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Weather shocks across seasons and child health: Evidence from a panel study in the Kyrgyz Republic

Hanna Freudenreich [a,*], Anastasia Aladysheva [b], Tilman Brück [a,c,d]

[a] Leibniz Institute of Vegetable and Ornamental Crops (IGZ), Großbeeren, Germany
[b] Green Climate Fund, Incheon, South Korea
[c] International Security and Development Center (ISDC), Berlin, Germany
[d] Natural Resources Institute (NRI), Greenwich, UK

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ABSTRACT

It has been shown consistently in the literature that early life exposure to extreme weather events affects children's nutritional status and related long-term health and well-being outcomes. The effects of weather shocks other than rainfall, as well as heterogeneous effects among population subgroups and moderators of this relationship, however, are less well understood. By combining a rich three-wave representative household panel dataset from Kyrgyzstan, a country where weather extremes such as droughts, floods but also cold spells are predicted to increase in frequency and severity due to climate change in the near future, with location-matched weather data, this paper analyzes how different weather shocks (cold winter, drought, excessive rainfall) affect the probability of stunting of children under five. Using fixed effects regression models, we find that children under 20 months are most severely affected by all three types of early life weather shocks. Most notably, we find that cold shocks experienced in winter increase the probability of stunting, and that this effect is particularly pronounced for households that mainly rely on electricity for indoor heating, potentially due to frequent power cuts occurring in winter. We do not find rural/urban differences, but we find some seasonal effects of shock exposure. Overall, effects are driven by boys, even though we do not find statistically significant gender differences. Identifying the geographical and sociodemographic subgroups of children most vulnerable to extreme weather events can support the design of targeted policies addressing child malnutrition.

1. Introduction

Even though substantial progress has been made worldwide in the last decades in improving the main indicators of child health, including child malnutrition (UNICEF et al., 2020; Vaivada et al., 2020), the unfolding climate crisis is threatening to reverse this process (Cooper, Brown, Hochrainer-Stigler et al., 2019; Philipsborn & Chan, 2018). In many regions of the world the climate crisis is increasing the frequency, intensity, and impacts of extreme weather events, mainly related to temperature and rainfall (IPCC, 2014). The detrimental consequences for human health, including hunger and malnutrition, are emphasized by leading scientists (Watts et al., 2018) and children in low income countries are expected to bear most of the burden (Helldén et al., 2021). Childhood malnutrition and developmental deficits have been shown to entail long term consequences for adult health and well-being (e.g. Black et al., 2013; Dewey & Begum, 2011; Victora et al., 2008; Walker et al., 2011), which makes studying its drivers in relation to climate extremes particularly relevant. While there is an unequivocal strong association between rainfall extremes, specifically drought, and child health (Cooper, Brown, Hochrainer-Stigler et al., 2019), the relationship between cold temperature extremes and child health is less well explored (Xu et al., 2012). However, cold spells in winter are a recurring problem in developing regions where people struggle with energy poverty, particularly Central Asia (Lampietti & Meyer, 2002) where such vulnerabilities are furthermore exacerbated by climate change (Tang et al., 2013). With a few exceptions (Groppo & Kraehnert, 2016) the effects of cold weather shocks on child health and overall well-being have not been analyzed in the literature, and less so in relation to housing characteristics, such as the heating source. Furthermore, in order for policy interventions to address child malnutrition caused by extreme weather, it is necessary to identify the most vulnerable subgroups by analyzing heterogeneous effects of different weather extremes by household and child demographics, such as age and gender.

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* Corresponding author.
E-mail address: hanna.freudenreich1@gmail.com (H. Freudenreich).

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The most widely used indicator for overall well-being and development of children is considered to be linear growth retardation and failure, also referred to as low height-for-age or stunting (Onis & Branca, 2016). Stunting is caused by a complex combination of deprivations that accumulate over time, such as inadequate nutrition, frequent infections and a deficit in psychosocial stimulation (Stewart et al., 2013). The increased global health focus on stunting is due to its associations with several severe short-, medium-, and long-term human capital and health consequences, such as delayed cognitive development, low academic achievement, lower adult earnings and worse overall health (Black et al., 2013). Whether these associations are actually causal is subject of an ongoing academic debate. It has been argued that the only confirmed causal effect consists in children born to stunted mothers having a higher risks of child mortality and low birthweight (Leroy & Frongillo, 2019). Other authors confirmed a direct causal and persistent effect of poor child health on cognitive function (Attanasio et al., 2020). Given these causalities studying stunting and its determinants is crucial from a public health and development perspective.

Based on the aforementioned literature gap this paper analyzes the effects of different types of weather shocks experienced early in life, including cold winters, droughts and extreme rainfall events, on stunting probabilities of 0 to 60 months old children in Kyrgyzstan. Kyrgyzstan has a dry continental and mainly arid climate with warm summers and cold winters and considerable regional variation (USAID, 2018). Being drought prone in general, changing rainfall patterns due to climate change are predicted to lead to periods of excessive precipitation and floods, and other extreme weather events in general, including cold spells, are predicted to occur more frequently (World Bank & Asian Development Bank, 2021). Kyrgyzstan has reduced neonatal mortality rates by 46% (Kamali et al., 2020) and stunting rates by roughly one third since the 1990s (Wigle et al., 2020). According to the latest data, 12% of children in the Kyrgyz Republic were stunted in 2018. This rate is lower compared to other low- and middle income countries with similar levels of human development, such as Morocco and Tajikistan with stunting rates of 15% and 18%, respectively (UNICEF et al., 2020).

In this paper, we combine three waves of a rich panel dataset from Kyrgyzstan including child anthropometrics, individual and household characteristics ("Life in Kyrgyzstan", Brück et al., 2014) with gridded historical temperature and precipitation data from University of East Anglia (CRU-TS, Mitchell & Jones, 2005). The literature on weather shocks and child anthropometrics is growing but still relatively thin (Cooper, Brown, Hochrainer-Stigler et al., 2019), particularly using panel data with multiple waves. We define cumulative precipitation anomalies using the monthly Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010) and cold shocks using temperature z-scores. Stunting probabilities are based on height-for-age Z (HAZ) –scores comparing the anthropometric measurements with values from the healthy reference population of boys and girls of the same age published by the World Health Organization (WHO Multicentre Growth Reference Study Group, 2006).

The contribution of this paper is (1) to analyze determinants of stunting over time using panel data and to exploit spatial and temporal variation in exposure to different types of shocks, (2) specifically taking into account cold temperature shocks, (3) to identify heterogeneous effects and mechanisms in order to inform policy debates, and (4) to focus on a country in a largely understudied developing region, namely Central Asia. The majority of existing studies on climate impacts on child health have a limited geographical focus on Sub-Saharan Africa (SSA), while the majority of stunted children is located in Asia (Niles et al., 2021).

Agricultural productivity and infectious diseases are generally regarded as the main mechanisms underlying the rainfall – child health relationship (Baker & Anttila-Hughes, 2020). For cold shocks no clear evidence on pathways exists. Therefore we test the hypothesis that the source of heating used by the household might affect child health in response to cold shocks: electric heating could be disrupted during extremely cold months, and stove heating could contribute to indoor air pollution, both negatively affecting child health.

Specifically, this paper contributes to three strands of literatures: (1) effects of early life exposure to weather shocks on child stunting, (2) heterogeneous effects among population subgroups, and (3) underlying mechanisms. The paper is organized as follows: section 2 reviews the three strands of literatures and presents the conceptual framework, section 3 describes the data used for this study, section 4 presents the estimation strategy, section 5 presents the results and robustness tests, and section 6 concludes with a discussion of the results and outlook.

2. Related literature and conceptual framework

2.1. Early-life exposure to drought and high temperature shocks

There is a relatively large literature on drought exposure and child stunting, however the evidence is mainly drawn from SSA.[1] Drought and deficient rainfall were found to be associated with lower HAZ-scores of children under five in Malawi (Abiona, 2017), India (Bharti et al., 2019), Ghana and Bangladesh (Cooper, Brown, Azzarri et al., 2019), Ethiopia (Dimitrova, 2021), as well as in cross-country studies focusing mostly on SSA (Baker & Anttila-Hughes, 2020; Cooper, Brown, Hochrainer-Stigler et al., 2019; Thiede & Strube, 2020). Equivalently, higher precipitation was found to be positively associated with HAZ scores of children in Indonesia (Cornwell & Inder, 2015), Nepal (Tiwari et al., 2017), Uganda (Shively, 2017; Ssentongo et al., 2020), Nigeria (Rabassa et al., 2014) and Ethiopia (Randell et al., 2020). While these studies all rely on (repeated) cross-sections of nationally representative data, the only study using a child level panel is by Nsabimana and Mensah (2020) who find that drought shocks significantly increase the probability of stunting of children in Tanzania

There is convincing evidence that the major pathway explaining the relationship between drought and stunting is agricultural productivity and related income and/or nutrition effects. Indirect evidence for this pathway consists in the fact that the drought-stunting relationship is stronger during the main agricultural season (Cornwell & Inder, 2015; Dimitrova, 2021; Rabassa et al., 2014; Randell et al., 2020; Shively, 2017; Tiwari et al., 2017), in rural locations (Baker & Anttila-Hughes, 2020; Nsabimana & Mensah, 2020) and where the adaptive capacity of food systems, such as the degree of crop diversification and irrigation is lower (Cooper et al. 2019b). Direct evidence derived from explicitly modelling the productivity of main crops as a mediator of the drought-stunting relationship (Bharti et al., 2019; Ssentongo et al., 2020) or relating vegetation anomalies to stunting (Mulmi et al., 2016) supports this pathway. Relatedly, it has also been found that high temperature is associated with lower dietary diversity among children (Niles et al., 2021). In Kyrgyzstan, droughts are a recurring phenomenon and regularly cause significant crop losses, specifically in vegetables, wheat, and potatoes, and contribute to degradation of pastures for livestock grazing. Thereby, food security is affected directly and indirectly, via increasing food prices (World Food Program, 2014). A second pathway specifically between

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[1] For a review of earlier papers on the relationship between climate and child health we kindly refer to Phalkey et al. (2015)

above-normal temperatures and stunting consists in increased incidence of infectious diseases such as diarrhea (Baker & Anttila-Hughes, 2020), particularly in urban areas. In Kyrgyzstan, it was documented that during a phase of local drought and water scarcity typhoid, diarrhea, and worm infections have increased (Bekturganov et al., 2016).

2.2. Early-life exposure to excessive rainfall and flood shocks

A few studies look at the effects of excessive rainfall and floods on stunting rates. A positive association was found in Malawi (Abiona, 2017), where it was not persistent over time, and in Mexico, specifically in central and elevated municipalities (Skoufias & Vinha, 2012). Excessive rainfall during the monsoon season increased stunting rates specifically in tropical wet regions in India (Dimitrova and Bora 2020). The major pathway for this relationship found in the literature is an increase in infectious diseases and specifically diarrhea due to contaminated drinking water in households lacking safe sanitation (Dimitrova & Bora, 2020; Rabassa et al., 2014). This pathway dominates a potential agricultural productivity and nutrition pathway (Skoufias and Vinha 2012). Due to its geographical location, specifically in Kyrgyzstan excessive precipitation is often associated with frequently occurring landslides or mudflows (World Bank & Asian Development Bank, 2021) that regularly damage roads, houses, and other infrastructure and could thereby negatively affect households' income and access to food or healthcare.

2.3. Early-life exposure to cold temperature shocks

There are only few studies explicitly looking at cold shocks and child health. Skoufias and Vinha (2012) find that the experience of negative temperature deviations lead to more child stunting in Mexico, and this was particularly pronounced in high altitude municipalities. Groppo and Kraehnert (2016) find that a winter shock experienced in-utero persistently increased child stunting among herding families in Mongolia. Ogasawara and Yumitori (2019) find that cold shocks measured as the average yearly number of days with temperatures lower than 0 °C for at least two consecutive days experienced in relatively warmer regions had a stronger effect on stunting probabilities of children in industrializing Japan. Sanchez (2018) finds that below-average temperature increases the stunting probability of children in the highlands of Peru. For the US several authors find that both heat and cold shocks increase mortality, especially among infants and the elderly (Barreca, 2012; Curriero et al., 2002; Deschênes & Greenstone, 2011).

