# CURRENT AND PAST CLIMATE VARIABILITY, AND MALNUTRITION AMONG FARMING HOUSEHOLDS IN ETHIOPIA*

Musa Hasen Ahmed    Stephan Dietrich    Franziska Gassmann

UNU-MERIT, Maastricht University, Netherlands

October 12, 2021

***Abstract***: *This study aims to estimate the effects of current and past weather variability on rural households' nutritional status. Using three waves of nationally representative panel data from rural Ethiopia, we show that the nutritional status of farming households, measured by daily intakes of micro-and macronutrients, is more sensitive to past weather variability than the current weather condition. We also find that adverse weather history can trigger responses that are linked to the deterioration of nutritional status.*

**Keywords**: Weather variability; Diet Quality; Poverty Trap.

**JEL Classification**:D13; I3; Q15; Q54

*The initial draft of this study was presented at the $94^{th}$ Annual Conference of the Agricultural Economics Society, the $3^{rd}$ Annual Internal Conference at UNU-MERIT, and the $GPAC^2$ workshop at UNU-MERIT in 2021. We thank the participants of the conferences for their insightful comments and constructive feedback.

# 1 Introduction

Despite considerable achievements in reducing under-nutrition over the last few decades, hunger has been on the rise again in Africa. The latest estimate from FAO et al. (2020) shows that more than 250 million people in Africa are undernourished and the figure is growing at a faster rate in the region than anywhere else in the world. Weather variability is a major driver of under-nutrition and is regarded to be among the main constraint for the region to accomplish Sustainable Development Goal-2[1] (Mason-D'Croz et al., 2019). This applies particularly to East Africa as droughts become both frequent with a recurring period of about three years and severe as in some cases a drought event stretches over two or more rainy seasons (Haile et al., 2019).

Numerous studies examined the implications of weather variability on food security (Wheeler and Von Braun, 2013; Funk et al., 2008; Demeke et al., 2011; Wossen et al., 2018), nutrition (Cooper et al., 2019b,a) and diet quality (Carpena, 2019). These studies examined the effects of weather variability in one season disregarding the long-term influence of historical weather patterns. By doing so, they overlook the long-term consequences of weather variability. However, since most agricultural decisions are made based on farmers' expectations about the upcoming weather condition, past weather patterns can also affect food and nutrition security by influencing farm investment decisions in future harvest periods. For instance, areas with historical weather variability might adjust their business and livelihood activities to mitigate the effects of current weather variability (Chuang, 2019). Recurring shocks in the past could also leave households with inadequate time to recover before encountering later shocks (De Silva and Kawasaki, 2018).

Hence, separating the effects of current and past weather variability is vital to thor-

[1]The goal aims at ending hunger, achieving food security, improving nutritional status, and promoting sustainable agriculture.

oughly understand the impacts of weather variability. To this end, few recent empirical works engaged in disentangling the effects of current and past weather patterns. These studies emphasized the effects on agricultural production (Burke and Emerick, 2016), rural livelihood diversification (Chuang, 2019; Call et al., 2019), and farm income (Sesmero et al., 2018). However, weather variability could also influence household consumption as in most cases the production and consumption decisions of agricultural households facing imperfect markets cannot be separated (De Janvry et al., 1991). A high degree of auto-subsistence in the Ethiopian rural economy is highlighted by Worku et al. (2017); Minten et al. (2018) and FAO (2018). Among them, FAO (2018) shows that only 21 percent of the total production of smallholder farmers is brought to the market.

Besides, the effects of weather variability on consumption could also differ from its effect on income. For instance, weather variability can lead to crop diversification (Piedra-Bonilla et al., 2020; Mulwa and Visser, 2020). This might affect farm income since farmers are allocating resources at suboptimal points (losing income from specialization). However, diversification can improve nutritional status since it leads to diet diversification (Tesfaye and Tirivayi, 2020; Sibhatu et al., 2015; Jones, 2017). Furthermore, the relation between farm income and nutritional status is not always straightforward as it depends on a series of factors including access to markets, and women's education and decision-making power (Gupta et al., 2019; Malapit and Quisumbing, 2015). Therefore, the effects of weather variability on income and nutrition can differ vastly, and a separate investigation of the effects on nutritional status is relevant from both policy and academic points of view. Our study contributes to the literature by focusing on the effects of current and past weather variability on the availability of micro-and macronutrients of rural households.

For the analysis, we combine three waves of nationally representative panel data from rural Ethiopia with Standardized Precipitation-Evapotranspiration Index (SPEI) data—a reliable water balance indicator that accounts for both changes in precipitation and evapotranspiration. Ethiopia provides an attractive framework for this study for the following reasons. Firstly, drought and rainfall variability are a recurring phenomenon in the country and the recurring period is significantly shortened (Mera, 2018). Secondly, rural livelihoods in the country are profoundly vulnerable to weather variability since rain-fed agricultural activities are the single most important livelihood strategy of the vast majority of rural households. Thirdly, unacceptably high rates of food insecurity, malnutrition, and deficiencies of essential micro and macronutrients among vulnerable groups are still widespread and continued to be a major public health problem in the country. As indicated in the Global Nutrition Report (2020), the country is off track to achieve most of the SDGs' nutritional targets. Therefore, the presence of widespread historical weather variability and the high level of malnutrition in the country coupled with the availability of detailed panel data collected in 2011/12, 2013/14, and 2015/16, provide an opportunity to examine the effects of two recent droughts that occurred in the country, alongside the effects of historic weather variability.

We implement three steps to address our objectives. We start by exploring the effects of current weather conditions on the nutritional status of farm households. In the second step, we include past weather variability in our model to examine its effects. Finally, we explore if the effects of current weather variability vary based on past weather patterns by introducing an interaction term between past and current weather variability. We use a household fixed effects approach hence our identification comes from the within-household variation in exposure to plausibly exogenous current and past weather variability.

We find that farming households' nutritional status is more sensitive to past weather variability than the current weather conditions, which signals the fact that the effects of adverse weather patterns may be considered as regressive. Our result also shows that adverse weather history might stimulate some responses that are associated with the deterioration of nutritional status. We find that adverse past weather conditions shrink farmers' market participation rate. Consistent with the recent work by Aragón et al. (2021), we also find that farmers respond to weather variability by adjusting their land-use decision that includes increasing the size of land allocated for staple crops. Besides, we provide empirical evidence on the role of livestock ownership as a buffering mechanism against past weather variability.

The remaining sections of the paper are organized as follows: the next section outlines our hypotheses. Section 3 provides an overview of the context of weather variability, agriculture, and nutrition programs in Ethiopia. Section 4 gives more detail on the data used. In section 5 we present the empirical strategy used to address the objectives of the study. We present and discuss the empirical results in section 6 and the last section gives concluding remarks.

## 2 Conceptual Framework

As in many developing countries, smallholder farmers in Ethiopia are also expected to face imperfect input, financial, and labor markets, and encounter both production and consumption decisions simultaneously. They are also assumed to maximize their well-being subject to the resources that they are endowed with and the productivity of these resources is expected to be influenced by exogenous factors such as weather conditions (Asfaw et al., 2012). As agricultural activities are the major sources of food and income for farm households, weather variability has the potential to limit the availability and accessibility of food for farm households. However, recent studies including Newman and Tarp (2020) and Nguyen et al. (2020) unveil that farm households smooth their consumptions from the adverse effects of current weather variability either by relying on food aids or by using their own coping strategies.

However, in the face of incomplete financial market, which is the common feature in most developing countries, coping strategies used by the farm households might involve the use of strategies that potentially affect the capital accumulation and productive assets, such as the selling of agricultural assets and livestock Newman and Tarp (2020); Nguyen et al. (2020). As farmers cope with adverse current weather conditions by relying on such types of strategies, over the long term, the occurrence of repeated adverse weather conditions might lead to a worsened nutritional status. This is because recurring weather fluctuations in the past could leave farm households with inadequate time to recover before encountering later shocks.

