Climatic shocks and child undernutrition in Ethiopia: A longitudinal path analysis

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Abstract:

Climate change poses a serious challenge to achieving the SDG2 of ending hunger by 2030 and leaves billions of people at risk of food insecurity, illness, and malnutrition. This paper analyzes the long-term impacts of climatic shocks on the nutritional status of 1,911 sample children in Ethiopia. To this end, the study employed a linear mixed effect model, random intercept probit model, and structural equation modeling. Accordingly, climatic shocks are negatively associated with child nutrition. Moreover, early life exposure to climatic shocks is negatively associated with nutritional status at later age. Therefore, if appropriate measures are not taken, the predicted increase in the frequency of extreme events might slow down the secular progress in reduction of child undernutrition in Ethiopia. The role of other covariates was also analyzed. Accordingly, despite their biological and behavioral advantage, girls were more likely to be stunted than boys. This finding highlights the need for a gender-sensitive intervention and the role of intra-household food allocation during shocks. This study also revealed that program participation by drought-affected households has a positive association with child nutrition. Therefore, programs targeted to shock affected households might have a potential to smooth the impact of climatic shocks on child undernutrition

Acknowledegment: The data used in this study come from Young Lives, a 15-year study of the changingnature of childhood poverty in Ethiopia, India, Peru and Vietnam (www.younglives.org.uk). Young Lives is funded by UK aid from the Department forInternational Development (DFID). The views expressed here are those of the author(s). They are not necessarily those of Young Lives, the University of Oxford, DFID or other funders.

JEL Codes: Q54, C33

#1576

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ABSTRACT

Climate change poses a serious challenge to achieving the Sustainable Development Goal (SDG2) of ending hunger by 2030 and leaves billions of people at risk of food insecurity, illness, and malnutrition. This paper analyzes the long-term impacts of climatic shocks on the nutritional status of 1,911 sample children in Ethiopia. To this end, the study employed a linear mixed effect and probit regression models to estimate the impacts of climatic shocks on linear growth (HAZ) and stunting, respectively. Additionally, the study used a structural equation model to estimate the long-term impact of climatic shocks on HAZ.

Results suggest that exposure to drought and frosts are negatively associated with HAZ. Children exposed to drought and flood were also more likely to develop stunting. Moreover, climatic shocks that have occurred before 6-7 years were negatively associated with today's HAZ. Therefore, if appropriate measures are not taken, the predicted increase in the frequency of extreme events including drought, flood, and frost might slow down the secular progress in reduction of child undernutrition in Ethiopia.

The role of child, household and community level covariates was also analyzed. Accordingly, despite their biological and behavioral advantage, girls were more likely to be stunted than boys. This finding highlights the need for a gender-sensitive intervention and the role of intra-household food allocation during shocks. This study also revealed that program participation by drought-affected households has a strong positive association with child nutrition. The implication is that programs specifically targeted to shock affected households have a potential to curb the negative impact of climatic shocks on child undernutrition.

Moreover, in this study, other determinants of child nutrition such as maternal education and access to a public health facility were positively associated with child nutritional status. This calls for the need to incorporate other determinants of nutrition into programs through increased access to health services, sanitation, and nutrition education. Furthermore, in this study, the same group of households were recurrently affected by climatic shocks. Therefore, diversifying the means of livelihoods should be considered as a policy alternative for recurrently affected populations. Future studies might investigate the association of climatic shocks and child nutrition based on meteorological data and the effectiveness of culturally sensitive interventions to tackle intra-household "food buffering" during climatic shocks.

Keywords: Climate change; climatic shock; Ethiopia; undernutrition; Young lives data; Structural Equation Modeling

INTRODUCTION

The past three decades have seen a striking change in climatic conditions. Globally, an increase in average temperature, greenhouse gas concentration, and anthropogenic CO2 emissions have been recorded[2,3]. These changes, in turn, will lead to the frequent occurrence of cyclones, droughts, floods, heat waves and wildfires[3]. Along with this change are the projected population boom reaching 10 billion by 2050 and the associated 50% increase in demand for agricultural products; change in dietary patterns; soaring demand for energy; increasing frequency and intensity of natural disasters, crises, and conflicts; food price surges etc. all adding to the scarcity of resources for food production[4].

The prospects of such changes are particularly grim for the developing world and even worse for the rural poor whose livelihood is entirely dependent on the mercy of nature. In this context, two aspects stand out. First is meeting the sustainable development goal (SDG) 2—*end hunger, achieve food security and improved nutrition and promote sustainable* agriculture' by 2030[5]. This is particularly challenging given the fixed nature of natural capitals, the projected decrease in the resource base due to climate change, and technological stagnation[4]. The other aspect, along with meeting the SDG, is designing coping strategies for people disproportionately affected by climate change and its adverse consequences based on the scant literature about the impact of climate change on important aspects of human life.

Malnutrition is one among the top five adverse impacts of climate change[6]. Currently, over 23% of under 5 children in the world are stunted and 7.4% are wasted[7]. Although the global figure is declining over the past decades, progress has been uneven and slow in Sub-Saharan Africa (SSA) and Asia[8] and it is evident that climate change will further decelerate this temporal decrease. In one estimate for SSA, malnutrition among children is estimated to increase by additional 10% due to climate change[8].

Notwithstanding the recent increase in the number of studies that explore the impact of climate change on undernutrition, it still remains scant and is rather dominated by cross-sectional studies. Moreover, the evidence draws on a few heterogeneous studies that have some methodological limitations[6]. Most of these studies have emphasized the impact of the change in temperature and precipitation at a country or regional level. In addition to overlooking climatic variations within country and regions, such estimates suffer from lack of quality climate and weather data. Therefore, generating evidence from longitudinal data on a range of factors (agricultural, environmental, socioeconomic, and health) contributes for designing appropriate policies and programs[6] and reorient development and humanitarian assistance/programming[9].

Therefore, this study aims to assess the longitudinal relationships of climatic shocks with child undernutrition. Unlike other studies published from the YL dataset[10-13], this paper uses more rounds of data and mixed effect model thereby allowing for missing data measurement and better representation of the correlation and covariance structure of the data. Moreover, this paper tries to investigate the impact of exposure to climatic shocks at an early age on nutritional status at later age using Structural Equation Modeling.

THEORETICAL AND EMPIRICAL BACKGROUND

The theoretical framework used in this study heavily draws on previous work on child health and nutrition by Behrman & Deolalikar (1988), Hoddinott & Kinsey (2001) and Rossel (2008). The model represents a collective HH(HH) preference function[1] whereby a HH maximizes inter-temporal utility being subjected to income and health constraints [25]12.

$$U = U(U_1,\ \ U_2, \ldots U_T) \qquad \text{for time } 1 = 1 \text{ to T} \tag{1}$$

The model is based on the following assumptions: (1) Preferences are additive; (2) Utility at any time t (U_t) is an increasing quasi-concave function of consumption of public goods (C_t^p) and private goods (C_t^i), health status of the HH members (H_t^i), HH members leisure time(L_t^i), and HH norms and tests (Z_t); (3) $C_t^i, C_t^p, H_t^i, L_t^i$, and Z_t are interrelated and have a positive relationship with the HH utility; (4) Future utility discount factor is constant[3]; and (5)Utility of the HH is constrained by HH wealth and health.

$$U_t = U\left(C_t^i, C_t^p, H_t^i, L_t^i, Z_t\right)\ for\ HH\ member\ i = 1\ to\ N \tag{2}$$

