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Climate Shocks, Coping Responses and Gender Gap in Human Development

Kaleab K. Haile[*], Nyasha Tirivayi[†] and Eleonora Nillesen[‡]

Abstract

This study examines the impact of drought on child health and schooling outcomes and investigates the contemporaneous relationship between these two main building blocks of human capital. We merge child-level longitudinal data from the Ethiopia Rural Socioeconomic Survey (ERSS) with geo-referenced climate data. Our findings from within-child variation estimators reveal that drought has a detrimental impact on the highest grade completed of female children. We show that the negative effect of drought on a female child's completed years of formal schooling is channelled, albeit not entirely, through ill health. Our result is robust to using recursive bivariate estimation with exclusion restriction to correct for biases associated with the endogeneity of child health due to time-varying heterogeneities. Gender bias in the household explains why the direct and mediated schooling effects of drought are concentrated only on female children. We find that households respond to drought-induced income shocks by decreasing the allocation of resources for the medical treatment of an ill female child. Moreover, households also increase the use of female child labour for non-agricultural activities, which is consistent with a disproportionate increase in school absenteeism of older girls during drought. We discuss how gender-responsive policy design and implementation may help alleviate gender inequality in human development in the face of climate change.

Keywords: Drought, coping capacity, human capital, gender bias, sub-Saharan Africa, Ethiopia
JEL Classification: D13, I31, J16, Q54

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1 Introduction

Households in sub-Saharan Africa (SSA) are disproportionately affected by climate change due to their often limited capacity to withstand its negative effects without sacrificing utilization of basic goods (food) and services (health and education) (Harvey et al., 2014; Seaman et al., 2014). Particularly children are among the most vulnerable household members and may suffer unduly from the consequences of climate shocks. A growing body of research has shown that climate shocks can impair human capital development of children (Alderman et al., 2006; Hoddinott, 2006; Thai and Falaris, 2014; Zamand and Hyder, 2016; Duque et al., 2018; Nguyen and Minh Pham, 2018) with irreversible long-lasting effects on their lifetime earning capacities (Dercon and Hoddinott, 2004; Maccini and Yang, 2009; Clarke and Hill, 2013; Abiona, 2017; Adhvaryu et al., 2018). Hence, climate shocks not only deteriorate the immediate welfare indicators of children but may also determine their lifetime socioeconomic status. Children with low human capital levels are most likely to create new poor families because of their consequent lower living standards and reduced prospects of social mobility in adulthood (Case et al., 2011). Promoting human capital development early in life may break this vicious cycle of intergenerational poverty transmission and enable young people to choose between different livelihood strategies that may, in turn, reduce their vulnerability to climate change. Moreover, these microeconomic gains translate into human capital accumulation and sustainable development at the macro level in the long-run (Horton and Steckel, 2013).

Climate shocks affect child health and schooling outcomes – the two main building blocks of human capital – via the income effect (see Baez et al. (2010), Phalkey et al. (2015) and Hanna and Oliva (2016) for recent reviews). The impact of income shocks on human capital may not be evenly distributed across all children in the household. Gender bias in the intrahousehold resource allocation may play a significant role in determining who bears the brunt of climate change between boys and girls. The existing evidence on gender bias mainly comes from Asia and shows that parents' gender preference plays a significant role in determining child health and education (Pande, 2003; Himaz, 2010; Jayachandran and Kuziemko, 2011; Azam and Kingdon, 2013; Sivadasan and Xu, 2019). By contrast, in the context of SSA where climate risk-induced income shocks widely prevail, households' differential resource allocation decisions concerning their children's health and education conditional on gender are rarely studied (Rossi and Rouanet, 2015; Valero, 2018). In this vein, the existing few studies provide mixed and inconclusive results; either no evidence of gender-based discrimination (Jensen, 2000; Rabassa et al., 2014) or gender bias against girls (Björkman-nyqvist, 2013; Valero, 2018).

However, there is concern about the extent to which we can causally interpret the results of previous studies unless the effects of climate shocks are estimated for a given child over time. Di Falco and Vieider (2018) argue that while it has been a common practice to use an objective measure of climate shock (i.e. deviation from historical mean rainfall), which is an exogenous variable, it does not mean the shock is random enough to ensure that all areas in a given country and all individuals in a given area have an equal probability of being affected. Moreover, accounting only for community or district fixed effects, which is the standard approach in previous empirical studies, allows computing variations in human capital assuming that the community- or district-average human capital is the same as the child-level panel average for all children in that area. This assumption completely ignores the effects of child- and household-level unobserved heterogeneities that may determine the extent of individual-level effects of climate shocks. For instance, by using community fixed effects, heterogeneities in gender bias across households cannot be accounted for without imposing a strict assumption of the equality of gender bias at the household and community level. We, instead, rely on within-child variation estimations by taking a given child and comparing the changes in human capital with herself to identify the impact of climate shocks. Our approach considers that every child is unique, and thus, the direct and indirect effects of climate shocks on human capital may not be similar for everyone in a given household that resides in a higher-level cluster (community or district).

Furthermore, previous empirical studies examine the effect of climate shocks on either child health or schooling separately. The possible link between child health and education outcomes, and how this relationship may vary between boys and girls in the face of climate shocks is not adequately investigated. To our knowledge, this study is the first empirical evidence that provides a gender-disaggregated investigation of the contemporaneous causal relationship between child health and a common set of schooling outcomes – school absenteeism and highest grade completed – in the presence of climate shocks and tests whether climate shock-induced ill-health serves as a mediating channel. We also assess the extent to which gender bias in child health care, schooling expenditure, and labour use, if exists at all, results in gender gap in education.

Our analyses are based on child-level balanced panel data from three rounds (2011/12, 2013/14, and 2015/16) of the Ethiopia Rural Socioeconomic Survey (ERSS) matched with georeferenced climate data. We use within-child variation estimators to identify the causal effect of drought on human capital. Our results show that drought significantly increases reported child illness of both sexes. However, the schooling impact of drought is robust only for female children. The negative effect of drought on the highest grade completed of female children is channelled, albeit not entirely, through illness. This finding is robust to using recursive bivariate estimations with exclusion restriction to correct for biases associated with the endogeneity of child health due to time-varying unobserved heterogeneities. As impact pathway, we find that households respond to drought shocks by adjusting their resource allocation to health care services and use of child labour in a manner that disfavour a female child, who consequently bears the adverse direct and mediated schooling effects of drought.

In considering the impact of climate shock-induced health impediments on schooling of children, our contribution is distinct from those that explore the intertemporal shock-human capital synergies. Studies by Dercon and Hoddinott (2004), Alderman et al. (2006), Maccini and Yang (2009), Shah and Steinberg (2017), Adhvaryu et al. (2018) demonstrate that climate shocks have a detrimental effect on early life health endowments via nutrition and influence future educational outcomes of children. A principal finding that emerges from such exercise is that shock-induced child health impediments in utero and during infancy and early childhood (preschool years) have lifelong effects on health, education and socioeconomic outcomes. This provides a powerful rationale for prioritizing policy interventions that target unborn children, infants and preschoolers for improvements in human development.[1] Concerning gender bias in early life and its long temporal reach, while Maccini and Yang (2009) find that early-life rainfall has strong positive effects on human capital and socioeconomic status of women, but not of men, Dercon and Hoddinott (2004) find no evidence that girls suffer more than boys regarding the impact of early-life drought on their long-term wellbeing – health, education and lifetime earnings during adulthood. However, there is much less known on how climate shock-induced poor health affects older children, in particular those of school-going age, conditional on gender. One could hypothesize that climate shocks happening to children of school-going age may generate different health effects and gender-based household coping responses from shocks happening to pre-schoolers, infants, and unborn children. Moreover, studying children of school-going age allows for a direct investigation of the potential short-run relationship between ill-health and schooling outcomes. Our paper does exactly that.

The analytical challenge in estimating a contemporaneous causal effect of health status on education is discussed in Behrman (1996) and Glewwe and Miguel (2007). They emphasised that the mere inclusion of health status – where child nutrition usually serves as an intermediate indicator – on the right-hand side of the child schooling model may introduce endogeneity and thus cannot guarantee a causal interpretation on the estimated coefficient. Without the context of climate shocks and gender-disaggregation, Ding et al. (2006) and Aturupane et al. (2013) address this issue and estimate the contemporaneous causal effect of child health on academic performance by making use of an instrumental variable approach. They, however, implicitly assumed that the effect of child health on education is the same for all children regardless of gender and underlying socio-cultural and environmental conditions. In contrast, we examine the impact of drought shocks on health among school-age children in Ethiopia, and subsequently how contemporaneous adverse health effects affect a child's schooling outcomes conditional on gender. Therefore, our study informs policy by examining poverty and human development implications of gender bias in households' decisions and intrahousehold resource allocation when income is constrained by climate shocks.

The rest of the paper is organized as follows. Section 2 presents the country context. Section 3 presents the theoretical framework focusing on health-schooling nexus. Section 4 describes the source of data and descriptive statistics. Section 5 explains the identification strategy. Section 6 presents the econometric results and discusses the main findings. Section 7 concludes and offers policy recommendations.

2 Country Context

Ethiopia has achieved remarkable economic growth over the last 15 years. According to World Bank's country overview in 2019, the real growth of gross domestic product (GDP) of Ethiopia averaged 10.3 percent a year

[1] Early childhood interventions are long-term economic investments that have favourable effects on economic outcomes during adulthood (Hoddinott et al., 2008) and in most contexts have the highest rates of returns (Alderman et al., 2017).

from 2006/07 to 2016/17. Given the current structure of the Ethiopian economy where rain-fed agriculture accounts for more than 40 percent of the GDP, recurrent and sometimes prolonged drought shocks have been a real challenge of sustaining economic growth (Shiferaw, 2017). In the last three decades, Ethiopia has faced 11 major drought shocks (Masih et al., 2014). About a century ago, the frequency of drought occurrence in the country was once every 10 years but, recently drought has become a common event in every 3 years (Suryabhagavan, 2017). Recently, a devastating drought triggered by El Nino weather events has affected over 50 million people who live in the drought-prone rural parts of East and Southern Africa, where Ethiopia was the most affected country (WFP, 2016).

Climate model predictions show that Ethiopia is going to face more climate-related aggregate shocks. In 2050, temperature in Ethiopia is expected to rise by 2.20C which will drastically increase the frequency of severe heatwaves and droughts (Conway and Schipper, 2011). The effect of a worsening climate on Ethiopia's agrarian economy will be mainly channelled through its impact on food production, income and prices. Based on Evangelista et al. (2013), bioclimatic variables related to rainfall explain a significant decline in cereal production that the country will experience. Moreover, they also noted the agricultural land that has been currently used to produce cereals will be uncultivable due to climate change. To tackle this multifaceted challenge, Ethiopia has designed a Climate Resilient Green Economy (CRGE) strategy that aims to enhance climate resilient livelihood for its more than 80 million rural people who are facing the imminent risk of income shocks due to weather anomalies.

The CRGE strategy recognized that the impacts of extreme weather would be more severe for vulnerable groups such as children, the elderly, the disabled and women (FDRE, 2011). In this regard, understanding the underlying demographic, socioeconomic and environmental conditions that determine households' decision-making process, mainly concerning the use and distribution of resources within the household, would facilitate identifying appropriate design features of a policy or programme intervention to target the most vulnerable groups. This has of great importance to increase the effectiveness of the intervention in buffering human development – food and nutrition security, health status, and education – from the effects of climate shocks and ensure inclusive growth in Ethiopia.

