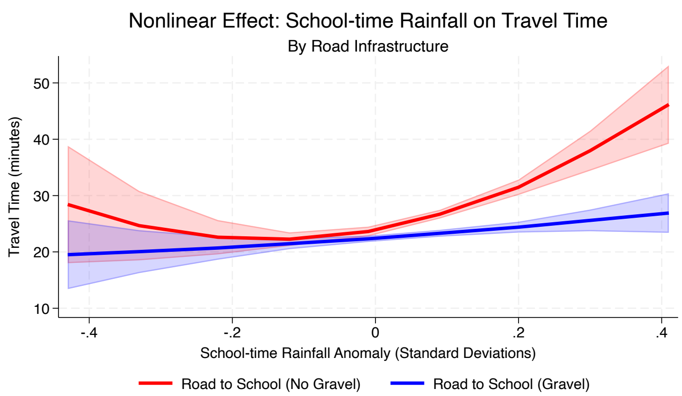
where Y_{ict} represents the outcome variable (enrollment, travel time, or test scores), R_{ct} is the school-term rainfall deviation from long-term village-month specific means, θ_i represents child fixed effects, γ_c represents community fixed effects, and ε_{ict} is the error term clustered at the child level. The predicted values from these regressions are plotted over the range of observed rainfall deviations, with separate curves for each road infrastructure type and 95% confidence intervals computed using the margins command.

Figure 3 reveals three key patterns that support the transportation mechanism. First, Panel A shows that school enrollment is nonlinear with rainfall deviations from the long-term average. Large deviations from average rainfall reduce enrollment, but the impact of excessive rain on reduced enrollment is much smaller when roads to school are gravel rather than dirt roads.

(a) Panel A: School Enrollment



(b) Panel B: Travel Time to School



(c) Panel C: Math Test Scores

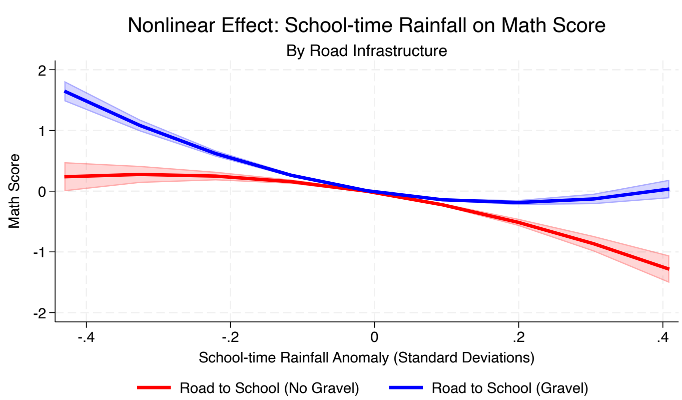


Figure 3: Nonlinear Relationship Between Rainfall and Educational Outcomes by Road Infrastructure

Notes: Red lines: communities where schools are connected by dirt roads. Blue lines: communities where schools are connected by gravel roads. Shaded areas: 95% confidence intervals. The curves are estimated using separate quadratic regressions for each road type, where travel time to school is regressed on linear and quadratic terms of school-term rainfall deviations and break-term rainfall deviations, controlling for child and community fixed effects with standard errors clustered at the child level. Source: Young Lives Ethiopia dataset (2002-2016) and University of Delaware climate data.

Second, Panel B demonstrates that when rainfall deviates from the mean, travel time to school increases significantly when roads to school are dirt, while travel time remains largely unaffected if roads to school are gravel. This nonlinearity explains why our drought analysis—which focuses on below-normal rainfall periods—finds positive educational effects, as these periods correspond to the lower, more stable portion of the travel time curve. This pattern supports our finding that drought can improve educational outcomes through the transportation channel, as communities where schools are connected by gravel roads maintain more stable cognitive performance across different rainfall conditions, further emphasizing how infrastructure quality buffers against weather-induced educational disruptions.

Third, Panel C reveals that when rainfall is around the mean, there is no statistical difference in math cognition among children in villages where roads to school are dirt or gravel. However, when rainfall deviates from the mean, the gap in cognition widens, with villages with gravel roads having significantly better cognition outcomes.