In addition to the depleting of productive assets, adverse weather history might also stimulate some responses that are associated with the deterioration of nutritional status. For instance, farmers residing in areas where there is historical rainfall variability abandon sensitive crops and specialize in less risky crop portfolios (Brown and Kshirsagar, 2015; Bezabih and Di Falco, 2012; Ponce, 2020). On top of this, since the demand for basic staples is inelastic to price and income changes, farmers become adamant to secure their access to staples unaffected in the face of any shocks including price and weather variability (Fafchamps, 1992). This may force farmers living in a riskier environment to allocate relatively more agricultural land to the production of staple crops to maintain a buffer stock for their consumption at the expense of commercialization since securing their food demand from the market may not be a reliable option during drought times. However, agricultural production needs to be diversified at the household level as this makes a wide range of different types of foods available and accessible (Tesfaye and Tirivayi, 2020; Sibhatu et al., 2015). Contrary to this, restricting crop portfolios to less risky crop items due to the challenge imposed by adverse weather history may limit farmers' ability to diversify their diets. Hence, based on the discussions presented above, we hypothesis:

*H1: Farm households protect their consumption from the adverse effects of current* *weather variability;*

*H2: Farm households would increase the share of agricultural land allocated to the production of staple crops and reduces their market participation rate in response to adverse past weather conditions;*

*H3: Past weather variability would reduce the availability of macro and micronutrients for farm households.*

# 3 The Context

The Ethiopian economy is largely dominated by the agricultural sector. The sector employs about 70% of the labor force and the country's exports almost entirely rely on agricultural products. Despite its considerable share in the economy, the sector is dominated by rain-fed subsistence farming that makes both the sector and the economy vulnerable to climate variability.[2]

Drought and rainfall variability are a recurring phenomenon in Ethiopia and the country has faced more than ten drought events since the 1970s (Mohammed et al., 2018; Degefie et al., 2019; Mera, 2018). Recent catastrophic droughts that happened in the country include 1983–1985, 2002–2003, 2010–2011, and the 2015 droughts (Kasie et al., 2020). Out of them, the 1983-85 drought is remembered for its devastating effects that include the death of an estimated number of people ranging from 500,000 to one million (Kidane, 1990). Studies also show that the drought has affected the long-run health status of the survivors (Dercon and Porter, 2014) and the cognitive and health status of their children (Tafere, 2016).

Experts argue that the severity of the 2015 drought, which was intensified by the El Nino effects, is comparable with the 1983-85 drought. For instance, Philip et al.

[2]An estimated 95 percent of agricultural output in the country is produced by about 12 million smallholders.http://www.fao.org/ethiopia/fao-in-ethiopia/ethiopia-at-a-glance/en/

(2018) claimed that the drought observed during 2015 in some areas like the central and north-eastern parts of the country is expected to happen only about once every 260 years whereas, FEWSNET (2015) labeled it as "the worst in more than 50 years". Similar to the 1983-85 drought, the 2015 drought also caused drastic crop failures, widespread livestock death, and affected about ten million people in the country. A severe drought that affected an estimated 4.5 million people was also observed in the southern, eastern, and north-eastern parts of the country in 2011 (Sandison, 2012).

In addition to those extreme drought events, rainfall variability is common in the country. In this context, several studies have shown that the rural livelihoods in the country are profoundly vulnerable to weather variability. To mention a few of them, rainfall variability is found to have a significant effect on food security, poverty and inequality (Demeke et al., 2011; Dercon et al., 2012; Thiede, 2014), consumption dynamics, and poverty trap (Barrett and Santos, 2014; Dercon, 2004; Dercon and Christiaensen, 2011), human capital development (education and health) (Porter et al., 2008; Miller, 2017; Randell and Gray, 2016; Dimitrova, 2021), migration, and population mobility (Ezra and Kiros, 2001; Meze-Hausken, 2000; Gray and Mueller, 2012), agricultural technology adoption, and farmers' risk-taking behavior (Alem et al., 2010; Di Falco et al., 2019), and livestock ownership, and their productivity (Megersa et al., 2014).

There are also success stories in the country that can enhance farmers' adaptive capacity. The country registered 10.9% average growth between 2004 and 2014 that enabled the country to reduce poverty rates substantially—as it declined from 55.3% in 2000 to 24% in 2016 (World Bank, 2019; **?**). Growth in the agricultural sector played a significant role in this progress. For instance, cereal production quadrupled between 1994/95 and 2014/15 (Dorodh and Rashid, 2015). The size of cultivated land also increased by 27 percent between 2004/5 and 2013/14, while fertilizer imports increased by 124 percent (Bachewe et al., 2019).

Despite the above achievements, the country still faces a broad range of hurdles including a high rate of food and nutrition insecurity, and deficiencies in essential micro and macro-nutrients. Diets for many Ethiopians remain very monotonous and the proportion of young children who meet the minimum acceptable diet remains less than 10% (Yadene, 2019). To curb the challenges, the government of Ethiopia has been working with its partners to establish and implement several interventions. This includes mainstreaming nutrition into the agricultural sector. For instance, the second National Nutrition Program[3] aims to end hunger by 2030 by integrating nutritional needs with improvements in the agriculture sector. Specifically, it aims, among others, to (i) support and promotes community-level production of fruits, vegetables, and enriched complementary food; and (ii) ensure market access for smallholder farmers by improving market linkages with local markets. Hence, as the effects of weather variability on the nutritional status of farming households come mainly through its effect on agriculture, exploring the effects of actual and expected weather variability on nutritional status and farmers' behavioral responses is essential from a policy point of view.

# 4 Data and Methodology

## 4.1 Ethiopian Socioeconomic Survey

This research mainly relies on the three rounds of the Ethiopian Socioeconomic Survey, which was administered by the Living Standards Measurement Study (LSMS) of the World Bank. The data was collected in 2011/12, 2013/14, and 2015/16. The survey produced rich geo-referenced data at the household, plot, and community levels using five questionnaires: household, community, post-planting, post-harvest, and livestock questionnaires. The household questionnaire was used to collect data on

[3] The document can be accessed at http://extwprlegs1.fao.org/docs/pdf/eth190946.pdf.

household characteristics such as basic demographic characteristics, asset ownership, welfare indicators, and access to institutions and infrastructure. The community questionnaire enabled the collection of socioeconomic indicators of the enumeration areas where the sample households reside. The remaining three questionnaires are related to agricultural practices. One questionnaire was used to collect information on livestock production and the other two questionnaires gathered plot-level data on both post-planting and post-harvest agriculture activities.

Each panel dataset is collected in three rounds. Accordingly, the post-planting agriculture questionnaire of the 2011/12 survey was administered between September and October 2011, while the livestock questionnaire was administered between November and December 2011. The household, community, and postharvest agriculture questionnaires were administered in the third round between January and March 2012. Similarly, the data regarding post-planting agriculture activities of 2013/14 was collected from September to October 2013, and the collection of information about livestock was conducted between November and December 2013. Information regarding household characteristics and post-harvest agriculture was collected during the third round between February and April 2014. Likewise, the 2015/16 survey was administered between September 2015 and April 2016. Particularly, data from the household, community, and post-harvest agriculture questionnaires were gathered between February 2016 and April 2016.

Regarding the sampling techniques, the 2011/12 survey was designed to draw a representative sample for rural and small-town areas of the country. Thus, respondents were selected from all regional states of the country using a two-stage probability sampling. In the first stage, 290 and 43 primary sampling units (enumeration areas) were selected from rural and small towns respectively (Figure 1). This stage was followed by the selection of 3,996 households to be interviewed from each enumeration area (EA). The same households with additional households from the newly included 100

EAs from urban areas of the country (that increased the number of sample households to 5,469) were re-interviewed in the second (2012/13) and third waves (2015/16). This study was carried out using data gathered from rural EAs.

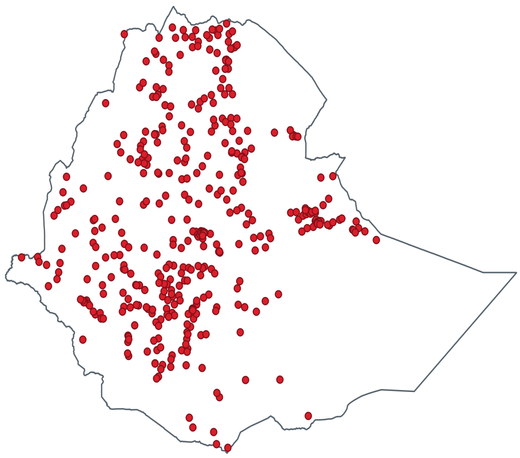

Figure 1: Locations of the enumeration areas in the country
Source: authors' illustration using data from the Ethiopian LSMS dataset.

The 2013/14 and 2015/16 surveys managed to re-interview 95 and 93 percent of those interviewed in the first wave, respectively. Attrition analysis is conducted to see if there is a systematic association between attrition and weather variability. The results presented in Table 1 show no indication of systematic bias.

