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Covariate Shocks Increase Calorie Consumption

Unraveling the Paradox

Meseret B. Abebe and Yonas Alem

Central America
Research Program in Economics and Environment for Development in Central America Tropical Agricultural Research and Higher Education Center (CATIE)

Chile
Research Nucleus on Environmental and Natural Resource Economics (NENRE)
Universidad de Concepción

China
Environmental Economics Program in China (EEPC)
Peking University

Colombia
The Research Group on Environmental, Natural Resource and Applied Economics Studies (REES-CEDE), Universidad de los Andes, Colombia

Ethiopia
Environment and Climate Research Center (ECRC), Policy Studies Institute, Addis Ababa, Ethiopia

Ghana
The Environment and Natural Resource Research Unit, Institute of Statistical, Social and Economic Research, University of Ghana, Accra

India
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Meseret B. Abebe[a] and Yonas Alem[b,c]

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JEL Code: D12; O13; Q18

Keywords: Drought, Nutrition; Food Security, Food Inflation

[a] Addis Ababa University
[b] University of Cape Town
[c] University of Gothenburg

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*Abebe: Addis Ababa University and University of Gothenburg, email; messamber@yahoo.com. Alem (Corresponding Author): University of Cape Town, University of Gothenburg, and Jameel-Poverty Action Lab (J-PAL), email; yonas.alem@gu.se. We thank Kefyalew Endale, Gunnar Köhlin, Måns Söderbom, Joseph Vecci, seminar participants at the University of Gothenburg, and participants at the 19th EfD annual meeting in Entebe (Uganda) for helpful comments on earlier versions of the paper. Financial support from the Swedish International Development Agency for Cooperation (Sida) through the Environment for Development (EfD) is gratefully acknowledged. All errors and omissions are of the authors.

1. Introduction

Weather shocks are notable covariate shocks that contribute to the persistence of poverty in many rain-dependent agricultural settings (Townsend, 1994; Bellemare and Christopher, 2013; IPCC, 2014, 2021). The prevalence and intensity of weather shocks have increased in the past two decades due to climate change (IPCC, 2014; Wang et al., 2019; IPCC, 2021), significantly threatening the livelihoods of farm households in poor communities who did not contribute to climate change. Households in these setups do not have access to formal financial institutions to mitigate and cope with weather shocks, and must rely on informal mechanisms (Bardhan and Udry, 1999; Hoddinott and Kinsey, 2001; Dercon, 2004; Dercon et al., 2005; Manccini and Yang, 2009; Lohmann and Lechtenfeld, 2015; Carrillo, 2020). The drought literature consistently documents that drought is a covariate shock not insured through informal risk-sharing networks, leading to a reduction in food and, consequently, calorie consumption (Bardhan and Udry, 1999; Dercon, 2004; Dercon et al., 2005; Manccini and Yang, 2009; Carrillo, 2020).

In this paper, we utilize three rounds of nationally representative panel data from Ethiopia—the Ethiopian Socioeconomic Survey (ESS)—matched with fine-resolution weather data to investigate the impact of drought on the nutritional intake of rural households. We convert all food types consumed by households, reported in local units, into standard units (e.g., kilograms). We then use standard nutrition guidelines and convert all consumed food into calories. We also construct other nutritional measures, including the household diet diversity score (HDDS) and the share of food expenditure in total consumption expenditure. Rural Ethiopia provides an ideal setting for examining the impact of drought on household nutritional intake. Ethiopia is Africa's second most populous country, with a total population of 125.3 million in 2022 (World Bank, 2022), approximately 70 % of whom directly depend on rain-fed agriculture for their livelihood. Ethiopia is also one of the most vulnerable countries to the impacts of climate change and weather shocks. The emergency events database (Guha-Sapir et al., 2016) shows that it experienced more than 15 drought events since the 1960s. Due to climate change, the country experienced an increase in the average temperature by 1^oC, which resulted in a 37.5 percent increase in the average number of hot nights between 1960 and 2003 (McSweeney et al., 2009).