Similar to other weather shocks, cold shocks could affect stunting via agricultural productivity and related income effects (Ogasawara & Yumitori, 2019; Skoufias & Vinha, 2012). Specifically in Kyrgyzstan, cold winter temperatures in the past have affected livestock mortality (Conti et al., 2018) and food prices (World Food Program, 2012), which in turn negatively affect households' real income and can thereby increase the likelihood of child stunting. An additional potential mechanism is related to energy poverty. During harsh winter months, especially the poorer households might face a tradeoff between "heat and eat" (Bhattacharya et al., 2003) and nevertheless fail on either objective. This circumstance may affect child stunting directly through a deficient nutrient and energy intake or infectious diseases. Harsh winters generally increase the likelihood of respiratory diseases such as influenza, which may increase the risk of child stunting (Ogasawara, 2017) on top of maternal stress and undernutrition.

Another pathway less explored in the literature is the nexus to indoor heating and energy supply options. Generally, the energy sector in Kyrgyzstan is found to be in a precarious situation (World Bank, 2017). Even though Kyrgyzstan has high hydroelectric potential, with hydroelectric power providing>90% of total electricity, the infrastructure is antiquated and depends on a steady supply of melted snow, which makes it susceptible to outages especially in winter. Together with exceptionally low tariffs and ever-rising demand (by 60% between 2007 and 2016 alone), the sector faces a growing supply gap (World Bank, 2017). Hence harsh winters often lead to power cuts and electricity shortages when generating capacities are insufficient to meet household demand for heating and cooking (World Bank, 2020). Outages occur regularly, for instance in 2012, when millions of people in whole Central Asia were affected.[2] Insufficient energy for heating and cooking could imply health consequences for the many households and their children relying on electricity for these purposes. While coal stoves are the most common heating source and used by around 60% of Kyrgyz households (World Bank, 2017), the second most important source is electricity.[3] Electricity is mostly combined with stove heating (26% of households), while around 5% rely on electricity exclusively (Gassmann & Trindade, 2019). Those who rely on stoves are likely to face another problem in winter, namely indoor air pollution. This especially affects the poorer households that use more inefficient and polluting stoves. In a recent World Bank study, around 70% of households found indoor air pollution to be a major issue (World Bank, 2020). Increased concentrations of particular matter has been shown to increase stunting when experienced in-utero and early in life (Kurata et al., 2020; Sinharoy et al., 2020). To summarize, both electric as well as stove heating have the potential to adversely affect child health and stunting during harsh winters. Without being able to predict the exact magnitude, we hypothesize that the effect of the cold shock on stunting will depend on the heating source of the child's household.

2.4. Age and gender

Nutrition's role in child development is particularly crucial in the very beginning of life: depending on the outcome, the first 500 (Mason et al., 2014) or 1,000 days (Cusick & Georgieff, 2016) or 24 months (Black et al., 2008) have been found to be crucial. This is in line with empirical evidence showing that shocks experienced during the first 12 (Nsabimana & Mensah, 2020; Rabassa et al., 2014) or 24 months (Dimitrova 2021) most severely affected children's height. Additionally, there is evidence of "catch-up" growth, meaning that HAZ-scores improve as children get older (Desmond & Casale, 2017) and, correspondingly, of deterioration of weather effects on stunting over time (Abiona 2017).

There is a general consensus that boys are more susceptible to stunting and wasting, at least in SSA (Wamani et al., 2007), and that this difference is biological to a certain extent (Wells, 2000). However, the evidence for gender differences in stunting following weather shocks is inconclusive. Dimitrova (2021) finds that boys' height-for-age is more negatively affected than girls' by droughts in Ethiopia. Mulmi et al. (2016) find that Nepalese boys are most affected by prenatal agro-climatic conditions, whereas girls are most vulnerable in the three months after birth, with overall effects being larger for boys. Similarly, Ogasawara and Yumitori (2019) find that prenatal exposure to cold shocks affects height of male children, while female children are affected by postnatal cold shocks. Generally, empirical evidence of gender differences in response to shocks remains limited (Dimitrova 2020, 21). No

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[2] "Central Asia: Struggling to Keep the Lights On", https://eurasianet.org/central-asia-struggling-to-keep-the-lights-on, accessed 17 June 2021.

[3] "World Bank to Help Kyrgyz Republic Improve Efficiency and Quality of its Heat Supply",https://www.worldbank.org/en/news/press-release/2017/10/27/world-bank-to-help-kyrgyz-republic-improve-efficiency-and-quality-of-heat-supply, accessed 17 June 2021.

gender differences were found by Thiede and Strube (2020) in their cross-country study, and by Rabassa et al. (2014) for Nigeria. Given these inconclusive results, we seek to explore potential differential impacts of weather shocks on boys and girls in our sample in order to add to the debate.

2.5. Other determinants of stunting

Other factors that have been found to play a role in child health are mothers' education and health, mothers' time allocation between agricultural, wage, and domestic labor, income and food prices, local infrastructure and public health services, hygiene and sanitary conditions, and conflict exposure (Thomas et al. 1991; Sahn 1994; Thomas et al., 1996; Strauss and Thomas 1998; Glick and Sahn 1998; Sahn and Alderman 1997; Buckley 2003; Alderman et al. 2009; Arcand et al. 2015; Becker et al. 2017; Akseer et al. 2018). Mothers' education and wealth have been found to decrease weather shock effects on stunting (Thiede and Strube 2020, Dimitrova 2021). Specifically in Kyrgyzstan, it was shown that improvements in child nutrition were primarily due to poverty reduction (61%), maternal nutrition (14%), paternal education (6%) (Wigle et al., 2020). In our analysis we will take into account these covariates.

3. Data

3.1. Life in Kyrgyzstan panel

The Life in Kyrgyzstan (LiK) survey (Brück et al. 2014) comprises 6 waves: 2010–2013, 2016 and 2019. The original 3,000 households were drawn through stratified two-stage random sampling. The strata were formed by Bishkek city, Osh city (largest city in the South), and the rural and urban areas of the seven *oblasts*: Issyk-Kul, Jalal-Abad, Naryn, Batken, Talas, Chui, and Osh oblasts, and 90 locations were randomly selected (Fig. 1). The data are representative at the national, urban/rural and North/South levels.[4] Most of the households in the survey were revisited annually with very low annual attrition rates. This is the first study in Kyrgyzstan that captures diverse set of information about adults and children, households and communities and follows them for several years.

In our analysis we use three waves of panel data (2010–2012) including child anthropometrics, household and community characteristics of children up to and including 59 months old. The key advantage of panel data is that it allows disentangling pathways more convincingly (Baker & Anttila-Hughes, 2020). The main outcome of interest is the stunting indicator derived from the child's height/length-for-age z-score (HAZ-score). For each sex and age month, HAZ-scores are calculated as standardized differences between length/height of children in our LiK sample and a healthy reference population according to World Health Organization (WHO) standards (WHO Multicentre Growth Reference Study Group, 2006) using the "zscore06" package (Leroy, 2011) in Stata16 (StataCorp, 2019). Children are defined to be stunted or extremely stunted with HAZ-score < -2 or HAZ-score < -3, respectively, i.e. when their height is two or three standard deviations below the WHO standards' median for the same age and sex (Onis et al., 2013). Our outcome of interest is whether a child is stunted (HAZ-score < -2).

Initially, our sample consists of 1,503, 1,481, and 1,443 children under 60 months in years 2010, 2011, 2012, respectively. As recommended, children with HAZ scores -6 or above 6 standard deviations are dropped from the analysis (Onis et al., 2013). Furthermore observations with inconsistent or missing information in terms of HAZ-score, age, height, weight, mothers' gender, and mothers' identity[5] are dropped. Furthermore we must take into account that mothers might have moved with their since the birth of their children and therefore they could have grown up in different climatic zones. Therefore we also drop children from our sample whose mothers either moved during the last five years prior to the survey or were outside of Kyrgyzstan or elsewhere in the country for longer than 1 month during last 12 months prior to the survey. This leaves us with a final analytical sample of 1,244, 1,150, and 1,206 children in the years 2010, 2011, and 2012 respectively. Details on the number of children dropped are laid out in detail in Table A1 in the appendix. By design the panel is unbalanced as children who become older than 59 months drop out.

3.2. Weather data

Weather data are obtained from the Climatic Research Unit of the University of East Anglia (CRU-TS 4.01) (Mitchell & Jones, 2005). The dataset contains high-resolution gridded time-series data of monthly temperatures and precipitation since 1901 with a resolution of 0.5° longitude by 0.5° latitude, which is equivalent to approximately 50 km land grid depending on the latitude. The data is obtained from weather stations and then interpolated on the ground using complex gridding routines in order to produce a 0.5° resolution. The 90 geo-coded primary sampling sites in our sample are merged with the enclosing weather grids of the CRU-TS data using latitude and longitude coordinates.

We define negative and positive rainfall shocks (i.e. drought and excess precipitation) using the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). The SPEI is a drought index based on the water balance which is defined as the difference between precipitation and potential evapotranspiration. The distribution of the water balance determined from the historical observations is transformed into a standard normal distribution using the years 1986–2012 as the historical reference period. For each value of the water balance, the position within the distribution can be expressed standard deviation. Hence a SPEI value of less than minus one (more than plus one) standard deviation is referred to as drought (excessive rainfall). It is possible to aggregate the water balance over several months which enables the detection of longer lasting droughts or excessive rainfall periods. However, for this study we use the monthly SPEI (SPEI01). SPEI01 is calculated using the package "SPEI" (Beguería et al.) in R (R Core Team, 2020). The definition of a cold shock follows the same logic. It is derived from the standard deviation of monthly winter temperatures for the five month heating period generally starting in November and ending in March (World Bank, 2015) from long term averages (1986 to 2012). Hence, we first calculate the temperature z-score during winter months November through March[6] in the $i = 1, 2, ..., 90$ locations in year $y = 2005,\ldots,2012$:

$$z_{iy} = \frac{x_{imy} - \overline{x}_i}{\sigma_i} \tag{1}$$

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[4] Because the data are representative at the national level, there are no weights assigned to individuals and households.

[5] Mothers of children are not explicitly identified in the 2010 wave of the survey. For children with missing mother IDs, their mothers' identity was inferred from the other survey years. In a second step, the mother IDs that were still missing were inferred from the household structure: (1) if household head is female and the child is an offspring to the household head, we infer that the household head is the mother; and (2) if household head is male, and child is an offspring to the household head's spouse, we infer that the spouse of the household head is the mother.

[6] For ease of calculation, November and December are assumed to be part of next year's winter.

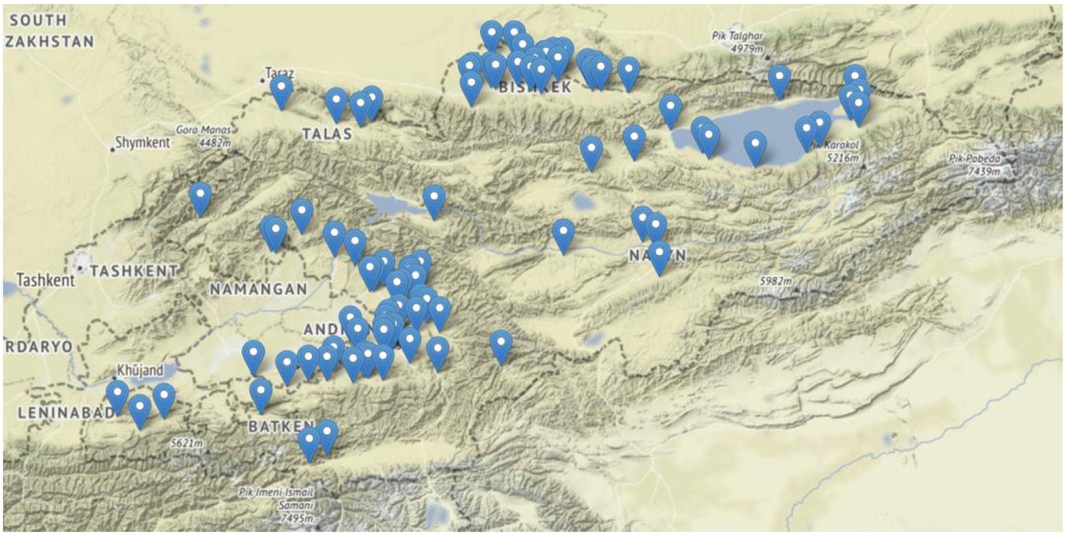

Fig. 1. Locations of Life in Kyrgyzstan (LiK) survey sites. *Source: Authors' own illustration.*

Here, $\overline{x_i}$ is the monthly temperature average for location i from 1985 to 2012, and σ_i is the respective standard deviation. The binary indicator for a cold shock at location i in month m and year y is defined by a z-score cutoff of -1:

$$s_{imy} = \begin{cases} 1\ if\ z_{imy} < -1 \\ 0\ otherwise \end{cases} \tag{2}$$

For all three shocks we calculate cumulative values for each child between month and year of birth and month and year of each survey interview/anthropometric measurement. Similar approaches using the SPEI were applied by Nsabimana and Mensah (2020) and Cooper et al. (2019).

