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Weather shocks and child nutrition

Evidence from Tanzania

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This publication results from Sustainable development solutions for Tanzania – strengthening research to achieve SDGs, a collaborative project between the UONGOZI Institute in Dar es Salaam, Tanzania, and UNU-WIDER in Helsinki, Finland, with a main research objective of informing the development and implementation of policies aiming for economic transformation and sustainable development in Tanzania and the East African region. With financial support provided by the Ministry for Foreign Affairs of Finland, the joint project launched in 2018 with key questions giving the partners a framework for collaboration and the research work to be undertaken. The project focuses on macroeconomic perspectives, domestic resource mobilization, extractives, industrialization, sustainable livelihoods, and gender as a cross-cutting issue. The project provides local stakeholders a platform for research and policy discussions on Tanzania and bridges these discussions to the regional and international development debate.

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Abstract: In this paper, we examine the relationship between childhood exposure to adverse weather shocks and nutritional and health outcomes of children in Tanzania. Using household panel data matched with spatially disaggregated data on weather shocks, we exploit the plausibly exogenous variations in the exposure to weather shocks to estimate the relationship. Our results reveal a positive association between exposure to dry weather shocks and stunting among children. The effects are profound in the first 12 months after childbirth. The findings, however, indicate that wet shocks such as flooding have no discernible impact on child health.

Key words: child nutrition, Tanzania, weather shocks

JEL classification: I15, Q54, O13

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1 Introduction

Several studies have documented long-term consequences of early-life exposure to shocks (Adhvaryu et al. 2015, 2018; Aguilar and Vicarelli 2011; Beuermann et al. 2017; Lavy et al. 2016; Maccini and Yang 2009; Singhal 2019). Early-life exposure to negative economic shocks induced by weather shocks, for instance, has been shown to have negative impacts on mental health (Adhvaryu et al. 2015; Singhal 2019), cognitive development and education (Adhvaryu et al. 2018; Lavy et al. 2016), physical disabilities (Dinkelman 2017), and employment (Adhvaryu et al. 2018) in adulthood. These long-term impacts of early-life exposure to shocks operate through the effects on nutritional intake and health outcomes of children exposed to these shocks. Adhvaryu et al. (2018), for instance, show that social assistance programmes such as cash transfers to families exposed to extreme weather shocks can ameliorate the long-term consequences of the shocks on their children.

In spite of this, there is limited evidence on the impact of early-life shocks on the nutritional and health outcomes of children in Sub-Saharan Africa (SSA) (Arslan et al. 2016; Blom et al. 2019) where exposures to weather shocks are high due to the heavy reliance on rain-fed agriculture and the limited access to safety nets (Haile et al. 2018; Letta et al. 2018).

In this paper, we examine the short-run effects of exposure to extreme weather shocks (a measure of resource availability) on the nutritional and health outcomes of children (under five years old) in Tanzania. Available data on Tanzania suggest that about one-third of all children under age five are stunted, with one in six children aged 24–35 months severely stunted (NBS 2016a). Thus, the goal of this paper is to estimate the extent to which exposure to extreme weather shocks explains the variation in the rate of stunting among children, given that agriculture is the mainstay of households in the country. In addition, the paper examines the potential pathways through which exposure to weather shocks affects the nutritional and health outcomes of children in the country.

To this end, we use geocoded panel data on households from the Tanzanian National Panel Survey (TNPS) matched with spatially disaggregated data on weather shocks using the Standard Evapotranspiration Index (SPEI). We focus solely on children aged 59 months and below (i.e. under five years) at the time of the survey. Using the SPEI data, we construct exposure to extreme weather shocks (negative/dry and positive/wet). Our identification strategy relies on the plausibly quasi-random weather patterns across space and time. In our study's agrarian setting, whereby agriculture is the mainstay of most households, extreme wet and dry weather shocks constitute a significant resource constraint that can inevitably influence the nutritional intake of children born during episodes of extreme weather shocks.[1]

Our findings reveal a positive association between exposure to dry weather shocks and the probability of stunting among children under five years. The effects are statistically and economically significant. Specifically, a one-month increase in exposure to dry weather shocks is associated with a 0.8 percentage point (or 2.4 per cent relative to the sample mean) increase in the probability of stunting. Exposure to wet shocks, however, has no effect on the rate of stunting. Further, our findings show that the effects are profound in the first 12 months after birth. Rural-living children are also more likely to be affected by dry weather shocks than their urban-dwelling counterparts.

This paper contributes to the growing literature on the effects of early-life exposure to shocks on socioeconomic outcomes (Adhvaryu et al. 2015, 2018; Aguilar and Vicarelli 2011; Beuermann et al. 2017; Deschênes et al. 2009; Dinkelman 2017; Kumar et al. 2016; Lavy et al. 2016; Maccini and Yang 2009;

[1] Wet shocks in principle constitute excess rainfall (flooding), which more often than not destroys farmlands and properties *in situ*.

Singhal 2019), particularly the strand of the literature that focuses on the short-run impacts of exposure to unfavourable shocks on child health (Akresh et al. 2012; Blom et al. 2019; Bundervoet et al. 2009; Kim 2010; Kumar et al. 2016). Andalón et al. (2016), for instance, using data from Colombia show that exposure to both hot and cold weather shocks *in utero* have negative impacts on child weight and length at birth. Similarly, Wang et al. (2009) document a positive effect of exposure to excess rainfall and extreme temperatures on the incidence of diarrhoea and weight-for-height among children under the age of three years in SSA. Deschênes et al. (2009) also document a strong positive relationship between extreme weather events and low birth weight in the USA, thus showing that the health consequences of extreme weather events pertain also in high-income countries with plausibly robust health infrastructure and adaptation mechanisms to cushion households from the impact of adverse shocks. In the African context, a recent paper by Blom et al. (2019) shows evidence of the association between heat exposure and prevalence of malnutrition in West Africa. Evidence from their paper suggests that a 2°C increase in temperature is associated with 3.9 percentage point increase in the incidence of stunting in the sub-region. Thus, our findings concur with prior evidence highlighting the effects of unfavourable weather shocks—particularly dry, hot conditions—on the health and nutrition outcomes of children.

The paper proceeds as follows: measuring child nutrition is presented in Section 2. We present and describe our dataset in Section 3. The empirical strategy and identifying of assumptions are presented in Section 4. Results are presented and discussed in Section 5, while the transmission channels are provided in Section 6. Section 7 concludes the paper with a summary of findings.