HH wealth at time t (W_t), can be explained as a function of wealth in the previous year (W_{t-1}) and its return ($W_{t-1}r$), net transfers at time period t (T_t), income at period t (Y_t), and expenditure on private and public goods ($P_t^i\ C_t^i$ & $P_t^p\ C_t^p$)[11].

$$W_t = w_{t-1}(r_t + 1) + T_t + Y_t - \left(P_t^p\ C_t^p + P_t^i\ C_t^i\right) \tag{3}$$

W_{t-1}*r, in turn, is determined by the initial wealth stock (W_{t-1}), rate of return on wealth (r_t), and shock if any that affected wealth $S_t w_t$.

$$rW_{t-1} = f(W_{t-1}, r, WS_t) \tag{4}$$

Income of the HH is a function of the level of technology (tech), capital stock (K_t), wages (w_t), working time (WT_t), leisure time (L_t), time devoted to health (TH_t), a vector of output and input prices (P_t), any shock that could have affected income (IS_t) and individual characteristics (e^i).

$$Y_t = f\left(tec_t, K_t, w_t, WT_{t,}L_t, TH_t, P_t, IS_t, e^i\right) \tag{5}$$

The choice of variables for the health production function (3) is based on UNICEF (1990) framework of child undernutrition[16]. The framework, identifies HH food security status, care for mother and children, and the health environment and services as the three underlying determinants of child undernutrition at the HH level[16].

$$H_t^i = H_{t-1}^i + h(C_t^i, C_t^p, E_t^i, E_t^c, L_t^i, TH_t^i, \cap_t, e^i;\ H_{t-1}^i \tag{6}$$

Child health at period t (H_t^i) can be explained by the initial health stock (H_{t-1}^i); the consumption of private goods (C_t^i) such as food intake; the consumption of public goods (C_t^p) which includes access to clean water and health infrastructure; the educational status of the

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[2] The assumption of a collective household model instead of the alternative bargaining models have the same implication for empirical specification of the structural and reduced-form with change only on the interpretation of some variables[14].

[3] A variable discount factor does not add any value to the final result other than making the calculation more complex[11].

caregiver (E_t^c) and the child (E_t^i); child's and care giver's leisure time (L_t^i); time invested on health-promoting practices (TH_t^i); the surrounding environment ($\cap_t$) such as availability of health infrastructure; and child endowments (e^i) which includes child's genetic makeup, age and sex.

Finally, maximizing the intertemporal utility function subjected to (2)-(6) constraints will give us a reduced health function that is dependent only on exogenous factors.

$$H_t^i = f\left(H_{t-1}^i, E_t^i, E_t^c, \cap_t, e^i, T_t, r, WS_t, tec_t, wt, IS_t, P_t^i, P_t^p, Z_t \right) \tag{7}$$

Following our theoretical model, we used HAZ and stunting as outcome variables. Initial health stock (H_{t-1}^i) is approximated by round 1 (R1) HAZ. Maternal education is used as a proxy for caregiver's educational status (E_t^c). Availability of public health facility in the community is used as environmental factors ($\cap_t$). Age and sex of the child are included as child endowments (e^i). Wealth stock (WS_t) is measured as an index of HH's ownership of items (See Methodology). Moreover, adjustment was also made for other child, HH and community level characteristics including child's general health status, child's dietary diversity score (DDS), HH food insecurity status, HHs participation in productive safety net program, HH dependency ratio and types of residence.

METHODOLOGY

Data

We used the second, third and fourth rounds of the YL Cohort Study Younger Cohort's dataset for Ethiopia. YL collects data on material and social circumstances as well as perspectives and aspirations of 12,000 children in Ethiopia, India, Peru, and Vietnam. YL used a prospective cohort design to follow 3,000 children in each country. The first round of data collection in Ethiopia dates to October and December 2002. At that time, 2,000 0.5-1.5-year-old children (younger cohort-YC) and 1,000 7.5-8.5 years old children (older cohort- OC) were recruited. The second, third and fourth rounds of the survey were carried out in 2006, 2009, and 2012 respectively. YL used a multistage stage sampling technique to collect data in 20 sentinel sites (clusters). In the first stage, four regional states (Amhara, Oromia, SNNPR, and Tigray) and one administrative city (Addis Ababa) were purposively selected. In the second stage, 3-5 Woredas[4] were selected. Woredas experiencing food deficit were oversampled as understanding child poverty is at the heart of the YL. To enable proper comparison and representation, appropriate numbers of richer Woredas were also included. In the third stage, one or more Kebeles[5] from each sample Woreda were selected and data from a randomly selected sample of 100 YC and 50 OC children were gathered. Children were traced in each subsequent rounds of the survey and at R4 only 2.2% the YC and 8.4% of the and OC children were lost to follow up. Details on methodology are available at http://www.younglives.org.uk.

Variable description

Dependent variables

This study has two dependent variables: HAZ and stunting. Anthropometry of each child was measured by trained data collectors using the World Health Organizations (WHO) standardized procedures[18]. Height was measured to the nearest 1mm using a local stadiometer that has a movable head and standing plates. Weight was measured to the nearest 0.1kg using a calibrated digital balance (Soehnle 7831, Germany). Sex and age-adjusted HAZ was computed using the WHO standards[19,20]. Children with implausible values of HAZ (below –6 or above +6) and children with missing values of HAZ for all rounds of the survey were excluded from the analysis[21]. For children with only one missing value, we did a multiple imputation using chained equations in Stata[26] and checked the sensitivity of estimates using complete case analyses. We found no major differences in the direction of the associations, beta coefficients, and p-values. Stunting ("1" if HAZ < -2SD and "0" otherwise) was generated and treated as outcome variables in the main analysis.

Independent variables

Climatic shock

Climatic shocks (drought, flood, and frost) are measured as dichotomous variables that takes

[4] Woreda means district

[5] Kebele is the smallest administrative unit in Ethiopian administration

a value of “1” if the HH had experienced such events in the past 12 months and “0” otherwise.

Dietary diversity score

YL used a 24-hour dietary recall questionnaire to gather information on child dietary diversity (DD). We aggregated child’s consumption of one or more of different variety of foods into 11 food groups according to FAO guide[23]. We summed up the number of food groups eaten and generated a dietary diversity score (DDS).

HH food insecurity (HHFI)

HHFI prevalence is measured using the Household Food Insecurity Access Scale (HFIAS) measurement. After computing the HFIAS measurement score based on Coates et al., we classified HHs as food secure, mildly FI, moderately FI, and severely FI[22]. We then categorized HHs food security status as food secure (coded as 0) and FI (coded as 1) if HHs were mildly, moderately, or severely FI.

Wealth index

Wealth index was computed using Principal Component Analysis (PCA). Items used in the construction of the wealth index include ownership of television, radio, car, motor, bicycle, landline phone, mobile phone, refrigerator, table, chair, sofa, bedstead; the number of rooms per HH member; the quality of toilet, drinking water, cooking material, floor, roof, and wall in the HH; and access to electricity. To account for the varying importance of items over time and lack and/or addition of some items over time, a separate index was constructed for each round. Correlation, internal consistency, and reliability of the items were checked using Cronbach’s alpha (α) and variables with low correlation with other items were excluded from the item list. For all rounds of the survey, α value >0.7 was obtained indicating an adequate internal consistency of the items[24]. All variables were standardized into dummy responses and a covariance matrix was used to obtain weights of PCs followed by Bartter’s and KMO tests of homogeneity of variance across samples (p=0.000 & KMO is >0.8)[25]. After computing the wealth index, we classified HH in to three wealth quintiles as low (1), medium (2) and high (3).