## 4.2 Current and Past Variability Indicators

This study uses the Standardized Precipitation Evapotranspiration Index (SPEI), which provides a more reliable water balance indicator by estimating deviations in total precipitation and evapotranspiration from historical means (Vicente-Serrano et al., 2010).[4] Recent evidence from both developed and developing countries (including Schlenker and Roberts (2009); Carleton and Hsiang (2016); Hsiang et al. (2017); Lo-

[4]Recent papers that used this index include (Azzarri and Signorelli, 2020; Von Uexkull et al., 2016; Mueller et al., 2014; Zipper et al., 2016; Nath et al., 2017).

Table 1: Attrition analysis

| VARIABLES | Attrition between 2011 and 2013 | Attrition between 2013 and 2015 |
|---|---|---|
| Current weather 2011 | -0.113 | |
| | (0.133) | |
| Current weather 2013 | 0.215 | 0.059 |
| | (0.131) | (0.131) |
| Current weather 2015 | | 0.265 |
| | | (0.169) |
| Past weather | 0.031 | 0.035 |
| | (0.028) | (0.029) |
| Other controls | Yes | Yes |
| Constant | -0.623*** | -1.646*** |
| | -0.216 | -0.314 |

Source: authors' calculation based on the three waves of Ethiopian LSMS
Note: Coefficients are estimated using the probit model. Other household characteristics included in the analysis are Sex, age, and educational status of the household head, family structure, and location indicators. Robust standard errors in parentheses, *** p<0.01,

bell et al. (2011)) shows that factors other than rainfall, such as temperature, can significantly affect agricultural yield even under optimal rain-fed conditions. Studies undertaken in East Africa (like Rowhani et al. (2011) and Ray et al. (2015)) also show that agricultural productivity in the region can only be explained by a complex link between precipitation and temperature variability. The SPEI that provides the index with a 0.5 degrees spatial resolution is used for this study.[5]

Since the study is designed to examine the effects of current and historical weather variability on nutritional status, separate indicators are produced to distinguish both phenomena. Accordingly, weather conditions during the agricultural seasons approximate current weather variability. There are two main cropping seasons in Ethiopia: Meher and Belg seasons. Meher is the main cropping season in the country, and about 90 percent of the total cereal output is produced in this season. The Belg season

[5]The index is constructed using the CRU TS 4.03 gridded precipitation and potential evaporation dataset of the University of East Anglia's Climate Research Unit. A comprehensive theoretical and estimation details of the index alongside the description of sources and types of data used to estimate the index can be found from Vicente-Serrano et al. (2010) and Beguería et al. (2014).

is essential for long-season crops, such as maize, and for the production of pasture for livestock. It is also useful for land preparation for the coming Meher production (Asfaw et al., 2018). Hence, current weather variability is represented by the SPEI constructed based on a time scale of six months— from April to September— of the survey years, which correspond to the two main cropping seasons in the country. The SPEI for each survey period during the two main cropping seasons is then merged with the household level observations using the enumeration area level latitude and longitude coordinates by utilizing the stata package called 'geodist'. The maps in Figure 2 show the current weather variability for each study period. The figures show that noticeable weather variability has occurred in all three survey years, though it varies in size and spatial coverage. Overall, an extensive water balance shortage was observed in 2011/12 and 2015/16, while 2013/14 showed a positive water balance in most regions of the country.

In addition to current weather variability, a proxy for historical weather patterns is constructed for each enumeration area. Following the works of Mulwa and Visser (2020), Rao et al. (2011) and Sesmero et al. (2018) who argue that the preceding ten years can be considered as a relevant boundary to construct the past weather pattern, we proxy historic weather variability by the coefficient of variation computed using SPEI of the main agricultural seasons within the previous ten years prior to the survey period.Table A1 provides descriptive statistics for the weather variability along with other working variables. In addition, Table A9 in the appendix shows the correlation between past weather variability and household characteristics. The results presented in the Table show no indication of a significant association between past weather variability and household characteristics.

Before concluding the data section, we summarize the timetable of the data collection stages in Table 2. Each column of the Table represents a specific period—panel wave, calendar year, or month. Six columns marked by a blue color (from April to


2011


2013


2015

Figure 2: Current weather variability during the survey periods (SPEI)
Source: authors' illustration

September) represent the two main agricultural seasons in the country. Hence, current weather conditions, for example, for wave-1 is the SPEI of the six agricultural months of 2011, and the outcome indicators are computed using the consumption data from the household questioner collected between January and March 2012.

Table 2: summary of data collection periods

| Wave | Year | J | F | M | A | M | J | J | A | S | O | N | D |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| I | 2011 | | | | | | | | | Post-planting | | Livestock | |
| | 2012 | Household, community, and post-harvest modules | | | | | | | | | | | |
| II | 2013 | | | | | | | | | Post-planting | | Livestock | |
| | 2014 | | Household, community, and post-harvest modules | | | | | | | | | | |
| III | 2015 | | | | | | | | | Post-planting | | Livestock | |
| | 2016 | | Household, community, and post-harvest modules | | | | | | | | | | |

Source: authors' illustration using data from the Ethiopian LSMS dataset.

## 4.3 Nutritional Status Indicators

Adequacy of macro and micronutrients is vital for the human body. Specifically, macronutrients such as calories and proteins are essential for the healthy functioning of the human body and they serve as building blocks for cellular activities (Headey and Masters, 2019). Similarly, micronutrients are fundamental for human health and, as each micronutrient has a specific role in the human body, the absence or deficiency of any given micronutrient can cause severe and sometimes irreversible adverse effects on health and economic outcomes (Kronebusch and Damon, 2019).

We consider the availability of calories, protein, iron, zinc, and calcium as indicators of nutritional status. The selection of these indicators is guided by previous studies (e.g.: Teklewold et al. (2019)) and the prevalence of the deficiency of the selected indicators in the study area (Amare et al., 2012; Abebe et al., 2008; Harika et al., 2017; EPHI, 2016). For instance, zinc deficiency is categorized as a public health problem in the country by the Ethiopian public health institute (EPHI, 2016), and it is found to be a major factor affecting cognition among pregnant women in the country (Stoecker et al., 2009). Likewise, Haidar (2010) found one in every two women in the country has iron deficiency. Besides, problems of micronutrient deficiencies are more prominent among rural residents in the country (EPHI, 2016). A recent survey by Poole et al. (2021) reveals that the deficiencies of micronutrients are among the widely recognized indicators of nutritional outcomes currently used by social researchers.

To estimate the availability of nutrients, the quantities of food consumed at the household level were converted into calorie and nutrient levels using the Kenya food composition table (FAO/GoK, 2018).[6] Following this, the estimated values of nutrients consumed at the household level were divided by family size measured in adult equivalents to adjust numbers to age- and sex-specific differences of household members Tedford et al. (1986).[7]

Table 3: Descriptive statistics of nutritional status indicators from the Ethiopian LSMS pooled panel data

| Variable | Mean | Std. Dev. |
|---|---|---|
| Daily energy availability (kilocalorie per adult equivalent) | 2768.94 | 1765.39 |
| Daily protein availability (g per adult equivalent) | 84.1 | 56.8 |
| Daily iron availability (mg per adult equivalent) | 34.12 | 25.17 |
| Daily calcium availability (mg per adult equivalent) | 535.7 | 495.04 |
| Daily zinc availability (mg per adult equivalent) | 19.29 | 13.14 |
| The ratio of households with deficiency of the identified nutrients | | |
| Protein | 0.31 | 0.46 |
| Iron | 0.49 | 0.5 |
| Energy (calorie) | 0.41 | 0.49 |
| Calcium | 0.86 | 0.35 |
| Zinc | 0.41 | 0.49 |

Source: The three waves LSMS of Ethiopia.

[6] To the best of our knowledge, there is no complete, user-friendly, and publicly available food composition table for Ethiopia.

[7] The conversion factor used to estimate adult equivalent can be found at http://microdata.worldbank.org/index.php/catalog/2053/download/40407.

Table 3 presents summary statistics of the nutritional status indicators. To avoid influential outliers, values are estimated after winsorizing the lowest and the highest one percent values. The table also shows the prevalence of the deficiencies of the identified nutrients using the daily intake recommendations of 52.5 mg protein, 27 mg iron, 1000 mg of calcium, 2100 kilocalories energy, and 14 mg zinc for a healthy life of adult male aged between 19 and 65 years (FAO, 2001; WHO et al., 2005).[8] As indicated in the Table, the availability of protein, iron, calcium, and zinc of 31, 49, 86 and 41 percent of households are not sufficient to meet the recommended daily intake levels.