The confidence intervals illustrate the precision of these estimates, showing that the differential effects by road quality are statistically significant, particularly during periods of above-normal rainfall. This infrastructure-dependent relationship provides compelling evidence that transportation costs represent a key channel through which weather conditions affect educational access and outcomes in Ethiopia.

4.2 School-term vs. Break-term Rainfall Effects

In Ethiopia, the July–August Kiremt rains play a critical role in sustaining agriculture, which remains the backbone of the economy and the primary livelihood for the majority of the population. Since around 80–85% of Ethiopians depend on rain-fed farming, the arrival and reliability of these rains largely determine the success of the agricultural year. The Kiremt season provides the bulk of the water needed for the Meher cropping cycle, which is the country's main harvest and the foundation of national food security. During this period, farmers cultivate staple crops such as teff, maize, wheat, and barley—grains that not only feed households across the country but also contribute to rural incomes and local markets. A strong and timely Kiremt rainfall can therefore ensure abundant harvests, while delays, shortages, or erratic rainfall patterns often translate into reduced yields, food shortages, and increased vulnerability for millions of people. In this way, the rains of July and August are not just seasonal weather events but essential lifelines for Ethiopia's agricultural system and overall well-being.

The distinction between school-term and break-term rainfall effects is crucial for understanding the transportation mechanism. Ethiopia's academic calendar, which runs from September to July, intersects with distinct seasonal rainfall patterns that have important implications for educational access and commuting conditions.

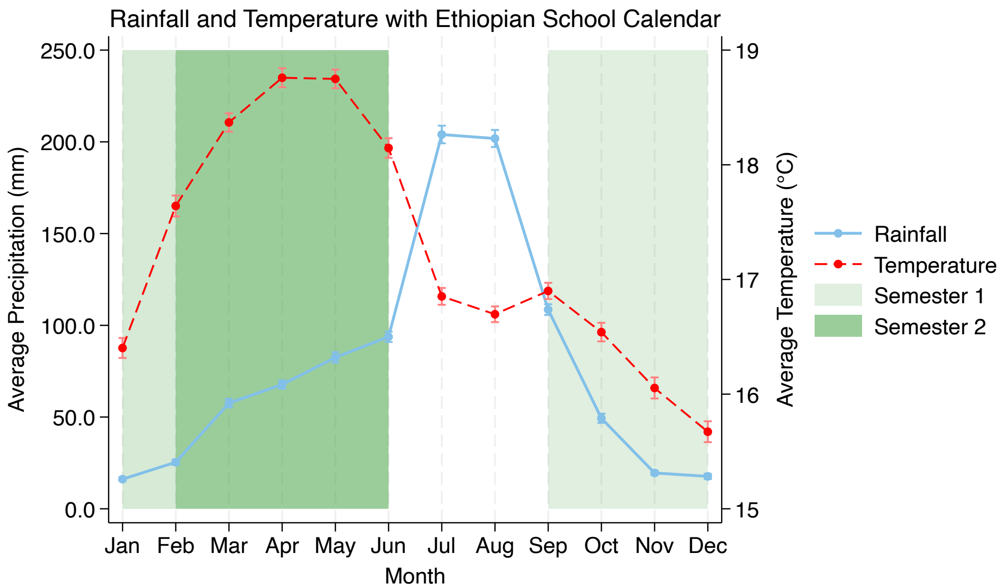


Figure 4: Rainfall and Temperature Patterns with Ethiopian School Calendar

Notes: This figure shows the monthly patterns of precipitation and temperature in Ethiopia overlaid with the academic calendar. Semester 1 (September-December) is highlighted in green, corresponding to the transition from the rainy season to the dry season. Semester 2 (February-June) is highlighted in blue, covering the dry season and short rainy season. The dual y-axis shows precipitation in mm (left axis) and temperature in °C (right axis). Error bars represent 95% confidence intervals. Source: University of Delaware climate data and Ethiopian Ministry of Education academic calendar.