Using fixed effects regressions, we show that drought in the previous year has a positive and statistically significant impact on households' per capita calorie intake. Specifically, a one-standard-deviation decrease in lagged rainfall increases per capita calorie consumption by approximately 5.5 %. This seemingly counterintuitive increase in calorie consumption is driven by the rise in staple food consumption in response to drought. More specifically, a one standard deviation decrease in lagged rainfall results in an 18.9 % decrease in per capita calorie consumption from vegetables, fruits, and pulses, and an 8.1 % increase in per capita calorie consumption from staples. The results suggest that during drought, rural households substitute relatively cheaper food items (staples) for more expensive ones (fruits, vegetables, and pulses). Consistent with this mechanism, drought reduces the Household Diet Diversity Score (HDDS), a key indicator of the diversity of a household's food consumption basket. A one standard deviation decline in rainfall results in a 3.1 % reduction in HDDS. However, heterogeneous analysis by consumption quartile shows that households in the highest consumption quartile mainly drive the increase in calorie consumption we document. Richer households have the resources to adjust their consumption basket in response to drought, resulting in increased calorie intake. Drought leads to a decrease in calorie consumption by households in the lowest consumption quartile.

To investigate if the increase in calorie consumption in response to drought is a rural phenomenon or a general response to covariate shocks in low-income setups, we use the urban sample of the data and investigate the impact of food price shocks, the key covariate shocks in an urban context (Dessus et al., 2008; Alem and Söderbom, 2012; Headey and Martin, 2016). We find that households reported to have experienced a food price shock experience a 6.2% increase in their daily per capita calorie consumption. The key mechanism that explains the increase in per capita calorie consumption is the reduction in the consumption of more expensive food items (oil source foods) and the increase in the consumption of staples. Experiencing a food price shock reduces per capita calories from oil-based food sources by 20.8% and increases per capita calorie consumption from staples by 18.3%. Households in urban Ethiopia make similar substitutions of cheaper foods for relatively expensive food items in response to food price shocks.

This paper contributes to the literature on the impact of shocks on the welfare of low-income households in developing countries. Previous studies in different contexts (e.g., Hoddinott and Kinsey, 2001; Dercon, 2004; Dercon et al., 2005; Manccini and Yang, 2009; Gao and Mills, 2018; Lohmann and Lechtenfeld, 2015; Hyland and Russ, 2019; Carrillo, 2020) have shown that weather shocks have significant and often long-term impacts on households through their negative effect on food consumption. Relatively few studies investigate the impact of weather shocks on direct measures of nutritional intake and food consumption using household food consumption data. Randell et al. (2022) uses panel data from rural Tanzania and shows that low rainfall leads to a low food consumption score. Raj and Sahoo (2025) use panel data from India and reveal that temperature anomalies have non-linear effects on household diet diversity, but the effect of precipitation variation is inconclusive. Hou (2010), Carpena (2019), and McLaughlin et al. (2023) are the only studies that use calorie consumption as an outcome variable. These studies document contradictory findings. Hou (2010) uses panel data on households participating in the PROGRESA safety net program in rural Mexico and shows that drought paradoxically increased total calorie consumption by shifting consumption toward cheaper staple grains. Carpena (2019) use panel data from rural India to show that drought negatively affects calorie consumption and diet diversity. McLaughlin et al. (2023) document that rainfall and temperature shocks lead to a decline in calories and daily consumption of micro and macronutrients.

Building on these studies, our contributions are three-fold. First, we utilized rich panel data from Ethiopia, Africa's second most populous country, and demonstrated that drought has a positive impact on households' average calorie consumption. We demonstrate that the primary mechanism driving increased calorie consumption is the substitution of cheaper food times for more expensive ones. Second, we employ a heterogeneous analysis and demonstrate that the consumption pattern of the wealthiest quartile of households drives the seemingly paradoxical finding that calorie consumption increases in response to drought. We show that the calorie consumption of the poorest consumption quartile of households is negatively affected by drought. Thus, we shed light on why previous studies document contradictory findings. Finally, and more importantly, we use the urban sample of the data and show that food price shocks (key covariate shocks in an urban context) have similar effects on the impact of calorie consumption. Our findings have significant implications for the delivery of weather forecasting and early warning information, as well as for the design and targeting strategies of safety nets during periods of shocks.

The rest of the paper is structured as follows. Section 2 provides an overview of drought and its impact on agriculture in Ethiopia. Section 3 describes the household panel and weather data, including the outcome variables and descriptive statistics. Section 4 presents the results from fixed effects regressions, including the corresponding robustness checks. Section 5 concludes the paper.

