‘No rain, no harvest, no food’: Impacts of droughts on undernutrition among children aged under five in Ethiopia

Anna Dimitrova[1] & Raya Muttarak[1,2]

[1] Wittgenstein Centre for Demography and Global Human Capital (IIASA, VID/ ÖAW and WU), International Institute for Applied Systems Analysis (IIASA), Austria
[2] School of International Development, University of East Anglia, UK

Abstract

Chronic seasonal crop and livestock loss due to heat stress and rainfall shortages can pose a serious threat to human health, especially in sub-Saharan Africa where subsistence and small-scale farming dominate. Young children, in particular, are susceptible to undernutrition when households experience food insecurity because nutritional deficiencies affect their growth and development. Whilst climate change can potentially pose serious health impacts on children, the evidence is inconclusive and rather limited to small-scale local contexts. Furthermore, little is known about the differential impacts of climatic shocks on health of population subgroups. This study therefore aims to investigate the impacts of climate variability on child health using data from three nationwide Demographic and Health Surveys for Ethiopia conducted in 2005, 2011 and 2016 (n=31,096). Chronic and acute undernutrition, measured as stunting, wasting and underweight for children aged under five, is used as a health indicator. Climate variability is measured by the Standardised Precipitation Evapotranspiration Index (SPEI). The results show a negative relationship between SPEI and stunting and underweight. Children exposed to droughts in utero or during infancy are particularly vulnerable to drought-induced stunting and underweight. The climate impacts vary with population subgroups whereby boys and children whose mothers have lower level of education and living in the rural area where households are engaged in agricultural activities are more vulnerable to drought exposure. This suggests that nutritional intervention should target these particularly vulnerable groups of children.

1. *Introduction*

Climate change poses serious risks to populations in Sub-Saharan Africa, mainly through undermining food security (Funk and Brown 2009). Millions of people in the region live in rural areas and depend on rain-fed agriculture for their subsistence. Rising temperatures and irregular rainfalls have increased the frequency of droughts in the region. At the same time, heavy precipitation is projected to rise and consequently increase the risk of floods and landslides. The consequences for the well-being of populations exposed to such climatic shocks are manifold – from the loss of lives, water contamination and home damage due to floods, to reduced agricultural production and food insecurity caused by droughts and floods.

Likewise, the increase in frequency and intensity of extreme weather events has raised concerns about their impacts on child undernutrition (Lloyd et al. 2011; Springmann et al. 2016). Not only is undernutrition one of the main causes of death for children age under 5 years, it also affects growth and development and has long-run effects on health, wellbeing and labour market productivity in adulthood (Martins et al. 2011; McGovern et al. 2017). A systematic review and meta-analysis of 18 studies on undernutrition in Ethiopia report an upward trend in the prevalence of stunting and underweight in recent years (2010-2014) with respect to the earlier period (1996-2010) (Abdulahi et al. 2017). Indeed, climate change may have played a role in delaying a progress in decreasing the levels of child undernutrition in Ethiopia. Understanding to what extent and how climate change can impact child health is of high policy relevance because this allows for interventions to reverse the course of undernutrition which hinder a country's economic and social progress towards the Sustainable Development Goals (Muttarak and Dimitrova 2019). There is however limited reliable evidence and robust study designs on the impacts of extreme climate events on child undernutrition (Belesova et al. 2019; Phalkey et al. 2015). Most studies focus on small-scale local context, fail to report data quality control procedures and represent shortcomings in the climate exposure assessment methods e.g. lack of drought definition and direct measures of drought. The lack of nationally representative study makes it difficult to assess the extent to which climate change affects child undernutrition.

To this end, this study aims to explore the impacts of droughts on the nutrition status of children aged under five in Ethiopia using the nationally representative data obtained from three rounds of the Demographic and Health Surveys for Ethiopia. We additionally consider differential vulnerability, investigating the extent to which droughts affect the health outcome of children of different demographic and socioeconomic groups. Specific age of exposure that are critical for children's physical development are also considered.