Other covariates

Child age, gender, nutritional status of the child at R1, child’s general health status and dietary diversity were included as child level characteristics. Child age was measured in number of months and both linear and quadratic specifications were used to account for the non-linear growth of a child with age. Child sex was treated as a dichotomous variable that takes a value of “0” for male and “1” for female child. Among the HH level covariates, maternal education was measured as a categorical variable that takes a value 0-4 if the mother had no, informal, primary, secondary and higher education respectively. Participation in productive safety net program (PSNP) was measured as a dummy variable that takes a value of “1” if the HH is a participant and “0” otherwise. Residence was also measured as a dichotomous variable that takes a value of “0” if the child lives in an urban locality and “1” otherwise. Access to a public health facility was also measured as a dichotomous variable that takes a value of “1” if the child lives in a community where there is a public health facility or “0” otherwise. Dependency ratio was computed as the number of non-working age members (0-12 yrs. & >60 yrs.) divided by the number of working age members (13-60 yrs.) multiplied by 100.

Empirical specification

The study utilized the second, third, and fourth rounds of the YL cohort study data set for the YC in Ethiopia. Three separate equations (random intercept model, random intercept probit model, and latent growth curve model) to estimate two dependent variables—HAZ and stunting.

Random intercept model

We used linear mixed effect model was used to examine the effect of climatic shock on HAZ. Commonly used models such as fixed effect (FE) and random effect (RE) can only accommodate general and spherical variance and covariance structures[25]. Moreover, such models omit observations with one or more missing values from the analysis reducing efficiency and probably introducing biases[25]. As a matter of fact, missing values are commonplace in repeated measure studies for reasons that are intended or unintended. In such circumstances, mixed effect models become handy given the necessary steps are carefully followed when choosing the appropriate model. Mixed methods allow for missing data measurement given the missing values are missing at random (MAR). They are more interpretable, they can handle unevenly spaced panel and more importantly can be used when the outcome variable assumes nonnormal distribution[25]. Furthermore, mixed effect model is appropriate for both fixed and time-varying covariates[25].

To choose between random intercept and random slope model, we fitted the mixed effects model using both models and run a post-estimation test using the *estat ic* command in Stata[26]. We then select random intercept model based on Akaike's and Schwarz's Bayesian information criteria. The random intercept model is given as:

$$Y_{ij} = \beta_0 + \beta_{ji}x_i + u_{0i} + \varepsilon_{ij} \tag{8}$$

Where Y is HAZ -score of child i at time j, u_{0i} captures individual i's effect on his/her repeated observations. To check for robustness, we fitted the data into FE and a pooled OLS in addition to random intercept model. The estimates show the same direction of relationship with change only on the significance and the magnitude of the effect (see table 6 annexed).

Random intercept probit model

We used a random intercept probit model to estimate the effect of climatic shock on the likelihood of being stunted. The probit function is given as

$$\Pr\left(y_{ij} = 1 \middle| x_{ij}, u_j\right) = H\left(\, x_{ij}\beta + z_{ij}u_j\right) \tag{9}$$

Where we estimate the probability that the outcome variable Y_{ij} is 1 subjected to a set of fixed effect x_{ij} and random effects u_j. H represents the standard normal distribution function of x_{ij}(fixed effect) and z_j(random effect) covariates. *i* stands for the number of observations in cluster *j*, β is the fixed effect regression coefficient for the random covariate x.

To check for we fitted the data using generalized linear model (GLM), FE probit model, linear probability model (LPM) and logit model. Estimates show a similar sign with a slight change in the magnitude and significance of some variables (see table 6 annexed).

Path model

The impact of climatic shock at an early age might have a long-lasting impact on child nutritional status at later age. To explore this, we used structural equation modeling approach. We fitted HAZ at R4 as an endogenous dependent variable, climatic shocks at R2 as exogenous independent variables, and HAZ at R2 and R3, and climatic shocks at R3 and R4 as endogenous dependent variables (mediators). To reduce bias introduced by missing values, all models were estimated using full information maximum likelihood (FEML) using the "sem" command in Stata software (27). All coefficients were standardized and the default standard error (observed information matrix-OIM) was used. Model fit was assessed using chi-square tests, comparative fit index (CFI), root mean square error of approximation (RMSEA), Pclose, and coefficient of determination(R^2) where adequate fit means a non-significant probability value for the chi-square test ($p<0.05$), CFI close to 1; RMSEA<0.08 and R^2 close to 1[28].

RESULTS

Socio-demographic and economic characteristics

Table 1 elucidates summary statistics of variables used in the analysis. A total of 1911 child, nearly equal proportion of boys (53%) and girls (47%), were included in the main analysis. 78% of the sample has reported the experience of climatic shocks (drought, flood and/or frost).

Table 1. Socio-demographic and economic characteristics, YL, Ethiopia

	Climatic shock		P-value
Variables	Shock[a] (n=1450)	No-shock[a](n=407)	
Child sex			
Female	692 (47.7%)	186 (45.7%)	0.47
Male	759(52.2%)	223 (54.3)	
Child age, median (IQR)	146.0 (143, 149)	145.0 (141, 148)	<0.001
Child height for age z-score			
HAZ (R1), mean (SD)	-1.6 (-2.6, -0.4)	-2.1 (-3.0, -0.8)	<0.001
HAZ (R2), mean (SD)	-1.4 (-2.1, -0.6)	-1.7 (-2.4, -1.0)	<0.001
HAZ (R3), mean (SD)	-1.1 (-1.8, -0.5)	-1.5 (-2.1, -0.8)	<0.001
HAZ (R4), mean (SD)	-1.4 (-2.0, -0.7)	-1.8 (-2.4, -1.2)	<0.001
DDS, mean (SD)	6.1 (1.3)	5.4 (1.3)	<0.001
General child health			
Very poor	24 (1.7%)	8 (2.0%)	
Poor	38 (2.6%)	15 (3.7%)	
Average	149 (10.3%)	58 (14.3%)	
Good	488 (33.7%)	170 (41.8%)	
Very good	748 (51.7%)	156 (38.3%)	
HH food insecurity			
Food Secure	349 (24.1%)	28 (6.9%)	<0.001
Mildly Food Insecure	250 (17.2%)	42 (10.3%)	
Moderately Food Insecure	744 (51.3%)	294 (72.2%)	
Severely Food Insecure	107 (7.4%)	43 (10.6%)	
Wealth index (tertile)			
Low SES	398 (27.5%)	220 (54.1%)	<0.001
Medium SES	460 (31.7%)	161 (39.6%)	
High SES	591 (40.8%)	26 (6.4%)	
Participation in PSNP (last 12months)	223 (15.4%)	125 (30.7%)	<0.001
Maternal education			
No education	477 (39.3%)	220 (58.8%)	<0.001
Informal education	136 (11.2%)	88 (23.5%)	
Primary education	412 (33.9%)	62 (16.6%)	
Secondary education	82 (6.7%)	2 (0.5%)	
Higher education	108 (8.9%)	2 (0.5%)	
Dependency ratio, median (IQR)	0.3 (0.2, 0.6)	0.4 (0.3, 0.8)	<0.001
Public healt facility in the community	524 (41.5%)	20 (5.2%)	<0.001
Residence			
Rural	713 (49.2%)	379 (93.1%)	<0.001
Urban	736 (50.8%)	28(6.9%)	

Shock refers to group of children who reported experience of either drought, flood and/or frost and no- shock refers to a group of children who did not experience climatic shock

In all rounds of the survey, mean HAZ was negative both groups and showed a slight increase over time. Children in the shocks group have a lower HAZ than the no-shock group. Children in the shock group had a higher mean DDS 6.1 (±1.3) than those in the shock group 5.4 (±1.3). Similarly, children who were exposed to drought had a better general health status than the no-shock group.