### 4.4 Summary and descriptive statistics of control variables

Table A1 presents the definitions and descriptive statistics of the working variables. About 75 percent of the households are headed by males. The average age of the household head is about 46 years and 38 percent of them at least read and write. The average family size, measured in terms of adult equivalent, is 4.04. Regarding their access to institutions, 34 percent of them have access to agricultural extension services and 22 percent of them have access to micro-financial institutions. On average, households travel about 66km to reach the nearest market and 55 percent of them have road access. Furthermore, 62 percent of them live in the community where there are irrigation schemes and 43 percent reside in communities where productive safety net programs (PSNP) operate.[9]

### 4.5 Empirical Strategy

To estimate the effects of weather variability on nutritional status, we implement the following three steps. In the first step, we investigate the extent to which current weather variability affects the nutritional status of farm households by estimating

[8] We take these thresholds assuming low bio-availability following related studies in the region.

[9] PSNP is a government-led social protection program that targets food-insecure households.

equation (1):

$$Y_{ivt} = \alpha_0 + \alpha_1 C_{tv} + \alpha_2 H_{ivt} + \alpha_3 year + \varepsilon_{ivt} \tag{1}$$

$Y_{ivt}$ represents a set of nutritional status indicators of household $i$ living in village $v$(i.e. enumeration areas) at time $t$. $C$ stands for the current weather condition and $H$ denotes the vector of control variables. These controls include household head characteristics (age, sex, and education), and access to institutions like market, and extension service, and community-level characteristics, which include the availability of road, irrigation, microfinance institutions, and productive safety net in the village. The year fixed effect is included in the model to account for unobserved time-varying effects, which might not be captured by the control variables included in the regression. $\varepsilon$ represents the error term.

This stage is followed by an examination of the effects of exposure to past weather variability on households' nutritional status. This is done by estimating equation 2, in which $P$ represents past weather variability indicator and all other remaining variables are defined under equation (1).

$$Y_{ivt} = \alpha_0 + \alpha_1 C_{tv} + \alpha_2 P_{tv} + \alpha_3 H_{ivt} + \alpha_4 year + \varepsilon_{ivt} \tag{2}$$

The effects of current weather variability could also vary across areas based on their historical weather patterns. For example, past weather variability encourages some forms of adaptation which, to a certain extent, might serve to lessen the effects of current weather variability. This, in turn, improves/or deters nutritional status as discussed in the earlier section. Hence, in our final step, we examine if the effects of current weather variability vary based on past weather patterns by introducing an interaction term between past and current weather variability in equation 2, as shown in equation 3.

$$Y_{ivt} = \alpha_0 + \alpha_1 C_{tv} + \alpha_2 P_{ivt} + \alpha_3 (C_{ivt} + P_{ivt}) + \alpha_4 H_{ivt} + \alpha_5 year + \varepsilon_{ivt} \tag{3}$$

To investigate if livestock ownership helps farm households mitigate the adverse effect of weather variability on the household's nutritional status, the interaction of livestock ownership and weather variability indicators will be introduced in equation 3. We estimate the above frameworks using a household fixed-effects regression approach. Although we see the incidence of weather variability to be beyond the control of farm households (exogenous), this framework helps to improve our identification by providing several key advantages. It enables, for instance, to account for any time-invariant household heterogeneities such as taste, preference, and religion that may determine consumption patterns and the extent of the effects of weather variability. It also purges the effect of any time-invariant community-level unobserved characteristics such as soil fertility, agroecology, and other environmental features that influence the types of crops produced and available in the community.

# 5 Results and Discussion

We begin by examining the relationship between current weather variability and farm households' nutritional status. Table 4 summarizes the results of regression equation 1. As indicated in the Table, the association between current weather conditions and nutritional status is not statistically significant. To check the robustness of the result, the same equation is re-estimated by using different definitions of weather variability, including a square term of the SPEI, a categorical variable that divides the SPEI into four groups, and self-reported drought shock. In all cases, as presented in Table A3-A7 in the appendix, the relationship between current weather indicators and nutritional status is statistically insignificant.

Table 4: The effects of current weather variability on the availability of nutrients

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| SPEI | 56.032 | 1.579 | -0.096 | 18.787 | -0.001 |
| | (67.778) | (2.086) | (0.84) | (15.511) | (0.476) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Number of observation | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses. The control variables included in the regression are household size; sex, age, and education status of the household head; access to microfinance institutions, road, market, and agricultural extension service; availability of irrigation and PSNP in the community, and time trend.
Source: The three waves LSMS of Ethiopia.

The result implies that farm households smooth their consumption from the adverse effects of current weather variability. The finding is consistent with existing studies. For instance, a recent study by Nguyen et al. (2020) from Cambodia shows that current droughts do not significantly affect household consumption. Similarly, Bachewe et al. (2017) analyzed the effects of the 2015 drought in Ethiopia on the accessibility of food by exploring the effects on food prices. They failed to find significant adverse effects of the drought on food prices. Surprisingly, they documented a significant food price reduction in most affected areas, and the authors linked this phenomenon with the effect of major food imports and food aid.

Indeed, a close look into households' self-reported coping strategies presented in Table 5[10] shows that only 2.9% of households who reported drought shock (or 0.56% of the total surveyed households) had changed their eating patterns to cope with the drought shock. More than 41% of households who reported drought shock relied on either their savings or accessed credit, whereas 40.5% of them relied on unconditional help received from relatives, government, or non-government organizations. The use of strategies that potentially affect households' capital accumulation and productive as-

[10] In the survey, households were asked to self-report the major shocks that they have encountered and their coping strategies. Table A1 in the appendix presents the distribution and transition matrix for households that report drought shock during each wave, and Table A2 summarizes the nutritional outcome of the households based on their coping strategies.

sets, such as the selling of agricultural assets, buildings, and livestock also reported by 36.8% of the households. However, as farmers cope with the adverse effects of current weather conditions by relying on strategies that can affect their capital accumulation and productivity over the long term, recurrent adverse weather conditions may lead to a worsening nutritional situation.

Table 5: Self-reported coping strategies for households reported drought shock

| Coping strategies | Percent | | | |
|---|---|---|---|---|
| | Pool | 2011 | 2013 | 2015 |
| Received unconditional help | 40.54 | 38.89 | 38.28 | 42.09 |
| Adjusted livelihood | 7.53 | 10 | 7.12 | 6.4 |
| Sold items | 36.82 | 36.85 | 46.88 | 33.62 |
| Relied on own savings or accessed credit | 41.83 | 45.93 | 27 | 44.44 |
| Changed eating pattern | 2.89 | 3.33 | 2.37 | 2.82 |
| Did not do anything | 13.62 | 9.81 | 12.76 | 15.82 |

Source: The three waves LSMS of Ethiopia.

### 5.1 The effects of past weather variability on nutritional status

Table 6 presents the result of equation 2, which jointly models the effects of current and past weather variability. We find that adverse past weather variability limits the availability of calories, protein, iron, calcium, and zinc significantly. However, the magnitudes of the effects are small. It shows that an increase in the coefficient of variation by 10 units leads to a reduction in the availability of kilocalories per adult equivalent by 4.7. Similarly, a 10 unit increase in the coefficient of variation causes a decrease in the availability of protein, iron, calcium, and zinc by 0.23, 0.07, 1.67, and 0.04 mg per adult equivalent, respectively. Furthermore, as shown in A8, past weather condition has the potential to push rural households even farther below the recommended daily intake values for macro and micronutrients.

Related studies from developing parts of the world also confirm the same fact. For

Table 6: The effects of current and past weather variability on the availability of nutrients

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| Current (SPEI) | 49.762 | 1.284 | -0.182 | 16.595 | -0.057 |
| | (67.818) | (2.085) | (0.839) | (15.505) | (0.476) |
| Past weather variability (CV) | -0.478*** | -0.023*** | -0.007*** | -0.167*** | -0.004*** |
| | (0.144) | (0.005) | (0.002) | (0.030) | (0.001) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Number of observation | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses, *** p<0.01. Source: The three waves LSMS of Ethiopia.

instance, Newman and Tarp (2020) from Vietnam fails to show evidence on the effects of adverse current weather conditions on consumption expenditure, but it shows that past weather conditions reduce consumption levels by decreasing investment in productive assets. Likewise, Azzarri and Signorelli (2020) showed that poverty rates in SSA are more significantly associated with past weather conditions than with the current shocks.[11] They argue farm households in SSA have achieved better drought resilience as a result of widespread adoption of drought-tolerant crop varieties and increased agricultural system adaptability to rainfall shortage.[12]

In the third stage of our analysis, we explore if there is an interaction effect between current and past weather variability by estimating equation 3. The result is presented in Table 7. As shown in the Table, the interaction term is not statistically significant. Hence, the effect of exposure to adverse past weather conditions on the nutritional status of farm households does not vary with the realization of adverse current weather variability.