4. Estimation strategy

Bellemare et al. (2015) argue that when modelling probabilities with fixed effects the advantage of using a linear probability model (LPM) outweigh the disadvantage of potential bias relative to a non-linear model. Furthermore, LPM coefficients have the advantage that they can be interpreted directly in terms of marginal effects, i.e. changes in probabilities. Given these considerations we estimate the following LPM:

$$\begin{aligned} Y_{ihct} = {} & \alpha_0 + \alpha_1 Wshock_{ct} + \alpha_2 Sex_i + \alpha_3 Age_{it} + \alpha_4 Age_{it}^2 + \alpha_4 Z_{ht} \\ & + FE_{bm} + FE_{t\times oblast} + FE_{h(i)} + \varepsilon_{ihct} \end{aligned} \tag{3}$$

where Y is a binary variable taking the value one if a child is stunted, i.e. its HAZ-score is below -2 (WHO Multicentre Growth Reference Study Group, 2006). *Wshocks* is a cumulative variable indicating the number of months since birth a child was affected by either (1) rainfall shocks (positive and negative) or (2) an extraordinary cold winter, as defined earlier. Furthermore we control for the child's gender and age in months as well as a square term of the latter, which are used in different specifications to identify heterogeneous effects. Z_{ht} includes a vector of household time-variant characteristics: dependency ratio[7], log of land size, and an asset index. The asset index is calculated through principal component analysis (PCA) as suggested in Filmer and Pritchett (2001) using binary information regarding ownership of 31 assets and comprises the standardized PCA scores. $FE_{oblast\times t}$ are year × oblast (state) fixed effects, $FE_{h(i)}$ refers to household or child fixed effects, depending on the specification, FE_{bm} refer to birth month dummies to control for child health differences due to season of birth, and ε is the error term. Using household (child) fixed effects, we are able to eliminate the influence of time-invariant characteristics at the household (child) level and effects can be interpreted as within-household (within-child) effects. Household fixed effects have the advantage of exploiting variation in child stunting within households with multiple children exposed to the same upbringing but different weather conditions due to age differences. Standard errors are clustered at the sampling cluster level.

To study heterogeneous effects, we interact the shock indicators with (1) a categorical variable of three equal sized age bins, (2) the child's sex, and (3) both, as well as (4) the household's main heating source (for cold shocks), (5) whether the household lives in a rural area and (6) the season of the rainfall or drought shocks.

5. Results

5.1. Descriptive results

Child anthropometrics by survey year and age group are summarized in Table 1. Across years, the average share of boys in our sample is 52%. Around 29%, 24%, and 33% of all children in our sample are stunted in years 2010, 2011, and 2012 respectively. These are considerably larger shares than reported by other surveys on Kyrgyzstan (e.g. UNICEF et al., 2020). Fig. 2 shows how the children's average HAZ-score drops rapidly during the first 6 months since birth, which is untypical, since the highest rate of decline is expected to occur after the first 6 months when many mothers stop breastfeeding. Stunting prevalence varies by age group and gender of the child. On average, we find that the prevalence of stunting is higher in the middle age group (20–39 months; 32%) compared to both the oldest (40–59 months; 26%) and the youngest age group (0–19 months, 28%) The overall prevalence of stunting in boys across all ages is 30% for boys and 27% for girls.

Monthly weather data for the range of birth years considered in our sample (2005 to 2012) as well as the respective cutoff points for our definition of shocks are depicted in Fig. 3. The left-side panel shows that monthly droughts (SPEI01 < -1) and excessive rainfall shocks (SPEI01 > 1) occur regularly, but the latter occur more frequently, for instance in 2009/2010. Cold shocks (monthly

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[7] The dependency ratio is defined as the number of household members younger than 14 and older than 65 years, divided by the number of household members 15 to 64 years old.

Table 1
Summary statistics for individual-level outcomes for children 0–5 years old.

	2010				2011				2012			
	female		male		female		male		female		male	
VARIABLES	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Age group 1: 0–19 months												
HAZ-score	−0.75	1.96	−0.95	1.92	−0.70	1.88	−0.88	2.14	−0.82	2.20	−1.13	2.19
Stunted (HAZ < -2)	0.25	0.44	0.27	0.45	0.24	0.43	0.30	0.46	0.26	0.44	0.35	0.48
Severely stunted (HAZ < -3)	0.10	0.31	0.10	0.30	0.09	0.28	0.17	0.38	0.14	0.34	0.18	0.38
Height (cm)	66.48	8.86	69.03	8.27	69.39	8.84	69.30	8.49	67.01	9.23	68.98	8.60
Weight (kg)	8.10	2.64	8.49	2.42	8.96	5.70	9.18	6.56	8.20	2.64	8.83	2.67
Observations	201		207		174		179		148		169	
Age group 2: 20–39 months												
HAZ-score	−0.98	2.19	−1.23	2.18	−0.76	1.90	−1.02	1.93	−1.40	1.72	−1.65	1.97
Stunted (HAZ < -2)	0.29	0.45	0.34	0.47	0.23	0.42	0.28	0.45	0.34	0.47	0.42	0.49
Severely stunted (HAZ < -3)	0.15	0.35	0.19	0.39	0.09	0.29	0.12	0.32	0.15	0.36	0.24	0.43
Height (cm)	86.32	8.57	86.96	8.16	87.96	7.87	88.06	7.91	85.54	7.38	86.16	8.12
Weight (kg)	12.46	2.55	12.75	2.58	13.67	7.41	13.67	6.84	12.93	2.12	13.19	2.07
Observations	226		226		21		227		21		235	
Age group 3: 40–59 months												
HAZ-score	−1.40	1.56	−1.39	1.56	−0.96	1.40	−1.07	1.52	−1.20	1.81	−1.14	1.86
Stunted (HAZ < -2)	0.29	0.46	0.28	0.45	0.19	0.39	0.20	0.40	0.30	0.46	0.29	0.45
Severely stunted (HAZ < -3)	0.12	0.33	0.12	0.33	0.05	0.22	0.07	0.25	0.10	0.31	0.09	0.29
Height (cm)	97.28	7.88	98.23	7.52	99.51	6.83	99.41	7.19	98.11	8.15	99.28	8.55
Weight (kg)	15.19	2.51	15.88	3.08	16.73	8.07	16.71	6.60	15.91	2.49	16.44	3.39
Observations	193		191		177		183		211		233	

Source: Authors' own illustration based on LiK 2010–2012.

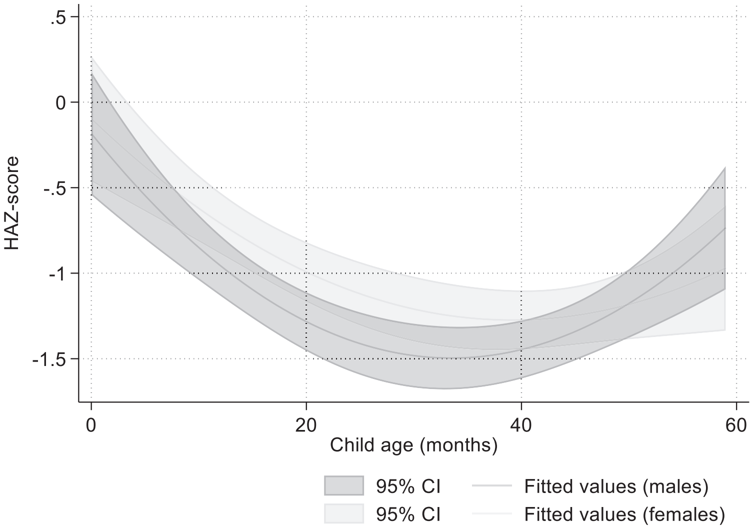


Fig. 2. Mean HAZ-score by gender and child age in months *Source: Authors' own illustration based on LiK 2010–2012.*

temperature z-score < -1) happen more irregularly and there is less variation across survey sites. Notably, extremely low temperatures in January 2008 were followed by untypically high temperatures in the months after.

By design, the cumulative number of shocks that children below 60 months are exposed to increases with age (Fig. 4), but the slope is steepest for excessive rainfall, followed by droughts. When children reach the age of 59 months they experienced on average 13.7 positive rainfall shocks (sd = 3.7), 10.3 negative rainfall shocks (sd = 2.5), and 3.5 cold shocks (sd = 1.2)

Characteristics of the children's households are summarized in Table 2. In the base year 2010, average household size was 6.9 and households had on average 1.3 children that were 0–59 months old at that time. The overall dependency ratio indicated that on average 1.2 times as many economically dependent as working age persons lived in the households. Around 67% of households lived in rural areas, 28% owned some land with an average land size of about 0.7 ha, and 42% reported to earn some income from agriculture (on average 58% of their total household income). Average monthly household income was around 11,947 Kyrgyz soms, corresponding to around 250 USD at the time of the survey. Around 9% of households indicated central or gas to be their major energy source for indoor heating, 8% used mainly electric heating, and the rest of the households, 72% use coal stoves. The remaining 8% had missing, other or no heating sources. Furthermore, 26% of households had two heating sources in 2010. The survey only asks for a second heating source in 2010, otherwise it only asks for the main one.

Table A2 in the appendix disaggregates sociodemographic characteristics of households by their major heating sources. It shows that households relying on central heating are almost exclusively concentrated in the capital of Bishkek, while stove heating is the

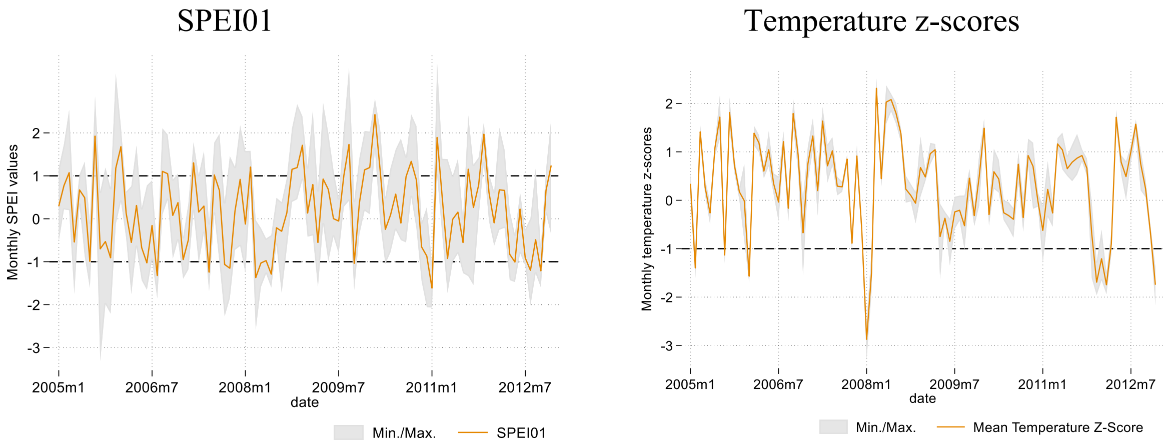


Fig. 3. Monthly SPEI01 and temperature z-scores over time. *Source: Authors' own illustration based on LiK 2010-2012 and CRU-TS 4.01.*

predominant heating source in rural areas. Almost 70% of electric heating households are located in smaller cities such as Jalal-Abad, and Osh City and Issyk-Kul. This ranking is also reflected by the households' wealth level: households with stoves (central heating) are poorer (richer) compared to households using electricity. While households' socio-economic characteristics vary significantly by heating source, their exposure to cold shocks does not.