As far as HH characteristics are concerned, shock group children live in HHs with better food security status. Participation in PSNP program participation is higher among the no-shock group HHs (30.7%) compared to those shock group (15.4%). In both groups, a significant proportion of mothers had no education yet compared to the no-shock groups, mothers in the shock group had a higher educational status. Moreover, average dependency ratio was higher among the no-shock groups (0.4) than the shock group (0.3). We also observed that shock affected HHs were wealthier than the no-shock group HHs. With regards to community characteristics, about half (49.2%) of the children in the shock group live in rural areas whereas 93.1% of children in the no-shock group live in rural areas. Similarly, 41.5% of the children in the shock group live in a community that has a public health facility, whereas only 5.2% of the children in the no shock group live in a community that has a public health facility.

Climatic shocks and linear growth (HAZ): Results of random intercept model

Table 2 reports random intercept model estimates of the association of climatic shocks and HAZ. Model 1 shows the sole effect of climatic shock on HAZ. In this model, experience of drought and frost were negatively associated with HAZ ($\beta = -0.078, p < 0.01$ & $\beta = -0.109, p < 0.01$). Experience of flood on the other hand was positively associated with HAZ ($\beta = 0.057, p = 0.1$), yet the effect was significant only at 1% level of alpha.

When we add child level covariates, the effect of drought and frost on HAZ has increased by 23% and 6% respectively ($\beta = -0.096, p < 0.01$ & $\beta = -0.106, p < 0.01$). The effect of flood turned negative yet insignificant ($\beta = -0.005, p > 0.1$). Child age and age squared were not significantly associated with HAZ ($\beta = 0.012, p > 0.1$& $\beta = 0.00001, p > 0.1$). Though the effect was not significant, being female was associated with lower HAZ ($\beta = -0.014, p > 0.1$). Child's DDS was positively associated with HAZ ($\beta = 0.029, p > 0.1$) yet the effect was not significant. Baseline HAZ and general child health status were positively associated with HAZ ($\beta = 0.221, p < 0.01$; $\beta = 0.038, p < 0.05$).

After adding HH and community level covariates in model 3, the effect of climatic shocks and other child level covariates remained virtually the same except for a significant negative association of the DDS with HAZ for older children ($\beta = -0.001, p < 0.05$). Living in FIHH was associated with lower HAZ ($\beta = -0.056,\ p < 0.1$). Living in HHs that belong to the middle and higher wealth quintile compared to the lowest quintile was positively associated with HAZ ($\beta = 0.043,\ p > 0.1$& $\beta = 0.163,\ p < 0.1$). Participation in PSNP program on the other hand was negatively associated with HAZ ($\beta = -0.109,\ p < 0.01$); however, when drought affected HHs participate in the program, the program has a strong positive association with HAZ ($\beta = 0.229,\ p < 0.01$). Dependency ratio was negatively associated with HAZ ($\beta = -0.130,\ p < 0.01$). Maternal education on the other hand was positively associated with HAZ ($\beta = 0.063,\ p < 0.01$). Considering community level covariates, both rural residence and availability of public health facility were not significantly associated with HAZ ($\beta = 0.002,\ p > 0.1$ & $\beta = 0.025,\ p > 0.1$).

Table 2. Parameter estimate of HAZ, random intercept model, YL, Ethiopia

	Height-for-age HAZ					
	Model1[a]		Model2[b]		Model3[c]	
Factors	β	SE	β	SE	B	SE
Drought	-0.078***	0.026	-0.096***	0.03	-0.165***	0.04
Flood	0.057*	0.031	-0.005	0.036	0.034	0.038
Frost	-0.109***	0.032	-0.116***	0.039	-0.093**	0.043
Age			0.012	0.011	0.015	0.012
Age square			-0.000	0	-0.000	0
Sex			-0.014	0.042	-0.012	0.043
HAZ/BMI-for-age R1			0.221***	0.013	0.222***	0.013
Child health			0.036**	0.015	0.042**	0.017
DDS			0.029	0.033	0.054	0.037
Age*DDS			-0.000	0	-0.000	0
Food insecure					-0.056*	0.031
Wealth (Medium Vs. poor)					0.043	0.038
Wealth (Medium Vs. rich)					0.163***	0.058
PSNP					-0.109***	0.042
Drought*PSNP					0.229***	0.058
Dependency ratio					-0.130***	0.031
Maternal education					0.063***	0.021
Type of site Rural					0.001	0.061
Public health facility					0.025	0.031
Constant	-1.355***	0.023	-1.600**	0.693	-1.864**	0.737
var(_cons)						
Observations	5,627		3,618		2,972	
N_clust	1911		1838		1591	
N	5627		3618		2972	
chi2	25.75		542.0		688.2	
P	1.08e-05		0		0	

a=unadjusted, b=adjusted for child-level characteristics, c=adjusted for HH and community level characteristics, SE=robust standard errors, β=regression coefficients, ***=p<0.01, **=p<0.05, *= p<0.1Climatic shocks an

Climatic shocks and stunting: Results of a random intercept probit model

The next set of models presented in table 3 elucidates the results of a random effects probit regression model estimate of the association of stunting and climatic shocks. Before adjusting for other covariates in model 1, exposure to drought and frost was positively associated with the likelihood of being stunted ($\beta = 0.302, p < 0.01$ & $\beta = 0.195, p < 0.1$). Exposure to flood on the other hand had no significant association with stunting ($\beta = -0.01, p > 0.1$).

After adjusting for child level covariates in model 2, exposure to drought and frost maintained a positive association with the likelihood of being stunted ($\beta = 0.228, p < 0.1, \beta = 0.33, p < 0.05$) and that of flood became positive and significant ($\beta = 0.373, p < 0.05$). Child's age and age squared showed no significant association with stunting ($\beta = 0.021, p > 0.1$ & $\beta = 0.0001, p > 0.1$). Being female and being stunted at baseline were positively associated with the likelihood of being stunted ($\beta = 0.323, p < 0.01$; $\beta = 2.296, p < 0.05$). Though the effect was insignificant, better general child health status was negatively associated with the likelihood of being stunted ($\beta = -0.079, p > 0.1$); however, the effect was not significant. Child's DDS and its interaction with age had no significant association with stunting ($\beta = -0.105, p > 0.1$ & $\beta = 0.001, p > 0.1$).