In addition to the depletion of productive assets and savings, the other possible justi-

[11]Somehow linked to this, Randell et al. (2021) also showed that neither current rainfall nor earthquake shocks affect the food security status of rural households independently.

[12]The role of adaption strategies in protecting farm productivity and household consumption in Ethiopia is also highlighted by Marenya et al. (2020); Kosmowski (2018).

Table 7: The effects of current and past weather variability with an interaction term

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| Current (SPEI) | 53.565 | 1.4 | -0.161 | 17.157 | -0.031 |
| | (68.419) | (2.104) | (0.847) | (15.699) | (0.481) |
| Past (CV) | -0.426*** | -0.021*** | -0.006*** | -0.159*** | -0.004*** |
| | (0.144) | (0.005) | (0.002) | (0.032) | (0.001) |
| SPEI#CV | 0.468 | 0.014 | 0.003 | 0.069 | 0.003 |
| | (0.343) | (0.012) | (0.005) | (0.087) | (0.003) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Number of observation | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses, *** p<0.01. Source: The three waves LSMS of Ethiopia. Control variables included in the analysis are listed under Table 4

fication for the worsening of nutritional status due to past adverse weather conditions could be that adverse weather history might have caused responses that are associated with the deterioration of nutritional status. As rural households encounter limited crop insurance coverage, their major strategy for coping with weather-related production risks is to rely on their own behavioral responses. This includes adjusting farm portfolio choices and resource allocation decisions (Mulwa and Visser, 2020). For instance, farmers living in riskier areas devote relatively more resources to staple crops like maize and less on other sources of income and spend less money on commercial inputs such as fertilizer and improved seed (Sesmero et al., 2018). As shown in Table 8, we also find a suggestive result that supports our arguments. More specifically, it shows that both the size of land allocated to the production of non-staple crops and farmers' market participation rate, measured by the proportion of crop output sold out of the total crop production weighted by the size of land allocated for each crop, shrink as farmers experience adverse past weather conditions. This past weather variability induced restriction of crop portfolios into staple crops and limited market participation may indicate farm households' desire to ensure their food security in the face of repeated climate shocks.

Table 8: weather variability, farmers land allocation, and market participation decisions

| VARIABLES | Share of marketed output | | Land allocated to non-staple |
|---|---|---|---|
| | annual crops | perennial crops | |
| SPEI | 3.298*** | 2.033*** | 0.049*** |
| | (0.813) | (0.558) | (0.012) |
| CV | -0.004** | -0.002*** | -0.000*** |
| | (0.002) | (0.001) | (0.000) |
| SPEI#CV | -0.004 | 0.002 | 0.000 |
| | (0.009) | (0.004) | (0.000) |
| Other controls | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes |
| Number of observation | 6,497 | 6,498 | 7,312 |

Note: Standard errors clustered at EA level in parentheses, *** p<0.01. Control variables included in the analysis are listed under Table 4. Source: The three waves LSMS of Ethiopia

## 5.2 Heterogeneity of the effects of weather variability based on Livestock size

We examined if there is heterogeneity in terms of the effects of past weather variability based on livestock ownership. Aragón et al. (2021); Acosta et al. (2021) and Hänke and Barkmann (2017) have previously shown that households use livestock sales as a viable coping strategy during unfavorable weather circumstances. We divided our observations into two groups by taking the median value of the size of livestock owned, measured in tropical livestock units, as a threshold. The results are presented in Table 9.[13] We find that past weather variability increases malnutrition in households with fewer livestock units and the effects are not statistically significant for households with more livestock.

It is also worthy to mention the limitations of our data. Firstly, though we rely on three rounds of panel data, the outcome indicators are constructed based on the food consumption data collected at the household level using a 7-day recall method. Hence,

[13] We also re-estimated the equation using a continuous variable of livestock measured in tropical livestock units and the result is presented in the appendix Table A10.

Table 9: The effects of weather variability on nutritional status: Heterogeneity based access to livestock ownership

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| Current (SPEI) | 20.709 | 0.593 | -0.559 | 9.202 | -0.221 |
| | (85.215) | (2.571) | (1.085) | (17.718) | (0.611) |
| Past (CV) | -0.494*** | -0.022*** | -0.007*** | -0.164*** | -0.004*** |
| | (0.176) | (0.005) | (0.002) | (0.041) | (0.001) |
| SPEI #CV | 0.462 | 0.015 | 0.003 | 0.076 | 0.003 |
| | (0.349) | (0.013) | (0.005) | (0.084) | (0.003) |
| Livestock#SPEI | 52.637 | 1.322 | 0.647 | 13.365 | 0.305 |
| | (75.343) | (2.242) | (1.081) | (16.829) | (0.564) |
| Livestock#CV | 0.142 | 0.002 | 0.001 | 0.006 | 0.001 |
| | (0.13) | (0.004) | (0.001) | (0.036) | (0.001) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses, *** p<0.01. Control variables included in the analysis are listed under Table 4. Source: The three waves LSMS of Ethiopia.

the study could not account for seasonal fluctuations in food supply. Our data also do not allow us to account for differences in intra-household food allocation. However, as shown by Coates et al. (2018) inequitable nutrition distribution among household members is not a major concern in rural Ethiopia. Secondly, the bioavailability of nutrients depends on the composition of the meal and the extraction of nutrients depends on the efficiency of the body to extract them from food but such information is not included in the dataset and the study could not control for such differences. However, as argued by Del Prete et al. (2019), such differences are not expected to create a systematic bias, since the same issues hold for all observations.

# 6 Conclusion

Unlike previous studies that examined the effects of climate variability by relying on current weather conditions disregarding the long-term influence of historical weather patterns, recent empirical works engaged in disentangling the effects of the current and historical weather patterns. These studies examined the effects on agricultural production, livelihood diversification, and farm income mostly in the developing parts of the world. The present article contributes to this growing literature by estimating the effects on the nutritional status of rural households by combining a rich household-level panel dataset from rural Ethiopia with the Standardized Precipitation Evapotranspiration Index (SPEI).

Our findings show that the household's nutritional status is more sensitive to adverse past weather variability than current weather conditions. We find that households manage to smooth their consumption in the face of current weather variability by relying on different coping strategies that include consuming own savings, acquiring credit, receiving unconditional help from relatives, government, or non-government organizations, and selling agricultural assets and livestock. Our result also suggests that the effects of past weather variability on households' nutritional status could be due to a past weather variability-induced reduction in the market participation rate and dependence on low-value, less nutritious staple crops.

The findings show that climate variability makes it difficult for the country to improve the well-being of rural households and achieve its development goals, such as Target 2.2 of the SDGs—which aims "to end all forms of malnutrition by 2030". Hence, any policies that focus on agricultural development and promoting the nutritional status of rural households need to recognize both current and past climate variability and have to consider the way how farmers are responding to these two forms of climatic stress.

A key general policy implication of our results is that, though farmers can withstand the effects of current weather shocks either through their coping strategies or with the help of the government and other donors, over the longer term, weather variability has a far-reaching effect that could aggravate the problem of malnutrition. We also underscore the importance of more interventions and additional research work that can assist policy-making in the process of strengthening the resilience and adaptive capacity of farmers. For instance, the effectiveness of specific policy responses, such as rainfall insurance that compensates farmers based on current shocks, could vary based on past weather experience. Hence, future studies are needed to explore the effectiveness of available instruments in the face of both current and past weather variability.

# References


Abebe, Y., Bogale, A., Hambidge, K. M., Stoecker, B. J., Arbide, I., Teshome, A., Krebs, N. F., Westcott, J. E., Bailey, K. B., and Gibson, R. S. (2008). Inadequate intakes of dietary zinc among pregnant women from subsistence households in sidama, southern Ethiopia. *Public health nutrition*, 11(4):379–386.