2 Child nutrition and measurement

A balanced diet and nutrition are the cornerstones of human health and development. Good nutrition plays a substantial role in people's health and well-being; poor nutrition can lead to anaemia, reduced immunity, and impaired physical and mental development (WHO 2014). Due to lack of adequate diversity and meal frequency, young children are vulnerable to under-nutrition, especially stunting and micronutrient deficiencies, and to increased morbidity and mortality. Micronutrients deficiencies (vitamins and minerals) or macronutrient deficiencies (carbohydrates, proteins, and fats) for children and pregnant women are likely to induce many adverse consequences for child survival and long-term well-being. It also has far-reaching consequences for human capital, economic productivity, and national development overall (Namugumya et al. 2014). This study uses the reported anthropometric measures (such as age, sex, height, and weight) of children under five years old to construct height-for-age z-scores based on the World Health Organization's (WHO) growth standards (Leroy 2011). The computed z-scores explain the difference between the value for an individual and the median value of the reference population for the same age or height, divided by the standard deviation of the reference population. For instance, the z-scores for weight-for-height describe how far a child's weight is from the median weight of a child of the same height in the reference value (World Food Program 2005). Therefore, the child nutrition indicator (height-for-age) is computed using the following expression:

$$Z_{score} = \frac{T_i - X}{X_{sd}} \tag{1}$$

where Z_{score} stands for standard deviations, representing the child health/nutritional outcome indicators (height-for-age scores); T_i stands for the observed measured value for individual i; X represents the median value of the reference population for the same age or height; and X_{sd} denotes the standard deviations of the reference population. The derived index (height-for-age scores) is therefore used to provide outcome measures of nutritional status. The height-for-age z-scores (HAZ) describes the cumulative linear growth, representing past or chronic inadequacies of nutrition and chronic or frequent illness, implying longer-term changes in malnutrition. In addition to HAZ, there are other nutritional indicators that can be derived using the same equation. These include weight-for-height z-scores (WHZ), which shows the body weight relative to height and is an indicator of current nutritional status, and the weight-for-age z-scores (WAZ), which is also used to assess the growth and changes in level of malnutrition over time (Harou 2018). In this study, our focus in on HAZ scores, which are commonly used as an effective malnutrition measurement tool.

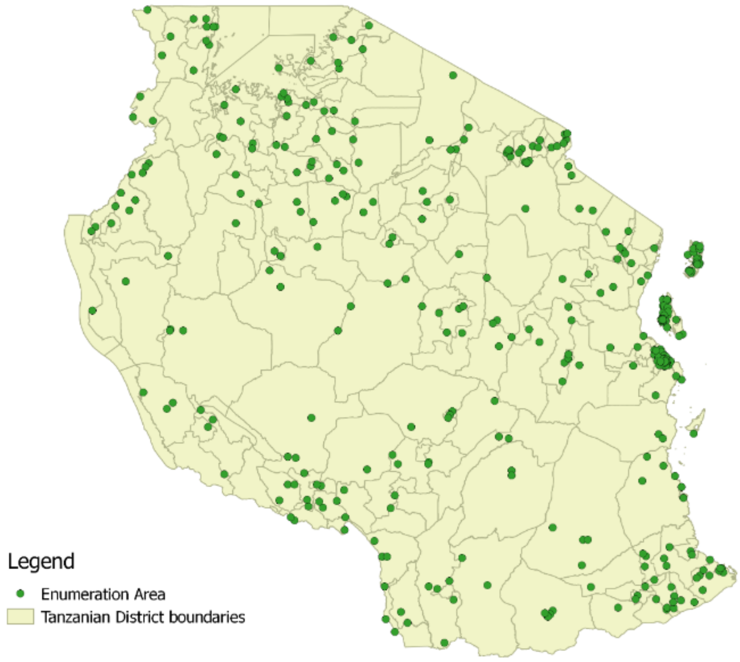
3 Data

This paper uses panel data on households from the TNPS complemented with weather data on the SPEI.

3.1 Tanzanian National Panel Survey

The TNPS is a nationally representative panel data of households collected by Tanzania's National Bureau of Statistics (NBS) with support from the World Bank as part of the Living Standards and Measurement Surveys Integrated Agriculture Surveys (LSMS-ISA) datasets. We utilize data from the first three waves of the dataset collected between 2008/09 through 2013.[2] The sampling design is two-stage stratified sampling and is nationally representative for both rural and urban households. The dataset is geo-referenced at the primary sampling unit (enumeration area), with Figure 1 showing the spatial distribution of the survey locations.

Figure 1: TNPS survey locations



Source: authors' compilation based on coordinates from the TNPS and SPEI data.

The survey, among other things, collects information on anthropometric measures (height and weight) for children under the age of five years old, thus allowing us to compute the standardized z-scores of height-for-age, taking into account the age and gender of the child. The indices are computed based on the WHO's growth standards and expressed in standard deviations (Leroy 2011).

[2] Although the fourth wave of the dataset is currently available, a new sample was surveyed differently and household identification was changed, thus making it impossible to trace the panel households across the fourth wave—hence our decision to exclude the fourth wave from our analysis.

The computed z-scores explain the difference between the value for an individual and the median value of the reference population for the same age or height, divided by the standard deviation of the reference population.

For instance, HAZ describes the cumulative linear growth, representing past or chronic inadequacies of nutrition and chronic or frequent illness, implying longer-term changes in malnutrition. Following the WHO recommendations, a child is classified as stunted if the HAZ is -2 or lower. Thus, our main outcome variable is an indicator variable equal to 1 if the HAZ score for a child is -2 or lower and 0 if otherwise. Tables 1 and 2 provide summaries of demographic statistics on child nutrition indicators and other main variables obtained from the TNPS for the analysis, respectively. Specifically, Table 1 shows that around 34 per cent of children below five years of age were stunted in the period 2008–13. In Table 2, we report demographic and farm attributes of the household under study. It is shown that around 75 per cent of Tanzanian households are located in rural areas, and this possibly indicates strong links to the rain-fed farming system in the country.