As shown in Figure 4, the two academic semesters are clearly marked: Semester 1 runs from September through December, coinciding with the transition from the primary rainy season (Kiremt) to the dry season (Bega), while Semester 2 spans January through June, covering the dry season and the short rainy season (Belg). This seasonal alignment provides a natural framework for testing whether rainfall effects on educational outcomes operate specifically through school-term transportation disruptions.

To provide additional empirical support for the transportation mechanism, Table 2 presents fixed-effects regression results examining how rainfall deviations from long-term means affect commuting time to school, differentiated by road infrastructure

Table 2: Effects of Rainfall Deviations on Commuting Time to School by Road Infrastructure Quality

	No Gravel Roads	Gravel Roads
School-term Rainfall Deviation	28.69***	10.04**
	(4.76)	(3.27)
	[21.66, 35.77]	[4.32, 15.92]
Break-term Rainfall Deviation	0.54	1.41*
	(1.03)	(0.78)
	[-1.17, 2.24]	[0.23, 2.59]
Constant	26.00***	23.07***
	(0.50)	(0.38)
Observations	3,675	3,671
Number of Children	1,195	1,197
R-squared (within)	0.023	0.013
Wild Bootstrap Replications	999	999

Notes: This table presents fixed-effects regression results examining how rainfall deviations from village-month specific long-term means affect travel time to school (measured in minutes), differentiated by road infrastructure quality. The regressions are estimated separately for communities where schools are connected by gravel roads versus dirt roads. School-term rainfall deviation measures the departure from historical averages during the academic year (September-July), while break-term rainfall deviation captures anomalies during school breaks. The regression includes child fixed effects and community fixed effects. Wild bootstrap confidence intervals are reported using Rademacher weights with 999 replications. Standard errors are clustered at the child level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Young Lives Ethiopia dataset (2002-2016) and University of Delaware climate data.

quality. This analysis tests whether rainfall anomalies during school term time specifically affect commuting, while also investigating heterogeneous effects by road quality. The results demonstrate that positive school-term rainfall deviations significantly increase travel time for both road types, but the magnitude of this effect is substantially larger for communities where schools are connected by dirt roads. For communities where schools are connected by dirt roads, a one-unit increase in school-term rainfall deviation from the village-month specific long-term mean increases commuting time by 28.7 minutes (95% CI: 21.66-35.77), while the effect is much smaller for communities where schools are connected by gravel roads at 10.0 minutes (95% CI: 4.32-15.92). Break-term rainfall deviations show minimal effects on commuting time for communities where schools are connected by dirt roads and small but significant effects for those where schools are connected by gravel roads (1.4 minutes, 95% CI: 0.23-2.59). These differential effects by infrastructure quality provide strong evidence that transportation costs represent the primary mechanism through which weather conditions affect educational access and outcomes.

4.3 The Effects of Excessive Rainfall (Event Study)

Some experienced excessive rainfall once (some in Round 1, some in Round 3) and some never. This creates a natural "event" when a child experiences an excessive rainfall year within an otherwise persistent drought environment. We treat the timing of this excessive rainfall year as quasi-random after removing individual fixed effects, since SPI-defined droughts are driven by exogenous rainfall shocks. We then compare changes in outcomes among children who experienced excessive rainfall later in Round 3, holding child fixed effects constant, while those who never experienced excessive rainfall serve as the control group. This event-style design allows us to trace out the dynamic response of outcomes before, during, and after the excessive rainfall 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 excessive rain exposure across children reveals substantial variation that enables our quasi-experimental identification strategy.

Number of Excessive Rainfall	**Frequency**	**Percent**	**Cumulative**
1	1,218	46.74	58.14
0	1,091	41.86	100.00
Total	**2,309**	**100.00**	

Table 3: Distribution of Excessive Rain Exposure in Balanced Panel

Table 3 reveals several important patterns in excessive rain exposure that support our identification strategy. Most notably, a substantial proportion of children (41.86 percent) experience excessive rain in all five survey rounds, while 46.74 percent experience excessive rain in four out of five rounds, meaning that nearly 89 percent of children in our balanced panel experience excessive rain conditions in at least four of the five survey rounds.