Acosta, A., Nicolli, F., and Karfakis, P. (2021). Coping with climate shocks: The complex role of livestock portfolios. *World Development*, 146:105546.

Alem, Y., Bezabih, M., Kassie, M., and Zikhali, P. (2010). Does fertilizer use respond to rainfall variability? panel data evidence from Ethiopia. *Agricultural economics*, 41(2):165–175.

Amare, B., Moges, B., Fantahun, B., Tafess, K., Woldeyohannes, D., Yismaw, G., Ayane, T., Yabutani, T., Mulu, A., Ota, F., et al. (2012). Micronutrient levels and nutritional status of school children living in northwest Ethiopia. *Nutrition journal*, 11(1):1–8.

Aragón, F. M., Oteiza, F., and Rud, J. P. (2021). Climate change and agriculture: Subsistence farmers' response to extreme heat. *American Economic Journal: Economic Policy*, 13(1):1–35.

Asfaw, A., Simane, B., Hassen, A., and Bantider, A. (2018). Variability and time series trend analysis of rainfall and temperature in northcentral Ethiopia: A case study in woleka sub-basin. *Weather and climate extremes*, 19:29–41.

Asfaw, S., Shiferaw, B., Simtowe, F., and Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence fromTanzania and Ethiopia. *Food policy*, 37(3):283–295.

Azzarri, C. and Signorelli, S. (2020). Climate and poverty in Africa south of the sahara. *World development*, 125:104691.

Bachewe, F. N., Berhane, G., Minten, B., and Taffesse, A. S. (2019). Agricultural growth in Ethiopia (2004-2014): Evidence and drivers. *Gates Open Res*, 3(661):661.

Bachewe, F. N., Yimer, F., Minten, B., et al. (2017). Agricultural price evolution in drought versus non-drought affected areas in Ethiopia: An updated assessment using national producer data (january 2014 to january 2017). Technical report, International Food Policy Research Institute (IFPRI).

Barrett, C. B. and Santos, P. (2014). The impact of changing rainfall variability on resource-dependent wealth dynamics. *Ecological Economics*, 105:48–54.

Beguería, S., Vicente-Serrano, S. M., Reig, F., and Latorre, B. (2014). Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International journal of climatology*, 34(10):3001–3023.

Bezabih, M. and Di Falco, S. (2012). Rainfall variability and food crop portfolio choice: evidence from Ethiopia. *Food Security*, 4(4):557–567.

Brown, M. E. and Kshirsagar, V. (2015). Weather and international price shocks on food prices in the developing world. *Global Environmental Change*, 35:31–40.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, 8(3):106–40.

Call, M., Gray, C., and Jagger, P. (2019). Smallholder responses to climate anomalies in rural Uganda. *World Development*, 115:132–144.

Carleton, T. A. and Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, 353(6304):aad9837.

Carpena, F. (2019). How do droughts impact household food consumption and nutritional intake? a study of rural India. *World Development*, 122:349–369.

Chuang, Y. (2019). Climate variability, rainfall shocks, and farmers' income diversification in India. *Economics Letters*, 174:55–61.

Coates, J., Patenaude, B. N., Rogers, B. L., Roba, A. C., Woldetensay, Y. K., Tilahun, A. F., and Spielman, K. L. (2018). Intra-household nutrient inequity in rural Ethiopia. *Food Policy*, 81:82–94.

Cooper, M., Brown, M. E., Azzarri, C., and Meinzen-Dick, R. (2019a). Hunger, nutrition, and precipitation: evidence from Ghana and Bangladesh. *Population and Environment*, 41(2):151–208.

Cooper, M. W., Brown, M. E., Hochrainer-Stigler, S., Pflug, G., McCallum, I., Fritz, S., Silva, J., and Zvoleff, A. (2019b). Mapping the effects of drought on child stunting. *Proceedings of the National Academy of Sciences*, 116(35):17219–17224.

De Janvry, A., Fafchamps, M., and Sadoulet, E. (1991). Peasant household behaviour with missing markets: some paradoxes explained. *The Economic Journal*, 101(409):1400–1417.

De Silva, M. and Kawasaki, A. (2018). Socioeconomic vulnerability to disaster risk: a case study of flood and drought impact in a rural Sri Lankan community. *Ecological Economics*, 152:131–140.

Degefie, D., Seid, J., Gessesse, B., and Bedada, T. B. (2019). Agricultural drought projection in Ethiopia from 1981 to 2050: Using coordinated regional climate downscaling experiment climate data for Africa. In *Extreme Hydrology and Climate Variability*, pages 311–323. Elsevier.

Del Prete, D., Ghins, L., Magrini, E., and Pauw, K. (2019). Land consolidation, specialization and household diets: evidence from Rwanda. *Food Policy*, 83:139–149.

Demeke, A. B., Keil, A., and Zeller, M. (2011). Using panel data to estimate the effect of rainfall shocks on smallholders food security and vulnerability in rural Ethiopia. *Climatic change*, 108(1):185–206.

Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia. *Journal of Development*

*Economics*, 74(2):309–329.
Dercon, S. and Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of development economics*, 96(2):159–173.
Dercon, S., Hoddinott, J., and Woldehanna, T. (2012). Growth and chronic poverty: Evidence from rural communities in Ethiopia. *Journal of Development Studies*, 48(2):238–253.
Dercon, S. and Porter, C. (2014). Live aid revisited: long-term impacts of the 1984 Ethiopian famine on children. *Journal of the European Economic Association*, 12(4):927–948.
Di Falco, S., Berck, P., Bezabih, M., and Köhlin, G. (2019). Rain and impatience: Evidence from rural Ethiopia. *Journal of Economic Behavior & Organization*, 160:40–51.
Dimitrova, A. (2021). Seasonal droughts and the risk of childhood undernutrition in Ethiopia. *World Development*, 141:105417.
Dorodh, P. and Rashid, S. (2015). Ethiopia's 2015 drought: No reason for a famine.
EPHI (2016). *Ethiopian National Micronutrient survey.* Intl Food Policy Res Inst.
Ezra, M. and Kiros, G.-E. (2001). Rural out-migration in the drought prone areas of Ethiopia: A multilevel analysis 1. *International Migration Review*, 35(3):749–771.
Fafchamps, M. (1992). Cash crop production, food price volatility, and rural market integration in the third world. *American journal of agricultural economics*, 74(1):90–99.
FAO (2018). *Small family farms country factsheet.* FAO.
FAO, IFAD, UNICEF, WFP, and WHO (2020). *The State of Food Security and Nutrition in the World 2020. Transforming food systems for affordable healthy diets.* Food & Agriculture Org.
FAO, F. (2001). Nutrition technical report series. *Human energy requirements. Report of a joint FAO/WHO/UNU Expert Consultation. Rome: FAO*, pages 17–24.
FAO/GoK (2018). Kenya food composition tables.
FEWSNET (2015). Ethiopia food security alert: Food security emergency in central/eastern Ethiopia follows worst drought in more than 50 years.
Funk, C., Dettinger, M. D., Michaelsen, J. C., Verdin, J. P., Brown, M. E., Barlow, M., and Hoell, A. (2008). Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development. *Proceedings of the national academy of sciences*, 105(32):11081–11086.
Global Nutrition Report (2020). Malnutrition burden: Ethiopia nutrition profile.
Gray, C. and Mueller, V. (2012). Drought and population mobility in rural Ethiopia. *World development*, 40(1):134–145.
Gupta, S., Pingali, P., and Pinstrup-Andersen, P. (2019). Women's empowerment and nutrition status: The case of iron deficiency in India. *Food Policy*, 88:101763.
Haidar, J. (2010). Prevalence of anaemia, deficiencies of iron and folic acid and their determinants in Ethiopian women. *Journal of health, population, and nutrition*, 28(4):359.
Haile, G. G., Tang, Q., Sun, S., Huang, Z., Zhang, X., and Liu, X. (2019). Droughts in East Africa: Causes, impacts and resilience. *Earth-science reviews*, 193:146–161.
Hänke, H. and Barkmann, J. (2017). Insurance function of livestock, farmers coping capacity with crop failure in southwestern Madagascar. *World Development*, 96:264–275.
Harika, R., Faber, M., Samuel, F., Mulugeta, A., Kimiywe, J., and Eilander, A. (2017). Are low intakes and deficiencies in iron, vitamin a, zinc, and iodine of public health concern in Ethiopian, Kenyan, Nigerian, and South African children and adolescents? *Food and*

*nutrition bulletin*, 38(3):405–427.