3 Theoretical Framework

Following Glewwe and Miguel (2007), the household is assumed to maximize the present discounted value of utility subject to an income constraint, a health production function and a schooling production function.

$$\sum_{t=1}^{T} E\left(\frac{1}{1+\sigma}\right)^{t} U_t \tag{1}$$

where t is period that extends from t =1 to a known final period, t = T; E is the expectation operator, σ

is the subjective discount rate, and U is utility to the household at period t is given by:

$$U_t = U(H_t, C_t, L_t; D_t) \tag{2}$$

where H is child health status, C is consumption of other goods (mainly food), L is leisure, and D is weather related exogenous taste shifters such as drought shocks. Health has direct utility to the households (Grossman, 1972; Currie, 2009) − having healthier children increases their satisfaction. On the contrary, schooling does not generate utility directly, but it has an investment effect which determines future earnings through its effect on the labor market participation (Ferreira and Schady, 2009). The set of constraints on the production function for child health (equation 3) and production function for child schooling (equation 4) describe the way that available home inputs can be transformed into health (Grossman, 1972, 2000) and schooling outcomes Glewwe and Miguel (2007), respectively. The variables included in the production function relationships are only those that exert a direct effect on child health and schooling at period t.

$$H_t = H(C_t^c(D_t), HE_t(D_t), HI_t(D_t), X_t, \mu; G) \tag{3}$$

$$S_t = S(H_t, SI_t(D_t), X_t, \mu; G) \tag{4}$$

S is schooling of the child, H(.) and S(.) indicate health and schooling production functions. Equation 4 highlights the role of child health as a determinant of children's schooling outcomes. C^c the child's consumption of the aggregate food consumption, C. D_t is expected to have a negative effect on food consumption of the households in general (Brown and Funk, 2008; Saronga et al., 2016) and children in particular (Perera, 2014). Food and nutrition insecurity of children are major factors that lead to poor health outcomes (Gundersen and Ziliak, 2015). HE is the local health environment, which is a function of climate shocks. The environmental and ecological alterations during climate shocks create conditions for widespread occurrences of vector-borne, water-borne, and infectious diseases (Bunyavanich et al., 2003; Lafferty, 2009; Stanke et al., 2013). HI is health input (household's allocation of resources to child health care services). Health care systems in SSA heavily rely on user (out-of-pocket) fees for the health services and prescribed medicines (Meessen et al., 2011; Ali, 2014; Masiye et al., 2016). Hence, HI is a function of D_t through its income effect. Similarly, SI is schooling input (sending the child to school and household's provision of school fees and school-related materials such as books, uniforms, etc). Parents' ability and willingness to bear the direct and opportunity costs of SI is determined by the effect of D_t. While the direct costs are related to school fees and supplies, the opportunity cost is the reduction in household's income due to loss of the child's labour for agricultural, non-agricultural and wage-paying activities (Alderman et al., 2012). X_t is observable characteristics particular to the child such as age and gender of the child, and household characteristics that affect income, wealth and life-cycle position. μ is unobserved time-invariant heterogeneities (such as innate healthiness and cognitive abilities of the child and parents' child-rearing practices) that affect the household's (health and school) input allocation.

The net effect of D_t on HI and SI is either positive or negative based on the relative size of the income and substitution effects. The income effect is negative because climate shocks adversely affect households' resources and raise the costs of education and health care services relative to household income, whereas the substitution effect is positive since weather shocks depress local economy wage prospects and result in lower opportunity cost for the labour of children and caregivers to engage in human capital-promoting activities compared to working for lower wages (Ferreira and Schady, 2009). Gender bias (G) in the intrahousehold resource allocation and labour supply decisions based on parents' perceived values of child labour is a crucial socio-cultural element that may dictate who bears the burden of the income effect and who enjoys the substitution effect of climate shocks among children in the household. In general, parents' gender bias may introduce variations in the within-household food allocation, health care and schooling expenditure, and child labour use, and ultimately result in two separate health and schooling production functions based on sex of the child.

The income constraint is the last constraint faced by a utility maximizing household at period t, such that:

$$Y_t = p_t^C \times C_t + p_t^H \times HI_t + p_t^S \times SI_t \tag{5}$$

where Y is total income; p^H price for health inputs; p^S is price for schooling inputs; and p^C prices of other consumption goods (mainly food).

Optimizing the utility in equation 2 with respect to the constraints in equations 3, 4 and 5 gives standard demand functions for Ct, HIt, and SIt variables that can be influenced by household decisions. The solution to this optimization problem is a set of demand functions for all the marketed goods (e.g. food, health care services, education) which depend upon prices of all market goods, child and household-related time-varying factors that directly affect income (e.g. experiencing drought shocks) and child and household-related time-invariant factors that may affect child schooling. Thus, the schooling demand function conditional on gender can be expressed as:

$$S_t = S(D_t, p_t^C, p_t^H, p_t^S, X_t, \mu; G) \tag{6}$$

The relationship in equation 6 shows that demand for child schooling is a function of climate shocks, the prices of consumption goods, health, and education – proxied by access to output markets, health care services, and education facilities – and other child and household level observed and unobserved heterogeneities. An empirical investigation of this contemporaneous relationship conditional on gender has valuable policy implications in prioritizing climate disaster responses that intend to mitigate the effect of climate shocks on children's human capital by taking into account the possible interdependence between child health and schooling and the effect of households' gender-based coping responses.

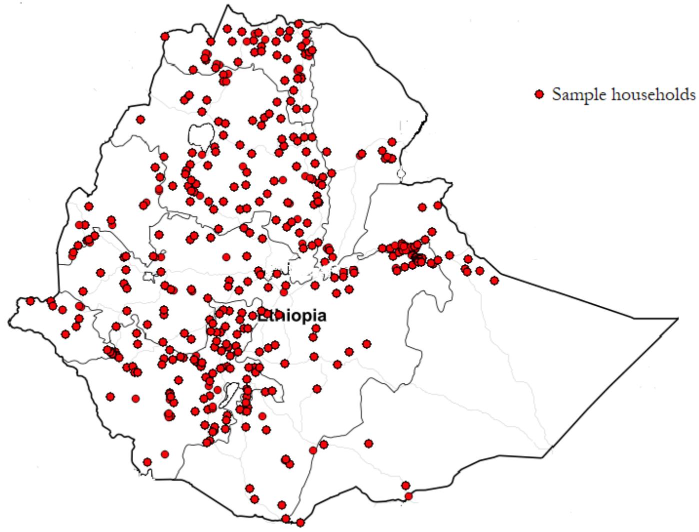


Figure 1: Sample households observed in all survey rounds

4 Data and Descriptive Statistics

4.1 Source and type of data

This study uses the Ethiopia Rural Socioeconomic Survey (ERSS), a nationally representative panel data set for the years 2011/12 - 2015/16. Figure 1 shows the locations of the sample households based on the GPS (longitude and latitude) coordinates of their communities (enumeration areas).[2] We merged an objective measure of drought shocks with 0.5 degrees spatial resolution that is made available by the University of East Anglia Climatic Research Unit (UEA-CRU)[3].

We use strongly balanced individual-level panel data from 3,639 households in 332 communities. Table 1 summarises the number of households and school-age children (i.e. between 7 and 18 years of age in 2011/12) that are present in all survey rounds. Accordingly, we conduct all of our econometric analyses on panel data that consist of 5,667 children that were between 7 and 18 years of age in the first wave and observed in the subsequent two survey waves – resulting in a total of 17,001 observations.

Table 1: Number of households and children in each survey rounds

	2011/12	2013/14	2015/16
Interviewed (re-interviewed) households	3,969	3,776	3,639
Observed (tracked) school-age children	5,900	5,769	5,667

Notes: Between the initial and last survey waves, only 233 school-age children could not be tracked.

[2] In order to maintain confidentiality of respondents, the GPS coordinates of sampled communities where the households reside are presented in the panel data.

[3] The database is available at: http://sac.csic.es/spei/database.html

The choice of the lower and upper bounds for the age range to be 7 and 18 years is based on Ethiopia's officially deemed proper age for a child to enrol to primary school (start first grade) and complete high school (complete grade 12), respectively. The use of 7 years as the lower age bound is also justified in our data since the education outcomes for children below the age of 7 years are missing in the initial survey wave (2011/12). Whereas, the choice of a wider upper bound (i.e. 18 years) is to accommodate a common scenario in rural Ethiopia where there is a high possibility for late (delayed) entry to school and grade repetition. Consequently, we encountered plenty children that can be considered over-age for their grades. Figure 2 demonstrates this by depicting age distribution and the highest grade completed of our sample children that are enrolled to school for the 2011/12 academic year. During that year, more than 90 percent of those children who are between 15 and 18 years of age were attending primary school – 35 percent 1^{st} cycle (grades 1 to 4) and 56 percent 2^{nd} cycle (grades 5 to 8). Similar fact is presented in UNESCO's 2012 report indicating that 20 percent of children enrolled in primary education in Ethiopia are above the intended primary school age (i.e. they are 15 years and above). This figure is 23 percent in our data. Incidences of children's age and sex misreporting are corrected by matching the accuracy of the registered age and sex information in the household roster with the verification questions, which entail information on the correct sex and age of the child, in the 2013 survey round.

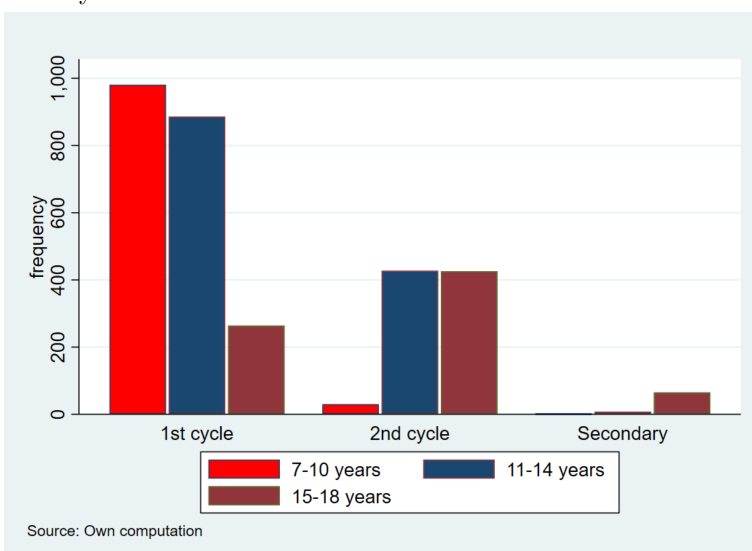


Figure 2: Age distribution and grade completed for enrolled school-age children in 2011/12

Note: 1^{st} and 2^{nd} cycles are grades 1-4 and 5-8, respectively. Secondary school comprises grades 9-12.

4.2 Main variables of interest

This section describes the outcome and explanatory variables of interest. The description and descriptive statistics on the child health and schooling variables, measure of drought shocks, and child, household and community characteristics for the pooled data are presented in Appendix Table A.1.

4.2.1 School outcomes

The outcome variables are for children between 7 and 18 years of age in 2011/12 and observed in 2013/14 and 2015/16 survey rounds (see section 4.1). Our study utilizes two school outcome indicators.

(a) School absenteeism: is a binary variable taking the value of 1 if the child was absent from school for more than a week in the past month during the survey year, and zero otherwise. Appendix Table A.1 shows that conditional on school enrolment, on average, 10 percent of children skip classes for more than a week within a month during the three survey rounds.

(b) Highest grade completed: is a count variable indicating the highest grade the child completed during the survey year. The highest completed formal years of schooling are on average 3.2 years during the span of the panel survey period (2011/12-2015/16).

4.2.2 Child health and medical treatment

Reported illness takes the value of 1 if a child between 7 and 18 years of age faced illness during the last 2 months in the survey year, and 0 otherwise. Conditional on illness, our "medical treatment" variable is binary taking the value of 1 if the ill child gets medical attention (treatment), and 0 otherwise. Furthermore, conditional on untreated illness, we also have a binary variable named inability to pay for medical treatment that takes the value of 1 if the household responded "lack of money" or "it is expensive" as a reason for not taking a child to medical treatment during illness, and 0 otherwise[4]. During the panel survey period, on average, illness occurred among 10 percent of the sample children. Out of these, 68 percent received medical treatment. Whereas, despite being ill, around 40 percent of children that donot receive medical treatment is due to liquidity constraints of the households.

4.2.3 Drought shock

Our drought shock variable is the standardized precipitation evapotranspiration index (SPEI), which is a multiscalar measure of drought pioneered by Vicente-Serrano et al. (2010). SPEI is computed by integrating the best qualities of the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI) to capture deviations in total precipitation and temperature from historical means.[5] The use of such relative measure instead of an absolute measure of rainfall and temperature is preferable because the same amount of rainfall and temperature may have different consequences in different regions based on variations

[4]We have few non-missing values under each reason for lack of medical treatment conditional on child illness. The value of zero in our variable includes households' reasons for the lack of medical attention that are not directly linked to liquidity constraints such as; "too far" (59 children), "lack of health professional" or "poor quality service" (26 children), "don't believe in medicine" or "other" (40 children).