After adjusting for HH and community level covariates in model 3, drought and flood maintained a significant positive associated with the likelihood of being stunted ($\beta = 0.477, p < 0.01$ & $\beta = 0.34, p < 0.1$). Unlike model 1, the effect of frost became insignificant ($\beta = 0.189, p > 0.1$). General child health was negatively associated with the likelihood of being stunted ($\beta = -0.120, p < 0.1$). Among the HH level covariates, living in a FIHH was

Table3. Parameter estimate of stunting, random effects probit regression model, YL, Ethiopia

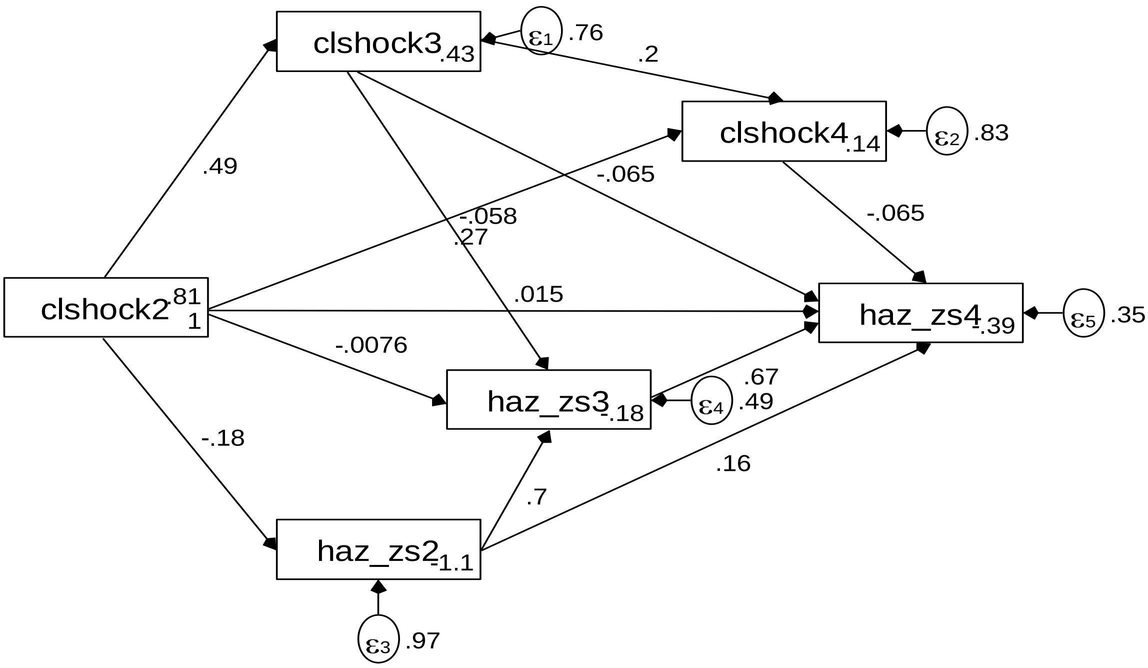
	Stunting					
	Model1[a]		Model2[b]		Model3[c]	
Factors	β	SE	B	SE	β	SE
Drought	0.302***	0.077	0.228*	0.131	0.477***	0.184
Flood	-0.010	0.094	0.373**	0.159	0.340*	0.175
Frost	0.195*	0.105	0.330**	0.163	0.189	0.18
Age			-0.021	0.055	-0.026	0.063
Age squared			0.000	0	0.000	0
Sex(Female)			0.323***	0.113	0.274**	0.136
Stunted/Thin at R1			2.296***	0.368	2.307***	0.5
Child health			-0.079	0.058	-0.120*	0.068
DDS			-0.105	0.169	-0.156	0.194
Age*DDS			0.001	0.001	0.002	0.002
Food insecure					0.283	0.183
Wealth (Poor Vs. Medium)					-0.292**	0.146
Wealth (Poor Vs. Rich)					-0.788***	0.22
PSNP					0.249	0.179
Maternal Education					-0.182**	0.077
Drought*PSNP					-0.868***	0.309
Dependency Ratio					0.180	0.121
Type of site (Rural)					-0.107	0.187
Public health facility					-0.270**	0.133
Constant	-1.407***	0.086	-2.722	3.35	-1.674	3.894
Var(_cons)	3.586	0.459	7.962	3.944	7.898	5.689
Observations	5,627		3,711		3,046	
N_clust	1,911		1,887		1,633	
Ll	-2668		-1620		-1275	
chi2_c	1157		515.8		378.8	
P	3.86e-05		8.09e-10		0.000303	
chi2	23.10		63.43		47.50	

a=unadjusted, b=adjusted for child-level characteristics, c=adjusted for HH and community characteristics, SE=robust standard errors, β=regression coefficients, ***=p<0.01, **=p<0.05, *= p<0.1

positively associated with the likelihood of being stunted ($\beta = 0.283, p > 0.1$), yet this effect was not significant. Living in HHs that belongs to the highest wealth quintile compared to the lowest was negatively associated with likelihood of being stunted ($\beta = -0.788, p < 0.05$). HHs PSNP participation was not associated with the likelihood of being stunted ($\beta = 0.249, p > 0.1$); however, when drought affected HHs participate in the program, PSNP participation showed a strong negative association with the likelihood of being stunted ($\beta = -0.868\ p < 0.05$). HH dependency ratio was not significantly associated with the likelihood of being stunted ($\beta = 0.018, p > 0.1$). Among the community level covariates, living in rural areas was not associated with the likelihood of being stunted ($\beta = -0.107, p > 0.1$) whereas the existence of public health facility in the community was negatively associated with the likelihood of being stunted ($\beta = -0.27, p < 0.05$).

Climatic shock and child undernutrition-Latent growth curve modeling

Figure1 elucidates growth curve mixture model of HAZ and climatic shocks. The fit statistics suggest an adequate fit of the data to the hypothesized relationship. The model elucidates two important points. First, shocks that have occurred in the last 12 months are negatively associated with today's HAZ. Second, climatic shocks that have occurred before 6-7 years was negatively associated with today's HAZ. Accordingly, climatic shock at R4 was negatively associated with HAZ at R4 and climatic shock at R3 was negatively associated with HAZ at R4 (p<0.01). However, Climatic shock at R2 does not show any significant association with HAZ at R4.

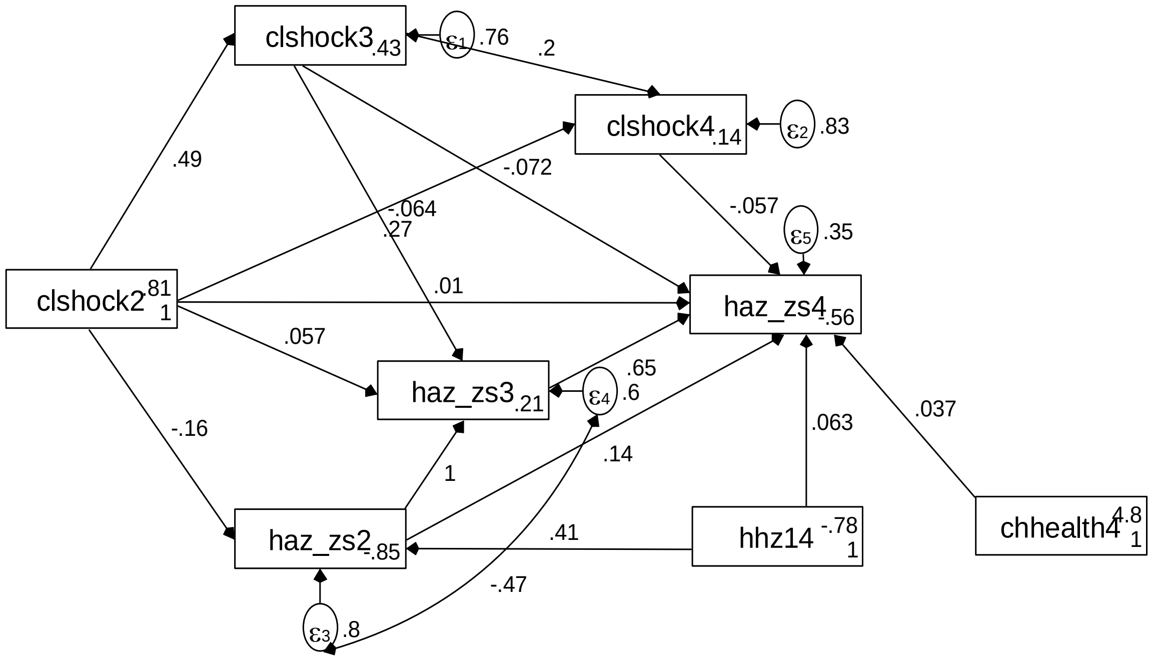


RMSEA = 0.067; Pclose = 0.119; AIC = 19923.561; BIC = 20056.891; CFI = 0.994; TLI = 0.969; CD = 0.307