Headey, D. and Masters, W. A. (2019). *Agriculture and Undernutrition through the Lens of Economics*, volume 1876. Intl Food Policy Res Inst.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D., Muir-Wood, R., Wilson, P., Oppenheimer, M., et al. (2017). Estimating economic damage from climate change in the united states. *Science*, 356(6345):1362–1369.

Jones, A. D. (2017). On-farm crop species richness is associated with household diet diversity and quality in subsistence-and market-oriented farming households in malawi. *The Journal of nutrition*, 147(1):86–96.

Kasie, T. A., Demissie, B. S., Bahry, M. J., Gessesse, G. M., and Wale, L. E. (2020). The impact of the 2015 el niño-induced drought on household consumption: evidence from rural Ethiopia. *Climate and Development*, 12(9):854–863.

Kidane, A. (1990). Mortality estimates of the 1984-85 Ethiopian famine. *Scandinavian Journal of Social Medicine*, 18(4):281–286.

Kosmowski, F. (2018). Soil water management practices (terraces) helped to mitigate the 2015 drought in Ethiopia. *Agricultural water management*, 204:11–16.

Kronebusch, N. and Damon, A. (2019). The impact of conditional cash transfers on nutrition outcomes: Experimental evidence from Mexico. *Economics & Human Biology*, 33:169–180.

Lobell, D. B., Bänziger, M., Magorokosho, C., and Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature climate change*, 1(1):42.

Malapit, H. J. L. and Quisumbing, A. R. (2015). What dimensions of women's empowerment in agriculture matter for nutrition in Ghana? *Food Policy*, 52:54–63.

Marenya, P. P., Gebremariam, G., Jaleta, M., et al. (2020). Sustainable intensification among smallholder maize farmers in Ethiopia: Adoption and impacts under rainfall and unobserved heterogeneity. *Food Policy*, 95:101941.

Mason-D'Croz, D., Sulser, T. B., Wiebe, K., Rosegrant, M. W., Lowder, S. K., Nin-Pratt, A., Willenbockel, D., Robinson, S., Zhu, T., Cenacchi, N., et al. (2019). Agricultural investments and hunger in Africa modeling potential contributions to sdg2–zero hunger. *World development*, 116:38–53.

Megersa, B., Markemann, A., Angassa, A., Ogutu, J. O., Piepho, H.-P., and Zaráte, A. V. (2014). Impacts of climate change and variability on cattle production in southern Ethiopia: Perceptions and empirical evidence. *Agricultural systems*, 130:23–34.

Mera, G. A. (2018). Drought and its impacts in Ethiopia. *Weather and climate extremes*, 22:24–35.

Meze-Hausken, E. (2000). Migration caused by climate change: how vulnerable are people inn dryland areas? *Mitigation and Adaptation Strategies for Global Change*, 5(4):379–406.

Miller, R. (2017). Childhood health and prenatal exposure to seasonal food scarcity in Ethiopia. *World Development*, 99:350–376.

Minten, B., Dereje, M., Bachewe, F. N., and Tamru, S. (2018). *Evolving food systems in Ethiopia: Past, present and future*, volume 117. Intl Food Policy Res Inst.

Mohammed, Y., Yimer, F., Tadesse, M., and Tesfaye, K. (2018). Meteorological drought assessment in north east highlands of Ethiopia. *International Journal of Climate Change Strategies and Management*.

Mueller, V., Gray, C., and Kosec, K. (2014). Heat stress increases long-term human migration in rural pakistan. *Nature climate change*, 4(3):182.

Mulwa, C. K. and Visser, M. (2020). Farm diversification as an adaptation strategy to climatic shocks and implications for food security in northern Namibia. *World Development*, 129:104906.

Nath, R., Nath, D., Li, Q., Chen, W., and Cui, X. (2017). Impact of drought on agriculture in the indo-gangetic plain, India. *Advances in Atmospheric Sciences*, 34(3):335–346.

Newman, C. and Tarp, F. (2020). Shocks and agricultural investment decisions. *Food Policy*, 94:101810.

Nguyen, T.-T., Nguyen, T. T., and Grote, U. (2020). Multiple shocks and households' choice of coping strategies in rural cambodia. *Ecological Economics*, 167:106442.

Philip, S., Kew, S. F., Jan van Oldenborgh, G., Otto, F., O'Keefe, S., Haustein, K., King, A., Zegeye, A., Eshetu, Z., Hailemariam, K., et al. (2018). Attribution analysis of the Ethiopian drought of 2015. *Journal of Climate*, 31(6):2465–2486.

Piedra-Bonilla, E. B., da Cunha, D. A., and Braga, M. J. (2020). Climate variability and crop diversification in brazil: An ordered probit analysis. *Journal of Cleaner Production*, 256:120252.

Ponce, C. (2020). Intra-seasonal climate variability and crop diversification strategies in the peruvian andes: A word of caution on the sustainability of adaptation to climate change. *World Development*, 127:104740.

Poole, N., Donovan, J., and Erenstein, O. (2021). Agri-nutrition research: revisiting the contribution of maize and wheat to human nutrition and health. *Food Policy*, 100:101976.

Porter, C. et al. (2008). The long run impact of severe shocks in childhood: Evidence from the Ethiopian famine of 1984. *University of Oxford. Department of Economics.*

Randell, H. and Gray, C. (2016). Climate variability and educational attainment: Evidence from rural Ethiopia. *Global environmental change*, 41:111–123.

Randell, H., Jiang, C., Liang, X.-Z., Murtugudde, R., and Sapkota, A. (2021). Food insecurity and compound environmental shocks in Nepal: Implications for a changing climate. *World Development*, 145:105511.

Rao, K., Ndegwa, W. G., Kizito, K., and Oyoo, A. (2011). Climate variability and change: Farmer perceptions and understanding of intra-seasonal variability in rainfall and associated risk in semi-arid kenya. *Experimental agriculture*, 47(2):267–291.

Ray, D. K., Gerber, J. S., MacDonald, G. K., and West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nature communications*, 6(1):1–9.

Rowhani, P., Lobell, D. B., Linderman, M., and Ramankutty, N. (2011). Climate variability and crop production inTanzania. *Agricultural and forest meteorology*, 151(4):449–460.

Sandison, P. (2012). Effectiveness review: Ethiopia drought response 2011/12.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

Sesmero, J., Ricker-Gilbert, J., and Cook, A. (2018). How do African farm households respond to changes in current and past weather patterns? a structural panel data analysis from malawi. *American Journal of Agricultural Economics*, 100(1):115–144.

Sibhatu, K. T., Krishna, V. V., and Qaim, M. (2015). Production diversity and dietary diversity in smallholder farm households. *Proceedings of the National Academy of Sciences*, 112(34):10657–10662.

Stoecker, B., Abebe, Y., Hubbs-Tait, L., Kennedy, T., Gibson, R., Arbide, I., Teshome, A., Westcott, J., Krebs, N., and Hambidge, K. (2009). Zinc status and cognitive function of pregnant women in southern Ethiopia. *European journal of clinical nutrition*, 63(7):916–918.

Tafere, K. (2016). Inter-generational effects of early childhood shocks on human capital: Evidence from Ethiopia. Technical report.

Tedford, J. R., Capps Jr, O., and Havlicek Jr, J. (1986). Adult equivalent scales once more—a developmental approach. *American Journal of Agricultural Economics*, 68(2):322–333.

Teklewold, H., Gebrehiwot, T., and Bezabih, M. (2019). Climate smart agricultural practices and gender differentiated nutrition outcome: An empirical evidence from Ethiopia. *World Development*, 122:38–53.

Tesfaye, W. and Tirivayi, N. (2020). Crop diversity, household welfare and consumption smoothing under risk: Evidence from rural Uganda. *World Development*, 125:104686.

Thiede, B. C. (2014). Rainfall shocks and within-community wealth inequality: evidence from rural Ethiopia. *World Development*, 64:181–193.

Vicente-Serrano, S. M., Beguería, S., and López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of climate*, 23(7):1696–1718.

Von Uexkull, N., Croicu, M., Fjelde, H., and Buhaug, H. (2016). Civil conflict sensitivity to growing-season drought. *Proceedings of the National Academy of Sciences*, 113(44):12391–12396.

Wheeler, T. and Von Braun, J. (2013). Climate change impacts on global food security. *Science*, 341(6145):508–513.