Table 1: Descriptive statistics on children under five

	All		Wave 1(2008/09)		Wave 2(2010/11)		Wave 3(2012/13)	
Variables	Mean	Std dev.	Mean	Std dev.	Mean	Std dev.	Mean	Std dev.
Child sex (1 = Male)	0.50	0.50	0.49	0.50	0.50	0.50	0.51	0.50
Age (months)	38.62	18.57	36.29	19.44	35.69	19.55	46.92	11.98
Height	90.49	15.30	89.17	15.11	87.84	17.00	96.70	10.34
Weight	13.31	4.96	13.07	4.97	12.78	5.86	14.52	2.74
Height-for-age z-score	–1.09	3.22	–0.72	4.32	–1.36	2.49	–1.27	1.67
Stunting	0.34	0.47	0.38	0.48	0.32	0.46	0.31	0.46
Observations	5,962							

Source: authors' compilation based on data from the TNPS.

Table 2: Farm and household summary statistics

Variable	Mean	Std dev.
Farm size (ha)	7.53	4.79
HH is educated	0.77	0.41
HH received farm credit	0.08	0.23
Total household land area (hectare)	1.58	2.92
Household received farm credit	0.08	0.27
Farm output (kg): beans	152	194
Farm output (kg): rice	667	886
Farm output (kg): maize	781	899

Source: authors' compilation based on data from the TNPS.

3.2 Weather data: SPEI

To identify exposure to weather shocks we use SPEI, which measures the water balance at a given location at a particular time (Vicente-Serrano et al. 2010). The database[3] was developed by the Climatic Research Unit at the University of East Anglia, and is available at the global scale at a 0.5×0.5 degree spatial resolution. Unlike other measures that rely solely on rainfall, SPEI measures the total moisture (water) availability by taking into account the degree of evapotranspiration at a given location. SPEI is a standardized measure reflecting the (standard) deviations in the average water balance from the long-run mean (i.e. the average water balance over a 100-year period). In other words, an SPEI value of 1 (-1) represents a one standard deviation increase (decrease) in precipitation level (water balance) above (below) the long-run mean.

Using SPEI to capture dry and wet weather shocks, we follow the recent literature on the nexus between weather shocks and agriculture development (Burke and Emerick 2016; Dinkelman 2017; Jagnani et al.

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

2017; Kurukulasuriya and Mendelsohn 2007; Mendelsohn 2008; Mendelsohn et al. 1994). The advantage of using SPEI to capture dry and wet shocks is that it is not only based on precipitation, but also considers the potential evapotranspiration (i.e. evaporation plus plant transpiration), a variable that has a significant contribution to local drought conditions and crop yield. The spatial specificity of the index is very useful, since the same quantitative rainfall deficit may explain insufficient precipitation in historically wetter villages but not in historically drier villages (Dinkelman 2017). Following the climatology literature, we define dry (negative) and wet (positive) weather shocks as having at least one standard deviation below and above the long-run mean, respectively.

4 Estimation strategy

To examine the effect of exposure to weather shocks on child health outcomes, our baseline model is specified as follows:

$$Y_{ihdt} = \beta \times WeatherShock_{idt} + \varphi \times Gender_i + \ \mathbf{FE}_{h(i),YOB,d\times t} + \varepsilon_{ihdt} \tag{2}$$

where Y_{ihdt} is a placeholder for our outcome variables (stunting) of child i in household h, district d, surveyed in year t. Specifically, our outcome variable is a dummy variable equal to 1 if the child is stunted (i.e. HAZ score ≤ -2) and 0 if otherwise. *WeatherShock* is a placeholder for the cumulative exposure to dry and/or wet weather shocks. For each child, we count the cumulative number of months between the time of birth and the time of the survey for which there were dry or wet shocks. Specifically, we define exposure to wet weather shocks as the cumulative number of months between time of birth and the survey for which the SPEI in district d was at least one standard deviation above the long-run mean. Conversely, exposure to dry shocks is defined as the cumulative number of months between time of birth and the survey for which the SPEI in district d was at least one standard deviation below the long-run mean. Thus, periods with SPEI index between 1 and -1 represent periods of normal weather conditions.

Further, we control for the gender of the child as well as fixed effects for households, birth year and district-survey year. Household fixed effects absorb time-invariant observable and unobservable differences across households that may correlate with child health outcomes. Implicitly, household fixed effects ensure that we utilize within-household variations in estimating the effect of (cumulative) exposure to weather shocks on child outcomes. On the other hand, birth year fixed effects absorb cohort-specific effects, while district $\times$ year fixed effects ensure that we purge our results from time-varying district specifications that may correlate with child health outcomes. Robust standard errors are clustered at the district level to allow for spatial correlation in the residuals within districts.[4]

Our coefficient of interest is β, which measures the effect of exposure to (wet and/or dry) weather shocks on the probability of stunting among children in our sample. Our main identifying assumption is that the deviation from long-run weather patterns in a given area is plausibly random and uncorrelated with other drivers of child health. In other words, conditional on locational factors, exposure to dry and wet weather shocks are plausibly exogenous, hence $\hat{\beta}$ measures the (causal) effect of these shocks on the outcome variable conditional on the fixed effects. We estimate Equation 2 via ordinary least squares (OLS). See Bellemare et al. (2015) for a discussion on the advantages of the linear probability models (LPM) over the traditional nonlinear models such as logit or probit models.

[4] We show that our results are robust to two-way clustering on district and birth year.

5 Results

5.1 Main results

In Table 3, we present our main results obtained from estimating our baseline model (Equation 2) with varying specifications. In columns 1–4, we focus exclusively on exposure to dry weather shocks and estimate the effect on stunting, while in columns 5–8 we focus on wet weather shocks and estimate the effects on stunting. The combined effects of these shocks are shown in columns 9–12. Also, we alternate between household fixed effect and child fixed effect. Overall, our results are consistent across various specifications. Nonetheless, our preferred specifications are in columns 4, 8, and 12, where we control for household, birth year, and district $\times$ survey year fixed effects.