2. Drought and Agriculture in Ethiopia: Overview

Ethiopia is located in the northeastern Horn of Africa, bordered by Kenya to the south, Djibouti and Somalia to the east, Eritrea to the north, and Sudan and South Sudan to the west. The country spans approximately 1.1 million square kilometers and had an estimated population of 99 million in 2016, with 81% residing in rural areas (World Bank, 2022). The rapid population growth is primarily driven by a high fertility rate of 4.2 children per woman (UNICEF, 2017).

Ethiopia's climate is classified as tropical monsoon but exhibits significant variation due to diverse topography. The country is divided into three major climatic zones: the cool zone (Dega), the temperate zone (Woina Dega), and the hot zone (Qola). The cool zone, found at elevations above 2,400 meters, experiences temperatures ranging from near freezing to 16°C. The temperate zone, between 1,500 and 2,400 meters above sea level, has temperatures varying between 16°C and 30°C. The hot zone, encompassing lowland areas below 1,500 meters, records temperatures between 27°C and 50°C (USAID, 2016). Annual precipitation varies considerably across the country, from approximately 2,000 mm in the southwestern regions to less than 100 mm in the Afar Lowlands, with a national average of 848 mm (FAO, 2016).

Ethiopia exhibited impressive economic growth during the last 15 years, averaging a real GDP growth rate of 10.8% per year since 2004/05 (WFP and CSA, 2019). However, the economy is still predominantly agrarian. Agriculture contributes approximately 41% of the GDP (WFP and CSA, 2014), 90% of export revenues, and 70% of industrial raw materials (WFP and CSA, 2019). The sector employs about 83% of the male workforce and 55% of the female workforce, with most agricultural activity concentrated in rural communities (CSA and ICF, 2016; World Bank, 2017). Smallholder farmers dominate the sector, managing over 96% of the cultivated land and producing 90% of the country's agricultural output. These farmers typically cultivate small plots averaging 0.95 hectares, with a substantial portion relying on plots smaller than 0.5 hectares for subsistence farming.

The livestock sub-sector is an important contributor to Ethiopia's agricultural sector and overall economy. The sub-sector contributes 45% of agricultural GDP, 19% of total GDP, and 16–19% of the country's foreign exchange earnings (UNIDO, 2017). Approximately 70% of Ethiopian households, or about 14 million households, own livestock. The sector serves multiple functions beyond economic contributions, including providing food, manure for crop production and fuel, draft power for agriculture, and acting as a store of wealth and a means of transportation. Ethiopia possesses the largest livestock population in Africa and the tenth largest globally. In 2015, the country's livestock population was estimated at 57 million cattle, 30 million sheep, 23 million goats, and 57 million chickens, producing over 5.6 billion liters of milk, 1.1 million tons of beef, and 419 million eggs (FAO, 2019). With favorable climatic conditions and a relatively disease-free environment, Ethiopia holds significant potential for livestock sector development (Ahmed et al., 2004).

Ethiopia is one of the most drought-prone countries in the world, with the agricultural and livestock sectors particularly susceptible to climatic shocks (Thornton et al., 2006; Stige et al., 2006; Di Falco et al., 2012). Since the 1960s, the country has experienced over 15 drought events (Guha-Sapir et al., 2016), including the severe 2015/16 El Niño-induced drought that left approximately 8.5 million people food insecure (USAID, 2017). The 2015/16 El Niño-induced drought also significantly impacted the livestock sector, reducing dairy production by 25.8% and livestock holding, more importantly, cattle holding, by 8.4% (Abebe and Alem, 2025). Climate change has led to observable trends, including an increase of 1°C in average temperature and a 37.5% rise in hot nights frequency between 1960 and 2003 (McSweeney et al., 2009). Rising temperatures have accelerated evapotranspiration, reducing soil moisture levels, particularly in central and highland regions (Ministry of Environment and Forest - MoEF, 2015). Additionally, Ethiopia has experienced long-term variability in precipitation, with an overall decline in rainfall over the past three decades. Some areas, particularly in the south-central region, have seen a 20% decrease in rainfall since 1960 (Ministry of Environment and Forest - MoEF, 2015). Future climate projections indicate that rising sea surface temperatures in the Indian Ocean will likely lead to more frequent and severe droughts, further affecting agricultural productivity (USAID, 2012).