5.2. Estimation results

The results from estimating equation (3) for cumulative drought, excessive rainfall, and cold shocks are shown in Table 3. The coefficients corresponding to the average effect of exposure to one additional month of deficient or excessive rainfall or below-average temperatures on the probability of child stunting are statistically insignificant, yet expectedly positive for cold shocks (columns 5–8). We also see that age is significantly positively and non-linearly related to a child's probability of stunting in all specifications.

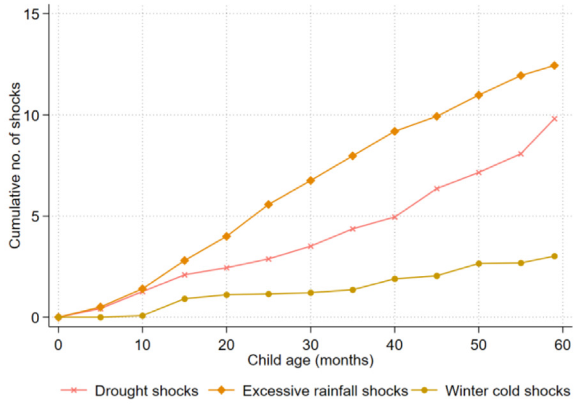


Fig. 4. Cumulative weather shocks by age. *Source: Authors' own illustration based on LiK 2010-2012.*

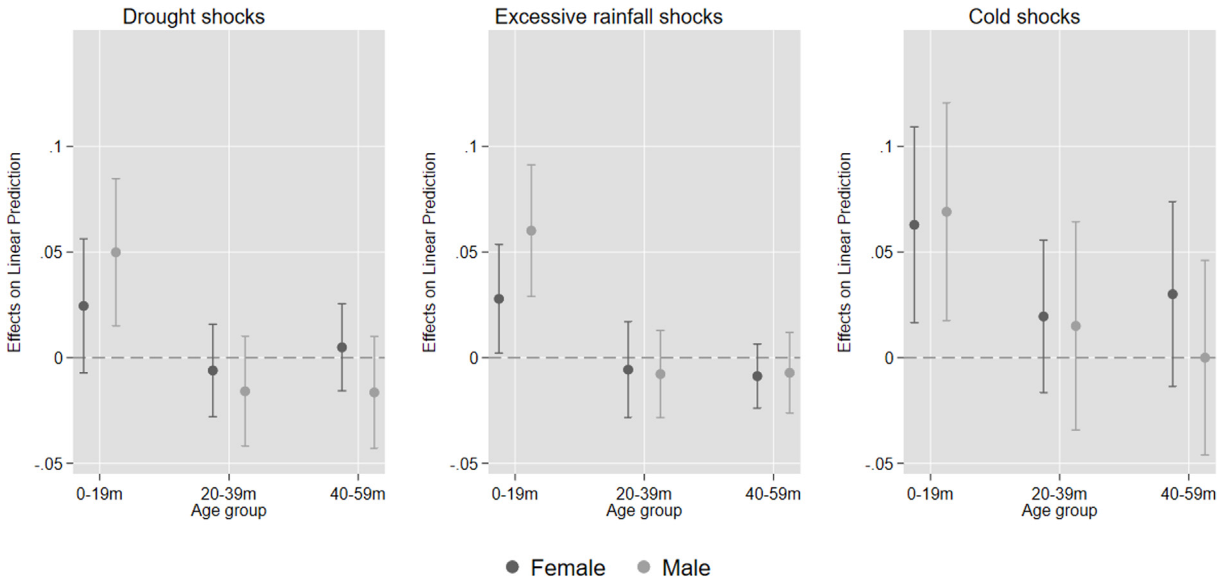


Fig. 5. Avg. marginal effects with 95% CIs of shocks on predicted stunting probability by age and gender (household fixed effects) *Source: Authors' own illustration based on LiK 2010–2012.*

Table 2
Household characteristics of children 0–5 years old.

	2010		2011		2012	
	mean	sd	mean	sd	mean	sd
Household size	6.90	(2.71)	6.93	(2.66)	7.22	(2.74)
No. of children<=60 *m*	1.33	(0.56)	1.32	(0.55)	1.35	(0.59)
Dependency ratio[1]	1.22	(0.79)	1.17	(0.81)	1.04	(0.69)
Household lives in rural area; dummy	0.67	(0.47)	0.67	(0.47)	0.67	(0.47)
Household owns land; dummy	0.28	(0.45)	0.27	(0.44)	0.26	(0.44)
Land size; ha	0.67	(2.05)	0.70	(2.14)	0.62	(1.43)
Monthly income in 2010 prices; KGS[2]	11,947	(10,893)	12,973	(9,458)	14,986	(12,006)
Agricultural income; dummy	0.42	(0.49)	0.43	(0.50)	0.47	(0.50)
Agricultural income; share of total[3]	0.58	(0.29)	0.50	(0.29)	0.45	(0.28)
Heating source = central/gas	0.09	(0.29)	0.11	(0.31)	0.10	(0.30)
Heating source = electric	0.08	(0.28)	0.10	(0.29)	0.09	(0.29)
Heating source = stove	0.74	(0.44)	0.80	(0.40)	0.81	(0.39)
Heating source = other/none[4]	0.08	(0.28)	na		na	
Hh had two heating sources in 2010[4]	0.26	(0.44)	na		na	
Observations	932		870		896	

[1] No. of household members younger than 14 and older than 65 years, divided by no. of members 15 to 64 years.
[2] Incomes in Kyrgyz soms (KGS) were deflated to 2010 prices using oblast-level consumer price indices.
[3] Only for those households that have any agricultural income.
[4] This information was only gathered in the 2010 survey.
Source: Authors' own illustration based on LiK 2010–2012.

Table 3
The effects of drought and rainfall shocks on the probability of child stunting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EXPLANATORY VARIABLES								
No. of excessive rainfall shocks	−0.002	−0.005	−0.002	−0.003				
	(0.023)	(0.023)	(0.010)	(0.010)				
No. of drought shocks	−0.028	−0.030	0.006	0.005				
	(0.026)	(0.026)	(0.011)	(0.011)				
No. of cold shocks					0.017	0.017	0.032	0.031
					(0.039)	(0.039)	(0.021)	(0.021)
Age; months	0.058*	0.058*	0.010**	0.011**	0.051*	0.050*	0.009***	0.009***
	(0.030)	(0.030)	(0.005)	(0.004)	(0.030)	(0.030)	(0.003)	(0.003)
Age^2; months	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dependency ratio[1]		−0.045**		−0.047		−0.043**		−0.047
		(0.021)		(0.031)		(0.021)		(0.031)
Log(landsize)		0.043		0.026		0.041		0.025
		(0.033)		(0.038)		(0.033)		(0.038)
Asset index[2]		0.033		−0.081		0.037		−0.078
		(0.151)		(0.192)		(0.151)		(0.190)
Child is male; dummy			−0.010	−0.009			−0.010	−0.009
			(0.036)	(0.036)			(0.035)	(0.036)
Constant	−0.639	−0.577	0.347***	0.423***	−0.570	−0.520	0.361***	0.436***
	(0.591)	(0.601)	(0.067)	(0.109)	(0.570)	(0.581)	(0.069)	(0.111)
Observations	2,910	2,910	3,325	3,325	2,910	2,910	3,325	3,325
R-squared	0.561	0.562	0.446	0.447	0.560	0.561	0.446	0.447
Year × Oblast dummies	YES	YES	YES	YES	YES	YES	YES	YES
Birth month dummies	NO	NO	YES	YES	NO	NO	YES	YES
Child fixed effects	YES	YES	NO	NO	YES	YES	NO	NO
Household fixed effects	NO	NO	YES	YES	NO	NO	YES	YES

Dependent variable = 1 if child is stunted (Height-for-age z-score < -2), 0 otherwise. Cluster-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
[1] No. of household members younger than 14 and older than 65 years, divided by no. of members 15 to 64 years.
[2] Asset index is the standardized principal component analysis score based on binary ownership information of 31 assets.
Source: Authors' own illustration based on LiK 2010–2012.

However, we do find statistically significant effects when interacting the weather shock variables with gender and age group of the child (Tables A3 and A4 in the appendix). The average marginal effects (Fig. 5 and Table A5 in the appendix) reveal that exposure to weather shocks significantly increases stunting probabilities of children only in the age group 0–19 months, suggesting that exposure at a later age does not affect HAZ-scores and/or that affected children catch up as they grow older. Experiencing an additional month of excessive rainfall or drought in the first 19 months of life increases the stunting probability of boys (girls) by around 6% (2.8%) and 5% (2.5%), respectively. The effect of exposure to drought shocks on 0 to 19 month old girls' stunting probabilities is not statistically significant. The experience of one additional month of unusually cold temperatures in the first 19 months of life significantly increases the stunting probability of girls and boys by around 6% and 7%, respectively, but the gender differences in the effect sizes of all three shocks are not statistically significant.

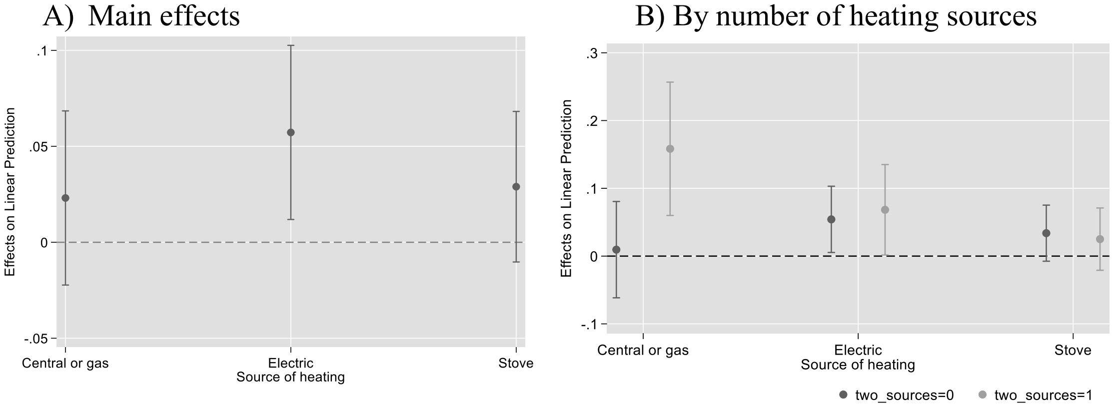


Fig. 6. Marginal effects with 95% CIs of cold shocks on stunting probability by heating source *Source: Authors' own illustration based on LiK 2010–2012.*

Even though it is an open debate in the literature whether such multiple subgroup comparisons need to be adjusted for in the same way as multiple simultaneous statistical tests (e.g. Rothman, 1990), we also present Bonferroni-adjusted p-values for the six age-gender-subgroups to account for the risk of false discoveries (Table A5 in the appendix). After adjusting, the effects of drought and rainfall shocks on the stunting probability of boys below 19 months remain statistically significant ($p < 0.01$), as well as the effect of cold shocks for girls for that age group ($p < 0.05$), thus confirming our substantial conclusions.

5.3. Mechanisms

In order to shed light on potential mechanisms of cold shocks, we are interested in heterogeneous effects by source of heating. We do not observe information on the households' heating source of children that were born before the start of the survey. However we assume that there is some consistency across time in these variables. Children from households that changed their main heating source across survey years were dropped ($n = 419$). We find a significant interaction effect ($p < 0.05$) when interacting cold shocks with the household's heating source in equation (3). The marginal effects indicate that experiencing one additional cold shock increases the average stunting probability of children younger than 60 months in households with electric heating by 5.7%, and this coefficient is statistically significant, also after adjusting for multiple comparisons ($p < 0.05$) (Fig. 6, panel A). The effects of cold shocks on children in households with stove or central heating is also positive but not statistically significant.