[5]The global SPEI database offers the SPEI values for the period between January 1901 and December 2015.

in agro-ecologies. The SPEI values are calculated on time scales between 1 and 48 months. Between January and December, the agricultural production year in Ethiopia is divided into two production seasons, belg and meher.[6]

Hence, our objective drought variable is measured using SPEI values that are constructed based on a time scale of 12 months for the months January-December of the survey year. The SPEI for each survey year is merged with the individual-level data using the longitude and latitude coordinates of the community (enumeration area) of the sample household where the child resides. The maps in Figure 3 show that drought shocks occur in all the three survey years, but vary in magnitude and spatial coverage. Moreover, as Figure 4 presents, the distribution of SPEI values varies across regions of Ethiopia and drought shocks are highly regionally correlated. Tigray, Amhara, Benshangul Gumuz, and Gambela regions have experienced negative deviations – drought shocks – for the entirety of the panel survey years. However, the histogram plot for the distribution of climate shocks of the pooled data shows that SPEI values for the whole sample of children are randomly distributed and clustered around the mean value of 0.11 (Appendix Figure A.1).

The drought shock variable for our analyses is left-bounded at zero and obtained by multiplying the SPEI by (-1) if the values are negative, which indicate drought shock.[7] While the average magnitude of drought for all survey rounds is greater than zero, the years 2011/12 and 2015/16 registered the highest and almost identical average magnitude of drought shock during the panel survey period. This reflects the frequency of severe drought shocks in the country.

$$Drought\ shock = \begin{cases} \text{SPEI} \times (-1) & \text{if SPEI} < 0 \\ 0 & \text{if SPEI} \geq 0 \end{cases}$$

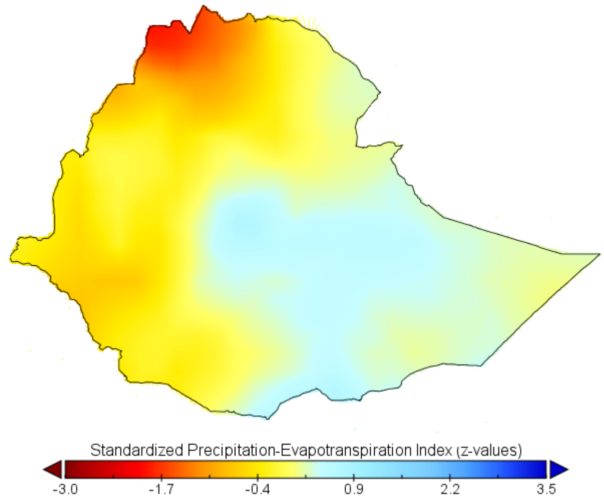
Our climate shock variable is exogenous only if households do not self-select into or out of experiencing drought. In this respect, attrition is a major challenge if the missing households were more or less exposed to drought. Household attrition rate is low (8 percent between the first and the third survey rounds), and not systematically related to exposure to drought shocks (Table 2). In addition, we examine whether attrition among children co-varies with child demographic and human capital variables – they do not (Table 3).

4.3 Control variables

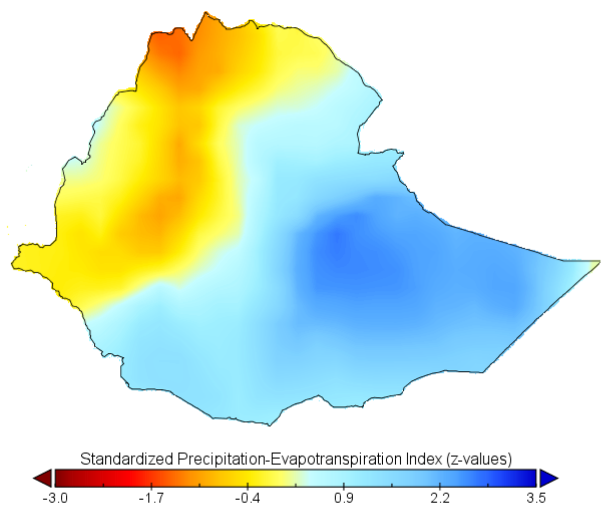
Appendix Table A.1 presents child and household level control variables that are included in our panel data regression models. These control variables capture: (a) demographic characteristics of the child, and (b) demographic and socioeconomic characteristics including proxies for wealth and access to markets, basic services, and infrastructure of the household that the child resides.

[6] *Belg* is the short rainy season that extends from March and early May. *Meher* is the main agricultural season extending between June and September.

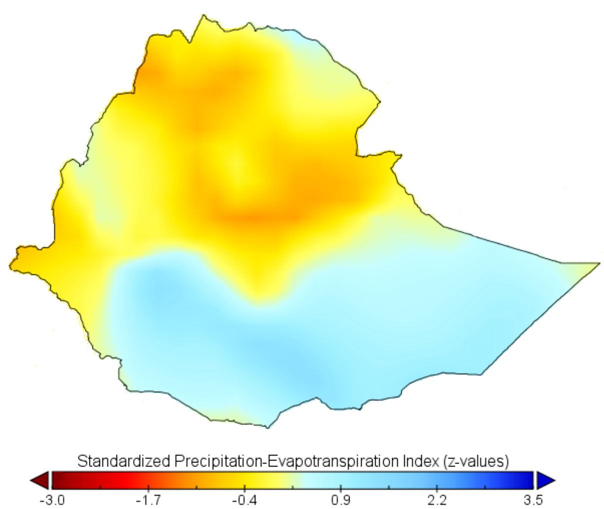
[7] Multiplying the negative deviations by -1 would ease the interpretation of the parameter estimates on our drought measure. Hence, higher values indicate higher magnitude of drought.



(a) SPEI values in 2011



(b) SPEI values in 2013



(c) SPEI values in 2015

Figure 3: SPEI values at the time scale of 12 months for the years 2011, 2013 and 2015

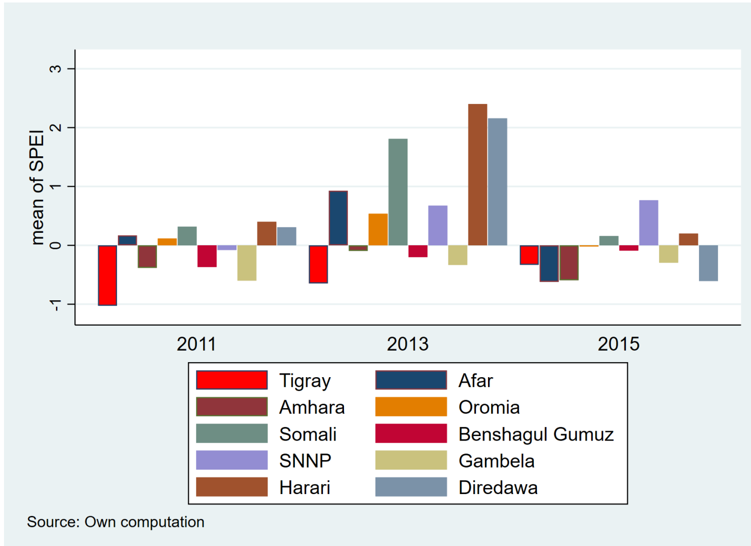


Figure 4: Distribution of SPEI values across regions by survey year

Table 2: Mean differences in exposure to drought based on attrition

	Between survey waves 1 and 2			Between survey waves 2 and 3		
	Mean magnitude of drought		Mean	Mean magnitude of drought		Mean
Variables	Re-interv. HHs	Attrited HHs	diff.	Re-interv. HHs	Attrited HHs	diff.
Drought in 2011	0.3074	0.3322	-0.0248			
			(0.0314)			
Drought in 2012	0.0925	0.0802	0.0123			
			(0.0229)			
Drought in 2013	0.2127	0.2135	-0.0008	0.213	0.1706	0.0424
			(0.0272)			(0.0309)
Drought in 2014				0.0778	0.0632	0.0146
						(0.0176)
Drought in 2015				0.278	0.2617	0.0163
						(0.0278)
Observations	3,740	177		3,639	136	

Standard errors in parentheses.

Notes: Out of the original 3,969 households that were surveyed in the first wave, a total of 330 households were not re-interviewed in the third survey wave. Between survey waves 1 and 2, 193 households were not re-interviewed. However, 52 (36 from the re-interviewed and 16 from the attrited) households do not have the latitude and longitude data and hence climate variables for these households are not available. Between waves 2 and 3, this figure declined to only 1 household that belongs to the attrited households.

Table 3: Mean differences in child human capital based on attrition

Variables	Children in re-interv. HHs		Children in attrited HHs		Mean diff.
	Number	Mean	Number	Mean	
Age	5667	11.7318	233	11.9914	-0.2596
					(0.2222)
Sex (% male)	5666	0.5224	233	0.4979	0.0246
					(0.0334)
Illness (%)	5611	0.1196	231	0.1515	-0.0319
					(0.0219)
Absenteeism (%)	3623	0.1336	135	0.1259	0.0077
					(0.0298)
Grade attainment	5533	2.3965	231	2.4416	-0.0450
					(0.1726)

Notes: Standard errors in parentheses.
The number of children in the re-interviewed and attrited households is not the same for all variables that we considered for the mean difference test due to missing values in the variable of interest.

5 Identification Strategy

Equation 7 relates H^*_{ihct} – a child's propensity to get ill where we only observe a binary reported child illness – to time-varying drought shock (D_{ct}) after adjusting for the effects of observed heterogeneities such that $X_{ihct} = \{X_{1ihct}, X_{2ihct}\}$. Similarly, Equation 8 is a linear representation of the latent schooling variable (S^*_{ihct}) for our observed (either binary or count) schooling outcomes. μ_{ihc} is child-level time-invariant unobserved heterogeneities and ε_{ihct} is independent and identically distributed (i.i.d) error term.

$$H^*_{ihct} = \beta_1 D_{ct} + \delta_1 X_{ihct} + \mu_{1ihc} + \varepsilon_{1ihct} \tag{7}$$

$$S^*_{ihct} = \beta_2 D_{ct} + \delta_2 X_{2ihct} + \mu_{2ihc} + \varepsilon_{2ihct} \tag{8}$$

where the subscripts indicate variation over children (i = 1, 2, ..., N), households (h=1, 2, ...,H), communities (c=1, 2, ...,C), and time (t = 1, 2, ..., T).

The coefficient of drought (β) can be estimated using pooled regressions by clustering the composite error terms ($\omega_{ihct} = \mu_{ihc} + \varepsilon_{ihct}$) at the community level. Cluster-robust pooled estimations result in heteroskedasticity-consistent standard errors by relaxing the assumption of i.i.d errors (Wooldridge, 2010; Millo, 2017) for a child across time and between children within a community.[8] Related empirical studies used cross-sectional variations (Bauer and Mburu, 2017) or district fixed effects (Björkman-nyqvist, 2013; Randell and Gray, 2016) methods to estimate the effect of climate shocks on either child health or education

[8] In the context of panel data with binary dependent variable, Wooldridge (2010) advocates the use of a partial MLE procedure of a pooled probit model using cluster-robust standard errors. The parameter estimates and the cluster-robust standard errors are consistent under the assumption that the variable of interest is exogenous.

outcomes. However, a causal inference based on the parameter estimates of climate shock variable after cross-sectional variation estimator can only be made if the shock is randomly determined at the individual level (Di Falco and Vieider, 2018). In this respect, the assumption that all communities (and children therein) have the same probability of experiencing drought regardless of their regional location is not satisfied in our data (Figure 4) despite climate shocks are exogenous[9] and random on average for the whole population in Ethiopia (Appendix Figure A.1). Moreover, community or district fixed effects would not account for child- and household-level unobserved time-invariant heterogeneities that may enhance or blunt the effect of climate shocks. We, therefore, rely on the within-child variation estimators as our preferred estimation strategy, instead of cross-sectional variations or community fixed effects, for identifying the impact of drought shock on the outcome variables of interest.[10]

The hybrid model splits within- and between-variation estimates for the time-varying variables (Alison, 2009; Schunck and Perales, 2017). Equations 9 and 10 transform equations 7 and 8, respectively, into the hybrid model by including both the deviations from panel-specific means ($D_{ct} - \overline{D}_c$) and the panel-specific means ($\overline{D}_c$) instead of the original drought measure (D_{ct}). The same holds for the remaining time-varying control variables.

$$H_{ihct} = \alpha_1 + \beta_3(D_{ct} - \overline{D}_c) + \beta_4\overline{D}_c + \delta_3(X_{ihct} - \overline{X}_{ihc}) + \delta_4\overline{X}_{ihc} + v_{1ihc} + \varepsilon_{3ihct} \tag{9}$$

$$S_{ihct} = \alpha_2 + \beta_5(D_{ct} - \overline{D}_c) + \beta_6\overline{D}_c + \delta_5(X_{2ihct} - \overline{X}_{2ihc}) + \delta_6\overline{X}_{2ihc} + v_{2ihc} + \varepsilon_{4ihct} \tag{10}$$

where β_3 and β_5 are the within-child effect estimates of drought, our parameters of interest. β_4 and β_6 are between-child effect estimates of the shock.[11] v_{ihc} and ε_{ihct} are time-invariant and time-varying child-level error terms, respectively.