Figure 1. Path model of climatic shocks and HAZ unadjusted for other covariates, YL, Ethiopia

HHs report of climatic shocks at R2 was positively associated with HH report of shock at R3 ($\beta = 0.493, p < 0.01$). HH report of shock at R2 and R3 in turn were positively associated with HH report of shocks at R4 which in turn was positively associated with HHs report of shocks at R4 ($\beta = 0.267, p < 0.01$& $\beta = 0.204, p < 0.01$). Similarly, HAZ at R2 was positivelly associated with HAZ at R3 ($\beta = 0.7045, p < 0.01$). HAZ at R2 and R3 were also positively assocaited with HAZ at R4 ($\beta = 0.158, p < 0.01$ & $\beta = 0.667, p < 0.01$). With regard to the association of climatic shocks with HAZ, climatic shock at R2 was negatively associated with HAZ at R 2 ($\beta = -0.1829, p < 0.01$). Climatic shocks at R3 was negatively associated with HAZ at R3 and R4 ($\beta = -0.057, p < 0.01$ & $\beta = -0.065, p < 0.01$). HHs report of climatic shocks at R4 was negativelly associated with HAZ at R4 ($\beta = -0.065, p < 0.01$).

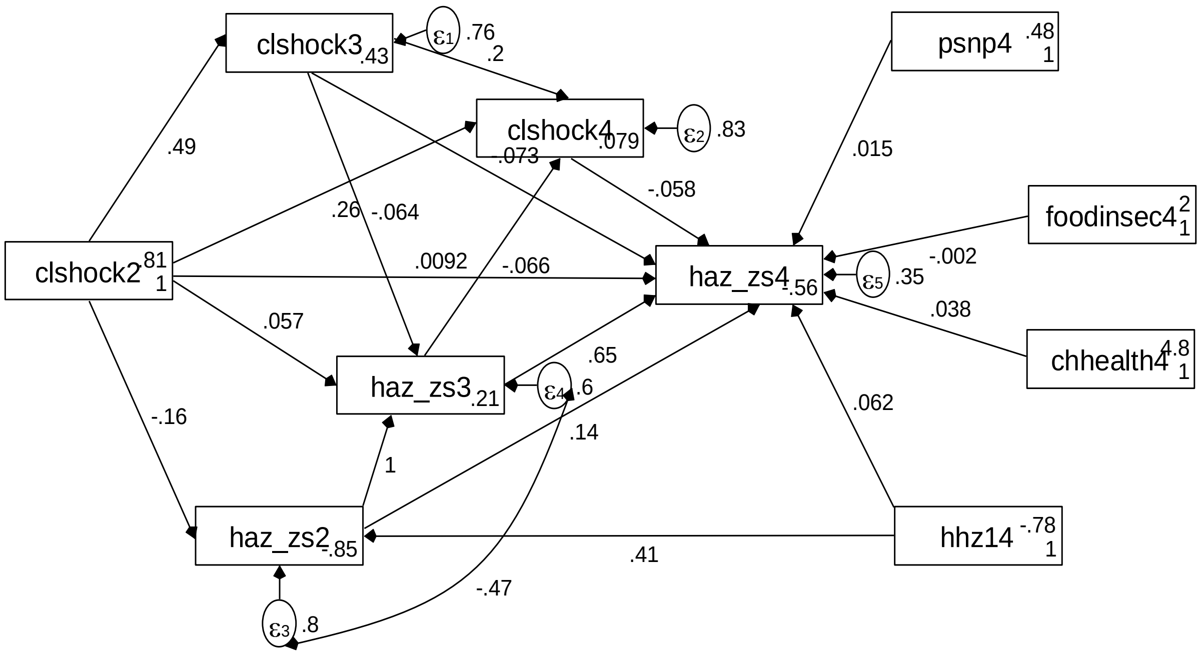
When we adjusted for child level characteristic (fig. 2), the association of climatic shocks and HAZ remained virtually the same. With regard to child level covariates, baseline HAZ was negatively associated with HAZ at R4 ($\beta = 0.063, p < 0.01$) and general child health status was positively associated with HAZ ($\beta = 0.0372, p < 0.01$).



RMSEA = 0.068; Pclose = 0.008; AIC = 19923.561; BIC = 20056.891; CFI = 0.983; TLI = 0.952; CD = 0.461

Figure 2. Path model of climatic shocks and HAZ score, adjusted for child level covariates, YL, Ethiopia

When we add HH level covariates that were significant in the random intercept model, the association of climatic shocks and child level covariates remained virtually the same. HHFI was negatively associated with HAZ ($\beta = -0.0019, p > 0.1$) whereas participation in PSNP was positively associated with HAZ ($\beta = 0.015, p > 0.1$). For more details see table 4 annexed.



RMSEA = 0.069; Pclose = 0.001; AIC = 35438.183; BIC = 35710.396; CFI = 0.970; TLI = 0.934; CD = 0.459

Figure 3 Path model of climatic shocks and HAZ score, adjusted for child and HH level covariates, YL, Ethiopia

DISCUSSION

Child malnutrition remains one of the public health concerns in Ethiopia. It has also been identified as one of the largest adverse impacts of climate change. Nonetheless, Empirical evidence on the effect of climatic shocks on child undernutrition is limited. Thus, the aim this study was to investigate the longitudinal relationship of climatic shocks and child undernutrition and assess the long-term impact of climatic shocks on child undernutrition. Four principal results emerged from our analysis. First, controlling for child, HH and community level covariates, climatic shocks are positively associated with child undernutrition. Second, exposure to climatic shocks at early life is negatively associated with nutritional status at later age. Third, female children are more likely to be stunted than their male counterparts. Fourth, program participation can smooth the negative impact of climatic shocks when program enrollment is based on shock exposure.

In this study, exposure to drought and frost was negatively associated with HAZ. Consistently, previous studies also reported the negative association of drought with HAZ[10-12,29]. Nevertheless, the findings were inconsistent with a study done in Ethiopia which reported no significant association of drought and HAZ[13]. Moreover, exposure to drought and flood was associated with higher likelihood of being stunted. This result is in line with Datar and colleagues finding In India, where the experience of small and medium disaster including flood increased child underweight and stunting by 7%[30].

The observed negative impact of climatic shocks on child nutrition might be due to their negative impact on consumption, healthcare expenditure and time available for child care. For a country like Ethiopia, where the majority of the population earns a living from a rainfed agriculture climatic shocks might lead to crop failure, higher food prices and depress economic activities and wages. This phenomenon, in turn, might reduce food consumption[31,32]; increase opportunity cost of time invested in child care as relatively older HH members might take on other alternative activities to cope with the shock; and also decrease child healthcare care expenditure[30,33] thereby affecting the underlying determinants of child undernutrition and leading to or exacerbating child undernutrition.