Consequently, because of Ethiopia's dependence on the agricultural sector, which is predominantly rain-fed, poverty and food insecurity remain pressing concerns. The Productive Safety Net Program (PSNP), launched in 2005, has provided food and cash transfers to chronically food-insecure households as part of Ethiopia's social protection strategy (Wiseman et al., 2010). However, poverty levels remain high, with 24.8% of the population living below the poverty line. Malnutrition is widespread, affecting 5.8 million children under five who suffer from stunting and 1.52 million children classified as underweight for their height (WFP and CSA, 2019). Additionally, 40% of Ethiopian households face food energy deficiencies, consuming less than 2,550 kilocalories per adult equivalent per day. The prevalence of poverty, stunting, and food insecurity is notably higher in rural areas than urban regions (WFP and CSA, 2014). Ethiopia ranks 126th out of 157 countries in progress toward achieving the Sustainable Development Goals (SDGs) (Sachs et al., 2017).

Because of its dependence on rain-fed agriculture, vulnerability to climatic shocks, and lack of formal insurance to insulate the income of smallholder farming communities during shocks, Ethiopia offers an important setting to explore the impact of climatic shocks, such as drought. This paper contributes to the drought literature by investigating the impact of drought on households' calorie and nutritional intake.

3. Data

3.1. Household Data

To assess the impact of drought on household nutritional intake, we utilize three rounds of nationally representative household survey data from rural Ethiopia, sourced from the Ethiopian Socioeconomic Survey (ESS). The ESS was conducted by collaborating with the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) and the Ethiopian Central Statistics Agency (CSA). The survey primarily aimed to understand the role of agriculture in the well-being of rural households.

The first round, the Ethiopian Rural Socioeconomic Survey (ERSS), was conducted in 2011/12 and focused exclusively on rural and small-town areas. It covered 333 enumeration areas (EAs) and surveyed 3,776 households. In the second and third rounds (2013/14 and 2015/16), the survey expanded to include urban areas, ensuring that the dataset became nationally representative. These rounds increased the total sample to 433 EAs and 5,262 households, forming the Ethiopian Socioeconomic Survey (ESS). The survey continued in 2018 and 2021, introducing a new panel dataset by drawing samples from different enumeration areas and households.[1]

Using a two-stage probability sampling approach, the ERSS was designed to represent Ethiopia's rural and small-town populations in the four major regions—Amhara, Oromia, Southern Nations, Nationalities and Peoples (SNNP), and Tigray. In the first stage, 290 rural and 43 small-town EAs were selected based on the Ethiopian Central Statistics Agency's enumeration framework, proportionate to the regional population sizes. In the second stage, 12 households were randomly chosen from each rural EA and 10 households from each small-town EA.

The second round, conducted in 2013/14, was rebranded as ESS and included an additional sample of 1,500 households from 100 EAs in large urban centers, including Addis Ababa. These urban households were selected using the same two-stage sampling approach, with 15 randomly chosen from each urban EA. This expansion increased the total sample to 433 EAs and 5,469 households. The third round (2015/16) surveyed the same EAs and households from the second round, with minimal attrition in the rural sample (less than 2%).

[1]See https://microdata.worldbank.org/index.php/catalog/2053 for a detailed description of ESS.

To minimize seasonal effects, data collection for each round began in September. The ESS gathered extensive socioeconomic information through five structured questionnaires. The first was the Household Questionnaire, which collected data on demographics, education, consumption, and labor market activities. Community Questionnaire – Captured insights from community members on EA-level resource management, community needs, and development initiatives. Post-Planting Agriculture Questionnaire – Focused on input use and early-stage agricultural activities. Post-Harvest Agriculture Questionnaire – Documented crop harvest details, utilization, and farming practices. Livestock Questionnaire – Recorded information on livestock types, changes in herd size, animal health, feed availability, and milk and egg production. The ESS is the most comprehensive and nationally representative panel dataset for Ethiopia, Africa's second most populous country.

3.2. Weather Data

In addition to household survey data, we incorporated rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). Previous studies examining the impact of drought on household welfare in Ethiopia have primarily relied on either self-reported drought measures (Dercon et al., 2005; Porter, 2012) or meteorological data provided by the Ethiopian Meteorological Agency (Dercon, 2004; Yamano et al., 2005; Thiede, 2014). However, both sources have limitations—self-reported data are prone to reporting bias, while meteorological data often contain missing observations and measurement errors due to the vast spatial coverage required.