2. *Data and measurement*

We use two datasets to assess the impacts of droughts on the nutrition status of children: 1) multiple rounds of Demographic and Health Surveys (DHS) for Ethiopia and 2) gridded climate data from the Global SPEI database (SPEIbase).

2.1. *Demographic and health variables*

The DHS surveys are based on nationally representative samples of households and women of reproductive age (15-49 years) with a focus on fertility behaviour, infant and child mortality, child and reproductive health, nutrition status, family planning and other health-related issues. The surveys also include socioeconomic information (such as parental education, household wealth, residence, and occupation), which are expected to influence the nutrition status of children. In this analysis, three rounds of DHS Ethiopia are merged – 2005, 2011 and 2016, with a combined sample size of 31,096 children under the age of five. The selected DHS rounds also include GPS coordinates of household clusters,[1] which are used to link the survey and climate data (see section 2.3).

To measure child undernutrition, we use anthropometric data for children aged under 5 and construct indicators for stunting, wasting and underweight as binary outcomes. Stunting refers to children with a low height-for-age (HAZ) defined as below -2 standard deviations (SD) of the WHO Child Growth Standards median. Wasting and underweight refer to children with a low weight-for-height (WHZ) and weight-for-age (WAZ), respectively, both defined as below -2 SD of the WHO Child Growth Standards median. Stunting captures the cumulative effects of undernutrition (chronic malnutrition) while wasting indicates acute weight loss. Being underweight can indicate both acute and chronic malnutrition. It is often used in combination with the above measures as an operational indicator.

2.2. Climate variables

Gridded climate data on Standardised Precipitation Evapotranspiration Index (SPEI) is retrieved from the Global SPEI database. The data are available at 0.5° spatial resolution for the whole globe and are based on Climatic Research Unit's TS 3.25 input data (monthly precipitation and potential evapotranspiration) for the period 1901-2016 (Harris et al. 2014).

SPEI measures the intensity and spatial distribution of droughts. It is considered superior to other drought indices (such as the SPI), since it captures the effects of evaporation and transpiration caused by temperature, along with precipitation (Vicente-Serrano et al. 2010). Additionally, SPEI can be calculated at different time scales (from 1 to 48 months) to account for the cumulative effect of deficient precipitation and/or excessive evapotranspiration over previous periods. In this analysis, we use a 3-month time scale, which has been found to detect drought conditions in the Sahel region more accurately than longer time scales (Beguería et al. 2010).

SPEI is measured on an intensity scale with both negative values, indicating drought conditions, and positive values, indicating wet conditions. The index can be used to further categorise drought conditions into mild ($-1 < \text{SPEI} < 0$), moderate ($-1.5 < \text{SPEI} \leq -1$), severe ($-2 < \text{SPEI} \leq -1.5$), and extreme ($\text{SPEI} \leq -2$) (Mckee et al. 1993; Paulo and Pereira 2006).

We restrict the SPEI data to the summer season only (months June to September), which is the main growing season for agricultural crops in Ethiopia. Seasonal averages are then estimated for each location based on the monthly SPEI values. Deficient or delayed rainfall during the summer season impacts both crop and livestock production. It can indirectly affect human health through reduced food intake and lower availability and quality of drinking water.

[1] Household clusters are enumeration areas used in DHS, which usually refer to villages in rural areas and city blocks in urban areas.