Our results show a strong and positive association between exposure to dry weather shocks and stunting. The effects are statistically and economically significant. Specifically, a one-month increase in exposure to dry weather shocks is associated with a 0.8 percentage points (pp) increase in the probability that a child is stunted. Relative to the sample mean, this corresponds to a 2.4 per cent increase in the rate of stunting. However, as shown in columns 5–8, we find a positive but statistically insignificant association between exposure to wet shocks and probability of stunting. This provides suggestive evidence that wet shocks (such as excessive rainfall or flooding) have little or no impact on the rate of stunting among children in the study area. Overall, our findings are similar to earlier findings by Blom et al. (2019). Combining anthropometric data on children under age five from five West African states (Benin, Burkina Faso, Ivory Coast, Ghana, and Togo) using the Demographic and Health Surveys with spatial data on temperature shocks, Blom et al. (2019) show a positive association between heat exposure and stunting. However, contrary to Andalón et al. (2016), who find statistically significant effects of dry and wet weather spells on child health outcomes, our findings suggest that the potential effects of wet weather spells are minimal. One possible explanation for the null effects associated with exposure to wet shocks could be attributed to adaptation strategies. Arguably, the effects of flooding are not randomly distributed: lowlands are more likely to be affected relative to highlands. Therefore, farmers or households may strategically adopt measures that minimize the effects of potential floods on socioeconomic outcomes.

How do exposures to wet and dry shocks affect health outcomes relative to children exposed to normal weather conditions? In columns 9–12 we show the results of estimating the effects of exposure to both dry and wet weather shocks jointly in the same equation. Once again, the results confirm our earlier findings that only dry weather shocks have a statistically significant association with stunting. The coefficients are qualitatively and quantitatively similar to the estimates in columns 1–8. Further, our results are robust to alternative clustering. In Table A1 in the Appendix, we present our baseline results using two-way clustering by clustering the standard errors by district and year of birth. Again the results are qualitatively and quantitatively similar to the baseline results (Table 3).

Table 3: Exposure to weather shocks and stunting among children

	Dep. var. stunting (0/1)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure dry shocks	0.0097*	0.0117**	0.0079**	0.0083**					0.0102*	0.0122**	0.0082**	0.0086**
	(0.0056)	(0.0059)	(0.0032)	(0.0034)					(0.0056)	(0.0059)	(0.0032)	(0.0034)
Exposure wet shocks					0.0113*	0.0084	0.0047	0.0039	0.0119*	0.0093	0.0054	0.0046
					(0.0063)	(0.0066)	(0.0045)	(0.0045)	(0.0063)	(0.0066)	(0.0045)	(0.0045)
Female			-0.0349*	-0.0379*			-0.0345*	-0.0372*			-0.0351*	-0.0380*
			(0.0202)	(0.0206)			(0.0203)	(0.0207)			(0.0202)	(0.0206)
Child FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
HH FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
District $\times$ survey year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean dep. var.	0.3465	0.3464	0.3407	0.3409	0.3465	0.3464	0.3407	0.3409	0.3465	0.3464	0.3407	0.3409
R-squared	0.6017	0.6674	0.4250	0.4849	0.6016	0.6667	0.4243	0.4841	0.6026	0.6678	0.4253	0.4851
Observations	4,930	4,858	5,962	5,916	4,930	4,858	5,962	5,916	4,930	4,858	5,962	5,916

Notes: the dependent variable is a dummy variable equal to 1 if a child is stunted and 0 if otherwise. Exposure measures the number of (potential) months between month of birth and survey month a child is exposed to dry or wet shocks. Dry and wet shocks are defined equal to 1 if the SPEI for a given month and district is at least one standard deviation below or above the long-run mean. Standard errors are clustered at district level. OLS estimations. * Significant at the 10 per cent level; ** significant at the 5 per cent level; *** significant at the 1 per cent level.

Source: authors' compilation based on data from the TNPS.

In order to minimize the welfare impacts associated with weather shocks, households in developing countries adopt several coping strategies, including but not limited to migration. Farmers and livestock herders often migrate to areas with relatively low weather variability. However, there are observable and unobservable determinants of migration decisions that are likely to be correlated with health and nutrition outcomes of children in such households. This results in the so-called 'endogenous-migration' problem, which is likely to influence the validity of our estimates. In other words, if children from migrant households are more likely to be malnourished, our baseline estimates are likely to capture these effects, thereby 'contaminating' our results. To ascertain the validity of our results, we conduct further analysis by focusing exclusively on non-migrants. Here, a non-migrant is defined as a household that has lived in a community for at least the 10 years prior to the survey; otherwise, they are defined as a migrant. The results, as shown in Table 4, provide credence to our baseline results as the estimates are qualitatively and quantitatively similar. In other words, we show that our findings are not driven by migration patterns.

So far, the main conclusion from our baseline results is that only exposure to dry weather shocks affect child health outcomes such as stunting. Exposure to wet shocks does not necessarily affect stunting rates. As a result, in the analysis hereafter, we focus exclusively on exposure to dry weather shocks and assess the effects of the intensity of exposure to these shocks on probability of stunting.

5.2 Heterogeneity

Effects across age groups

How are the effects of exposure to dry weather shocks distributed on stunting across age groups? To answer this question we estimate

$$\begin{aligned} Y_{ihdt} = \beta \times WeatherShock_{idt} \quad &+ \quad \alpha_k \times Age_{it}^{k} \quad + \quad \gamma_k \left(Age_{it}^{k} \times WeatherShock_{idt}\right) \\ \varphi \times Gender_i + \ \mathbf{FE}_{h(i),d\times t} + \varepsilon_{ihdt} & \end{aligned} \tag{3}$$

where Age_i^k are age dummies, while all other variables are as previously defined. The coefficient of interaction ,γ_k, measures the effect of exposure to the shocks across age groups.

In Figure 2 we plot $\hat{\gamma_k}$ and show the estimated effects of (cumulative) exposure to dry weather shocks on children in the respective age groups. The results show statistically significant effects of exposure to dry shocks on the incidence of stunting for children aged one year or below, as well as those aged 3–4. Surprisingly, the effect on 1–2-year-old children is statistically insignificant. Further, the effect is strikingly higher and statistically significant for children aged one or younger. Specifically, we find that each additional month of exposure to dry weather shocks during the first 12 months increases the probability of stunting by 4.3 pp relative to children of 4–5 years old (the reference group). Despite the statistically insignificant result on the effect of weather shocks on the 1–2-year-old age group, the results provide suggestive evidence that exposure to dry weather shocks has a positive impact on the probability of a child being stunted. More importantly, the effect is more pronounced in the first 12 months of a child's life, where the child is plausibly most vulnerable to nutritional shocks. Evidence from Blom et al. (2019) also points to a similar conclusion. Findings from the paper suggest that the effect of exposure to extreme heat on growth of children (HAZ) occurs between the ages of 6 and 12 months.