Moreover, in the face of climate shocks, we pose a question on the assumption of independence between the contemporaneous child health and education that the existing empirical studies impose for identification reasons – endogenous child health status. As presented in the theoretical framework of this study (section 3), child health and education may not be independent in the short-run. Thus, the effect of drought on child schooling may also be channelled through its effects on health. Following the discussion by MacKinnon et al. (2012) and Hayes (2017) on the approaches to total and mediation effect analyses, Figure 5 relates drought and schooling outcomes taking child health as having an indirect (a mediating) effect.

Figure 5(a) is a total effect estimation and can be presented in formal econometric models using equations 9 and 10. Equation 11 is the mediation analysis depicted in Figure 5(b). Any correlation between the child health and time-invariant unobserved heterogeneities (μ_{ihc}) is captured by including panel-specific means of

[9]We showed that attrition in our panel data is random and thus drought shocks are exogenous to the households (Table 2).

[10](Di Falco and Vieider, 2018) show the merits in relying on within-individual variation (individual fixed effect) estimation for causal inference when one cannot guarantee idiosyncratic climate shocks across individuals and a uniformly distributed dependent variable prior to the shocks.

[11]In panel-data analysis, it is questionable whether the between-cluster effects (cross-sectional variations) are of substantial interest at all since the interest lies mainly on the within-cluster effects (Schunck and Perales, 2017; Di Falco and Vieider, 2018).

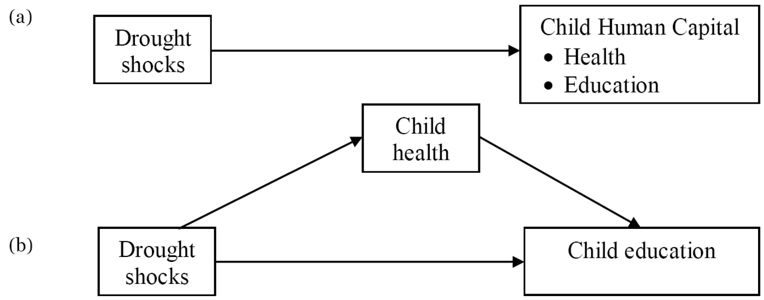


Figure 5: Diagrammatic representation of (a) the total effect (b) mediation effect analyses

child illness and other time-variant variables in child schooling model (equation 11).[12]

$$
\begin{aligned}
S_{ihct} = & \alpha_3 + \beta_7(D_{ct} - \overline{D}_c) + \beta_8\overline{D}_c + \theta_1(H_{ihct} - \overline{H}_{ihc}) + \theta_2\overline{H}_{ihc} + \\
& \delta_7(X_{2ihct} - \overline{X}_{2ihc}) + \delta_8\overline{X}_{2ihc} + v_{3ihc} + \varepsilon_{5ihct}
\end{aligned} \tag{11}
$$

where the within-child variation estimate (θ_1) captures the effect of health status on schooling outcomes of a given child after adjusting for the endogeneity that arises due to time-invariant heterogeneities.

We estimated the within- and between-cluster (child) effects of the variables of interest in a single model (equations 9-11) using probit and poisson estimators for the binary and count dependent variables, respectively. In this approach, the child-specific time-invariant and time-varying error terms in the equations are combined as: $\omega_{ihct} = v_{ihc} + \varepsilon_{ihct}$. The main advantage of this approach is that we can compute the average marginal effects (AMEs), which are easy to interpret and understand. As a robustness check, we also use the multilevel mixed-effects generalized linear model (meglm) to account for the presence of the separate time-invariant and time-varying i.i.d error terms. All our estimations are undertaken separately for the whole sample, female children, and male children.[13] The error terms are clustered at the community level to allow for serial and spatial correlations.

A serious concern with the within-variation estimators is the possible endogeneity that may arise from the correlation between time-varying unobserved heterogeneity (ε_{ihct}) and child illness, which may bias our parameter estimate (θ_1) in equation 11. Moreover, within-variation estimators may also suffer from simultaneity bias (reverse causality). For instance, education may equip children with disease prevention attitude and hence may enable them to avoid illness. Therefore, we use a maximum likelihood estimator of a binary or continuous outcome with a binary endogenous regressor under the recursive bivariate analysis, as proposed by (Maddala, 1983), to improve causal inference on the effect of child health on schooling outcomes. The binary reported child illness variable is an endogenous regressor in the equation determining the child's schooling outcomes. In this specification, child health can be correlated to both time-invariant

[12] This approach was initially proposed by Mundlak (1978) and further extended by Chamberlain (1980, 1982) to allow unobserved time-invariant heterogeneities to be correlated to the explanatory variables. This is achieved by modelling the time-invariant disturbance as a linear projection onto the panel-specific means of time-variant variables, such that: $\mu_{ihc} = \alpha + \theta\overline{H}_{ihc} + \delta_8\overline{X}_{ihc} + v_{ihc}$.

[13] We used Wald chi-square to examine whether coefficients differ across gender.

and time-varying heterogeneities while taking into account the non-independence among children in the same community.

The real challenge of the approach is finding an instrumental variable that satisfactorily addresses both the statistical and conceptual scrutiny. Drawing on medical and public health literature, improved hygiene and sanitation facilities have strong and consistent impact on health outcomes. Evidence from randomized control trials and observational research shows reasonably strong and consistent impacts of hygiene and sanitation interventions on the incidences of contagious diseases such as diarrhoea, parasitic worms and other infections including trachoma, influenza and rhinorrhoea (see recent reviews by Freeman et al. (2017), and McMichael (2019)). Previous studies also show that the effects of improved hygiene and sanitation facilities on child education are channelled through their effects on child health. Children with access to better hygiene and sanitation conditions in their schools are less likely to dropout out of school due to illness (Talaat et al., 2011; Trinies et al., 2016) and they are more likely to attain better cognitive learning and learning performance in the long-term (Ezeamama et al., 2018). We, therefore, employ the proportion of children that have access to improved toilet facilities[14] in the community as the excluded variable (X_{1ihct}) from the educational outcomes model specification. Aturupane et al. (2013) also use children's access to a toilet facility as an instrumental variable to measure the effect of child health on education performance. We test the admissibility of our instrument – whether the improved toilet facility embodies an exogenous source of variation affecting only child health but not education outcomes – using a simple falsification test suggested by Di Falco et al. (2011). According to this test, the proportion of children in the community that have access to improved toilet facilities should not be a significant determinant of non-ill children's education.

6 Results and Discussion

In the subsequent sections, we provide point estimates on the impact of drought on child human capital based on within-child variation estimators.[15] We also explore potential channels that may explain the observed relationship between drought and human capital of children.

6.1 Impact of drought on child schooling

Table 4 presents the total effect of a drought on contemporaneous child schooling outcomes. Regardless of gender, drought shock has a positive impact on school absenteeism, but the within child estimates are not statistically significant in any of the specifications (columns 1 and 2). We introduce an interaction term

[14]Improved toilet (sanitation) facilities include: flash toilet (private or shared), pit latrine ventilated (private or shared), pit latrine (private or shared) with slub, and composting toilet (private or shared). Sanitation classifications as improved or unimproved are based on those defined by the WHO/UNICEF Joint Monitoring Programme (JMP), which is available at: http://www.who.int/water_sanitation_health/publications/jmp-2017/en/.

[15]For brevity and the identification reasons presented in section 5, we only interpret and discuss the within-child effect estimates.

between age of the child and magnitude of drought (columns 3 and 4) to explore varitions in the relationship between climate shocks and school attendance for a unit change in the age of the child. We find a statistically significant positive and robust within-child effect of drought on school absenteeism of older female children. On average, the impact of drought on school absenteeism of a female child increases by an additional 1.4 percentage points for a unit increase in her age. In terms of the meglm estimate, for a given female child, the effect of drought on the odds of absenteeism from school increases by 20 percent for a year increase in her age. A study by Björkman-nyqvist (2013) in Uganda also shows that the adverse effect of negative deviations in rainfall on children's probability of going to school grows stronger for older girls.

We also find evidence on the negative within-child impact of drought on the highest grade completed in both panel models (Table 4 columns 5 and 6). For a given child, a one standard deviation increase in drought shock − a unit standard deviation decrease in SPEI for values less than 0 − results in decline in the expected count of grade attainment by 0.18. The negative effect of drought on a female child's highest completed formal school years is stronger in magnitude and robust under alternative panel model specifications. An increase in the magnitude of drought disproportionately affects a female child's human capital by lowering her expected count of highest completed formal school years on average by 0.25 − a 6 percent decrease based on meglm model. Hence, in the context of SSA, the impacts of drought on child schooling via its income effects are gender-specific where female children bear the brunt of climate change.

Figure 6 presents the relationship between the predicted probability of school absenteeism of children and the magnitude of drought after running a probit model on equation 10. The probability of a given child's absenteeism increases with an increase in the magnitude of drought. This relationship is slightly stronger for male children (Panel a). However, when we add age dimension besides gender, the within-child effect of drought is much stronger for older female children (Panel b). Alternatively, Appendix Figure A.2 depicts the predicted probability of school absenteeism conditioning on drought against age of the child, and it infers a similar relationship that we observe in Figure 6(b) − a stronger effect of drought on older female children. Figure 7 plots predicted completed school years against within-child variations in the magnitude of drought after linear regression. Accordingly, for a given child, the magnitude of drought and the highest grade completed have a stronger inverse relationship for female children, as shown by a steeper slope.

6.2 Drought and child health

(a) Impact of drought on reported child illness

The binary reported child illness variable captures whether the child faces illness in the past two months during the survey period. Table 5 shows that reported illness significantly increases with the increase in the magnitude of drought. The within-child variation analysis in Panel A column 1 shows that, on average, reported child illness increases by around 4 percentage points for an increase in the magnitude of drought.

Table 4: The impact of drought shock on child schooling

variables	(1) Absenteeism Probit (AME)	(2) Absenteeism meglm-Logit	(3) Absenteeism Probit (AME)	(4) Absenteeism meglm-Logit	(5) Grade comp. Poisson (AME)	(6) Grade comp. meglm-Poisson
A. All Children						
drought (within effect)	0.0139	0.1164	-0.1304**	-1.5527**	-0.1764***	-0.0502**
	(0.0210)	(0.2564)	(0.0513)	(0.6840)	(0.0652)	(0.0213)
droughtXage (within effect)			0.0114***	0.1355**		
			(0.0043)	(0.0569)		
drought (b/n effect)	0.1213***	1.2019***	0.0824	0.8079	-0.1780	-0.1020
	(0.0322)	(0.3078)	(0.0527)	(0.6086)	(0.2870)	(0.1007)
droughtXage (b/n effect)			0.0031	0.0305		
			(0.0039)	(0.0448)		
constant		-3.2456***		-3.0869***		-0.8589***
		(0.4102)		(0.4413)		(0.1311)
Observations	9,795	9,795	9,795	9,795	14,595	14,595
B. Female Children						
drought (within effect)	0.0115	-0.0113	-0.1669**	-2.1875**	-0.2540***	-0.0588**
	(0.0227)	(0.2973)	(0.0675)	(0.9784)	(0.0910)	(0.0287)
droughtXage (within effect)			0.0144***	0.1824**		
			(0.0055)	(0.0829)		
drought (b/n effect)	0.1208***	1.3062***	0.0656	0.9429	0.2018	0.0056
	(0.0332)	(0.3202)	(0.0726)	(0.8911)	(0.2907)	(0.1067)
droughtXage (b/n effect)			0.0046	0.0292		
			(0.0055)	(0.0666)		
constant		-2.9474***		-2.8143***		-0.7882***
		(0.4705)		(0.5483)		(0.1558)
Observations	4,706	4,706	4,706	4,706	6,801	6,801

Table 4: Continued

variables	(1) Absenteeism Probit (AME)	(2) Absenteeism meglm-Logit	(3) Absenteeism Probit (AME)	(4) Absenteeism meglm-Logit	(5) Grade comp. Poisson (AME)	(6) Grade comp. meglm-Poisson
C. Male Children						
drought (within effect)	0.0132	0.1937	-0.0802	-0.8993	-0.1120	-0.0433*
	(0.0241)	(0.2981)	(0.0604)	(0.8208)	(0.0885)	(0.0257)
droughtXage (within effect)			0.0073	0.0863		
			(0.0047)	(0.0629)		
drought (b/n effect)	0.1230***	1.1248***	0.1267**	1.1666	-0.5007	-0.2015
	(0.0378)	(0.3801)	(0.0633)	(0.7302)	(0.3602)	(0.1284)
droughtXage (b/n effect)			-0.0003	-0.0030		
			(0.0045)	(0.0536)		
constant		-3.4275***		-3.4216***		-0.9434***
		(0.5445)		(0.5730)		(0.1498)
Observations	5,089	5,089	5,089	5,089	7,794	7,794
Wald chi-square	78.76***		85.58***		106.65***	

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables − child and household characteristics, and region and survey year dummies (Appendix Table A.1) − but the results for these variables are not reported for brevity.

AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for the meglm regressions.

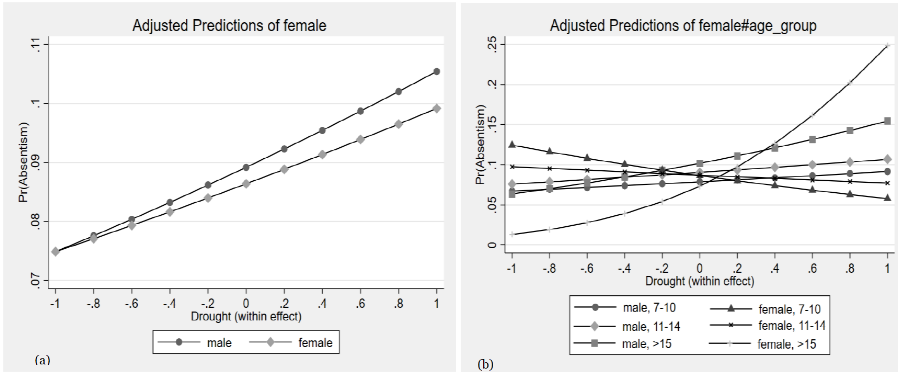


Figure 6: Relationship between school absenteeism and drought

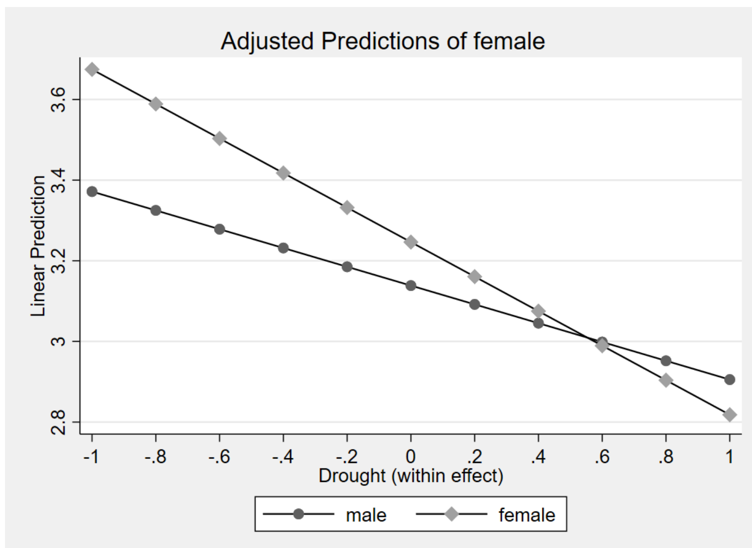


Figure 7: Relationship between highest grade completed and drought

The within-effect estimate of drought on child illness remains robust under meglm model specification. Accordingly, for a given child, the odds of illness (relative to non-illness) are more than 50 percent higher for a standard deviation increase in the magnitude of drought (Table 5 Panel A columns 2). As shown in Panels B and C of the same Table, the health impact of drought is statistically significant and robust regardless of gender. Moreover, the within-child effect of drought on child health does not vary based on age (columns 3 and 4).

As explained by (Gundersen and Ziliak, 2015), climate shocks can negatively affect child health through the effects on food and nutrition security. Households experiencing drought shocks may employ consumption destabilizing coping responses by lowering the quantity and quality of meals (Saronga et al., 2016). Low food availability, access, and utilisation during drought periods may consequently induce child illness. Unfortunately, we do not have information on individual-level food consumption to verify this mechanism

Table 5: The effect of drought shock on reported child illness

	(1) Child illness (Probit)		(2) Child illness	(3) Child illness (Probit)		(4) Child illness
variables	Coeff.	AME	meglm-Logit	Coeff.	AME	meglm-Logit
A. All Children						
drought (within effect)	0.2230**	0.0363**	0.4331**	0.2285	0.0371	0.2394
	(0.0886)	(0.0144)	(0.1854)	(0.2245)	(0.0366)	(0.4822)
droughtXage (within effect)				-0.0002	-0.0000	0.0156
				(0.0160)	(0.0026)	(0.0340)
drought (b/n effect)	0.6945***	0.1130***	1.3285***	0.2581	0.0419	0.8036
	(0.1348)	(0.0219)	(0.2375)	(0.2803)	(0.0455)	(0.5588)
droughtXage (b/n effect)				0.0327*	0.0053*	0.0387
				(0.0174)	(0.0028)	(0.0343)
constant	-1.6693***		-3.2149***	-1.5343***		-3.0420***
	(0.1786)		(0.3465)	(0.1907)		(0.3735)
Observations	14,680	14,680	14,680	14,680	14,680	14,680
B. Female Children						
drought (within effect)	0.2335**	0.0397**	0.4750**	0.0114	0.0019	-0.2417
	(0.1095)	(0.0186)	(0.2230)	(0.3090)	(0.0526)	(0.6628)
droughtXage (within effect)				0.0173	0.0029	0.0569
				(0.0225)	(0.0038)	(0.0492)
drought (b/n effect)	0.4821***	0.0820***	0.9047***	0.3619	0.0616	1.0361
	(0.1760)	(0.0297)	(0.2935)	(0.3809)	(0.0645)	(0.7152)
droughtXage (b/n effect)				0.0097	0.0017	-0.0090
				(0.0262)	(0.0045)	(0.0468)
constant	-1.5445***		-2.8613***	-1.5069***		-2.8880***
	(0.2371)		(0.4468)	(0.2508)		(0.4821)
Observations	6,840	6,840	6,840	6,840	6,840	6,840
C. Male Children						
drought (within effect)	0.2165*	0.0336*	0.3977*	0.4359	0.0675	0.5696
	(0.1114)	(0.0173)	(0.2414)	(0.3229)	(0.0502)	(0.6752)
droughtXage (within effect)				-0.0157	-0.0024	-0.0117
				(0.0227)	(0.0035)	(0.0469)
drought (b/n effect)	0.8709***	0.1350***	1.7289***	0.2456	0.0380	0.8172
	(0.1364)	(0.0218)	(0.2659)	(0.3261)	(0.0506)	(0.6820)
droughtXage (b/n effect)				0.0455**	0.0070**	0.0659
				(0.0203)	(0.0031)	(0.0419)
constant	-1.8665***		-3.7197***	-1.6725***		-3.4214***
	(0.1970)		(0.4122)	(0.2191)		(0.4567)
Observations	7,840	7,840	7,840	7,840	7,840	7,840
Wald chi-square	37.61			39.70		

Robust standard errors in parentheses: Clustered at community level. $***p < 0.01, **p < 0.05, *p < 0.1$
All estimations include control variables listed in Appendix Table A.1. AME stands for average marginal effects.
We used a Stata command written by Schunck and Perales (2017) for the meglm regressions.

and assess intrahousehold variations in the allocation of food. Instead, we rely on household-level analysis to examine the impact of drought on food consumption expenditure and the average number of meals taken per day across time. Based on our investigation using within-household variation estimators, we find no evidence that suggests drought has an effect on food consumption expenditure and behaviour for a given household (Appendix Table A.2). Therefore, the plausible channel for the impact of drought on child health is through its effect on the health environment. Drought conditions create a conducive environment for widespread occurrences of vector-borne, water-borne, and infectious diseases (Bunyavanich et al., 2003; Lafferty, 2009; Stanke et al., 2013).

(b) Drought and intra-household resource allocation for child health care

We now explore household-level decisions concerning the allocation of resources to health care services in the face of drought-induced income shocks. Our assessments on the gender-disaggregated impact of drought on households' decision to seek medical treatment during child illness and inability to pay for treatment reveal that there is gender bias in the allocation of resources for health care, female children being worse-off. Table 6 Panel C shows that for an increase in the magnitude of drought, a given male child is more likely to get medical treatment conditional on illness. This is plausibly due to the severity of ill health a child suffers during harsh environmental conditions of drought that may compel parents to seek medical attention. On the contrary, conditional on illness, a given female child has no chance of getting medical attention with an increase in the severity of drought (Table 6 Panel B columns 1 and 2). Moreover, for a unit standard deviation increase in the magnitude of drought, the probability that an ill female child does not receive medical treatment due to household's liquidity constraints increased by 32 percentage points (Table 6 Panel B column 3). Our results show that female children are disfavoured by the intra-household resource allocation to health care in the presence of climate shocks. As such, while male children are protected, households tend to divert health care spending away from female children as a coping response to drought-induced income shocks.

6.3 Drought and contemporaneous link between child education and health

The short-run within-child effects of climate shocks on human capital after running separate analyses on the impact of drought on children's schooling and health outcomes are presented in previous sections. In this section, we examine the possible contemporaneous link between education and drought-induced ill health of children to deepen our understanding of the short-run climate shocks-human capital nexus. This also allows us to examine whether the relationship between child education and health in the presence of drought vary due to gender bias in households' coping responses that we observe above.

The seemingly unrelated multivariate analysis reported in Appendix Table A.3 shows that the equations for health (equation 9) and education (equation 10) are not independent after adjusting for the effects of

Table 6: **Impact of drought on medical treatment and inability to pay for treatment**

	(1)		(2)	(3)	
	Med. treat.		Med. treat.	Inability to pay	
variables	Coeff.	Probit (AME)	meglm-Logit	Coeff.	Probit (AME)
A. All Children					
drought (within effect)	0.2917	0.0947	1.5271**	0.5851	0.1883
	(0.2251)	(0.0726)	(0.6467)	(0.4561)	(0.1437)
drought (b/n effect)	0.4802**	0.1559**	0.6516*	0.4131	0.1329
	(0.2433)	(0.0789)	(0.3374)	(0.3960)	(0.1279)
constant	-0.6095*		-0.6189	-1.4248**	
	(0.3669)		(0.6369)	(0.6843)	
Observations	1,410		1,410	405	
B. Female Children					
drought (within effect)	0.0117	0.0037	0.3562	1.0838*	0.3181*
	(0.2289)	(0.0733)	(0.7303)	(0.6059)	(0.1712)
drought (b/n effect)	0.8032**	0.2571**	0.8801*	0.7334	0.2153
	(0.3308)	(0.1053)	(0.4975)	(0.6438)	(0.1892)
constant	-0.9577*		-1.1640	-1.9288**	
	(0.4930)		(0.9768)	(0.9724)	
Observations	694		694	206	
C. Male Children					
drought (within effect)	0.5616*	0.1843*	2.7161***	0.1840	0.0538
	(0.3305)	(0.1074)	(0.8987)	(0.5755)	(0.1681)
drought (b/n effect)	0.3709	0.1217	0.5946	0.0012	0.0004
	(0.3152)	(0.1030)	(0.3990)	(0.4690)	(0.1373)
constant	-0.3818		-0.0415	-0.7389	
	(0.4910)		(0.8359)	(1.0384)	
Observations	716		716	199	
Wald chi-square	45.07			64.89***	

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables listed in Appendix Table A.1.

AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for the meglm regressions.

drought shock and other control variables. The correlation parameters (ρ) provide evidence for the presence of statistically significant dependence between children's health (as measured by reported child illness), and schooling outcomes – absenteeism and highest grade completed – in the expected direction. In particular, the correlation between health status and highest grade completed is statistically significant only for female children. We conducted further gender-disaggregated analyses to directly examine child illness as a mediating factor – the effect of child health on schooling outcomes – using within-child variation estimators.