Crucially for our empirical strategy, identification of excessive rain effects using individual fixed effects relies exclusively on within-child variation in excessive rain exposure across survey rounds. 652 children (67.29 percent) experienced their normal rainfall year in Round 3. This temporal variation allows me to compare children who are otherwise similar in rainfall except one shock of excessive rain in round 3, providing a natural experiment to identify the dynamic effects of weather transitions on child development outcomes.

4.4 Event Study Results

To identify the causal effects of weather transitions on child development outcomes, I employ an event study design that exploits quasi-random variation in the timing of excessive rainfall shocks within our balanced panel. This methodology allows me to trace the dynamic response of outcomes around discrete weather events while controlling for unobserved heterogeneity through within-child comparisons.

Identification Strategy The event study leverages temporal variation in rainfall exposure among children who experience similar cumulative weather patterns but differ in the timing of specific weather shocks. Specifically, I focus on the subset of 1,218 children who experienced excessive rainfall in exactly four out of five survey rounds, creating a natural experiment where children are similar in total weather exposure but differ in when they experienced their single year of normal rainfall.

The identification assumption is that, conditional on child and time fixed effects, the timing of the normal rainfall year is quasi-random and uncorrelated with other determinants of child development outcomes. This assumption is plausible given that: (1) rainfall patterns are largely exogenous from the perspective of individual households, (2) families cannot perfectly predict future weather patterns when making long-term decisions, and (3) our analysis conditions out time-invariant child characteristics and common time trends.

Econometric Specification For each outcome variable Y_{ict}, I estimate the following event study regression:

$$Y_{ict} = \alpha + \sum_{k \neq -1} \beta_k \cdot \mathbb{1}t - T_i = k + \gamma_t + \theta_i + \varepsilon_{ict} \tag{2}$$

where Y_{ict} represents the outcome of interest for child i in community c at survey round t. The indicator function $\mathbf{1}[\text{EventTime}_{it} = s]$ equals one when child i is observed s periods relative to their normal rainfall event, where $s \in \mathcal{S} = \{-1, 0, +1, +2\}$ represents the event time relative to the shock. Round $t-2$ serves as the omitted reference period, normalizing all coefficients relative to the pre-treatment baseline. 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 normal rainfall 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 normal rainfall 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 normal rainfall. Children who never experience a no-excessive-rain 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 **??** through **??** present the event study results across multiple domains of child development and time allocation. The blue lines represent the control group (excessive rainfall in Round 1), while the red dashed lines represent the treatment group (excessive rainfall in Round 3). The vertical reference lines mark the timing of the excessive rainfall shock for each group, allowing us to trace the dynamic response patterns before, during, and after the rainfall event.