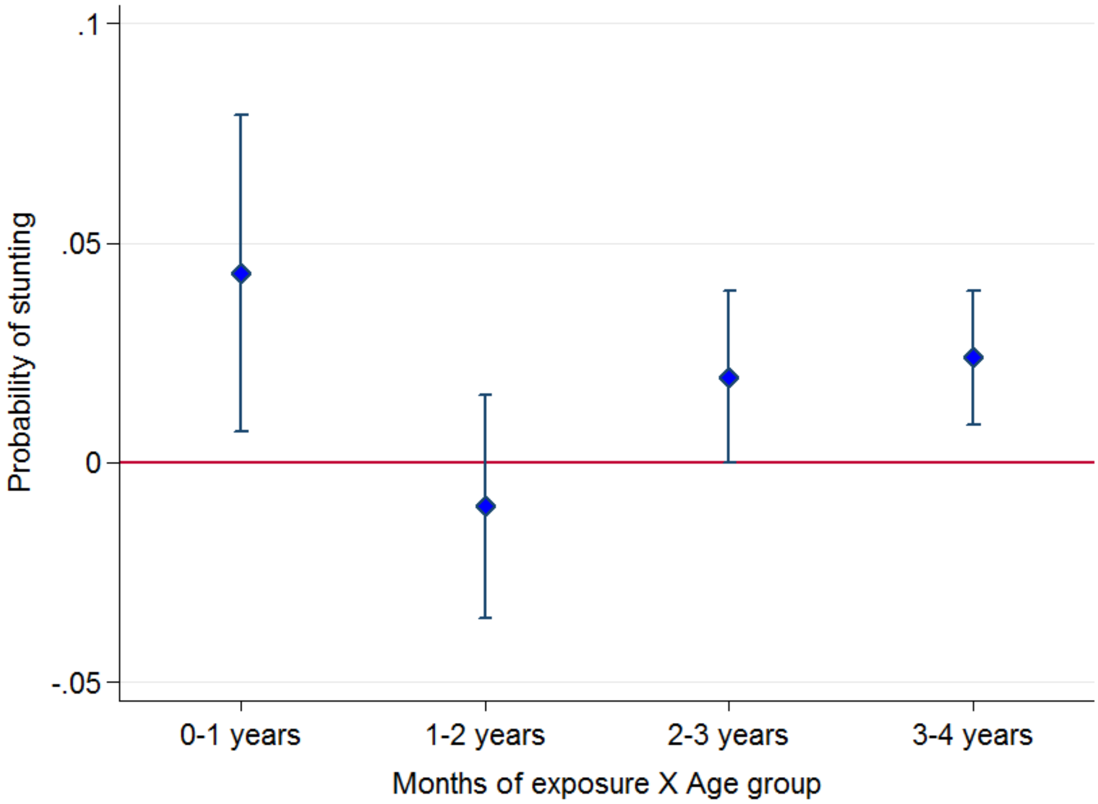
Table 4: Exposure to weather shocks and stunting: excluding migrant households

	Sample: non-migrants			
	(1)	(2)	(3)	(4)
Exposure dry shocks	0.0078*		0.0082**	
	(0.0041)		(0.0041)	
Exposure wet shocks		0.0056	0.0064	
		(0.0055)	(0.0054)	
Exposure to dry shocks				
1 month				0.1108**
				(0.0522)
2 months				0.1984***
				(0.0428)
3 months				0.1826***
				(0.0508)
4 months				0.2377***
				(0.0473)
5 months				0.1879***
				(0.0503)
6 months				0.2167***
				(0.0502)
7 months				0.2298***
				(0.0617)
8 months				0.1710**
				(0.0721)
9 months				0.2089***
				(0.0739)
10 months				0.2292***
				(0.0806)
11 months				0.2148***
				(0.0680)
$\geq$12 months				0.1948***
				(0.0703)
Female	–0.0352	–0.0347	–0.0355	–0.0351
	(0.0225)	(0.0227)	(0.0224)	(0.0233)
HH FE	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes
District $\times$ survey year FE	Yes	Yes	Yes	Yes
Mean dep. var.	0.3580	0.3580	0.3580	0.3580
R-squared	0.4982	0.4977	0.4985	0.5046
Observations	4,210	4,210	4,210	4,210

Notes: the dependent variable is a dummy equal to 1 if a child is stunted and 0 otherwise. Exposure measures the number of (potential) months between month of birth and survey month a child is exposed to dry shocks. Dry shocks are defined equal to 1 if the SPEI for a given month and district is at least one standard deviation below the long-run mean. Non-migrants are defined as households who have stayed in the community for at least the last 10 years. Standard errors are clustered at the district level. OLS estimations. * Significant at the 10 per cent level; ** significant at the 5 per cent level; *** significant at the 1 percent level.

Source: authors' compilation based on data from the TNPS.

Figure 2: Effects of exposure to dry weather shocks on stunting across age groups