To shed more light on this mechanism, we furthermore take into account whether the household has a second source of heating, which is common in Kyrgyzstan (Gassmann and Trindade 2019). Unfortunately the survey only gathers this information in the year 2010, but for the subsequent analysis we make the strong assumption that those who rely on two sources in 2010 still do so in the following years, and drop children from households that are not in the 2010 sample ($n = 339$). In 2010, 26% of children lived in households with two heating sources. Of those, 90% relied on a combination of electricity and stove heating. Of those who lived in households with one source of heating, 83% had only stoves and 7% only electric heating. Potentially, both for households with electricity and stoves, having access to a second backup heating option could buffer negative effects of cold shocks on child health. The marginal effects for the interaction between heating source and number of heating sources is depicted in Fig. 6, panel B (regression results are shown in Tables A6 and A7 in the appendix). Surprisingly, we find that children's stunting probability in households with central heating and a secondary heating source are significantly affected by cold shocks, even after controlling for multiple comparisons. Households may rely on a secondary, inferior heating source when central heating is deficient. However, this result should be interpreted with caution since only a small fraction of observations have central heating and a second heating source ($n = 19$). No differences are found for electric and stove heating by number of heating sources.

To explore agricultural production as a mechanism, we look both at geographical as well as seasonal heterogeneities in terms of drought and rainfall effects. First, we look at whether the effect of rainfall shocks is moderated by the rural environment of the household. Therefore, we estimate interaction effects of a variable indicating a household's rural location with the child's age group and the cumulative shock variable. Average marginal effects of this estimation are shown in Table 4. The results suggest that before adjusting for multiple comparisons, all shocks have statistically significant effects on the youngest age group in both rural and urban locations. The effect of drought shocks however is not robust to adjusting for multiple testing. In any case, the differences between the effects of all three weather shocks on urban and rural children are not statistically significant.

Second, we vary the seasons of drought and excessive rainfall shocks. We make separate analyses for excessive rainfall and drought shocks occurring over the child's lifespan in either winter (Dec-Feb), the period where precipitation is more likely in the form of snow, spring (Mar-May), the critical period for agriculture, summer (Jun-Aug), or autumn (Sep-Nov). The distribution of shocks across seasons is shown in Fig. A1 in the appendix. Compared to the other seasons, drought shocks tend to occur more frequently in spring and autumn, while excessive rainfall shocks occur more frequently in winter and autumn. Table A8 in the appendix shows the main effects of shocks by season on stunting probabilities and HAZ scores, which are statistically insignificant.

More insights can be derived from analyzing the interaction effects of shocks with age group and gender (Table 5 and Fig. 7). Excessive rainfall exposure (Panel A of Fig. 7) across all seasons has a statistically significant positive effect on the stunting probability of children in the age group 0 to 19 months. After adjusting for multiple hypothesis tests, the effect remains statistically significant for rainfall shocks experienced in autumn ($p < 0.01$) and spring for boys ($p < 0.05$). Drought shocks (Panel B of Fig. 7) only have a statistically significant effect on stunting probabilities of boys and girls in the youngest age group when experienced in spring ($p < 0.05$), but this effect is not robust to adjusting for multiple hypothesis testing.

Table 4
Average marginal effects of shocks on stunting probability by age group and location.

	Coef.	se	p-value	Adj. p-value[1]	95% conf	interval	Test(rural = urban)
Excessive rainfall							
0–19 m × urban	0.055	0.016	**0.001*****	**0.003*****	0.024	0.087	p = 0.39
0–19 m × rural	0.038	0.014	**0.005*****	**0.031****	0.011	0.064	
20–39 m × urban	0.002	0.017	0.906	1	−0.032	0.036	
20–39 m × rural	−0.010	0.010	0.297	1	−0.030	0.009	
40–59 m × urban	0.005	0.015	0.729	1	−0.023	0.034	
40–59 m × rural	−0.015	0.007	0.030**	0.177	−0.029	−0.002	
Drought							
0–19 m × urban	0.054	0.027	**0.044****	0.266	0.001	0.106	p = 0.48
0–19 m × rural	0.033	0.015	**0.030****	0.178	0.003	0.062	
20–39 m × urban	0.006	0.014	0.658	1	−0.021	0.033	
20–39 m × rural	−0.017	0.011	0.104	0.624	−0.038	0.004	
40–59 m × urban	−0.004	0.020	0.831	1	−0.043	0.034	
40–59 m × rural	−0.005	0.009	0.580	1	−0.021	0.012	
Cold shocks							
0–19 m × urban	0.081	0.030	**0.006*****	**0.036****	0.023	0.139	p = 0.57
0–19 m × rural	0.061	0.023	**0.008*****	**0.050****	0.016	0.107	
20–39 m × urban	0.033	0.026	0.201	1	−0.018	0.084	
20–39 m × rural	0.010	0.020	0.616	1	−0.029	0.049	
40–59 m × urban	0.021	0.021	0.312	1	−0.020	0.061	
40–59 m × rural	0.010	0.025	0.696	1	−0.039	0.058	

Coef. = Avg. marginal effects on linear stunting probability. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Marked in bold: p-values < 0.05.
[1] Bonferroni-adjustment. Adjusted p-value = min{p × m, 1} where m is the number of simultaneously tested hypotheses.
Source: Authors' own illustration based on LiK 2010–2012.

Table 5
Average marginal effects of shocks on stunting probability by season, age group 0–19 months.

	coeff.	se	p-value	adj. p-value[1]	95% confidence interval	
Winter						
Excessive rainfall × female	0.024	0.036	0.495	1.000	−0.046	0.095
Excessive rainfall × male	0.099	0.040	**0.012****	0.072	0.022	0.177
Drought shocks × female	0.056	0.052	0.275	1.000	−0.045	0.158
Drought shocks × male	0.106	0.074	0.153	0.918	−0.039	0.251
Autumn						
Excessive rainfall × female	0.090	0.032	**0.005*****	**0.028****	0.028	0.152
Excessive rainfall × male	0.110	0.035	**0.002*****	**0.009*****	0.042	0.177
Drought shocks × female	−0.018	0.051	0.725	1.000	−0.119	0.082
Drought shocks × male	0.078	0.052	0.129	0.775	−0.023	0.179
Summer						
Excessive rainfall × female	0.131	0.062	**0.034****	0.203	0.010	0.251
Excessive rainfall × male	0.127	0.062	**0.042****	0.255	0.004	0.249
Drought shocks × female	0.056	0.039	0.155	0.932	−0.021	0.133
Drought shocks × male	0.057	0.044	0.195	1.000	−0.029	0.143
Spring						
Excessive rainfall × female	0.073	0.060	0.222	1.000	−0.044	0.189
Excessive rainfall × male	0.166	0.063	**0.008****	**0.049***	0.043	0.290
Drought shocks × female	0.105	0.057	0.069	0.411	−0.008	0.217
Drought shocks × male	0.123	0.055	**0.026****	0.158	0.015	0.232

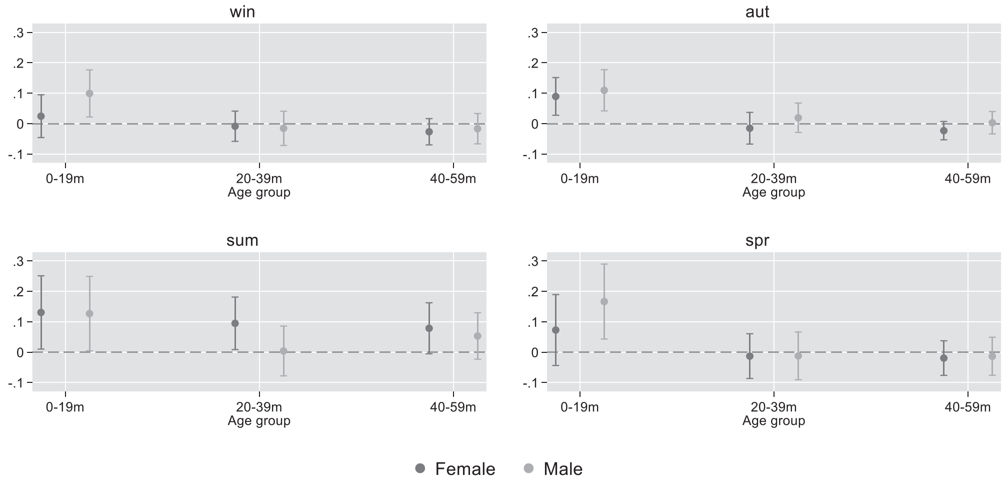
Coef. = Avg. marginal effects on linear stunting probability. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Marked in bold: p-values < 0.05.
[1] Bonferroni-adjustment. Adjusted p-value = min{p × m, 1} where m is the number of simultaneously tested hypotheses.
Source: Authors' own illustration based on LiK 2010–2012.

5.4. Robustness tests

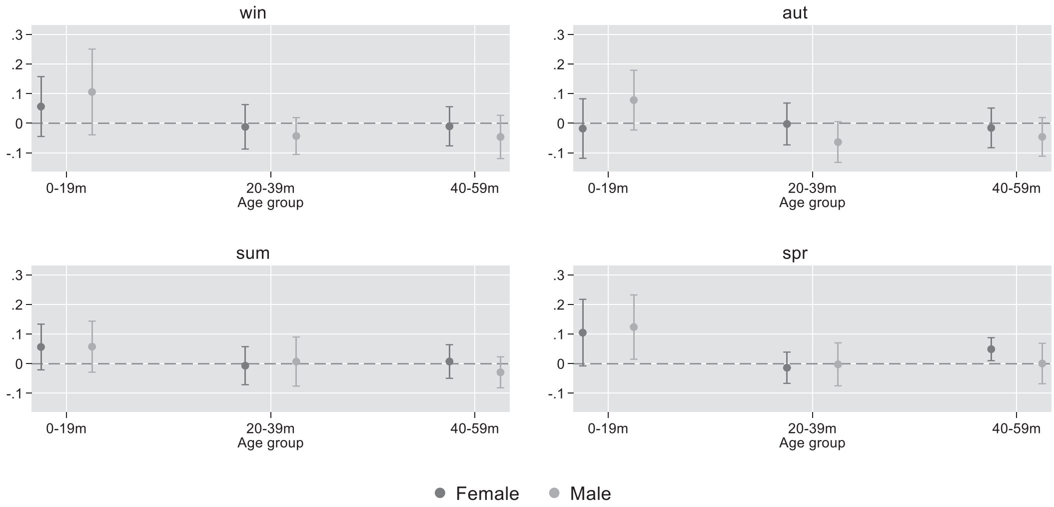
As a first robustness test, we vary the definition of shocks. As indicated in equation (2), shocks were defined as a monthly z-score of below −1 (drought and cold shocks) and above + 1 (positive rainfall shocks) relative to historical monthly averages. As a robustness test for the results, we use different z-score cut-offs (-0.5 to −1.5 for cold and drought; +0.5 to 1.5 for excessive rainfall in steps of 0.1) to define shocks. The estimations underlying Fig. 5 were repeated for different shock cut-offs and are depicted in Figs. A1 through A3 in the appendix. Note that as the cutoffs go to the extremes (-1.5 or + 1.5), the cumulative number of shocks that a child has experienced according to that definition also decreases, and hence the standard errors become larger. The graphs indicate that the results are robust to more or less extreme cut-offs. Consistently we see that all weather shocks significantly increase stunting probabilities for children below 19 months even for milder rainfall deviations of only 0.5 standard deviations below or above historical values.

As a second robustness test, we use the continuous HAZ-score instead of the stunting status of the child as a dependent variable (Tables A9, A10 and Fig. A4 in the appendix). The results reflect the findings for the stunting probability: experiencing any of the three shocks in the first 19 months of life significantly decreases HAZ-

A) Excessive rainfall shock



B) Drought shocks



y-
x-axis: avg. marginal effects of shocks on linear stunting probability. Error bars: 95% Cis. win=winter (Dec-Feb), spr=spring (Mar-May), sum=summer (Jun-Aug), aut=autumn (Sep-Nov)

Fig. 7. Average marginal effects of seasonal shocks on stunting by age and gender. *Source: Authors' own illustration based on LiK 2010–2012.*

scores for girls and boys. Exposure to cold shocks decreases children's' HAZ-scores by 0.38 ($p < 0.01$), positive rainfall shocks by 0.16 ($p < 0.01$) and excessive rainfall shocks by 0.25 ($p < 0.01$) of a standard deviation, and even though the difference is not statistically significant, the effects are larger for boys. (See Fig A5).