WHO et al. (2005). Vitamin and mineral requirements in human nutrition.

Worku, I. H., Dereje, M., Minten, B., and Hirvonen, K. (2017). Diet transformation in Africa: The case of Ethiopia. *Agricultural Economics*, 48(S1):73–86.

World Bank (2019). *Seventh Ethiopia Economic Update : Special Topic : Poverty and Household Welfare in Ethiopia, 2011-2016*.

Wossen, T., Berger, T., Haile, M. G., and Troost, C. (2018). Impacts of climate variability and food price volatility on household income and food security of farm households in East and West Africa. *Agricultural systems*, 163:7–15.

Yadene, N. (2019). What's next for Ethiopia's nutrition programs?

Zipper, S. C., Qiu, J., and Kucharik, C. J. (2016). Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. *Environmental Research Letters*, 11(9):094021.

# A Tables

Table A1: Definition and descriptive statistics of the variables used in the study from the Ethiopian LSMS pooled panel data

| Variable | Mean | Std. Dev. |
|---|---|---|
| Sex of the household head (1= male; 0= female). | 0.75 | 0.43 |
| Age of the household head | 46.16 | 15.5 |
| Educational status of the household head (1= can read or write; 0= otherwise) | 0.38 | 0.49 |
| Family size (in adult equivalent) | 4.04 | 1.94 |
| Access to microfinance institutions (1= yes 0= no) | 0.22 | 0.41 |
| Access to agricultural extension service (1= yes 0= no) | 0.34 | 0.47 |
| Access to road (1= yes 0= no) | 0.55 | 0.5 |
| Distance to Nearest Market (in KM) | 66.97 | 50.84 |
| Irrigation in the community (1= yes 0= no) | 0.62 | 0.49 |
| PSNP operates in the community (1= yes 0= no) | 0.43 | 0.49 |
| SPEI | 0.19 | 0.72 |
| Ten years coefficient of variation for SPEI | 9.22 | 149.36 |

Source: The three waves LSMS of Ethiopia.

Table A2: Self-reported drought shock and transition matrix

| 2011/12 | 2013/14 | 2015/16 | Percent |
|---|---|---|---|
| No | No | No | 59.13 |
| Yes | No | No | 6.16 |
| No | Yes | No | 2.31 |
| No | No | Yes | 19.19 |
| Yes | Yes | No | 0.86 |
| Yes | No | Yes | 5.58 |
| No | Yes | Yes | 3.76 |
| Yes | Yes | Yes | 3.01 |

Note: Note: 'No' denotes those who have not experienced drought shock, whereas 'Yes' denotes those who have experienced drought shock within the specified time period. For instance, 59.13% is the percentage of the respondents traced during the three waves who do not report drought shock in all rounds while 0.86% is the proportion of households who report during 2011/12 and 2013/14 but not in 2015/16. Source: The three waves LSMS of Ethiopia

Table A3: The effects of current weather variability on the availability of nutrients (subjective drought)

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| Subjective Drought | -22.74 | 0.29 | -0.777 | -53.441** | 0.104 |
| | (99.124) | (2.873) | (1.394) | (23.909) | (0.641) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Number of observation | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses, ** $p<0.05$. Control variables included in the analysis are listed under Table 4. Source: The three waves LSMS of Ethiopia.

Table A4: The effects of current weather variability on the availability of nutrients (binary indicator)

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| SPEI | 56.032 | 1.579 | -0.096 | 18.787 | -0.001 |
| | (67.778) | (2.086) | (0.84) | (15.511) | (0.476) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Number of observation | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses. SPEI is a binary variable variable that takes a value of 1 if the village experienced negative SPEI at time t and 0 otherwise. Control variables included in the analysis are listed under Table 4. Source: The three waves LSMS of Ethiopia.

Table A5: The effects of current weather variability on the availability of nutrients (binary indicator)

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| SPEI less than -1 | 80.762 | 2.801 | 1.215 | -50.848 | 1.071 |
| | (160.133) | (5.302) | (2.08) | (47.365) | (1.242) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses. SPEI is a binary variable that takes a value of 1 if the village experienced SPEI lower tha -1 at time t and 0 otherwise. Control variables included in the analysis are listed under Table 4. Source: The three waves LSMS of Ethiopia.

Table A6: The effects of current weather variability on the availability of nutrients (categorical drought indicator

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| -0.99<SPEI<0.01 | -85.786 | -3.17 | -1.29 | 44.328 | -1.066 |
| | (162.034) | (5.332) | (2.1) | (47.043) | (1.253) |
| 0.01<SPEI<1.00 | -85.474 | -1.856 | -1.01 | 74.125 | -1.196 |
| | (179.785) | (5.926) | (2.352) | (51.644) | (1.379) |
| SPE>1 | 121.032 | 3.214 | -0.112 | 112.258** | -0.38 |
| | (210.768) | (6.679) | (2.578) | (55.161) | (1.563) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 8782 | 8782 | 8782 | 8782 | 8782 |

Note: Standard errors clustered at EA level in parentheses. Control variables included in the analysis are listed under Table 4. Source: The three waves LSMS of Ethiopia.

Table A7: The effects of weather variability on the availability of nutrients (SPEI squared)

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| SPEI | -329.397 | -8.138 | -3.543 | -9.015 | -2.784 |
| | (188.652) | (5.525) | (2.314) | (49.897) | (1.159) |
| Square of SPEI[14] | 78.73 | 1.985 | 0.704 | 5.679 | 0.568 |
| | (329.397) | (8.138) | (3.543) | (9.015) | (2.784) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Number of observation | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses. Control variables included in the analysis are listed under Table 4. Source: The three waves LSMS of Ethiopia.

Table A8: The effects of current weather variability on the deficiency of nutrients

| VARIABLES | Calorie | Protein | Iron | Zinc | Calcium |
|---|---|---|---|---|---|
| SPEI | -0.007 | -0.012 | 0.018 | 0.004 | -0.012 |
| | (0.018) | (0.016) | (0.018) | (0.018) | (0.010) |
| Past (CV) | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,782 | 8,782 | 8,782 | 8,782 | 8,782 |

Note: Standard errors clustered at EA level in parentheses. The dependent variables are binary, with 1 indicating that daily nutrient intakes are insufficient to meet recommended daily consumption levels and 0 indicating that they are enough. Control variables included in the analysis are listed under Table 4. Source: The three waves LSMS of Ethiopia .

Table A9: Association between past weather variability and household characteristics

| VARIABLES | Coefficient of variation |
|---|---|
| Sex of the head | 9.533 |
| | (13.241) |
| Age of the head | -0.438 |
| | (0.88) |
| Educational status of the head | 0.512 |
| | (5.413) |
| Family size in the adult equivalent | 0.682 |
| | (1.114) |
| Distance to road | -0.413 |
| | (0.422) |
| Distance to market | 0.039 |
| | (0.235) |
| year | 10.545*** |
| | (4.060) |

Note: Standard errors clustered at EA level in parentheses; Source: The three waves LSMS of Ethiopia .

Table A10: The effects of weather variability on nutritional status: Heterogeneity based access to livestock ownership (livestock in a continuous variable)

| VARIABLES | Calorie | Protein | Iron | Calcium | Zinc |
|---|---|---|---|---|---|
| SPEI | 21.511 | 0.513 | -0.256 | 6.068 | -0.148 |
| | (84.989) | (2.580) | (1.095) | (18.748) | (0.605) |
| CV | -0.474** | -0.019*** | -0.006** | -0.191*** | -0.004*** |
| | (0.192) | (0.006) | (0.002) | (0.042) | (0.001) |
| SPEI #CV | 0.432 | 0.016 | 0.003 | 0.044 | 0.004 |
| | (0.355) | (0.012) | (0.005) | (0.071) | (0.003) |
| Livestock #CV | 0.022 | 0.000 | 0.000 | 0.009 | 0.000 |
| | (0.025) | (0.001) | (0.000) | (0.008) | (0.000) |
| Livestock #SPEI | 9.629* | 0.289* | 0.074 | 2.213* | 0.054 |
| | (5.755) | (0.172) | (0.067) | (1.182) | (0.043) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Time fixed | Yes | Yes | Yes | Yes | Yes |
| HH fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 8782 | 8782 | 8782 | 8782 | 8782 |

Note: Standard errors clustered at EA level in parentheses, *** p<0.01. Source: The three waves LSMS of Ethiopia.