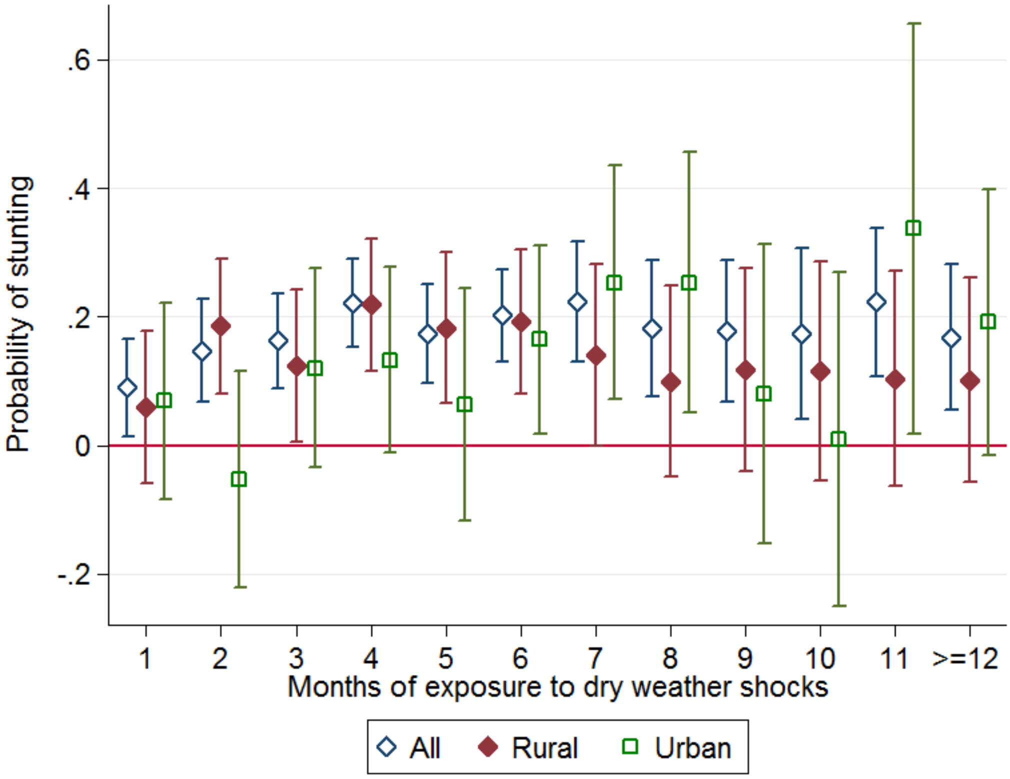
Notes: this figure plots estimates of the effect of intensity of exposure to dry weather shocks on the probability of stunting across age groups. Bars indicate the 95 per cent confidence interval. The estimates are the coefficients of the interaction between age dummies and cumulative number of months a child has been exposed to dry weather shocks between the time of birth and the survey. These are obtained by regressing the outcome variable (stunting (0/1) on the number of months of dry weather spells, age group dummies, and the interaction between the age dummies and the months of exposure. Fixed effects for household and district × survey year are included. Robust standard errors are clustered at the district level.

Source: authors' illustration based on data from the TNPS.

Rural–urban gap

In this subsection, we examine the effect of exposure to dry shocks on stunting rates among rural and urban children. Specifically, we assess the variations in the effects of exposure at varying levels of exposure for both rural and urban children. As a result, we estimate Equation 2 while replacing *WeatherShocks* with dummy variables representing the number of months between time of birth and the survey period for which there was a dry weather shock in their respective localities. Results are summarized in Figure 3, with details shown in Table A2. As indicated in Figure 3, each level of exposure is positively associated with stunting, albeit the extent of the effect increases marginally with an increase in the level of exposure. For urban kids, the effects are mostly statistically insignificant albeit positive, thus suggesting dry weather shocks have little impact on stunting rates in urban areas. On the other hand, for rural kids the effects are largely significant and positive, suggesting that rural kids are relatively more vulnerable to the effects of dry weather conditions on their health.

Figure 3: Rural–urban differences in the impact of exposure to weather shocks on stunting



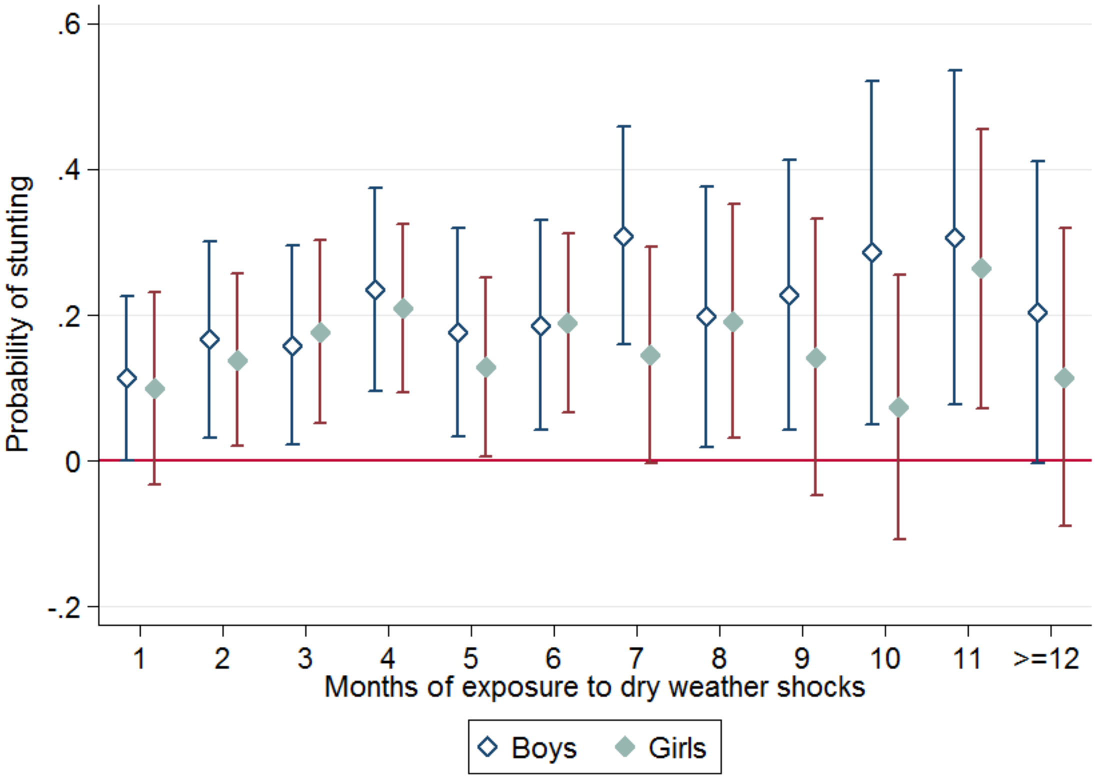
Notes: this figure plots estimates of the effect of intensity of exposure to weather shocks on the probability of stunting. It shows estimates from Equation 2, which includes fixed effects for household, birth year, and district × survey year.

Source: authors' illustration based on data from the TNPS.

Gender gaps

Next, we examine the differences in the intensity of the impact of exposure to dry weather shocks across male and female cohorts. Studies suggest that gender preference by parents can contribute to gender gaps in nutritional outcomes of children in the household (Jose 2017). To this end, we estimate a variant of the baseline model separately for boys and girls and present the results in Figure 4. The effects are similar qualitatively and quantitatively for boys and girls, thus suggesting that exposure to dry weather shocks in the country may not explain the variations of stunting rates between boys and girls under age five.

Figure 4: Gender differences in the impact of exposure to weather shocks on stunting



Notes: this figure plots estimates of the effect of intensity of exposure to weather shocks on the probability of stunting. It shows estimates from Equation 2, which includes fixed effects for household, birth year, and district × survey year.