6. Discussion and conclusion

In many poor regions of the world the climate crisis is increasing the frequency, intensity, and impacts of extreme weather events. The detrimental consequences for human health, including hunger and malnutrition, are frequently emphasized by the scientific literature. However, the heterogeneous impacts on malnutrition of weather extremes other than rainfall and drought, and specifically on children of different demographics are not yet well understood. This paper investigated how children's probability of stunting (being too short for their age), a common indicator of overall child health and well-being, is affected by different adverse weather conditions. Stunting remains a significant problem in Central Asia, and despite recent progresses, also in the Kyrgyz Republic (Wigle et al., 2020). The country is prone to various weather shocks due to its geographic location, including cold shocks, which have not been studied in relation to child health.

By combining a rich three-wave panel dataset of children aged 0–59 months and location-matched weather data, this paper identifies the impact of three weather shocks (cold, drought, excessive rainfall) on the probability of child stunting. Using fixed effects regression models, heterogeneous effects of weather shocks by gender and age of the child are identified. The probability of stunting for the youngest group of children (0–19 months) is unanimously increased by all types of shocks, a result resonating with the recent literature. Average effect sizes vary between 3.9% for drought, 4.3% for excessive rainfall, and 6.7% for drought shocks, which is comparable to the study by Nsabimana and Mensah (2020), who find that children's stunting probability increased by about 4% due to exposure to a drought shock defined as in this paper. Male children tend to be more strongly affected, specifically by exposure to months of deficient rainfall, which echoes findings from the literature (Dimitrova, 2021; Mulmi et al., 2016; Ogasawara & Yumitori, 2019), but in our case gender differences are not statistically significant. Even though biological gender differences in child health and morbidity are documented (Wells, 2000), these do not explicitly concern differences in response to shocks. In Kyrgyzstan, cultural differences in the upbringing of boys and girls are only documented for adolescents (for instance, boys are often withdrawn from school in order to work, while girls assume responsibility for tasks around the house) (Asian Development Bank, 2019) but not infants.

Children living in rural areas are not differently affected from those living in urban areas, and unlike other studies (Dimitrova, 2021) the effects of weather shocks are only weakly related to agricultural seasons, ruling out agricultural production as an exclusive pathway of the weather-stunting relationship. However, it is still plausible that we do not observe differences because rural and urban households are equally affected by weather shocks through price increases of agricultural products, or that the relationship between weather and crop growth is more complex and the critical period depends on the specific crop. It goes beyond the scope of this paper to explore this in more detail. An increase in infectious diseases following periods of water scarcity is another plausible pathway which should be addressed by future research.

Excessive rainfall shocks in autumn seem to be most impactful in terms of child health. This could be due to the specific geography of the country. Kyrgyzstan is very mountainous and most of the population lives in the valleys and foothills. Particularly the Southern valleys are vulnerable to flooding and landslides, which are considered the most frequent and impactful disasters (World Bank & Asian Development Bank, 2021), regularly damaging homes, roads and other infrastructure, and thereby potentially increasing food prices or impeding access to health care. Furthermore, flooding might lead to an increase in infectious diseases due to contaminated water specifically in households lacking safe sanitation, as found elsewhere (Dimitrova & Bora, 2020; Rabassa et al., 2014). Indeed, children living in households without access to safe piped water were found to have a higher likelihood of being stunted across Central Asia (Bomela, 2009). Furthermore, autumn precipitation could be synonymous with early snowfall, which is harmful to agriculture and livestock. It is up to further investigation to study flooding impacts and pathways in relation to child health in more detail.

Most notably, however, the paper finds that cold temperature shocks in winter increase the probability of child stunting, and that this effect is related to the source of heating that the child's household relies on. Specifically, children from households that mainly use electricity for heating are highly prone to stunting when experiencing cold winters. This finding is in line with the recent reports on Kyrgyzstan's malfunctioning energy infrastructure and frequent power cuts in winter (World Bank, 2020). Hence children in households relying primarily on electricity as their source of heating might be exposed to cold indoor temperatures, suffering more infections, and therefore have a higher risk of stunting. When electricity is the main heating source, having access to a second heating source does not buffer this negative effect.

Finally, some words on the limitations of this study are due. While best efforts were made in disentangling pathways by exploring subgroup effects, more insights could be gained with additional data. For the agricultural productivity pathway, this includes information on households' crop and livestock production as well as market prices by crop starting with the date of birth of the child. For the infectious disease pathway, this includes information on the number and type of infections experienced by the child since birth, as well as the specific impacts of excess rainfall and flooding on water quality and sanitation. Furthermore, there is also a large literature looking at in-utero shocks and child malnutrition (e.g. Farris et al., 2018; Kumar et al., 2016; Le & Nguyen, 2021; Rocha & Soares, 2015; Shah & Steinberg, 2017). While this relationship is highly relevant, the use of fixed effects models in this paper is not compatible with studying time-invariant in-utero shocks. Hence, this paper cannot draw any conclusions about the effects of prenatal weather shocks on child health.

This paper has identified weather effects on child stunting in a country that is largely understudied, and explored potential mechanisms of the found relationships as well as vulnerable sub-groups in-depth. These findings can support the design and timing of targeted policies reducing the long-run risks of child malnutrition. Further research is required to explore the spatio-temporal effects, as well as agricultural production, price and energy usage pathways of the weather-child health relationship in more detail.

CRediT authorship contribution statement

Hanna Freudenreich: Methodology, Writing – original draft, Data curation, Software, Formal analysis. **Anastasia Aladysheva:** Conceptualization, Investigation. **Tilman Brück:** Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome. The research has been funded by the German Federal Ministry of Education and Research (BMBF) under the grant "Agricultural Systems of the Future".

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

We understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author and which has been configured to accept email from (freudenreich@igzev.de).

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Appendix A

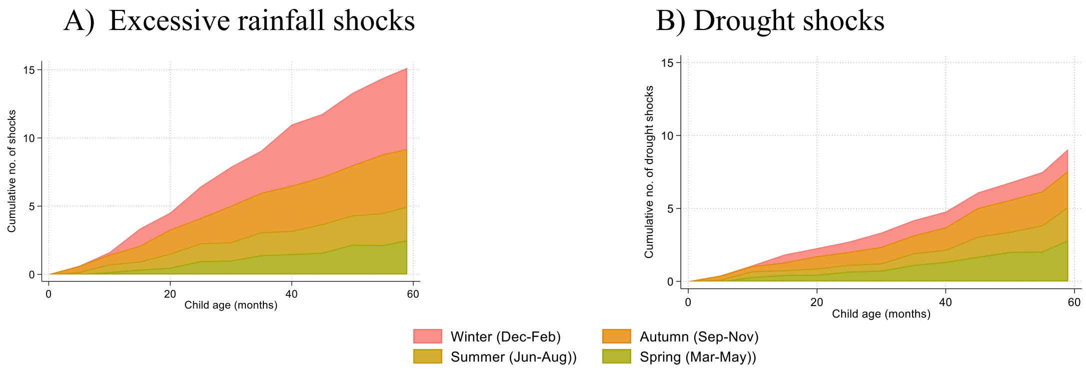
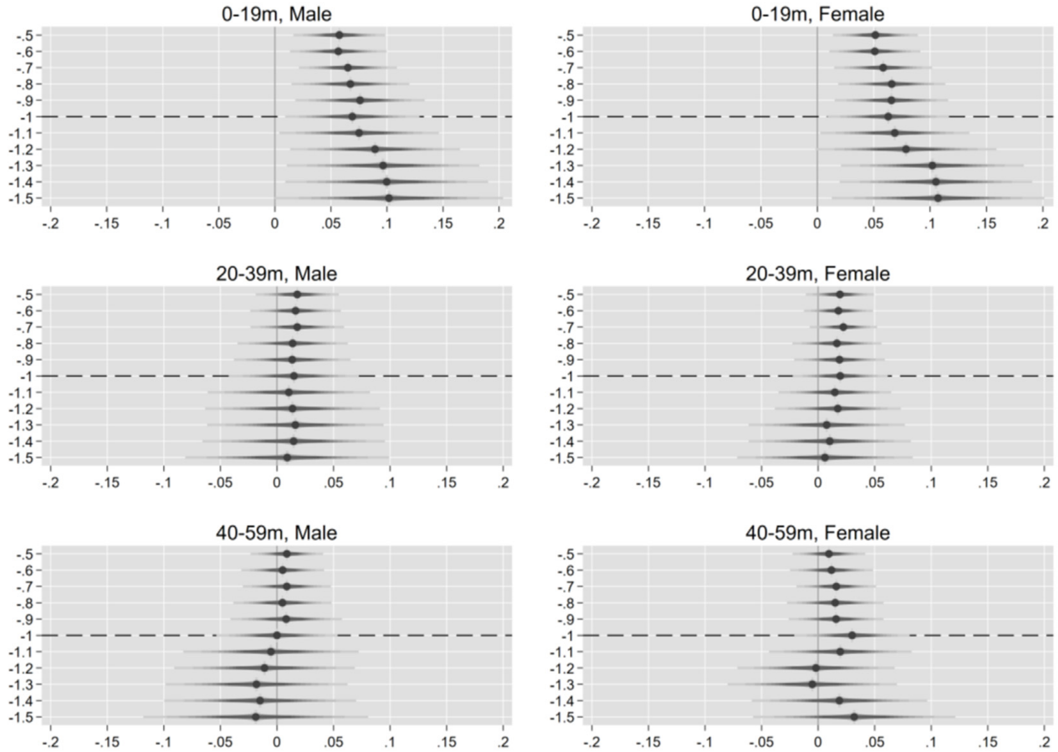
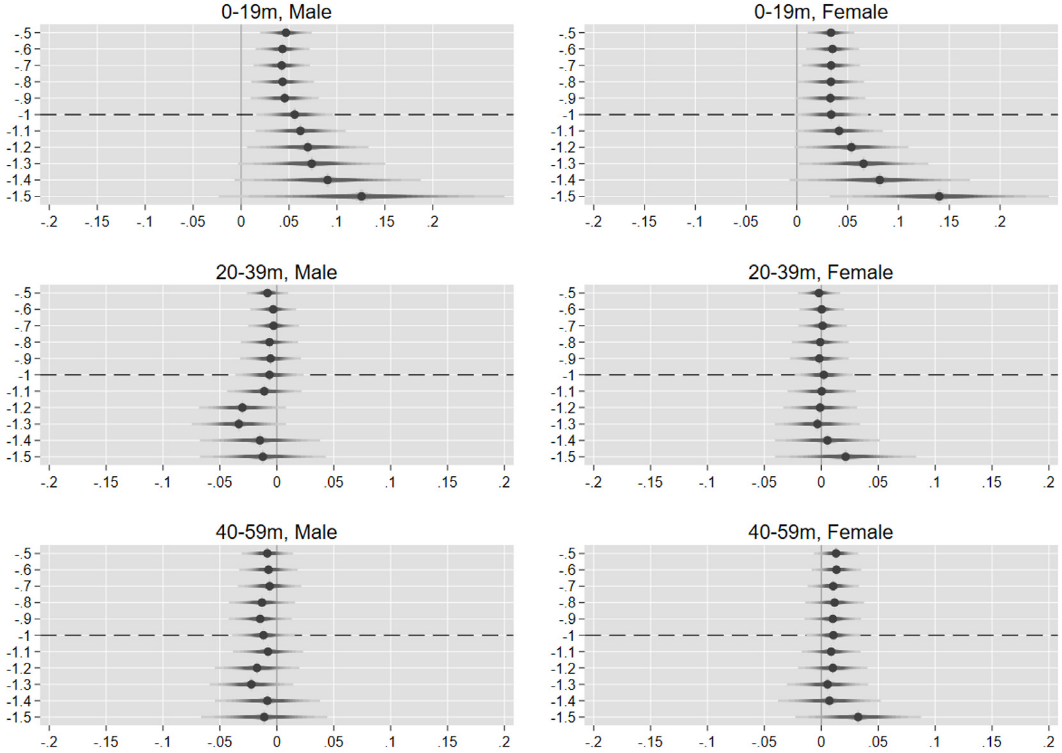


Fig. A1. Cumulative rainfall shocks by child age and season.