A significant challenge in using meteorological data is Africa's declining number of weather stations. Research by (Lorenz and Kunstmann, 2012) indicates that the number of reporting weather stations has drastically decreased from approximately 3,500 in 1990 to around 500 in recent years. Additionally, (Alem and Colmer, 2021) highlight that Ethiopia has, on average, only 0.03 weather stations per woreda (district), with most stations located in high-production agricultural areas. This uneven distribution could introduce an upward bias in estimates derived from weather station data.

CHIRPS provides over 35 years of quasi-global rainfall data, offering monthly, pentadal (five-day), and daily precipitation records from 1981 to the present. The dataset has a high spatial resolution of 0.05 degrees (approximately 5×5 km) generated using satellite imagery, in-house climatology, and in-situ station data. This fine resolution allows for creating gridded time-series rainfall data, making CHIRPS particularly useful for trend analysis and seasonal drought monitoring

(Funk et al., 2015).

For this study, we utilized CHIRPS rainfall data with a spatial resolution of approximately 5 km (at the equator) and a temporal resolution of one month. CHIRPS has been widely used in previous research investigating the effects of weather shocks (Aragón et al., 2021; Tambet and Stopnitzky, 2019; Hirvonen et al., 2020; Abebe and Alem, 2025), demonstrating its reliability and applicability in climate-related economic studies.

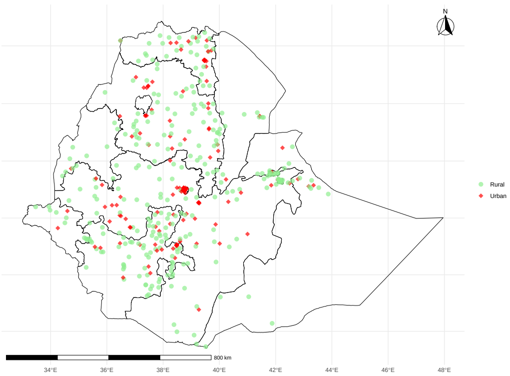
3.3. Matching Weather Data with Household Data

We use the household latitude and longitude coordinates from the Ethiopian Socioeconomic Survey (ESS) to match the CHIRPS data using an inverse-distance weighted average of the four nearest satellite observations. After matching the two data sets, we followed Shah and Steinberg (2017), Mahajan (2017), and Abebe and Alem (2025) and defined drought, our primary explanatory variable of interest, as the absolute standardized deviation of the previous year's rainfall from the long-term mean (1981-2015). If the standardized deviation is less than zero or negative, we take its absolute value; otherwise, we set it to zero. For robustness checks, we also explored alternative definitions of drought, including mean deviation, percentage deviation, and a dummy weather shock variable, which takes a value of one if the previous year's rainfall is below the 20^{th} percentile of the long-term mean. We use the lagged (previous year's) rainfall to construct the rainfall shock because it is exogenous to current choices and is a reliable proxy for income (Alem et al., 2010; Dercon and Christiaensen, 2011).

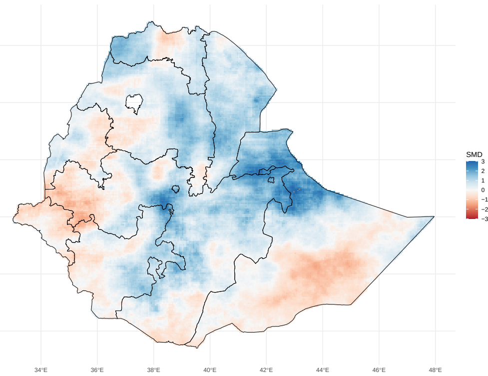
In figure 1, we present the map of Ethiopia, capturing the different regions, the distribution of the sample households, and the prevalence of drought in the three rounds. Panel (a) shows that the ESS enumeration areas are distributed throughout the country except in the two eastern regions - Afar and Somali- predominately nomadic and dispersedly populated. Panels (b), (c), and (d) show the distribution of drought (as measured by the lagged standardized mean difference of rainfall) throughout the country during the three waves of the EUSS data collected in 2011/12, 2013/14, and 2015/16. The prevalence of drought is evident in all three waves, but more importantly, in wave 2 (2015/16), when the country experienced the large-scale El-Nino-induced drought.