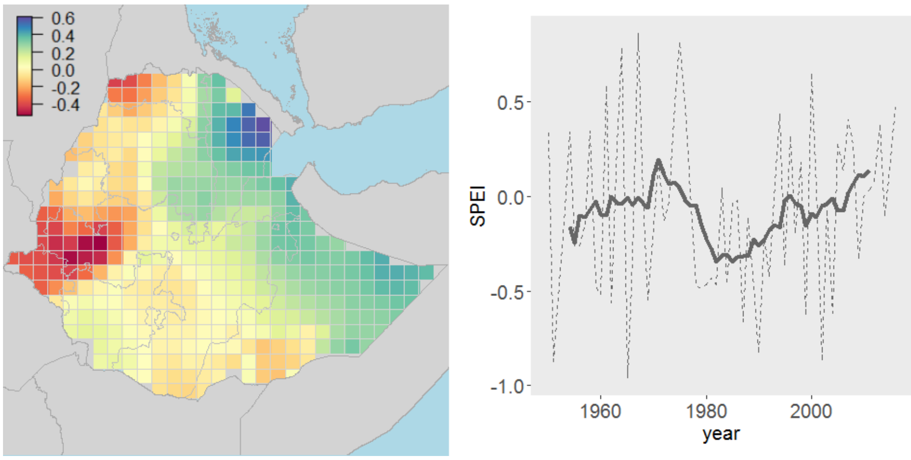

Figure 1: Mean summer SPEI by grid cell 2000-2016 (left) and country average of summer SPEI from 1950 to 2016 (right). Notes: Own estimates based on CRU TS 3.25 monthly temperature and precipitation data. Dotted line indicates yearly values; solid line indicates a 10-year running mean.

2.3. Matching the surveys and climate data

More recent rounds of DHS have collected information on the geographical location of household clusters. We use GPS coordinates to geo-locate children's residence and match them with the gridded climate data. To keep the identity of survey participants confidential, DHS displaces household clusters in a random direction by 2km for urban areas, 5km for rural areas, and additional 10km for 5% of all clusters (Burgert et al. 2013). We account for this by creating a 10km radius around each cluster and averaging the climate information for all grid cells that fall within that area. The 10km buffer area also accounts for the fact that household's nutritional status may be affected not only by climate conditions in their immediate location but also in nearly locations.

3. Methods

We use logistic regression models to quantify the impact of climate shocks on child nutrition status. The basic model takes the following form:

$$Health_{i,g} = \beta_1 SPEI_{t,g} + \beta_2 Z_i + \beta_3 Survey_i + f(a_6, a_{12}, a_{18}, a_{24}, a_{36}, a_{48}) + \alpha_g + \epsilon_{i,g}$$

where *Health* takes the value 1 if child *i* at interview in location *g* is stunted/wasted/underweight, and 0 otherwise. SPEI is the climate condition in period of exposer *t* at grid-cell *g*. *Z* is a vector of individual and household characteristics, which are expected to affect a child's neutrino status. *Survey* are dummy variables for each of the survey rounds. The function *f(·)* is a restricted cubic age spline with knots at 6, 12, 18, 24, 36, and 48 months of age at interview. The spline function fits polynomials of degree 3 between the defined knots in a way which ensures that levels and derivatives are equal on each side, and quadratic terms at each end. α_g are grid fixed effects. Errors are clustered at the grid-cell level. Household clusters are allocated in 50x50km grid-cells.

The following control variables are included in vector *Z*: sex of the child, if the child is a twin or not, quarter of birth (January to March, April to June, July to September, October to December), highest level of education of the mother, household wealth quintile, sex of the household head, mother's age at giving birth, mother's height, residence (urban or rural), and occupation of the household head.

For stunting, we look at exposer to climate shocks at each year of the child's life, starting from in-utero (while the child was in the womb) until the year when the survey was conducted. We also average climate conditions during the entire period. For wasting and underweight, we consider exposer to climate shocks during the latest agricultural season prior to the interview because we expect a more immediate response to droughts.

4. Results

4.1. Descriptive statistics

Table 1: Summary statistics

	Number of observations	Nutrition status		
		% stunted	% wasted	% underweight
Sex of child				
Male	15,925	42.13	13.38	30.13
Female	15,171	38.53	10.87	26.73
Mother's level of education				
No education	21,855	44.2	13.57	32.53
Primary	6,897	36.03	9.78	22.51
Secondary	1,707	21.02	6.92	11.2
Tertiary	637	14.14	5.68	5.62
Household's wealth				
Lowest quintile	9,623	44.69	16.12	35.44
Lower quintile	5,643	45.87	12.78	33.04
Middle quintile	5,092	42.36	11.92	29.43
Higher quintile	4,704	40.73	8.91	24.34
Highest quintile	6,034	25.56	7.58	14.47
Residence				
Urban	5,002	24.62	8.8	14.04
Rural	26,094	43.35	12.77	31.16
Occupation of household head				
Non-agriculture	6,944	31.59	9.5	19.45
Agriculture	19,425	44.81	12.57	32.06
Not working	3,991	36.47	14.94	28.08
Other	736	32.73	11.35	24.07
Survey year				
2005	9,722	47.03	13.28	33.48
2011	11,187	43.17	11.85	30.76
2016	10,187	34.25	11.94	23.53
Sample size	**31,096**			