Table 7 shows that child illness significantly reduces school attendance and the highest grade completed after adjusting for the direct effect of drought shocks and the effects of other observed and time-invariant unobserved confounders. On average, child illness increases the probability of school absenteeism of both a female and male child by 15 and 12 percentage points, respectively. In the meglm models, on average, the odds of school absenteeism is around 5 times higher for a female child and around 4 times higher for a male child for an increase in the magnitude of drought. Child illness also has a negative effect on completed formal school years for both sexes. In terms of magnitude, however, the negative effect of illness on the expected number of count on the highest grade completed of a given female child is twice as large as its effect on a male's child (Columns 3 and 4 in Panels B and C). This implies that a female child is twice as likely to lag behind in her human development as a male child due to illness. Moreover, the adverse effect of illness on the highest formal school years completed is robust only for female children.

As described in section 5, we also used a recursive bivariate analysis with exclusion restriction to test the robustness of our findings presented in Table 7 and improve causal inference on the effect of child health on schooling outcomes. For identification, we exploit the exogenous variation in reported child illness related to access to an improved toilet facility, which is found to be a significant correlate to health status of a given child. The health equations in Table 8 show that reported child illness significantly decreases if the proportion of children in the community with access to improved toilet increases. Di Falco et al. (2011)'s falsification test in Appendix Table A.4 shows that access to improved toilet facility in the community can be a valid instrument since it does not affect schooling outcomes of non-ill children. Our estimation results presented in Table 8 provide robust evidence to suggest that drought shocks cause illness that ultimately poses a detrimental impact on the education of children. On average, the probability of reported illness of a child increases by around 5 percentage points for a unit standard deviation increase in the magnitude of drought regardless of gender. In turn, child illness significantly decreases the highest completed formal schooling by around two years after accounting for observed and unobserved confounders. The adverse effect of child illness on the highest grade completed is statistically significant only for female children.

Our results imply that the gender bias in the intra-household resource allocation to health care may explain the disproportionately large schooling effects of child illness on female children. We show in section 6.2 that there is no significant variation in the impact of drought shock on reported child illness based on sex of the child (Table 5). Therefore, female children are not more susceptible to drought-induced illness. Rather, households tend to divert health care spending away from them (Table 6). Consequently, female

Table 7: Mediation analysis − the effect illness on schooling in the presence of drought

	(1)		(2)	(3)		(4)
	Absenteeism		Absenteeism	Grade comp.		Grade comp.
variables	Coeff.	AME	meglm-Logit	Coeff.	AME	meglm-Poisson
A. All Children						
illness (within effect)	0.8583***	0.1376***	1.6423***	-0.0675***	-0.2151***	-0.0595***
	(0.0809)	(0.0130)	(0.1806)	(0.0189)	(0.0602)	(0.0172)
drought (within effect)	0.0412	0.0066	0.0355	-0.0516**	-0.1643**	-0.0463**
	(0.0904)	(0.0145)	(0.2722)	(0.0206)	(0.0652)	(0.0212)
illness (b/n effect)	0.6422***	0.1030***	1.4122***	-0.0182	-0.0578	0.0065
	(0.0979)	(0.0157)	(0.1856)	(0.0533)	(0.1698)	(0.0707)
drought (b/n effect)	0.6546***	0.1049***	1.0594***	-0.0543	-0.1730	-0.1033
	(0.1265)	(0.0203)	(0.3366)	(0.0910)	(0.2897)	(0.1014)
constant	-1.8942***		-3.5157***	-0.6356***		-0.8575***
	(0.1951)		(0.4378)	(0.1042)		(0.1309)
Observations	9,795		9,795	14,595		14,595
B. Female Children						
illness (within effect)	0.9547***	0.1482***	1.7328***	-0.1009***	-0.3141***	-0.0849***
	(0.1180)	(0.0179)	(0.2484)	(0.0268)	(0.0832)	(0.0250)
drought (within effect)	0.0477	0.0074	-0.0504	-0.0759***	-0.2364***	-0.0531*
	(0.1426)	(0.0222)	(0.3160)	(0.0290)	(0.0900)	(0.0281)
illness (b/n effect)	0.8526***	0.1324***	1.7382***	-0.0363	-0.1132	0.0054
	(0.1314)	(0.0210)	(0.2211)	(0.0746)	(0.2321)	(0.0869)
drought (b/n effect)	0.6713***	0.1042***	1.1657***	0.0674	0.2100	0.0047
	(0.2071)	(0.0326)	(0.3439)	(0.0939)	(0.2921)	(0.1066)
constant	-1.7203***		-3.2988***	-0.6152***		-0.7866***
	(0.2803)		(0.5141)	(0.1236)		(0.1556)
Observations	4,706		4,706	6,801		6,801
C. Male Children						
illness (within effect)	0.7621***	0.1235***	1.5601***	-0.0373	-0.1213	-0.0374*
	(0.1033)	(0.0172)	(0.2425)	(0.0229)	(0.0746)	(0.0208)
drought (within effect)	0.0300	0.0049	0.0837	-0.0324	-0.1053	-0.0409
	(0.1498)	(0.0243)	(0.3150)	(0.0274)	(0.0888)	(0.0258)
illness (b/n effect)	0.4166***	0.0675***	1.0071***	0.0177	0.0575	0.0381
	(0.1458)	(0.0234)	(0.2695)	(0.0693)	(0.2252)	(0.0923)
drought (b/n effect)	0.6818***	0.1105***	1.0111**	-0.1574	-0.5115	-0.2077
	(0.2350)	(0.0387)	(0.4146)	(0.1127)	(0.3645)	(0.1301)
constant	-2.0299***		-3.6084***	-0.6790***		-0.9416***
	(0.2833)		(0.5721)	(0.1205)		(0.1497)
Observations	5,089		5,089	7,794		7,794
Wald chi-square	76.66***			107.70***		

Robust standard errors in parentheses: Clustered at community level. $***p < 0.01, **p < 0.05, *p < 0.1$

All estimations include control variables listed in Appendix Table A.1. AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for the meglm regressions.

Table 8: Recursive bivariate estimates on the impact of child illness on schooling outcomes

	(1)		(2)	
variables	Child illness Probit (AME)	Absenteeism Probit (AME)	Child illness Probit (AME)	Grade comp. Linear
child illness		-0.0563		-1.7595***
		(0.1008)		(0.6078)
imp. toilet use	-0.0600***		-0.0711***	
	(0.0128)		(0.0144)	
drought (within effect)	0.0477***	0.0321	0.0456***	-0.2838***
	(0.0158)	(0.0236)	(0.0158)	(0.0889)
drought (b/n effect)	0.1201***	0.1436***	0.1133***	-0.0710
	(0.0221)	(0.0393)	(0.0221)	(0.3341)
constant				-1.2888***
				(0.3656)
Observations	14,532		14,579	
child illness		-0.0607		-2.0926***
		(0.1829)		(0.6685)
imp. toilet use	-0.0493**		-0.0718***	
	(0.0196)		(0.0200)	
drought (within effect)	0.0478**	0.0338	0.0417**	-0.3776***
	(0.0196)	(0.0282)	(0.0187)	(0.1130)
drought (b/n effect)	0.0880***	0.1393***	0.0876***	0.2472
	(0.0299)	(0.0473)	(0.0301)	(0.3455)
constant				-1.2265***
				(0.4397)
Observations	6,777		6,794	
child illness		-0.1326		-0.8788
		(0.0962)		(1.2229)
imp. toilet use	-0.0667***		-0.0698***	
	(0.0149)		(0.0174)	
drought (within effect)	0.0482***	0.0373	0.0477**	-0.2312**
	(0.0185)	(0.0278)	(0.0190)	(0.1152)
drought (b/n effect)	0.1447***	0.1683***	0.1353***	-0.4434
	(0.0211)	(0.0419)	(0.0222)	(0.4205)
constant				-1.4473***
				(0.4101)
Observations	7,755		7,785	
Wald chi-square	53.92***		79.18***	

Robust standard errors in parentheses: Clustered at community level. $***p < 0.01, **p < 0.05, *p < 0.1$

All estimations include control variables listed in Appendix Table A.1. AME stands for average marginal effects.

We used a Stata command written by Roodman (2011) for the estimation.

children are worse-off than male children in receiving medical treatment during illness when households experience income shocks. This ultimately results in significant variations between male and female children with respect to the effect of illness on schooling outcomes. In this respect, illness may linger on female children and negatively affects their education plausibly by affecting active engagement in schooling activities. Thus, households' gender-based coping response to drought-induced income shock results in variations in the effect that illness has on schooling outcomes of female and male children.

6.4 Pathways for the direct effect

The direct within-child effects of drought, after accounting for its indirect (medicated) effect through child illness, on schooling outcomes are also shown in Tables 7 and Table 8. The within-child variation estimates reveal that drought on average resulted in a significant decline in the expected count of the highest grade completed. This effect is robust under alternative panel models only for female children. The expected number of count of a given female child's highest grade completed decreases on average by 0.3 as a result of an increase in the magnitude of drought by one standard deviation. Therefore, for a female child, drought bears a robust direct negative impact on her human development besides its mediated effect through ill health.

After controlling for the negative and statistically significant effect of illness, the presence of a robust effect of drought on the education of female children implies that the income effect persists. Björkman-nyqvist (2013) and Randell and Gray (2016) suggest that households' measures to increase income or reduce expenditures during drought seasons may adversely affect children's schooling. They argue that households respond to income shocks by forcing children to drop out of school to engage in farm or non-farm activities and due to the reduced ability for households to pay for school fees and supplies. We explore these two mechanisms – education expenditure (school fees and supplies) and use of child labour – as plausible pathways for the direct effect of drought conditioning on gender.

Unlike the gender bias in health care that we observe in 6.2, we do not find gender-based variations in the intrahousehold resource allocation to education expenditure in the presence of drought. Appendix Table A.5 shows that drought has a negative but not statistically significant within-child effect on annual school expenditure. On the other hand, Table 9 shows that households' decision to use child labour in response to drought significantly vary based on gender. Drought increases the weekly hours of female child labour on non-agricultural activities on average by more than 50 percent (Panel B columns 3 and 4). Björkman-nyqvist (2013) also found similar findings in Uganda where female children handle the majority of non-agricultural activities during periods of negative rainfall shocks. Thus, committing female children on non-farm activities may compete for their time that is needed for attending classes and studying to ensure progression to higher grades.