As far as the role of child level covariates is considered, better general child health status was positively associated with HAZ and lower likelihood of being stunted. This result is supported by a well-established evidence that documents a positive association between child health and nutritional status[16]. Along the same line, availability of public health facility in the community was positively associated with HAZ and lower likelihood of being stunted. This shows that increased access to healthcare services might improve child health which in turn has a positive impact on nutritional status.

In this study, female children were more likely to be stunted than their male counterparts. From a biological point of view, female sex hormones regulate lipid level and boost immune reaction which leads to better health outcome and longevity[35-37]. From a behavioral point of view, adolescent girls are less likely to consume drugs, alcohol, and unhealthy foods in addition to being less likely to engage in risky activities[38,39]. However, from a socio-cultural point of view, some cultures favor boys than girls[40]. Therefore, a higher likelihood of being stunted among girls than boys might be partly explained by higher negative socio-cultural pressure beyond their biological and behavioral advantages.

Considering HH level covariates, HH food insecurity was negatively associated with HAZ and positively associated with stunting. This result is in line with a study by Ali et al., that showed a positive association of food insecurity with child stunting[41]. The association may be attributed to decrease in food consumption due to climatic shocks as in Dercon et al. [31,32]. Among other HH level covariates, HH wealth was positively associated with HAZ and lower likelihood of being stunted. This finding is in line with Boyle and colleagues finding in 42 developing countries that showed a positive association of HH wealth with child HAZ[42]. Considering the items used in the construction of the index, this result entails a positive association of ownership of HH durables, having access to clean water and sanitation, electricity and dwelling quality which creates a favorable environment for better child nutrition.

In this study, maternal education was associated with higher HAZ and lower likelihood of being stunted. This finding is consistent with other studies in developing countries that[42-46]. The positive association of maternal education with child nutrition might be due to the direct impact of education on maternal income that could be spent on nutritious food and healthcare services, health and nutrition-related information gained through school engagement and self-exploration, increased self-confidence of mothers and hence power over decision related to child nutrition and health and in seeking advice from health care professionals, etc[47].

We also observed that the impact of climatic shock at an early age has a long-lasting effect, i.e. early life shock exposure is negatively associated with nutritional status at later age. Similar to in previous studies[11,13], higher HAZ in previous rounds was positively associated with HAZ in later rounds. We also observed a significant negative association of early exposure to climatic shocks on later HAZ. A study from Tanzania also showed that experience of drought at early age decreases the HAZ of 12-36 months old children and further reduces height during adolescence[29]. This could be due to persistent impact of climatic shocks on consumption as in Dercon et al. [48] and hence decrease in linear growth which results in stunted growth later in life. Along the same line, Hoddinott & Kinsey's work also showed the negative effect of drought on the growth rate of children from poor HHs in Zimbabwe[15]. Moreover, we found a positive association of HH report of shocks indicating that the same group of HHs was repeatedly affected by climatic shocks.

Evidence on the impact of productive safety nets on child nutrition and food insecurity is inconclusive. Berhane et al. (2017) suggest that even though the program had improved food security it had no impact in reducing child undernutrition measured by HAZ and BMI z-score [50]. Similarly, Zamand & Hyder (2016) reported no impact of the program on child HAZ and BMI z-score. On the other hand, Debela et al. (2015) reported the positive impact of the program in reducing undernutrition measured in weight-for-height in Tigray region[52]. However, our study revealed that participation in PSNP by drought-affected HHs decreases the likelihood of being stunted and increased HAZ. The difference might be due to the type of analysis pursued, the type of anthropometric indices considered, sample size and self-selection bias amongst others.

In addition, we observed that socioeconomic and demographic factors at child, HH and community levels also play a substantial role in mediating or moderating the nutritional impacts. In this study, age was associated with a decrease in the magnitude of stunting. Even though other studies have reported the positive association of DD with HAZ and decreased the likelihood of beings stunted, in our study, DD had no significant association with stunting. However, higher DD was associated with higher HAZ, yet the effect turns negative for relatively older children. Higher dependency ratio and living in rural areas was also associated with lower HAZ.

As a final note, these estimates vary from other studies in target population under study, sample size and estimation power. In addition, there are differences in factors such as severity of the shock, duration of the shock, stage of the development of the child at the start of malnutrition, HH-level characteristics, etc. Therefore, lack of consistency with other studies can be partly due to such differences.

Strength and limitations of the study

Our analyses are robust in the face of a wide number of economic concerns including those related to sample specifications, endogeneity, measurement error and unobservable variables at the community, HH, and child levels. Notwithstanding, our estimates have some methodological limitation in measurement, atomistic fallacy and complexity of relationships. In this study, we assumed that the exposure to climatic shocks to be similar for HHs residing in the same sentinel site as a covariate shock than idiosyncratic shocks. However, we estimated the association of climatic shocks with child undernutrition at child level due to the high percentage of intra-cluster variation at child level. Therefore, any inference from our study results about climatic shocks as a covariate shock might leads to atomistic fallacy. Moreover, in the study, the occurrence of climatic shocks was assessed based on HH subjective report of the occurrence of drought, flood and/or frost/hailstorm. Furthermore, the level and pattern of drought, flood and/or frost/hailstorm was not checked and the accuracy of HH report of shocks was not triangulated using meteorological data. Although self-reported shocks at HH level give some picture of the variation in climatic conditions across different regions within a country, if available, a high-quality meteorological data specific to the residence of HHs would have been more accurate. Additionally, even though many studies have demonstrated the effect of seasonality on food insecurity, dietary diversity and child nutrition, our analysis does not take in to account the effect of seasonality.

CONCLUSIONS AND RECOMMENDATIONS

The aim of this study was to investigate the longitudinal association of climatic shocks with child undernutrition and assess the long-term impact of climatic shocks on child undernutrition. Controlling for child, HH and community level covariates, climatic shocks were positively associated with child undernutrition. Moreover, early life exposure to climatic shocks has a significant negative impact on child nutrition at later age. Therefore, if appropriate measures are not taken, the predicted increase in the frequency of extreme events including drought, flood, and frost due to climate change might slow down the existing secular progress in reduction of child undernutrition in Ethiopia and impose a serious challenge to achieve the SDG2.

Socioeconomic and demographic factors at the child, HH and community levels also play a substantial role in mediating or moderating the impacts of climatic shocks. In this study, despite their biological and behavioral advantage, girls were more likely to be stunted than boys. This shows that socio-cultural factors in Ethiopia favor boys than girls. This calls for gender-sensitive interventions targeting female children. Moreover, the effectiveness of culture-sensitive interventions to tackle the intraHH food allocation bias and “food buffering hypothesis” during climatic shock need further investigation.

Our data suggest a strong positive impact of PSNP on child nutrition for drought-affected households. This shows the potential for safety net programs in smoothing the negative impact of climatic shocks on child nutrition when specifically target to shock affected households.

As far as the role of other covariates is considered, better general child health status and availability of public health facility in the community was positively associated with HAZ and lower likelihood of being stunted. This calls for incorporation of other determinants of child nutrition into programs through increased access to health service, clean water, sanitation and nutrition education and expanding access to public health facility and hence improving child health will have a significant contribution in reducing child undernutrition

In our study, HH report of climatic shocks was positively associated i.e. the same group of the population was recurrently affected by climatic shocks. Therefore, programs or interventions targeting to counter the negative impact of climatic shocks should consider diversifying the means of livelihood for recurrently affected populations. Moreover, for the most part, the cause of climate change and hence frequent occurrence of climatic shocks are human activities including increasing population size and deforestation. Therefore, programs should also consider incorporating population control mechanism, and awareness creation on the effect of climate change and deforestation. Future studies might use meteorological data to assess the effect of climatic shocks and child nutrition and also look at the effectiveness of culturally sensitive interventions to tackle intra-HH “food buffering” during climatic shocks.