4.2. Main results

Table 2 presents regression estimates of the odds of stunting, wasting and underweight for children aged under 5. We find that higher SPEI during the observed life-course reduces the odds of a child being stunted and underweight by 23% and 17%, respectively, both at 1% significance level. An increase in SPEI during the latest summer season does not affect the odds of a child suffering from wasting or underweight.

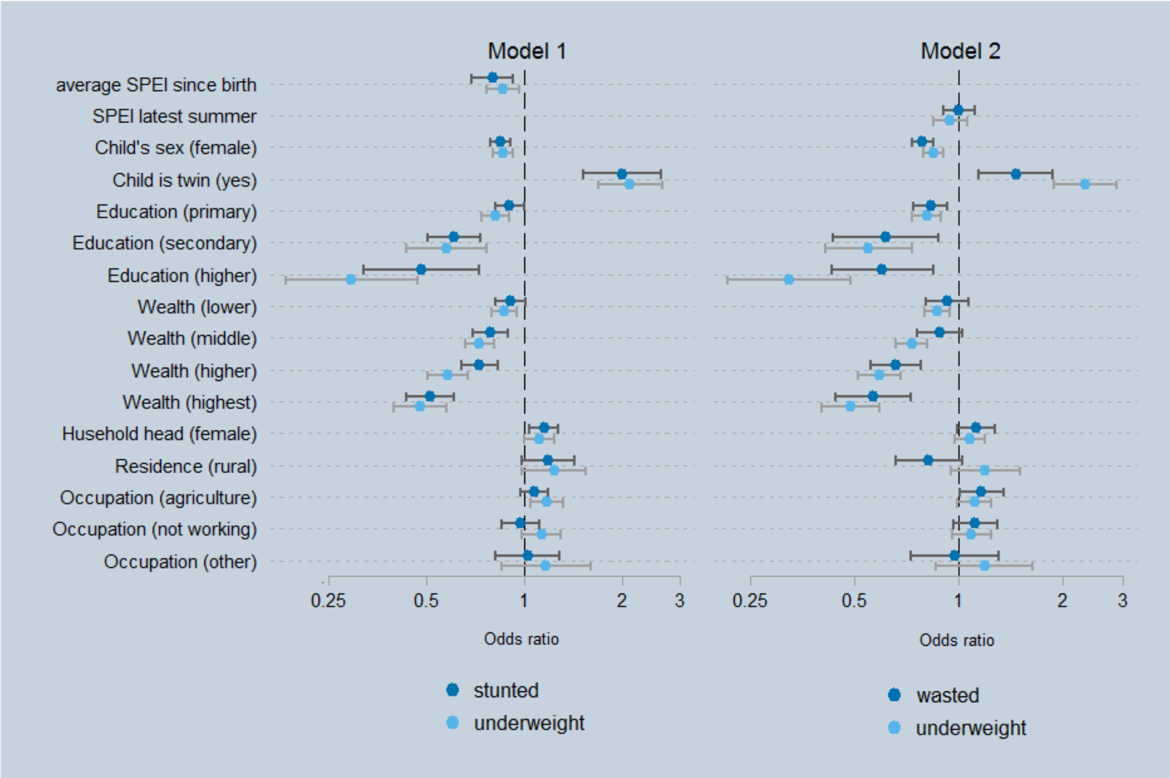

Figure 2: Effects of summer season SPEI on undernutrition of children aged 0-5. Notes: The coefficients are obtained from logistic regression estimates. Odds ratios are displayed on a log scale.