3.4. Outcome Variables

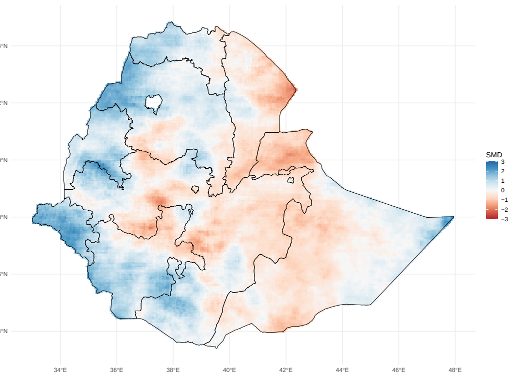
To identify the impact of covariate shocks on household food consumption and nutrition, we use three key outcome variables - household caloric intake, household



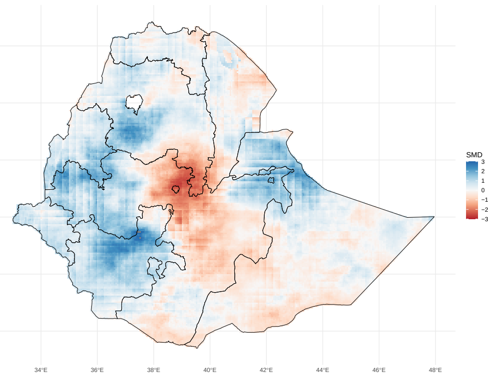
(a) Regions and ESS EAs



(b) Standardized Mean Deviation-Wave 1



(c) Standardized Mean Deviation-Wave 2



(d) Standardized Mean Deviation-Wave 3

Figure 1: Maps of Ethiopia: Sample EAs and the distribution of drought.

diet diversity score (HDDS), and household food share in total expenditure. We draw on FAO (1996) and Smith and Subandoro (2007) to motivate these outcome variables. FAO (1996) defines food and nutrition security as: "When all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life." The definition is based on four foundational pillars: availability, access, utilization, and stability. Availability implies the presence of food through production, reserves, and commerce. Access involves the capacity of households to procure food, influenced by financial means, market prices, and availability. Utilization encompasses the metabolic processing of food into energy and nutrients, affected by factors such as diet variety, nutrient intake, equitable distribution within households, and sanitary food handling. Stability examines the resilience of the other three pillars against temporal fluctuations and unforeseen events (FAO, 2009). Based on these definitions, Smith and Subandoro (2007) proposes using caloric consumption, HDDS, and food share to measure households' food access, utilization, and economic vulnerability, respectively.

The food consumption module of the ESS asked households detailed questions on food items consumed in the past seven days. Consistent with FAO (1996) and Smith and Subandoro (2007), we constructed our first outcome variable (daily calorie consumption per capita) by dividing the total calories consumed by the household by the number of household members in adult equivalent units. Before computing the total household calorie consumption, we converted every food item consumed and reported in local units into standard units (e.g., kilograms). To do so, we used the Ethiopia Food Composition Table (EHNRI, 1997), which shows the number of calories in each food item. Using adult equivalent units, we estimate household food and energy needs more precisely by considering variations in individual dietary requirements due to age and gender differences.

Micronutrient deficiencies are prevalent in diets in many parts of the developing world, leading to significant long-term health impacts such as stunting, impaired cognitive development, and chronic diseases (Kennedy et al., 2003). While individuals may satisfy their caloric requirements, micronutrient insufficiency can prevent a healthy and active lifestyle (Welch, 2001). These deficiencies often do not manifest immediate symptoms, earning the moniker "hidden hunger" (Kennedy et al., 2003). Following previous studies (Gebrehiwot and Castilla, 2019; Dillon et al., 2015), we use the Household Diet Diversity Score (HDDS) as the key indicator of nutritional intake. The HDDS is calculated based on twelve distinct food categories as per the Food and Agriculture Organization's guidelines (Kennedy et al., 2011).[2] According to Ruel (2003a), a strong positive relationship exists between diet diversity measures and nutritional adequacy in developing countries. The HDDS is the key nutritional intake measure used to investigate the nutritional status of children and adults in various developing countries (Arimond and Ruel, 2004; Ruel, 2003a; Steyn et al., 2006).

Finally, we use the proportion of total expenditure devoted to food, one of the most widely used measures of household food security, as our final outcome variable of interest. This indicator is derived from the ratio of household food expenditure to overall household spending. The significance of this measure is rooted in Engel's Law, which states that poorer and more vulnerable people devote a greater proportion of their resources to obtaining food (Lele et al., 2016). Many empirical papers support this law, suggesting that households allocating a substantial portion of their income to food are at higher risk of food insecurity, irrespective of their

[2] The food groups include: cereals; root and tuber; vegetables; fruits; meat, poultry and offal; eggs; fish and seafood; pulses, legumes, and nuts; milk and milk products; oil and fat; sugar and honey; and miscellaneous.

present consumption patterns. Consequently, we use the share of food expenditure to total household expenditure as a measure of the economic vulnerability of households to food insecurity.