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ANNEX

Table 4. SEM result of the association of climatic shocks with HAZ, YL, Ethiopia

	Model [a]		Model [b]		Model [c]	
Variables	β	p	β	p	β	p
Clshock_3 <-						
Clshock_2	.4932961	0.000	.4933928	0.000	.5008157	0.000
_cons	.4323441	0.000	.4322213	0.000	.2080979	0.000
Clshock <-						
Clshock_3	.2047712	0.000	.20474	0.000	.1629523	0.000
HAZ_3	.2678696	0.000	.2678487	0.000	-.0223864	0.009
Clshock_2	.1408323	0.000	.1408879	0.000	.2204397	0.000
_cons					.0370291	0.015
HAZ_2 <-						
Clshock_2			-.1587489	0.000	-.3636091	0.000
HAZ_1			.4095494	0.000	.2279002	0.000
_cons			-.8455248	0.000	-.9534641	0.000
HAZ_3<-						
Clshock_3	-.0575593	0.002	-.064096	0.001	-.1268978	0.002
HAZ_2	.7045368	0.000	1.039844	0.000	.9944759	0.000
Clshock_2	-.007579	0.687	.0573099	0.008	.1179426	0.014
_cons	-.1756189	0.000	.2111545	0.000	.2159548	0.000
HAZ_4<-						
Clshock_3	-.0650545	0.000	-.0722463	0.000	-.1492065	0.000
Clshock_4	-.0650562	0.000	-.0569981	0.000	-.1403487	0.000
HAZ_2	.1583877	0.000	.1397568	0.000	.1265295	0.000
HAZ_3	.6675707	0.000	.6519162	0.000	.5956362	0.000
Clshock_2	.0145213	0.381	.0104829	0.526	.0225523	0.513
HAZ_4			.0630612	0.000	.0311827	0.000
Child health_4			.0372842	0.008	.039795	0.013
Food insecure_4					-.00941	0.794
PSNP_4					.038772	0.296
_cons	-.3944372	0.000	-.561804	0.000	-.5534254	0.000
N	1911		1911		1780	
p > chi2	0.000		0.000		0.000	
RMSEA	0.067		0.068		0.07	
pclose	0.092		0.008		0.001	
CFI	0.994		0.983		0.97	
TLI	0.969		0.952		0.933	
CD	0.307		0.461		0.457	

a=unadjusted, b=adjusted for child level characteristics, c=adjusted for HH and community characteristics, SE=robust standard errors, β=regression coefficients, ***=p<0.01, **=p<0.05, *= p<0.1

Table 5. Model specification of HAZ, YL, Ethiopia

	OlS		FE		RI	
Factors	β	SE	β	SE	β	SE
Drought	-0.306***	0.047	-0.093**	0.044	-0.198***	0.038
Flood	-0.077	0.048	0.048	0.043	0.000	0.038
Frost	-0.069	0.048	-0.011	0.046	-0.044	0.041
Age	-0.024***	0.003	-0.026***	0.002	-0.026***	0.002
Age square	0.000***	0	0.000***	0	0.000***	0
Sex (Female)	0.135***	0.03			0.176***	0.037
Stunted in R1	0.261***	0.008			0.276***	0.013
Child health	0.026	0.017	0.027*	0.015	0.026*	0.015
DDS	0.010	0.037	-0.041	0.032	-0.024	0.029
Age*DDS	-0.000	0	0.000*	0	0.000	0
Food insecure	0.012	0.042	-0.055	0.037	-0.038	0.031
Wealth (Poor Vs. Medium)	0.145***	0.038	-0.032	0.048	0.081**	0.035
Wealth (Poor Vs. Rich)	0.391***	0.054	-0.048	0.074	0.235***	0.053
PSNP	-0.217***	0.047	-0.034	0.06	-0.131***	0.042
drought*PSNP	0.329***	0.074	0.066	0.065	0.186***	0.058
Dependency ratio	-0.119***	0.031	-0.090**	0.042	-0.114***	0.028
Maternal education	0.017	0.015	0.022	0.124	0.031*	0.018
Residence	0.152***	0.045	0.535**	0.239	0.047	0.052
Public health faciliy	0.014	0.031	-0.041	0.033	0.006	0.027
Constant	0.293	0.242	-0.268	0.44	0.706***	0.203
N	4,014		4,014		4,014	
p	0.000		0.000		0.000	
sigma_u			1.126		0.8	
sigma_e			0.5		0.5	
rho			0.83		0.7	

OLS=Ordinary Least Square, FE=Fixed Effect, RE=Random Effect, β=regression coefficients, SE=robust standard errors, ***=p<0.01, **=p<0.05, *= p<0.1. All models are adjusted for child, household and community level covariates.

Table 6. Model specification of stunting, YL, Ethiopia

	RE		FE		GLM		LPM	
Factors	β	SE	β	SE	β	SE	β	SE
Drought	0.63***	0.15	0.47	0.35	0.37***	0.07	0.03	0.02
Flood	0.43***	0.15	0.43	0.34	0.26***	0.07	0.02	0.02
Frost	-0.01	0.15	0.17	0.33	-0.01	0.07	0.00	0.02
Age	0.07***	0.01	0.11***	0.02	0.03***	0.01	0.01***	0
Age square	-0.00***	0	-0.00***	0	-0.00***	0	-0.00***	0
Sex (Female)	-0.40***	0.12			-0.14***	0.05		
Stunted in R1	2.28***	0.31			1.11***	0.06		
Child health	-0.10*	0.06	-0.15	0.13	-0.04	0.03	-0.02**	0.01
DDS	0.07	0.12	0.26	0.29	-0.06	0.07	0.02	0.02
Age*DDS	-0.00	0	-0.00	0	0.00	0	-0.00	0
Food insecure	0.30**	0.14	0.75**	0.33	0.03	0.08	0.04**	0.02
Wealth (PoorVs.Medium)	-0.33***	0.13	-0.00	0.39	-0.19***	0.06	0.01	0.03
Wealth (Poor Vs. Rich)	-0.83***	0.2	0.20	0.63	-0.63***	0.11	0.02	0.04
PSNP	0.28*	0.16	-0.19	0.48	0.17**	0.08	0.03	0.03
drought*PSNP	-0.67***	0.23	-0.67	0.5	-0.38***	0.11	-0.05	0.03
Dependency ratio	0.26**	0.1	0.31	0.43	0.11**	0.04	0.02	0.02
Maternal education	-0.10*	0.06	6.36	460.38	-0.04	0.03	0.04	0.07
Residence	-0.11	0.17	0.01	1.88	-0.19**	0.08	-0.01	0.13
Public health faciliy	-0.12	0.11	-0.48	0.31	-0.00	0.05	-0.00	0.02
Constant	-7.39***	1.21			-3.64***	0.44	-0.37	0.24
N	4,128		540		4,128		4,128	
chi2	89.05		106.5		752.0			
p	0.000		0.000		0.000		0.000	
ll	-1750		-133.9					
sigma_u							0.406	
sigma_e							0.271	
rho							0.692	

RE=Random Effect, FE=Fixed Effect, GLM=Generalized Linear Model, LPM=Linear Probability Model, β=regression coefficients, SE=robust standard errors, ***=p<0.01, **=p<0.05, *= p<0.1. All models are adjusted for child, household and community level covariates.