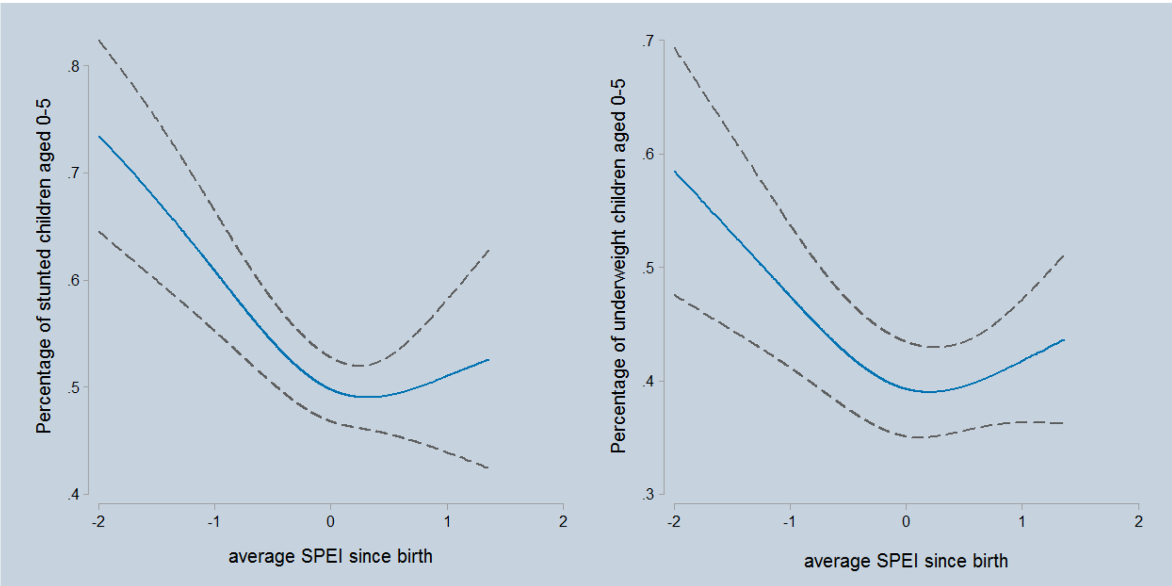

Figure 3: Impacts of summer season SPEI on stunting and being underweight (percentage points with 95% Cis)

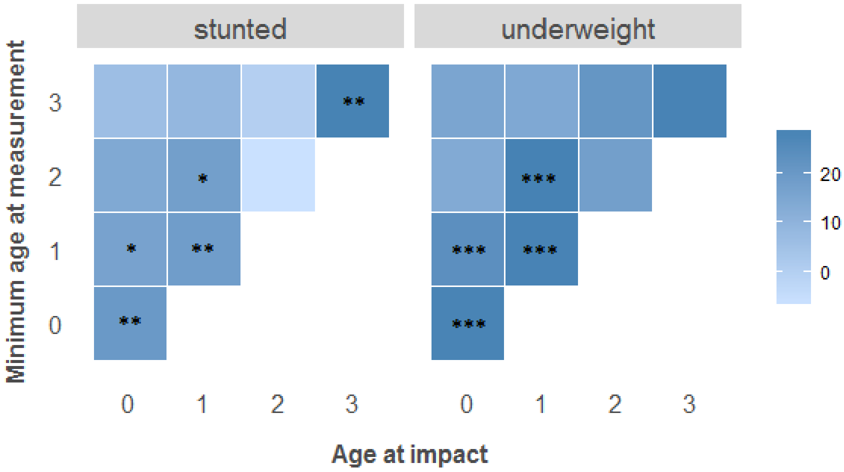

Table 4: Impacts of summer droughts on stunting and being underweight by age at exposure and age at measurement (percentage points). Notes: *** p<0.01, **p<0.05, * p<0.1.