Source: authors' illustration based on data from the TNPS.

6 Potential mechanisms

There are at least two plausible channels through which weather shocks affect child nutrition. First, in societies where households mainly depend on rain-fed agriculture for their livelihoods, adverse weather shocks such as droughts affect farm productivity, thereby creating shortages in the food supply. The associated food insecurity has the potential to reduce the dietary intake of farm households, particularly among infants and pregnant women, which ultimately results in malnutrition-associated health implications such as stunting, wasting, and infant mortality (Aguilar and Vicarelli 2011; Arslan et al. 2016; Maccini and Yang 2009). Second, the effect of adverse weather shocks is not limited to farm (rural) households, but affects urban non-farm households as well. Low agricultural productivity reduces the food supply to markets, thereby resulting in high food prices. As a result, low-income households (both urban and rural) are likely to be most affected by food price inflation, with potential adverse implications for dietary intake of children in these households (Levine and Yang 2014; Mirzabaev and Tsegai 2012; Völker et al. 2013).

In this section, we test these mechanisms by evaluating the association between weather shocks and farm productivity for households in our dataset. Given that most agriculture in Tanzania is primarily rain-fed, we focus primarily on shocks during the lean and growing seasons of the main food staples (maize, rice, and beans). Also, since our preceding analysis provides suggestive evidence that the health effects are driven largely by exposure to dry shocks, our analysis here focuses exclusively on the association between dry weather shocks on farm yield (per hectare).

We focus on farm yield of the main food staples in Tanzania: maize, rice, and beans.[5] Given that the growing cycles of these crops vary, we measure for each crop production season the incidence of dry shocks across various locations in the country, and estimate the association between these shocks and farm yields. Specifically, we compute the number of months during the pre-planting and planting seasons for which there was adverse (dry) weather shocks. It is important to note that the spatial specificity of our measure of weather shocks is very useful, since the same quantitative rainfall deficit may explain insufficient precipitation in historically wetter villages but not in historically drier villages (Dinkelman 2017). Consequently, we estimate the relationship between weather shocks and farm yield using the reduced-form equation:

$$Y_{hdt} = \alpha \times WeatherShock_{hdt} + \varphi \times X_{hdt} + \mathbf{FE}_{h,d\times t} + \varepsilon_{hdt} \tag{4}$$

where Y_{hdt} is a placeholder for the outcome of household h in district d at time t. Our main outcome variables include: the yield (kg) per hectare of beans, maize, and rice, and total annual farm output values. $WeatherShock_{hdt}$ represents the share of months in the agricultural season of each crop for which there was a dry weather shock in the respective districts. X_{hdt} is a vector of household controls, including gender of th household head, household size, education level of the household head, and access to farm credit. All other variables remain as previously defined.

Results from the estimations are presented in Table 5. We examine the effects of dry weather shocks on farm yield of the three staple crops (maize, beans, and rice), as well as total farm output. As shown in the results, we find a negative association between the intensity of dry weather shocks and farm productivity, as proxied by yield per hectare. The findings are in line with the existing literature (Arslan et al. 2017; Buhaug et al. 2015; Kubik and Maurel 2016; Letta et al. 2018). This provides suggestive evidence that dry weather shocks have a negative impact on food supply and, as a result, credit-constrained households, particularly in rural areas, may struggle to meet their nutritional requirements. Thus we argue that the result, a decline in farm productivity, is a plausible channel through which adverse weather shocks affect child health.

Table 5: Weather shocks and agricultural productivity (yield per hectare)

	Beans		Maize		Rice		Farm output	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dry shocks	–0.070	–0.140	–0.075	–0.070	–0.052	-0.085	-0.099	-0.095
	(0.061)	(0.059)**	(0.040)*	(0.039)*	(0.035)	(0.049)*	(0.035)***	(0.030)***
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	No	Yes	No	Yes	No	Yes	No
District x survey year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	817	854	1,520	1,360	845	860	2,537	2,407
R-squared	0.680	0.755	0.740	0.819	0.795	0.875	0.730	0.798

Notes: robust standard errors, clustered at the district level, are reported in parentheses. The dependent variables are, respectively, the log of farm crop yield per hectare of beans, maize, and rice, and total annual farm output per hectare. Dry shocks refers to the share of months in the agricultural (pre-planting and planting) season of each crop for which the SPEI in the district was at least one standard deviation below the long-run mean. * Significant at the 10 per cent level; ** significant at the 5 per cent level; *** significant at the 1 per cent level.

Source: authors' compilation based on data from the TNPS.

[5] According to the Tanzanian National Bureau of Statistics, the most produced and consumed food crops in the country are maize, beans, rice, and groundnut. Their production accounts for around 60 per cent of the total national food production, with maize yield alone representing around 32 per cent of total produce in households (TNBS 2016b). The rest accounts for 11, 9, and 8 per cent for beans, rice, and groundnut, respectively.

7 Conclusion and policy implications

Changing weather and climatic patterns have become a common feature in many parts of the world. The consequences of the changing weather conditions are myriad, ranging across low agricultural productivity, natural disasters, low quality of health, and others. The effects are particularly large in developing countries (mostly in SSA) due to substantial reliance on subsistence agriculture for livelihoods and the lack of income to invest in adaptation measures.

In this paper, we examine the short-run impact of childhood exposure to (unfavourable) weather shocks on the health and nutritional outcomes of children under age five years old, using national household panel data from Tanzania. We also access the effects of weather shocks across heterogeneous groups: age, gender, and rural/urban residence status of the children. Our identification strategy exploits the plausibly exogenous variations in exposure to dry and wet weather shocks induced by timing of birth across space.

Overall, the results suggest that exposure to dry weather shocks is associated with an increase in the incidence of stunting in Tanzania. However, the effect of exposure to wet shocks such as flooding or excessive rainfall appears to be statistically insignificant. On average, we find that exposure to one additional month of dry weather shocks is associated with a 2.4 per cent increase in the rate of stunting among children under five years old. Another interesting finding is that the effect appears to be muted in urban areas relative to rural areas. In other words, we find that exposure to dry weather shocks is strongly associated with stunting among children in rural communities compared to children in urban communities. This suggests that since rural households are heavily dependent on agriculture for food and income, negative shocks to farm productivity affect nutrition and health outcomes of children in these communities more compared to their counterparts in urban centres that are less directly dependent on agriculture—at least in terms of income—and hence less susceptible to weather shocks. We further show that reduced farm productivity is a potential pathway through which adverse weather shocks affect the health and nutritional outcomes of children in affected areas.