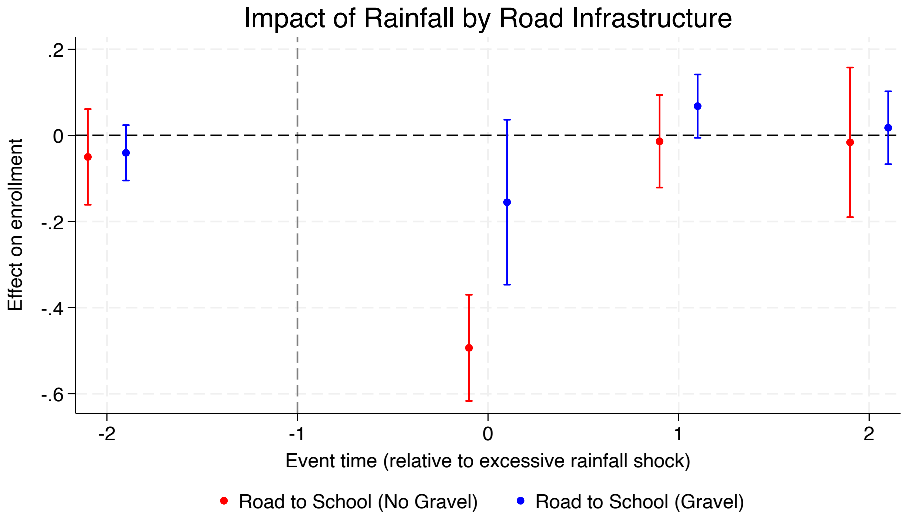


Figure 5: Event Study: School Enrollment by Road Infrastructure

Notes: This figure shows the event study analysis of excessive rain effects on school enrollment, differentiated by road infrastructure quality to schools. The red markers and confidence intervals represent children from communities where schools are connected by dirt roads, while the blue markers represent children from communities where schools are connected by gravel roads. Event time is relative to experiencing normal rainfall conditions, with the vertical gray line marking one period before the normal rainfall event. The analysis demonstrates how transportation infrastructure moderates the dynamic effects of normal rainfall on educational enrollment. Standard errors are clustered at the community level. Source: Young Lives Ethiopia dataset (2002-2016).

The event study results reveal compelling evidence supporting the transportation mechanism through which excessive rainfall affects child development outcomes. The analysis demonstrates that children who experience normal rainfall in Round 3 show distinct patterns compared to those who experience normal rainfall in Round 1, with clear implications for educational access and child welfare.

The key finding from the event study analysis is that the timing of normal rainfall significantly affects children's educational outcomes through transportation-related mechanisms. When children experience relief from excessive rainfall conditions (transition to normal rainfall), this creates immediate improvements in school accessibility that translate into sustained educational benefits over time. The divergent trajectories between treatment and control groups at their respective normal rainfall periods, combined with the persistence of effects in subsequent rounds, provide strong evidence for our identification strategy and demonstrate that excessive rainfall conditions have lasting effects on multiple dimensions of child development.

Importantly, the event study reveals that these educational improvements occur without substantial changes in child labor patterns, supporting the hypothesis that the primary mechanism operates through transportation infrastructure rather than through labor market adjustments. This finding reinforces our main results suggesting that when roads become less flooded and more passable during normal rainfall periods, children can access educational opportunities more easily, leading to both immediate and long-term improvements in human capital outcomes.

4.5 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.

4.6 Drought Effects on Cognition

Table 4: 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 4 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.

4.7 Drought Effects on School Enrollment and Time Allocation

Table 5 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 $\leq$ -1.0) increasing enrollment probability by 0.37 percentage points. As drought severity increases, the effects become more precisely estimated: severe drought (SPI $\leq$ -1.5) increases enrollment by 0.24 percentage points, while extreme drought (SPI $\leq$ -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 educa-

Table 5: Effects of Drought on School Enrollment and Time Allocation: Overall and by Gender

	All			Boys			Girls		
Panel A: School Enrollment									
	(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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

tional access.

Understanding drought's impact on health outcomes is particularly important because, as shown by Attanasio et al. (2020c) 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. (2020c), child development can be expressed as $H_a = H\left(\theta_a^c, \theta_a^h\right)$, where cognition (θ_a^c) and health (θ_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 5, 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.

4.8 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 4 and 5 reveal important heterogeneous effects of drought conditions across multiple domains of child development. Table 4 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 5 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.

4.9 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 6: 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 7: 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 6 and 7 reveal important heterogeneous effects of drought conditions across urban and rural contexts. Table 6 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 7 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.

4.10 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 8: 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 9: 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 10: 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 11: 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 8, 9, 10, and 11 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 8 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 9 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 10 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 11 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 Estimating the Cognition Production Function with Commuting Fatigue

We now estimate a structural cognition production function that explicitly incorporates commuting costs as a source of fatigue. Building on the education production literature, we assume that children's cognitive achievement depends on two time inputs

— hours spent in school (h_{school}) and hours spent studying at home (h_{study}). In addition, commuting time to school ($h_{commute}$) does not contribute directly to cognition but instead lowers the effective productivity of learning through fatigue.