4.3. Differential vulnerabilities

In Table 4, we include interaction terms between the climate measure and various household characteristics in order to identify what types of households are more vulnerable to climate variabilities. The household characteristics include mother's level of education, family's occupation, residence and sex of the household head. Our findings suggest that children whose mothers' have lower levels of education are more likely to be malnourished during drought periods. We also find that boys and children living in rural areas are more vulnerable to droughts.

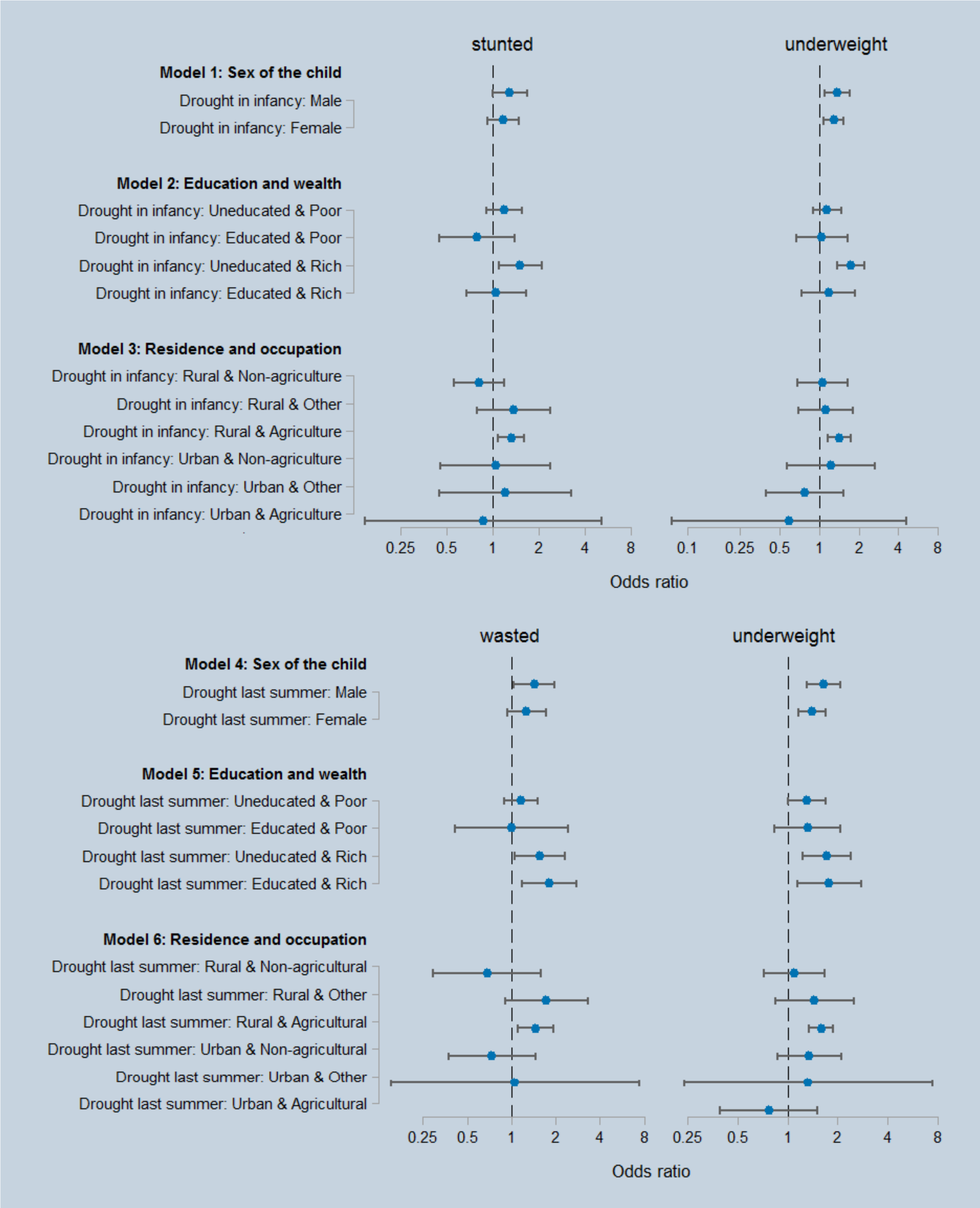

Figure 5: Interaction effects between summer drought and individual and household characteristics. Notes: Models 1 to 6 show the results of separate logistic regression models. Odds ratios are displayed on a log scale.