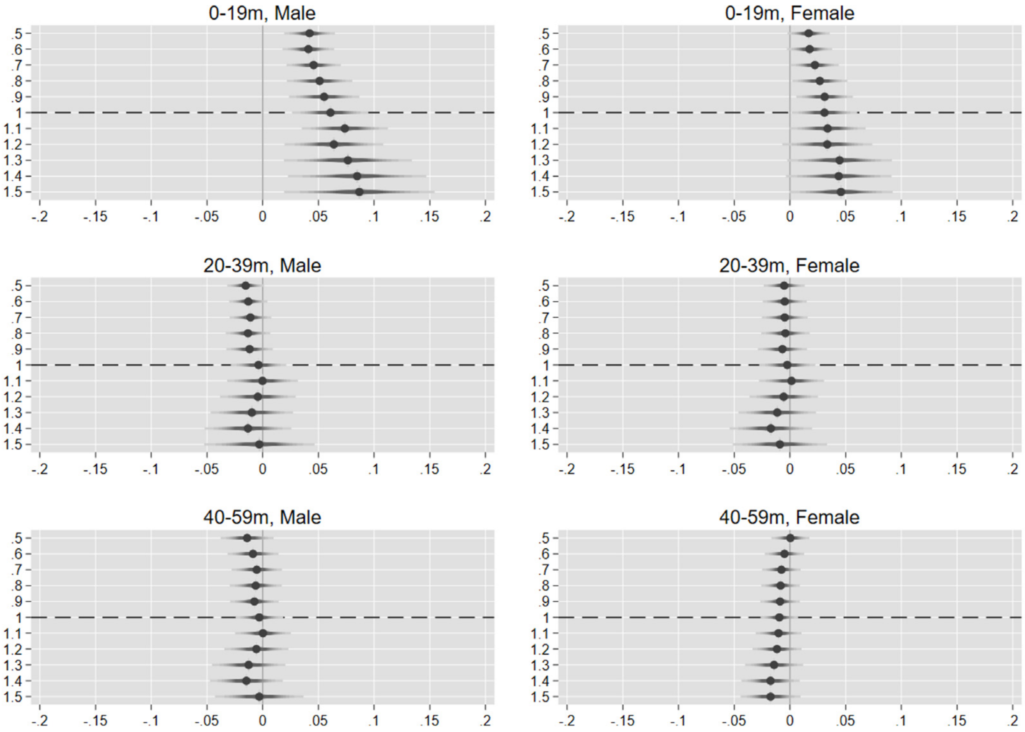
x-axis: Effect of shock on linear prediction of stunting probability, y-axis: temperature z-scores (baseline cutoff z= -1)

Fig. A2. Avg. marginal effects of cold shocks on stunting for different cutoffs x-axis: Effect of shock on linear prediction of stunting probability, y-axis: temperature z-scores (baseline cutoff z = -1).



x-axis: Effect of shock on linear prediction of stunting probability, y-axis: SPEI01 values (z-scores) (baseline cutoff= -1)

Fig. A3. Avg. marginal effects of droughts on stunting for different cutoffs x-axis: Effect of shock on linear prediction of stunting probability, y-axis: SPEI01 values (z-scores) (baseline cutoff = -1).



x-axis: Effect of shock on linear prediction of stunting probability, y-axis: SPEI01 values (z-scores) (baseline cutoff= +1)

Fig. A4. Avg. marginal effects of excessive rainfall on stunting for different-cutoffs x-axis: Effect of shock on linear prediction of stunting probability, y-axis: SPEI01 values (z-scores) (baseline cutoff= +1).

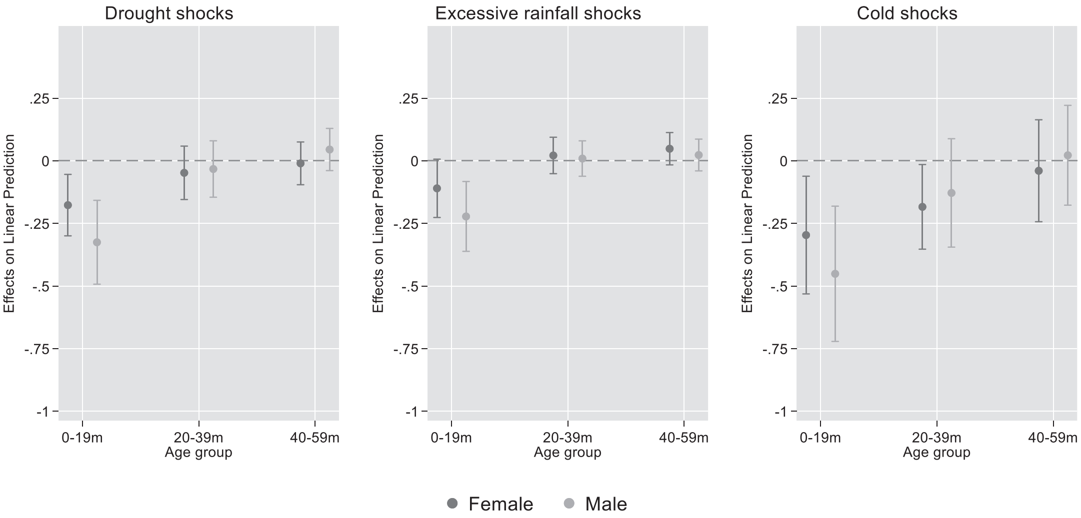


Fig. A5. Avg. marginal effects with 95% CIs of shocks on predicted HAZ score by age and gender (household fixed effects).

Table A1
Generation of final sample.

	2010	2011	2012
No. of households in sample	3,000	2,863	2,816
Of those, households with children < 60 m	1,096	1,079	1,034
Total no. of children < 60 months	1,503	1,481	1,443
Dropped:			
Outlier (HAZ score < -6)	28	18	44
Outlier (HAZ score > 6)	83	191	41
Missing weight	40	150	10
Missing length	59	173	13
Mother is not identified	88	75	62
Mother's identity inconsistent	19	36	33
Mother has moved during last 5 yrs	72	79	110
Total no. of children kept	1,244	1,150	1,206
Total no. of households kept	932	870	896

Table A2
Household descriptive characteristics by heating source in base year 2010[*]

	Central or gas		Electric		Stove		p-value[1]
	mean	sd	mean	sd	mean	sd	
Household size	4.921	1.521	5.846	2.453	7.382	2.738	<0.01
Head is male; dummy	0.684	0.468	0.865	0.345	0.817	0.387	0.501
Dependency ratio	0.948	0.584	1.262	0.946	1.274	0.817	<0.01
Hh lives in rural area; dummy	0.0263	0.161	0.365	0.486	0.785	0.410	<0.01
Asset index	0.506	0.175	0.386	0.151	0.307	0.126	<0.01
Distance to main road; km	0.389	0.532	0.441	1.116	2.611	39.12	<0.01
No. of cold shocks	0.783	0.943	0.449	0.720	0.727	0.859	0.253
No. of excessive rainfall shocks	9.737	3.831	6.708	3.667	6.927	3.811	<0.01
No. of drought shocks	2.125	2.439	2.522	2.708	2.837	2.747	<0.01
oblast==Issyk-Kul	0.013	0.115	0.115	0.323	0.101	0.302	<0.01
oblast==Jalal-Abad	0	0	0.250	0.437	0.189	0.392	<0.01
oblast==Naryn	0	0	0.115	0.323	0.0491	0.216	<0.01
oblast==Batken	0	0	0	0	0.0997	0.300	<0.01
oblast==Osh	0	0	0.0192	0.139	0.255	0.436	<0.01
oblast==Talas	0	0	0.0769	0.269	0.0445	0.206	<0.01
oblast==Chui	0.0395	0.196	0.154	0.364	0.167	0.373	<0.01
oblast==Bishkek	0.921	0.271	0.0385	0.194	0.0598	0.237	<0.01
oblast==Osh city	0.0263	0.161	0.231	0.425	0.0353	0.185	<0.01
Observations	76		52		652		

[1] Kruskal-Wallis equality-of-populations rank test.

[*] only households that did not change major heating source between 2010 and 2012.

Table A3
Heterogeneous effects of drought and excessive rainfall shocks on stunting probability by gender and age.

VARIABLES	(1) P(stunted)	(2) HAZ score
No. of excessive rainfall shocks	0.028**	−0.110*
	(0.013)	(0.059)
Age group = 20–39 *m*	0.209*	−0.806**
	(0.108)	(0.363)
Age group = 40–59 *m*	0.131	−1.330**
	(0.138)	(0.513)
Age group = 20–39 m × No. of excessive rainfall shocks	−0.034**	0.131**
	(0.016)	(0.065)
Age group = 40–59 m × No. of excessive rainfall shocks	−0.037**	0.158**
	(0.014)	(0.068)
Male	−0.100	0.389
	(0.082)	(0.347)
Male × No. of excessive rainfall shocks	0.032*	−0.112
	(0.019)	(0.088)
Age group = 20–39 m × Male	0.166	−0.455
	(0.133)	(0.499)
Age group = 40–59 m × Male	0.223	−0.415
	(0.223)	(0.698)
Age group = 20–39 m × Male × No. of excessive rainfall shocks	−0.034	0.100
	(0.022)	(0.097)
Age group = 40–59 m × Male × No. of excessive rainfall shocks	−0.031	0.087
	(0.021)	(0.098)
No. of drought shocks	0.025	−0.177***
	(0.016)	(0.063)
Age group = 20–39 m × No. of drought shocks	−0.031	0.129*
	(0.019)	(0.074)
Age group = 40–59 m × No. of drought shocks	−0.020	0.167**
	(0.019)	(0.065)
Male × No. of drought shocks	0.025	−0.148
	(0.021)	(0.102)
Age group = 20–39 m × Male × No. of drought shocks	−0.035	0.164
	(0.025)	(0.116)
Age group = 40–59 m × Male × No. of drought shocks	−0.047*	0.204*
	(0.027)	(0.108)
Dependency ratio[1]	−0.044	0.147
	(0.034)	(0.117)
Log(landsize)	0.036	−0.019
	(0.038)	(0.146)
Asset index[2]	−0.101	0.298
	(0.190)	(0.728)
Constant	0.249**	−0.668*
	(0.110)	(0.360)
Observations	3,325	3,325
R-squared	0.450	0.537
Birth month dummies	YES	YES
Year × Oblast dummies	YES	YES
Household fixed effects	YES	YES

Dependent variable = 1 if child is stunted (HAZ < -2), 0 otherwise. Cluster-robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster-robust standard errors in parentheses.

[1] No. of household members younger than 14 and older than 65 years, divided by no. of members 15 to 64 years.

[2] Asset index is the standardized principal component analysis score based on binary ownerhip information of 31 assets.

Table A4
Heterogeneous effects of cold shocks on linear stunting probability by gender and age.

	(1)	(2)
VARIABLES	P (stunted)	HAZ score
No. of cold winter shocks	0.063***	−0.296**
	(0.024)	(0.120)
Age group = 20–39 *m*	0.041	−0.159
	(0.052)	(0.170)
Age group = 40–59 *m*	−0.073	−0.371
	(0.070)	(0.263)
Age group = 20–39 m × No. of cold winter shocks	0.000	0.000
	(0.000)	(0.000)
Age group = 40–59 m × No. of cold winter shocks	−0.043	0.113
	(0.027)	(0.127)
Male	−0.033	0.257*
	(0.031)	(0.131)
Male × No. of cold winter shocks	0.011	−0.008
	(0.056)	(0.193)
Age group = 20–39 m × Male	0.006	−0.155
	(0.029)	(0.138)
Age group = 40–59 m × Male	−0.008	−0.111
	(0.073)	(0.272)
Age group = 20–39 m × Male × No. of cold winter shocks	0.039	−0.014
	(0.094)	(0.339)
Age group = 40–59 m × Male × No. of cold winter shocks	−0.011	0.210
	(0.038)	(0.156)
Dependency ratio[1]	−0.036	0.216
	(0.036)	(0.159)
Log(landsize)	−0.040	0.142
	(0.035)	(0.116)
Wealthscore[2]	0.040	−0.060
	(0.038)	(0.140)
Constant	−0.085	0.197
	(0.184)	(0.690)
Observations	3,325	3,325
R-squared	0.439	0.528
Birth month dummies	YES	YES
Year × Oblast dummies	YES	YES
Household fixed effects	YES	YES

Dependent variable = 1 if child is stunted (HAZ < -2), 0 otherwise. Cluster-robust standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.
Robust standard errors in parentheses.

[1] No. of household members younger than 14 and older than 65 years, divided by no. of members 15 to 64 years.