Table 9: The impact of drought shock on child labour use

variables	(1) Agri. work (ln) Linear	(2) Agri. work(ln) meglm-Linear	(3) Non-agri. work(ln) Linear	(4) Non-agri. work(ln) meglm-Linear	(5) Paid work(ln) Linear	(6) Paid work(ln) meglm-Linear
A. All Children						
drought (within effect)	-0.1697	-0.2463	0.3632*	0.4002*	-0.0106	0.0046
	(0.3042)	(0.3097)	(0.2075)	(0.2066)	(0.0354)	(0.0363)
drought (b/n effect)	-0.9195	-0.6669	-0.5498**	-0.4832**	0.1232***	0.0796*
	(0.5725)	(0.5107)	(0.2248)	(0.1911)	(0.0467)	(0.0414)
constant	-1.5899**	-1.8514***	-6.5233***	-6.4250***	-7.1049***	-7.0834***
	(0.6442)	(0.6087)	(0.3197)	(0.3049)	(0.0635)	(0.0619)
R-squared	0.1161		0.1123		0.0156	
Observations	14,403	14,403	14,389	14,389	14,392	14,392
B. Female Children						
drought (within effect)	-0.0448	-0.1060	0.5162**	0.5281**	-0.0288	-0.0249
	(0.3793)	(0.3773)	(0.2591)	(0.2498)	(0.0316)	(0.0333)
drought (b/n effect)	-1.3165**	-0.9597*	-0.4133	-0.2821	0.0219	0.0039
	(0.6376)	(0.5752)	(0.3354)	(0.2903)	(0.0408)	(0.0361)
constant	-1.3029*	-1.5288**	-6.5090***	-6.4330***	-7.0952***	-7.0780***
	(0.7830)	(0.4929)	(0.4274)	(0.4606)	(0.0672)	(0.0751)
R-squared	0.0658		0.1305		0.0155	
Observations	6,701	6,701	6,712	6,712	6,712	6,712
C. Male Children						
drought (within effect)	-0.2572	-0.3383	0.2477	0.3051	0.0078	0.0279
	(0.3327)	(0.3455)	(0.2019)	(0.2089)	(0.0538)	(0.0547)
drought (b/n effect)	-0.5960	-0.4041	-0.6686***	-0.6438***	0.2000***	0.1448**
	(0.6173)	(0.5522)	(0.2289)	(0.2018)	(0.0723)	(0.0654)
constant	-0.0759	-0.4492	-6.8004***	-6.7212***	-7.0852***	-7.0667***
	(0.7182)	(0.6682)	(0.3454)	(0.3416)	(0.0850)	(0.0889)
R-squared	0.1083		0.0982		0.0205	
Observations	7,702	7,702	7,677	7,677	7,680	7,680
Wald chi-square	481.09***		74.93***		53.36**	

Robust standard errors in parentheses: Clustered at community level. $***p < 0.01, **p < 0.05, *p < 0.1$

7 Conclusion

While households in SSA are disproportionately affected by climate change and variability, children are the most vulnerable household members to the worst consequences of climate shocks. Previous studies examine the effect of climate shocks on human capital of children relying on either cross-sectional variations or (beyond the household) higher-cluster level fixed effects. Both approaches impose arguably unattainable assumptions concerning either the randomness of a climate shock variable or equality of unobserved time-invariant heterogeneities at the child, household and higher-cluster levels. Instead, to improve causal identification, we take into account the presence of child- and household-level fixed effects that may either enhance or blunt the impact of climate shocks on a given child's human capital. We also examine the possible short-run link between health and education to provide valuable insight into the contemporaneous direct and indirect (mediated) impacts of drought on child schooling outcomes – school absenteeism and highest grade completed – in the context of SSA. To this end, we merge child-level longitudinal data from the Ethiopia Rural Socioeconomic Survey (ERSS) with climate data.

Using within-child variation estimators, we find that drought affects health status, school attendance, and the highest grade completed of children. Drought significantly increases reported child illness of both sexes. On the contrary, the impact of drought on education is disproportionately concentrated on female children. The detrimental effect of drought on a female child's completed years of formal schooling is channelled, albeit not entirely, through illness. Our empirical assessment on the impact pathway shows that households respond to drought shocks by altering the intra-household resource allocation to health care in a manner that diverts medication spending away from female children. Consequently, the negative effect of child illness on the highest grade completed is statistically significant and robust across alternative identification strategies only for female children. Besides the mediated effect through illness, drought has a direct and robust negative impact on a female child's number of formal school years completed, through increasing demand for the child's labour for non-agricultural activities. This is consistent with our finding that the adverse effect of drought on school attendance grows stronger with age for a female child, while boys and younger girls are not affected.

In rural areas of SSA, households' income is highly constrained during drought seasons. The gender bias in the intrahousehold resource allocation and labour supply decisions introduces significant variations on the consequences of drought-induced income shocks on human development of children. Households' lack of coping capacity to maintain their spending on a female child's health care presumably limits her chance to recover and proceed with her schooling activities. Moreover, due to low expected return from agricultural practices in the presence of drought, households may look for options to supplement their income. In this respect, non-agricultural activities can be considered as a livelihood diversification strategy and may render the possibility to raise households' income and smooth food consumption. However, a female child bears the burden of handling the tasks associated with the households' non-agricultural activities, which ultimately compete with her schooling time.

Our study contributes to the evidence base on the climate shocks-human capital nexus and provides valuable insight into the role of gender bias in shaping the effects of drought on human development. Unfortunately, due to lack of data, our study cannot verify why gender bias in the context of SSA exists. Is it due to cultural taboos – parents' expectations that female children should endure hardship – or intertemporal utility-maximizing choice? In the former case, parents might be less cautious and protective against the discomforts of their female children during ill health or longer working hours, which in turn may generate negative externalities on health and education of a female child. In the latter case, parents may take into account intertemporal division of labour as their "pension plan". Patriarchal societies characterize most developing countries where males have dominance in access to and control over resources. In this light, parents may enforce the physical well-being and schooling of a male child expecting financial support at old ages from him, regardless of forming his own family. On the flip side, female children may not be expected to be educated and able to leave the community. Instead, parents may expect them to stay around and keep providing their unaccounted labour for domestic and non-agricultural tasks in the short- and long-run. Future observational and experimental studies in this direction will give behavioural and economic explanations to the root cause of gender bias, which is a major impact pathway in our study.

Unpacking the pathways through which climate shocks affect human development is not just an exercise in scientific enquiry, it is also crucial for designing policies aimed at enhancing climate resilience and child welfare. Based on our findings, we propose policy recommendations that either enhance households' income or minimize the costs of human capital investments in the face of climate change. On the income side, risk management policies and practices such as weather index insurance, social assistance, and climate-smart practices may ensure stable household income to allow investments on child health and education in the aftermath of drought. As such, easing households' liquidity constraints may eliminate adverse coping responses that lead to gender inequalities in human development. Understanding the contemporaneous links between child health and education in the presence of climate shocks is essential to setting policy priorities in health and education sectors. For instance, allowing free health care at public health facilities or school health programmes would pay "double dividend" by improving both health and schooling outcomes of children in the face of severe and frequent drought shocks.

Since female children bear the brunt of the welfare effects of climate shocks, the issue of gender should be at the heart of the conditionality in targeting beneficiaries of a policy or programme intervention that intends to spur human development in SSA in general and in Ethiopia in particular. For instance, conditional cash transfers to households based on female children's health visits and school attendance may eliminate the negative consequences of gender bias in the intrahousehold resource allocation for health care services and simultaneously may enable female children to attend school by reducing the opportunity cost of giving up a female child's labour. Future rigorous (comparative) evaluation studies would shed light on the effectiveness of such resilience-promotive policy options in SSA.

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Appendix Table A.1: Description and statistics of variables from the Ethiopian LSMS-ISA pooled panel data

Variables	Obs.	Description and coding	Mean	Std.Dev.	Min	Max
Variables of interest						
absenteeism	9,948	binary; =1 if the child was absent from school for more than a week in the past month, 0 otherwise.	0.101	0.302	0	1
highest grade completed	14,855	a count variable indicating the highest grade completed.	3.191	2.868	0	18
illness	14,953	binary; =1 if the child faced illness during the last 2 months, 0 otherwise.	0.096	0.295	0	1
medical treatment	1,437	binary; =1 if the ill child gets medical treatment, 0 otherwise.	0.683	0.465	0	1
inability to pay for treatment	413	binary; =1 if “lack of money” or “it is expensive” is a reason for not taking an ill child to medical treatment, 0 otherwise.	0.414	0.493	0	1
annual education expenditure (*ln*)	9.831	*ln* of child-level total annual education expenditure.	4.333	1.66	-6.908	9.045
agri. work hrs. per week (*ln*)	14,649	*ln* of the total hours in the last seven days that the child spend on household agricultural activities.	-2.278	4.888	-6.908	4.585
non-agri. work hrs. per week (*ln*)	14,636	*ln* of the total hours in the last seven days that the child spend to help any non-agricultural activities.	-6.167	2.567	-6.908	4.585
paid work hrs. per week (*ln*)	14,639	*ln* of the total hours in the last seven days that the child spend in any work for a wage, salary, or any payment.	-6.855	0.732	-6.908	4.564
annual food consp. exp. (*ln*)	7,172	*ln* of real annu. consumption exp. per ad. equ.	8.148	0.774	5.988	12.286
less meals per day	7,284	binary; =1 if the number of meals per day for the HH is twice or less, 0 for more than twice.	0.208	0.406	0	1
drought shock	16,987	a censored variable indicating magnitude of drought shock.	0.257	0.356	0	1.9
Control variables						
age of the child	16,916	continuous variable for the age of the child.	13.69	3.744	7	25
sex of the child	16,998	binary; =1 male child, 0 otherwise.	0.522	0.5	0	1
age of the HH head	16,890	Continuous; age of the household (HH) head.	48.45	12.26	15	98
sex of the HH head	16,993	binary; =1 male HH head, 0 otherwise.	0.799	0.401	0	1
attend school	16,901	binary; =1 if the HH head attended formal education, 0 otherwise.	0.35	0.477	0	1

Appendix Table A.1: Continued

Variables	Obs.	Description and coding	Mean	Std.Dev.	Min	Max
family size	17,001	continuous variable indicating family size.	7.206	2.323	1	18
non-farm income sources	16,988	binary; =1 if the HH engage in activities that generate non-farm income, 0 otherwise.	0.324	0.468	0	1
private transfer	17,001	binary; =1 if the HH receive private transfers, 0 otherwise.	0.148	0.355	0	1
social assistance	16,951	binary; =I if the HH receive social transfers, 0 otherwise.	0.184	0.387	0	1
credit	16,913	binary; =1 if anyone in the HH borrow over the past 12 months, 0 otherwise.	0.27	0.444	0	1
total land	17,001	continuous variable indicating total land holdings in ha.	1.625	3.355	0	87.37
productive assets	17,001	continuous variable for productive assets index	0.495	1.058	-1.183	14.13
road distance	16,987	continuous variable for HH distance in (kms) to nearest road.	15.5	19.35	0	242
admin. center dist.	16,987	continuous variable for HH distance in (kms) to capital of zone.	167.7	126.8	1	773.1
district town	16,987	binary; =1 if the community is in a woreda (district) town, 0 otherwise.	0.119	0.323	0	1
region dummy1 (base group)	17,001	binary; =1 if Tigray region, 0 otherwise.	0.1006	0.3008	0	1
region dummy2	17,001	binary; =1 if Afar region, 0 otherwise.	0.0325	0.177	0	1
region dummy3	17,001	binary; =1 if Amhara region, 0 otherwise.	0.201	0.401	0	1
region dummy4	17,001	binary; =1 if Oromia region, 0 otherwise.	0.225	0.418	0	1
region dummy5	17,001	binary; =1 if Somali, 0 otherwise.	0.0586	0.235	0	1
region dummy6	17,001	binary; =1 if Benshangul Gumuz, 0 otherwise.	0.0309	0.173	0	1
region dummy7	17,001	binary; =1 if SNNP, 0 otherwise.	0.263	0.44	0	1
region dummy8	17,001	binary; =1 if Gambela, 0 otherwise.	0.0281	0.165	0	1
region dummy9	17,001	binary; =1 if Harari, 0 otherwise.	0.0289	0.168	0	1
region dummy10	17,001	binary; =1 if Diredawa, 0 otherwise.	0.0311	0.173	0	1
Survey year dummy1 (base year)	17,001	binary; =1 if the survey year is 2011, 0 otherwise.				
Survey year dummy2	17,001	binary; =1 if the survey year is 2013, 0 otherwise.				
Survey year dummy3	17,001	binary; =1 if the survey year is 2015, 0 otherwise.				

Appendix Table A.2: Impact of drought on households' food consumption

	(1)	(2)	(3)		(4)
	Real food exp. per ad.eq. (ln)	Real food exp. per ad.eq. (ln)	Less meal-Probit		Less meal
variables	Linear	meglm-Linear	Coeff.	AME	meglm-Logit
drought (within effect)	0.0456	0.0493	0.0453	0.0122	0.0930
	(0.0480)	(0.0488)	(0.1106)	(0.0297)	(0.2370)
drought (b/n effect)	-0.1560*	-0.1462*	0.2914	0.0782	0.6018
	(0.0866)	(0.0839)	(0.1797)	(0.0483)	(0.3880)
constant	8.7382***	8.7418***	-1.3184***		-2.7858***
	(0.1001)	(0.0995)	(0.2110)		(0.4687)
R-squared	0.1145				
Observations	7023	7023	7139	7139	7139

Robust standard errors in parentheses: Clustered at community level.

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

The dependent variable in column 1 and 2 is annual food consumption expenditure of the household after adjusting for inflation and households' composition (measured by adult equivalent), which are readily available in the ERSS panel data. The dependent variable in columns 3 and 4 is binary taking the value of 1 if the average number of meals in the household is twice or less, and 0 for three times or more.

All estimations include control variables listed in Appendix Table A.1.

AME stands for average marginal effects.

We used a stata command written by Schunck and Perales (2017) for the meglm regressions.