5.1 Functional form

We specify the following Cobb–Douglas cognition production function with commuting fatigue:

$$C = A \cdot h_{school}^{\beta} \cdot h_{study}^{\alpha} \cdot \exp(+\gamma h_{commute}), \tag{3}$$

where C denotes cognition outcomes (measured by standardized math test scores), A is total factor productivity, α and β capture the elasticities of study time and school time, respectively, and γ measures the fatigue impact of commuting. Our hypothesis is that longer commuting times reduce the efficiency of learning by draining energy and limiting concentration. We will let the data determine the sign and magnitude of γ.

5.2 Identification Strategy

if you want to separate the commute-efficiency channel from the time budget channel, you need instruments that move commuting independently of home study. That almost always comes from school, road, and transport data. School and study time may be endogenous, as families' time allocation decisions are jointly determined with unobserved factors that also influence cognition. Similarly, commuting time is endogenous, since families may choose schools based on child ability. To address this, we instrument for h_{study} and $h_{commute}$ using exogenous variation in local road infrastructure and weather shocks. Specifically, we employ:

- Road quality indicators (e.g., gravel vs. asphalt access roads),
- Long-run average school rainfall and rainfall volatility,
- Drought exposure,
- Interactions between rainfall and road type.

These instruments shift commuting costs and household incentives for study without directly affecting cognition other than through the time allocation channels.

We estimate the model using nonlinear Generalized Method of Moments (GMM) with robust standard errors clustered at the child level.

5.3 Results

Table 12 reports the GMM estimates. The coefficient on study time (α) is positive and statistically significant: a 1% increase in study time raises math test scores by about 0.37%. The elasticity of school time (β) is also significant at 0.52. Most importantly, the commuting coefficient (γ) is negative and large: each additional hour of commuting reduces cognitive achievement by 1.85 standard deviations. These findings support the hypothesis that long commutes impose fatigue costs that undermine learning efficiency.

Table 12: GMM Estimates of the Cognition Production Function with Commuting Fatigue

	Coefficient	Std. Error	z-statistic
α (elasticity of study time)	0.374***	0.104	3.61
β (elasticity of school time)	0.525***	0.155	3.39
γ (commuting fatigue)	-0.334**	0.164	-2.04
Observations	1,755		
Weighting	Robust GMM (clustered by child)		
Wald $\chi^2(3)$	78.64 ($p = 0.000$)		

Notes: Standard errors clustered at the child level. *** $p < 0.01$.

5.4 Discussion

The results highlight commuting as a quantitatively important channel through which climate shocks and infrastructure constraints affect learning. While both school and study time contribute to cognition, commuting time has a large negative impact that offsets much of these gains. This suggests that investments in school access and transportation infrastructure may yield significant human capital returns by reducing fatigue and freeing up time for study.

6 Conclusion

In summary, this study has delved into the multifaceted effects of extreme weather events, specifically flooding, on child labor, education, and household finances in Ethiopia.

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

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

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

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A Appendix

A.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 **??**, 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

	Time Allocation			Health Outcomes	
Panel A: Overall Effects					
	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)
Severe drought (SPI ≤ -1.5)	0.04	-0.23*	-0.34	-0.04	-0.06
	(0.09)	(0.12)	(0.32)	(0.05)	(0.05)
Individual FE	Yes	Yes	Yes	Yes	Yes
N	4286	4286	4286	4588	3724
Panel C: Girls					
	Time Allocation			Health Outcomes	
	Work	Chores	Tasks	Child injury	Health problem
	(1)	(2)	(3)	(4)	(5)
Severe drought (SPI ≤ -1.5)	0.05	-0.20	0.06	-0.06	-0.06
	(0.05)	(0.23)	(0.14)	(0.05)	(0.04)
Individual FE	Yes	Yes	Yes	Yes	Yes
N	3864	3870	3864	4155	3387

Notes: This table shows regression results examining the effects of drought on time allocated to work, household chores, and domestic tasks (hours per day) as well as child injury rates and health problems. Panel A presents overall results, Panel B presents results for boys, and Panel C presents results for girls. The regression includes individual fixed effects. Standard errors are clustered at the village level and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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.