[2] Asset index is the standardized principal component analysis score based on binary ownership information of 31 assets.

Table A5
Avg. marginal effects of shocks on linear stunting probability by age and gender.

	Coef.	se	p-value	Adj. p-value[1]	95% conf	interval
Excessive rainfall shocks						
Age group = 0–19 m × female	0.028	0.013	**0.033****	0.200	0.002	0.054
Age group = 0–19 m × male	0.060	0.016	**<0.001*****	**0.001*****	0.029	0.091
Age group = 20–39 m × female	−0.006	0.012	0.626	1	−0.028	0.017
Age group = 20–39 m × male	−0.008	0.011	0.464	1	−0.028	0.013
Age group = 40–59 m × female	−0.009	0.008	0.261	1	−0.024	0.006
Age group = 40–59 m × male	−0.007	0.010	0.464	1	−0.026	0.012
Drought shocks						
Age group = 0–19 m × female	0.025	0.016	0.129	0.776	−0.007	0.056
Age group = 0–19 m × male	0.050	0.018	**0.005*****	**0.030****	0.015	0.085
Age group = 20–39 m × female	−0.006	0.011	0.589	1	−0.028	0.016
Age group = 20–39 m × male	−0.016	0.013	0.231	1	−0.042	0.010
Age group = 40–59 m × female	0.005	0.011	0.639	1	−0.016	0.026
Age group = 40–59 m × male	−0.016	0.014	0.224	1	−0.043	0.010
Cold shocks						
Age group = 0–19 m × female	0.063	0.024	**0.008*****	**0.047****	0.017	0.109
Age group = 0–19 m × male	0.069	0.026	**0.009*****	0.052*	0.018	0.121
Age group = 20–39 m × female	0.020	0.018	0.288	1	−0.017	0.056
Age group = 20–39 m × male	0.015	0.025	0.549	1	−0.034	0.064
Age group = 40–59 m × female	0.030	0.022	0.177	1	−0.014	0.074
Age group = 40–59 m × male	0.000	0.023	0.999	1	−0.046	0.046

Coef. = Avg. marginal effects on linear stunting probability. *** p < 0.01, ** p < 0.05, * p < 0.1
Marked in bold: p-values < 0.05.

[1] Bonferroni-adjustment. Adjusted p-value = min{p × m, 1} where m is the number of simultaneously tested hypotheses.

Table A6
Effects of cold shocks on stunting probability by heating source.

VARIABLES	P(stunted)
No. of cold shocks	0.0106
	(0.024)
Electric heating × No. of cold shocks	0.0698**
	(0.028)
Stove heating × No. of cold shocks	0.0276**
	(0.011)
Two heating sources × No. of cold shocks	0.1630***
	(0.005)
Electric heating × Two heating sources × No. of cold shocks	−0.2037***
	(0.066)
Stove heating × Two heating sources × No. of cold shocks	−0.1785***
	(0.021)
Child is male; dummy	0.0082
	(0.036)
Asset index	−0.1106
	(0.189)
Log(land size; ha)	0.0203
	(0.038)
Age, months	0.0099***
	(0.003)
Age^2; months	−0.0002***
	(0.000)
Constant	0.2194**
	(0.085)
Observations	3,100
R-squared	0.442

Household fixed effects regression. Birth month dummies and year × oblast dummies included.
Cluster robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A7
Avg. marginal effects of shocks on stunting probability heating source.

	coefficient	se	p	adj. p	95% CI	
Central, only source	0.010	0.036	0.793	1.000	−0.062	0.081
Central, second source	0.158	0.050	**0.002*****	**0.010****	0.060	0.257
Electricity, only source	0.054	0.025	**0.030*****	0.179	0.005	0.103
Electricity, second source	0.068	0.034	**0.045****	0.269	0.002	0.135
Stove, only source	0.034	0.021	0.109	0.653	−0.008	0.075
Stove, second source	0.025	0.023	0.286	1.000	−0.021	0.071

Coef. = Avg. marginal effects on linear stunting probability. *** p < 0.01, ** p < 0.05, * p < 0.1
Marked in bold: p-values < 0.05.
[1] Bonferroni-adjustment. Adjusted p-value = min{p × m, 1} where m is the number of simultaneously tested hypotheses.

Table A8
Regression results for seasonal rainfall shocks on linear stunting probability (main effects).

	P(stunted)		HAZ score	
	Coef.	SE	Coef.	SE
Panel A: Winter shocks				
No. of excessive rainfall shocks	−0.026	(0.022)	0.179*	(0.093)
No. of drought shocks	0.001	(0.029)	0.079	(0.135)
Child's gender = male	−0.006	(0.036)	0.000	(0.146)
Age, months	0.013***	(0.004)	−0.078***	(0.014)
Age^2, months	−0.000***	(0.000)	0.001***	(0.000)
Dependency ratio	−0.043	(0.031)	0.166	(0.106)
Ln(landsize)	0.032	(0.037)	−0.018	(0.140)
Asset index	−0.072	(0.191)	0.214	(0.731)
Constant	0.264***	(0.097)	−0.581*	(0.322)
R-squared	0.441		0.530	
Panel B: Spring shocks				
No. of excessive rainfall shocks	−0.005	(0.030)	0.039	(0.119)
No. of drought shocks	0.028	(0.023)	−0.172*	(0.100)
Child's gender = male	−0.005	(0.036)	−0.004	(0.142)
Age, months	0.010***	(0.003)	−0.056***	(0.012)
Age^2, months	−0.000***	(0.000)	0.001***	(0.000)
Dependency ratio	−0.043	(0.031)	0.160	(0.106)

Table A8 (*continued*)

	P(stunted)		HAZ score	
	Coef.	SE	Coef.	SE
Ln(landsize)	0.029	(0.038)	−0.001	(0.142)
Asset index	−0.075	(0.193)	0.230	(0.742)
Constant	0.268***	(0.097)	−0.659**	(0.307)
R-squared	0.441		0.529	
Panel C: Summer shocks				
No. of excessive rainfall shocks	0.057*	(0.034)	−0.074	(0.125)
No. of drought shocks	0.021	(0.022)	−0.161	(0.101)
Child's gender = male	−0.004	(0.037)	−0.006	(0.142)
Age, months	0.009***	(0.003)	−0.055***	(0.010)
Age^2, months	−0.000***	(0.000)	0.001***	(0.000)
Dependency ratio	−0.043	(0.031)	0.160	(0.107)
Ln(landsize)	0.031	(0.037)	0.001	(0.137)
Asset index	−0.074	(0.189)	0.212	(0.728)
Constant	0.259***	(0.098)	−0.602**	(0.303)
R-squared	0.442		0.529	
Panel D: Autumn shocks				
No. of excessive rainfall shocks	−0.017	(0.017)	0.013	(0.067)
No. of drought shocks	−0.023	(0.026)	−0.041	(0.119)
Child's gender = male	−0.006	(0.036)	0.001	(0.144)
Age, months	0.013***	(0.004)	−0.058***	(0.013)
Age^2, months	−0.000***	(0.000)	0.001***	(0.000)
Dependency ratio	−0.044	(0.031)	0.159	(0.109)
Ln(landsize)	0.027	(0.037)	−0.002	(0.136)
Asset index	−0.075	(0.191)	0.213	(0.737)
Constant	0.274***	(0.095)	−0.617**	(0.303)
R-squared	0.441		0.528	
Observations	3,325		3,325	

All regression models contain year × oblast dummies, birth month dummies and household fixed effects.
Dependent variable = 1 if child is stunted (HAZ < -2), 0 otherwise. Cluster-robust standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.
Dependency ratio = No. of household members younger than 14 and older than 65 years, divided by no. of members 15 to 64 years.
Asset index is the standardized principal component analysis score based on binary ownership information of 31 assets.

Table A9
Effects of weather shocks on HAZ score.

EXPLANATORY VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. of excessive rainfall shocks	0.134	0.140	0.011	0.011				
	(0.106)	(0.105)	(0.042)	(0.042)				
No. of drought shocks	0.061	0.064	−0.072	−0.071				
	(0.090)	(0.090)	(0.054)	(0.054)				
No. of cold shocks					0.106	0.108	−0.183*	−0.182*
					(0.167)	(0.167)	(0.096)	(0.095)
Age; months	−0.242**	−0.242**	−0.051***	−0.052***	−0.218*	−0.217*	−0.047***	−0.047***
	(0.115)	(0.115)	(0.018)	(0.018)	(0.118)	(0.118)	(0.011)	(0.011)
Age^2; months	0.0011***	0.0011***	0.0009***	0.0009***	0.0011***	0.0011***	0.0008***	0.0009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dependency ratio[1]		0.154*		0.170		0.151*		0.172
		(0.083)		(0.109)		(0.084)		(0.108)
Log(landsize)		−0.069		0.010		−0.047		0.013
		(0.114)		(0.142)		(0.114)		(0.140)
Asset index[2]		−0.438		0.233		−0.441		0.218
		(0.626)		(0.754)		(0.637)		(0.741)
Child is male; dummy			0.018	0.020			0.022	0.024
			(0.145)	(0.144)			(0.146)	(0.145)
Constant	2.218	2.144	−0.748***	−1.040***	2.551	2.501	−0.810***	−1.100***
	(2.366)	(2.352)	(0.271)	(0.394)	(2.219)	(2.199)	(0.270)	(0.401)
Observations	2,910	2,910	3,325	3,325	2,910	2,910	3,325	3,325
R-squared	0.675	0.675	0.533	0.534	0.674	0.675	0.534	0.534
Year × Oblast dummies	YES	YES	YES	YES	YES	YES	YES	YES
Birth month dummies	NO	NO	YES	YES	YES	YES	YES	YES
Child fixed effects	YES	YES	NO	NO	YES	YES	NO	NO
Household fixed effects	NO	NO	YES	YES	NO	NO	YES	YES

Dependent variables: Height-for-age z (HAZ)-score. Cluster-robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

[1] No. of household members younger than 14 and older than 65 years, divided by no. of members 15 to 64 years.

[2] Asset index is the standardized principal component analysis score based on binary ownership information of 31 assets.

Table A10
Avg. marginal effects of shocks on HAZ score by age and gender (household fixed effects).

	Coef.	se	p-value	Adj. p-value[1]	95% conf	interval
Excessive rainfall shocks						
Age group = 0–19 m × female	−0.110	0.059	**0.064***	0.386	−0.226	0.007
Age group = 0–19 m × male	−0.222	0.071	**0.002*****	**0.011****	−0.361	−0.083
Age group = 20–39 m × female	0.021	0.037	0.565	1.000	−0.051	0.094
Age group = 20–39 m × male	0.009	0.036	0.802	1.000	−0.062	0.080
Age group = 40–59 m × female	0.048	0.033	0.143	0.856	−0.016	0.113
Age group = 40–59 m × male	0.023	0.032	0.474	1.000	−0.040	0.087
Drought shocks						
Age group = 0–19 m × female	−0.177	0.063	**0.005*****	**0.028****	−0.300	−0.054
Age group = 0–19 m × male	−0.325	0.085	**0.000*****	**0.001*****	−0.493	−0.158
Age group = 20–39 m × female	−0.048	0.054	0.378	1.000	−0.155	0.059
Age group = 20–39 m × male	−0.033	0.057	0.569	1.000	−0.145	0.080
Age group = 40–59 m × female	−0.010	0.044	0.815	1.000	−0.096	0.075
Age group = 40–59 m × male	0.045	0.043	0.294	1.000	−0.039	0.129
Cold shocks						
Age group = 0–19 m × female	−0.296	0.120	**0.013****	0.080*	−0.531	−0.062
Age group = 0–19 m × male	−0.451	0.138	**0.001*****	**0.006*****	−0.721	−0.181
Age group = 20–39 m × female	−0.184	0.086	0.033	0.198	−0.353	−0.015
Age group = 20–39 m × male	−0.128	0.110	0.246	1.000	−0.345	0.088
Age group = 40–59 m × female	−0.040	0.104	0.702	1.000	−0.243	0.164
Age group = 40–59 m × male	0.022	0.102	0.828	1.000	−0.177	0.221

Coef. = Avg. marginal effects on linear stunting probability. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Marked in bold: p-values < 0.05.

[1] Bonferroni-adjustment. Adjusted p-value = min{p × m, 1} where m is the number of simultaneously tested hypotheses.

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