Our findings concur largely with previous evidence in the literature that suggests that exposure to hot or dry weather conditions during childhood has negative consequences for child health even in the long run (Adhvaryu et al. 2015; Beuermann and Pecha 2020; Dinkelman 2017). The findings therefore suggest that measures or policies that cushion households against weather shocks may have positive spillover effects on child health. Given that the incidence of stunting is more pronounced among rural children, social protection policies such as safety nets (cash transfer) to vulnerable households are encouraged. In addition, the provision of weather insurance to agricultural households has been identified as instrumental in assisting households to cope with the adverse impacts of climate change (Selemani et al. 2012).

Finally, a few limitations of the study are worth mentioning. First, while the use of SPEI for the measurement of weather shocks has the advantage of capturing the long-run changes in the overall water balance at a given location, changes in rainfall patterns remain a key determinant of agricultural productivity. As a result, robustness checks using rainfall measures may be needed. Second, our estimates capture only the short-run effects of exposure to weather shocks. Meanwhile, as shown by Adhvaryu et al. (2018), the effect of these shocks can persist over time in the life cycle of affected people. This provides avenues for future research.

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Appendix

Table A1: Exposure to weather shocks and stunting: two-way clustering

	Dep. var. stunting (0/1)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure dry shocks	0.0097	0.0117*	0.0079*	0.0083**					0.0102	0.0122*	0.0082**	0.0086**
	(0.0063)	(0.0055)	(0.0034)	(0.0030)					(0.0059)	(0.0054)	(0.0033)	(0.0029)
Exposure wet shocks					0.0113	0.0084	0.0047	0.0039	0.0119	0.0093	0.0054	0.0046
					(0.0072)	(0.0050)	(0.0048)	(0.0044)	(0.0070)	(0.0049)	(0.0047)	(0.0043)
Female			–0.0349	–0.0379			–0.0345	–0.0372			–0.0351	–0.0380
			(0.0211)	(0.0231)			(0.0216)	(0.0236)			(0.0212)	(0.0232)
Child FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
HH FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
District $\times$ survey year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean dep. var.	0.3465	0.3464	0.3407	0.3409	0.3465	0.3464	0.3407	0.3409	0.3465	0.3464	0.3407	0.3409
R-squared	0.6017	0.6674	0.4250	0.4849	0.6016	0.6667	0.4243	0.4841	0.6026	0.6678	0.4253	0.4851
Observations	4,930	4,858	5,962	5,916	4,930	4,858	5,962	5,916	4,930	4,858	5,962	5,916

Notes: the dependent variable is a dummy variable equal to 1 if a child is stunted and 0 otherwise. Exposure measures the number of (potential) months between month of birth and survey month for which a child is exposed to dry or wet shocks. Dry and wet shocks are defined equal to 1 if the SPEI for a given month and district is at least one standard deviation below or above the long-run mean. Standard errors are clustered by district and birth year. OLS estimations. * Significant at the 10 per cent level; ** significant at the 5 per cent level; *** significant at the 1 per cent level.

Source: authors' compilation based on data from the TNPS.

Table A2: Intensity of exposure to dry weather shocks and stunting

	All	Rural	Urban	Boys	Girls
	(1)	(2)	(3)	(4)	(5)
1 month	0.0897**	0.0595	0.0695	0.1137**	0.1002
	(0.0386)	(0.0598)	(0.0769)	(0.0570)	(0.0665)
2 months	0.1476***	0.1855***	–0.0535	0.1666**	0.1386**
	(0.0402)	(0.0533)	(0.0848)	(0.0677)	(0.0599)
3 months	0.1627***	0.1242**	0.1205	0.1588**	0.1770***
	(0.0371)	(0.0600)	(0.0780)	(0.0691)	(0.0633)
4 months	0.2212***	0.2190***	0.1331*	0.2352***	0.2101***
	(0.0349)	(0.0518)	(0.0732)	(0.0705)	(0.0583)
5 months	0.1729***	0.1830***	0.0644	0.1763**	0.1287**
	(0.0388)	(0.0595)	(0.0911)	(0.0722)	(0.0617)
6 months	0.2021***	0.1930***	0.1645**	0.1857**	0.1888***
	(0.0362)	(0.0565)	(0.0738)	(0.0726)	(0.0619)
7 months	0.2239***	0.1405*	0.2535***	0.3086***	0.1451*
	(0.0470)	(0.0717)	(0.0917)	(0.0754)	(0.0745)
8 months	0.1829***	0.0998	0.2536**	0.1980**	0.1916**
	(0.0537)	(0.0755)	(0.1025)	(0.0903)	(0.0812)
9 months	0.1775***	0.1179	0.0807	0.2277**	0.1426
	(0.0556)	(0.0801)	(0.1176)	(0.0932)	(0.0953)
10 months	0.1733**	0.1153	0.0091	0.2857**	0.0736
	(0.0672)	(0.0865)	(0.1314)	(0.1186)	(0.0916)
11 months	0.2232***	0.1033	0.3375**	0.3065***	0.2635***
	(0.0583)	(0.0845)	(0.1610)	(0.1152)	(0.0969)
$\geq$12 months	0.1678***	0.1017	0.1923*	0.2040*	0.1147
	(0.0572)	(0.0800)	(0.1043)	(0.1045)	(0.1031)
Female	–0.0370*	–0.0377	–0.0721**		
	(0.0208)	(0.0294)	(0.0317)		
HH FE	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes
District $\times$ survey year FE	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	0.3409	0.3779	0.2897	0.3216	0.3624
R-squared	0.4906	0.5249	0.5536	0.5753	0.6036
Observations	5,916	3,329	1,757	2,677	2,721

Notes: the dependent variable is a dummy equal to 1 if a child is stunted and 0 otherwise. Exposure measures the number of (potential) months between month of birth and survey month for which a child is exposed to dry shocks. Dry shocks are defined as equal to 1 if the SPEI for a given month and district is at least one standard deviation below the long-run mean. Standard errors are clustered at the district level. OLS estimations. * Significant at the 10 per cent level; ** significant at the 5 per cent level; *** significant at the 1 per cent level.

Source: authors' compilation based on data from the TNPS.