Appendix Table A.3: Seemingly unrelated model estimates child health and schooling outcomes

	(1)		(2)	
	Health (illness) Probit-AME	Absenteeism Probit-AME	Health (illness) Probit-AME	Grade Comp. Linear
A. All Children:				
drought (within effect)	0.0384***	0.0156	0.0367**	-0.3286***
	(0.0145)	(0.0216)	(0.0145)	(0.0816)
drought (b/n effect)	0.1181***	0.1301***	0.1152***	-0.309
	(0.0217)	(-0.0323)	(0.0219)	(0.3167)
constant				-1.2896***
				(0.3637)
rho (ρ)	0.3930***		-0.0337*	
	(0.0304)		(0.0175)	
Observations	14580	14580	14580	14580
B. Female Children				
drought (within effect)	0.0441**	0.0191	0.0413**	-0.4311***
	(0.0187)	(0.0231)	(0.0187)	(0.1069)
drought (b/n effect)	0.0874***	0.1289***	0.0853***	0.0297
	(0.0293)	(0.0329)	(0.0295)	(0.3340)
constant				-1.2439***
				(0.4356)
rho (ρ)	0.4649***		-0.0595**	
	(0.0375)		(0.0243)	
Observations	6794	6794	6794	6794
C. Male Children				
drought (within effect)	0.0341**	0.0124	0.0333*	-0.2393**
	(0.0173)	(0.0255)	(0.0174)	(0.0967)
drought (b/n effect)	0.1395***	0.1329***	0.1360***	-0.5904
	(0.0216)	(0.0383)	(0.0218)	(0.3638)
constant				-1.3934***
				(0.4121)
rho (ρ)	0.3232***		-0.008	
	(0.0396)		(0.0232)	
Observations	7786	7786	7786	7786
Wald chi-square	70.18***		86.37***	

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables listed in Appendix Table A.1.

AME stands for average marginal effects.

We used a Stata command written by Roodman (2011) for the estimation.

Appendix Table A.4: Falsification test: test for the validity of the exclusion restriction

	(1) Absenteeism-Probit		(2) Absenteeism	(3) Grade comp.-Poisson		(4) Grade comp.
	Coeff.	AME	meglm-Logit	Coeff.	AME	meglm-Poisson
A. All Children:						
imp. toilet (within effect)	-0.0058	-0.0008	0.0896	-0.0071	-0.0229	0.0188
	(0.1828)	(0.0262)	(0.3687)	(0.0340)	(0.1092)	(0.0304)
drought (within effect)	0.1155	0.0166	0.1432	-0.0591***	-0.1899***	-0.0581***
	(0.1368)	(0.0197)	(0.3025)	(0.0218)	(0.0698)	(0.0217)
constant	-2.0321***		-3.7929***	-0.6458***		-0.8213***
	(0.2639)		(0.4762)	(0.1073)		(0.1274)
Observations	8854		8854	13154		13154
B. Female Children:						
imp. toilet (within effect)	-0.0618	-0.0084	-0.1215	0.0098	0.0307	0.0628
	(0.2211)	(0.0299)	(0.4644)	(0.0471)	(0.1483)	(0.0407)
drought (within effect)	0.1897	0.0257	0.1389	-0.0990***	-0.3119***	-0.0693**
	(0.1530)	(0.0210)	(0.3472)	(0.0333)	(0.1047)	(0.0306)
constant	-1.6880***		-3.3095***	-0.6905***		-0.7544***
	(0.3256)		(0.5730)	(0.1275)		(0.1500)
Observations	4238		4238	6098		6098
C. Male Children:						
imp. toilet (within effect)	0.088	0.013	0.3228	-0.0188	-0.0616	-0.0109
	(0.2073)	(0.0307)	(0.4399)	(0.0410)	(0.1340)	(0.0368)
drought (within effect)	0.0337	0.005	0.0862	-0.0222	-0.0726	-0.0469*
	(0.1595)	(0.0236)	(0.3605)	(0.0305)	(0.0994)	(0.0261)
constant	-2.2484***		-4.0151***	-0.6436***		-0.8976***
	(0.3191)		(0.6216)	(0.1241)		(0.1496)
Observations	4616		4616	7056		7056
Wald chi-square	77.41***			116.25***		

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables listed in Appendix Table A.1.

AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for meglm estimation.

Appendix Table A.5: Impact of drought on total annual education expenditure

variables	(1) Total edu.exp. (*ln*) Linear	(2) Total edu.exp. (*ln*) meglm-Linear
A. All Children		
drought (within effect)	-0.1338	-0.1541
	(0.0916)	(0.0945)
drought (b/n effect)	0.1028	0.0688
	(0.1548)	(0.1221)
constant	2.5750***	3.0014***
	(0.2082)	(0.2612)
R-squared	0.1072	
Observations	9,684	9,684
B. Female Children		
drought (within effect)	-0.1048	-0.1884
	(0.1113)	(0.1189)
drought (b/n effect)	0.1059	0.1560
	(0.1758)	(0.1335)
constant	2.4320***	2.8218***
	(0.2535)	(0.3646)
R-squared	0.1071	
Observations	4,639	4,639
C. Male Children		
drought (within effect)	-0.1685	-0.1212
	(0.1160)	(0.1202)
drought (b/n effect)	0.0927	-0.0339
	(0.1742)	(0.1502)
constant	2.7189***	3.1655***
	(0.2414)	(0.2454)
R-squared	0.1196	
Observations	5,045	5,045
Wald chi-square	44.28	0.1914

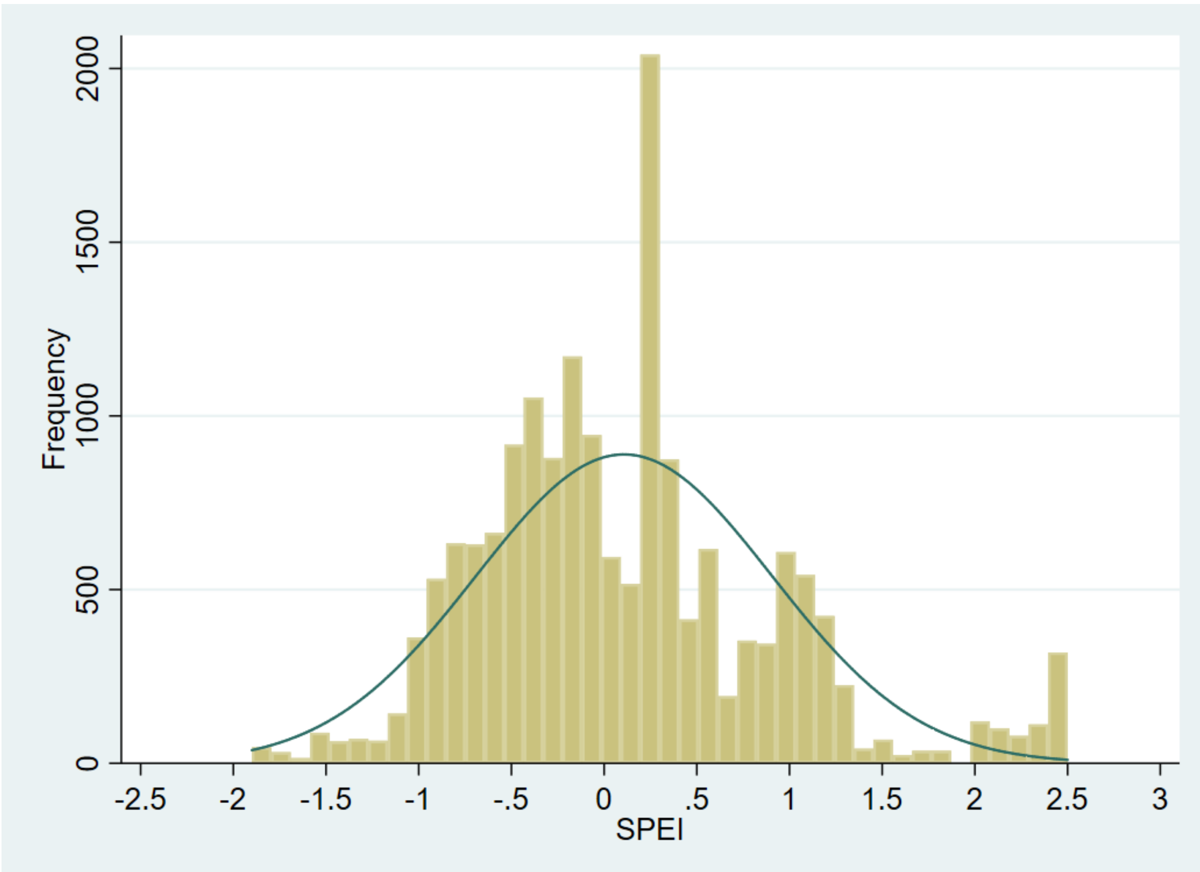
Robust standard errors in parentheses: Clustered at community level.

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

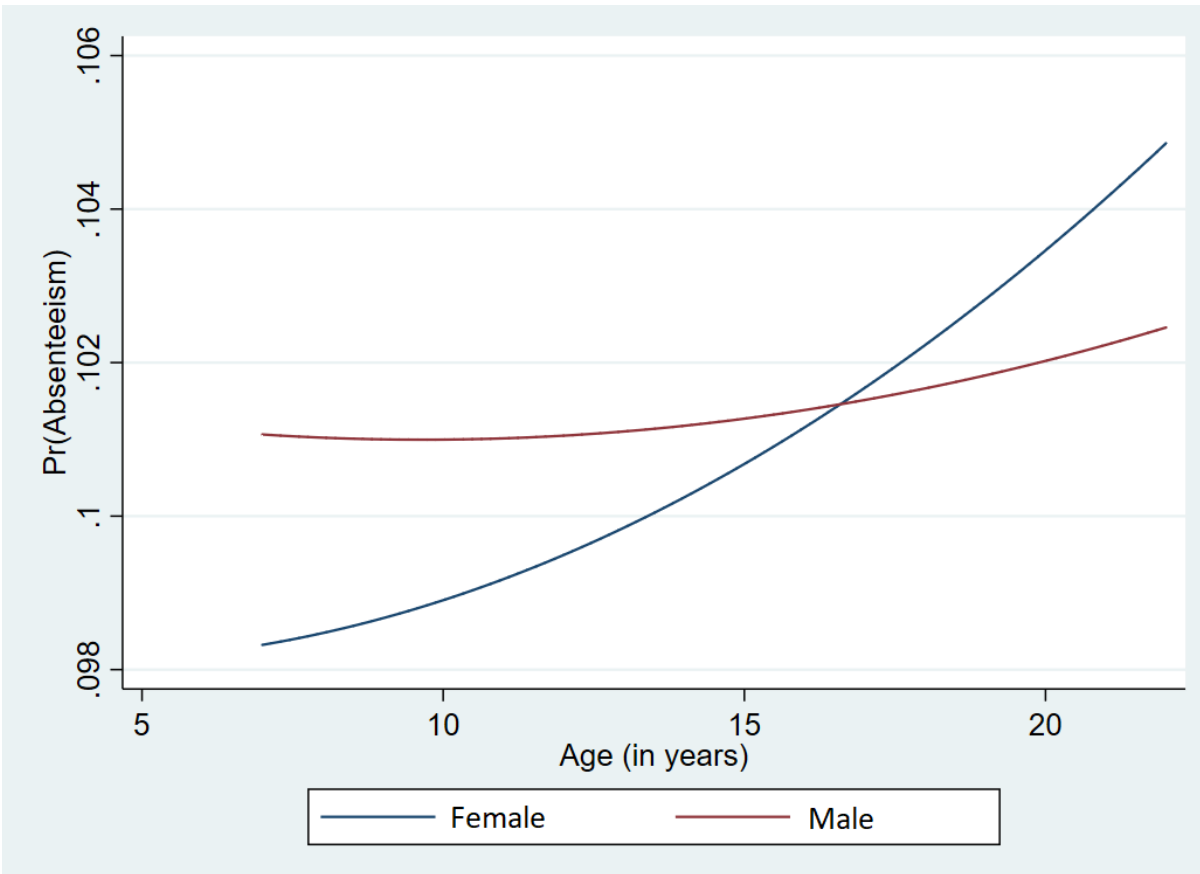
All estimations include control variables listed in Appendix Table A.1.

AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for meglm estimation.



Appendix Figure A.1: Distribution of SPEI values for the pooled data



Appendix Figure A.2: Predicted school absenteeism against age of the child

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