5. Discussion and conclusions

We find that exposure to droughts increases the likelihood of stunting and underweight for children age under five in Ethiopia. Children who were exposed to droughts in utero or during infancy (age 0 to 1 year) are particularly vulnerable to undernutrition. Boys are more likely to be undernourished compared to girls both in normal time and time of droughts. Unlike in southern Asian countries like India (Muttarak and Dimitrova 2019), we find no evidence of gender preferential feeding practice in

Ethiopia whereby the risk of undernutrition in girls catch up with that of boys (given that naturally boys require more calories when growing up and hence are more likely to be stunted or underweight). Furthermore, children whose mothers have lower level of education and living in the rural area where households are engaged in agricultural activities are more vulnerable to drought exposure. This suggests that nutritional intervention should target these particularly vulnerable groups of children.

References

Abdulahi, A., Shab-Bidar, S., Rezaei, S., & Djafarian, K. (2017). Nutritional Status of Under Five Children in Ethiopia: A Systematic Review and Meta-Analysis. *Ethiopian Journal of Health Sciences*, *27*(2), 175–188.

Beguería, S., Vicente-Serrano, S. M., Angulo-Martínez, M., Beguería, S., Vicente-Serrano, S. M., & Angulo-Martínez, M. (2010). A Multiscalar Global Drought Dataset: The SPEIbase: A New Gridded Product for the Analysis of Drought Variability and Impacts. *Bulletin of the American Meteorological Society*, *91*(10), 1351–1356. https://doi.org/10.1175/2010BAMS2988.1

Belesova, K., Agabiirwe, C. N., Zou, M., Phalkey, R., & Wilkinson, P. (2019). Drought exposure as a risk factor for child undernutrition in low- and middle-income countries: A systematic review and assessment of empirical evidence. *Environment International*, *131*, 104973. https://doi.org/10.1016/j.envint.2019.104973

Burgert, C. R., Colston, J., Roy, T., & Zachary, B. (2013). Geographic Displacement Procedure and Georeferenced Data Release Policy for the Demographic and Health Surveys [SAR7].

Funk, C. C., & Brown, M. E. (2009). Declining global per capita agricultural production and warming oceans threaten food security. *Food Security*, *1*(3), 271–289. https://doi.org/10.1007/s12571-009-0026-y

Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. *International Journal of Climatology*, *34*(3), 623–642. https://doi.org/10.1002/joc.3711

Lloyd, S. J., Kovats, R. S., & Chalabi, Z. (2011). Climate change, crop yields, and undernutrition: development of a model to quantify the impact of climate scenarios on child undernutrition. *Environmental Health Perspectives*, *119*(12), 1817–1823. https://doi.org/10.1289/ehp.1003311

Martins, V. J. B., Toledo Florêncio, T. M. M., Grillo, L. P., Franco, M. do C. P., Martins, P. A., Clemente, A. P. G., et al. (2011). Long-Lasting Effects of Undernutrition. *International Journal of*

Environmental Research and Public Health, *8*(6), 1817–1846. https://doi.org/10.3390/ijerph8061817

McGovern, M. E., Krishna, A., Aguayo, V. M., & Subramanian, S. (2017). A review of the evidence linking child stunting to economic outcomes. *International Journal of Epidemiology*, *46*(4), 1171–1191. https://doi.org/10.1093/ije/dyx017

Mckee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Eighth Conference on Applied Climatology*, 17–22.

Muttarak, R., & Dimitrova, A. (2019). Climate change and seasonal floods: potential long-term nutritional consequences for children in Kerala, India. *BMJ Global Health*, *4*(2), e001215. https://doi.org/10.1136/bmjgh-2018-001215

Paulo, A. A., & Pereira, L. S. (2006). Drought Concepts and Characterization. *Water International*, *31*(1), 37–49. https://doi.org/10.1080/02508060608691913

Phalkey, R. K., Aranda-Jan, C., Marx, S., Höfle, B., & Sauerborn, R. (2015). Systematic review of current efforts to quantify the impacts of climate change on undernutrition. *Proceedings of the National Academy of Sciences*, *112*(33), E4522–E4529. https://doi.org/10.1073/pnas.1409769112

Springmann, M., Mason-D'Croz, D., Robinson, S., Garnett, T., Godfray, H. C. J., Gollin, D., et al. (2016). Global and regional health effects of future food production under climate change: a modelling study. *The Lancet*, *387*(10031), 1937–1946. https://doi.org/10.1016/S0140-6736(15)01156-3

Vicente-Serrano, S. M., Beguería, S., López-Moreno, J. I., Angulo, M., & El Kenawy, A. (2010). A New Global 0.5° Gridded Dataset (1901–2006) of a Multiscalar Drought Index: Comparison with Current Drought Index Datasets Based on the Palmer Drought Severity Index. *Journal of Hydrometeorology*, *11*(4), 1033–1043. https://doi.org/10.1175/2010JHM1224.1

Annex: Logistic regression results (full tables)

Table 1: Effects of monsoon season SPEI on nutritional status of children aged 0-5

	(1) stunted	(2) underweight	(3) wasted	(4) underweight
Climate variables				
Average SPEI since birth	0.779***	0.847***		
	(0.059)	(0.053)		
SPEI last summer			0.972	0.925
			(0.057)	(0.055)
Drought last summer				
Controls				
Sex (female)	0.845***	0.854***	0.788***	0.848***
	(0.030)	(0.027)	(0.033)	(0.027)
Twin (yes)	2.024***	2.142***	1.533***	2.343***
	(0.263)	(0.288)	(0.220)	(0.303)
Mother's educ (primary)	0.917*	0.833***	0.850***	0.830***
	(0.046)	(0.043)	(0.051)	(0.039)
Mother's educ (secondary)	0.618***	0.576***	0.629***	0.552***
	(0.071)	(0.090)	(0.100)	(0.079)
Mother's educ (tertiary)	0.496***	0.301***	0.589***	0.329***
	(0.104)	(0.069)	(0.100)	(0.070)
Wealth (poorer)	0.915*	0.888**	0.962	0.886**
	(0.048)	(0.046)	(0.064)	(0.044)
Wealth (middle)	0.797***	0.752***	0.917	0.752***
	(0.050)	(0.041)	(0.072)	(0.041)
Wealth (richer)	0.729***	0.596***	0.701***	0.603***
	(0.047)	(0.042)	(0.055)	(0.040)
Wealth (richest)	0.505***	0.490***	0.591***	0.502***
	(0.048)	(0.045)	(0.064)	(0.045)
Household head (female)	1.125**	1.105*	1.145**	1.077
	(0.065)	(0.064)	(0.077)	(0.060)
Age at birth (years)	0.994**	0.998	1.002	0.998
	(0.003)	(0.003)	(0.004)	(0.003)
Mother's height (cm)	0.995***	0.996***	0.999	0.996***
	(0.000)	(0.000)	(0.000)	(0.000)
Residence (rural)	1.180	1.187	0.763**	1.160
	(0.154)	(0.167)	(0.090)	(0.160)
Occupation (agriculture)	1.053	1.167**	1.203**	1.117*
	(0.064)	(0.073)	(0.089)	(0.065)
Occupation (not working)	0.985	1.075	1.076	1.043
	(0.069)	(0.079)	(0.078)	(0.073)
Occupation (other)	0.999	1.172	1.017	1.194
	(0.129)	(0.152)	(0.157)	(0.168)
Pseudo R2	0.118	0.093	0.075	0.107
Observations	18,503	18,897	21,409	22,150

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

Notes: The coefficients are obtained from logistic regression estimates. Controls included but not displayed: age splines, quarter of birth, quarter and year of interview, grid fixed effects. Errors are clustered at the grid-cell level. Odds ratios are displayed on a log scale.