3.5. Descriptive Statistics

Table 1 presents the summary statistics of the key explanatory variables and outcome variables of interest used in the empirical analysis. Panel A shows that men head the majority of households (75%) of households, with only 25% being headed by women. The average household comprises about 5.6 members, has a member with maximum years of schooling of 4 years, and a household head with an average age of 46. Based on our definition of drought, approximately 35% of households experienced rainfall below the long-term average or faced drought conditions in the three rounds, with the highest incidence (52%) occurring in 2015/16, when the country was affected by the large-scale El-Nino-induced drought.

Moving on to the outcome variables of interest in Panel B, we note that there has been an overall rise in nutritional intake between 2011/12 and 2015/16, with the average household diet diversity score increasing from 5.424 to 5.833. Despite this improvement, many households continue to consume highly undiversified diets. Around 69% of households consume six or fewer food items, and 12% consume three or fewer food groups out of a total of twelve. Conversely, the daily per capita calorie intake decreased from approximately 3,426 in 2011/12 to about 2,947 in 2015/16. The average calorie intake per adult equivalence is around 3,221 kilocalories, which exceeds the minimum required value. Nevertheless, about 44% of rural Ethiopian households remain food insecure, consuming less than the benchmark of 2,550 kilocalories per day per adult equivalent unit. On average, households allocate a staggering 80.5% of their expenditure to food consumption.

We provide more informative descriptives of the nutritional outcome variables of rural Ethiopian households - per capita calorie consumption, household diet diversity score, and the share of food expenditure - together with the distribution of weather shocks in kernel densities in Figure 2.

4. Results

4.1. Empirical Strategy

To identify the impact of drought on the nutritional outcome variables of interest for households in rural Ethiopia, we estimate the following fixed effects specification:

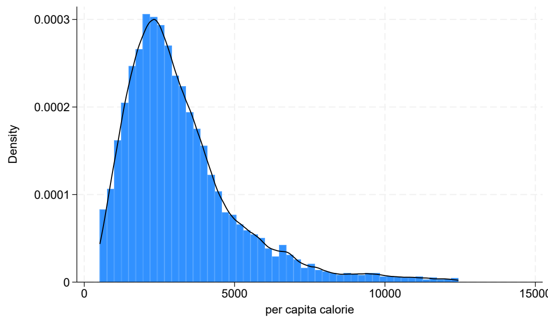
$$Y_{ivt} = \beta_0 + \beta_1 D_{vt-1} + \psi X_{ivt} + \varphi_i + \eta_t + \epsilon_{it}$$

Table 1: Descriptive Statistics

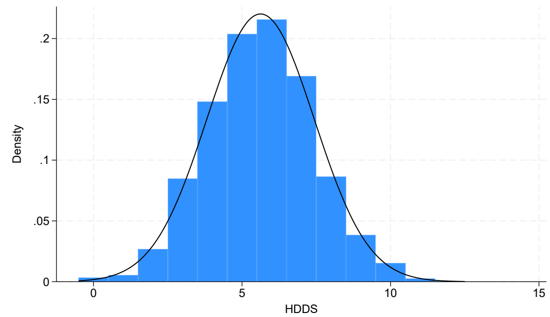
VARIABLES	(1) 2011/12	(2) 2013/14	(3) 2015/16	(4) Pooled
Explanatory Variables				
Rainfall shock	0.0841	0.301	0.195	0.192
	(0.195)	(0.397)	(0.451)	(0.372)
Drought (dummy)	0.246	0.518	0.274	0.346
	(0.431)	(0.500)	(0.446)	(0.476)
Age of head	44.46	46.47	48.19	46.31
	(15.73)	(15.49)	(15.44)	(15.63)
Head, male (dummy)	0.765	0.753	0.744	0.754
	(0.424)	(0.431)	(0.436)	(0.430)
Maximum edu. in hh. (years)	4.060	4.421	4.797	4.414
	(3.568)	(3.661)	(3.767)	(3.675)
Household size	4.964	5.622	6.189	5.571
	(2.347)	(2.450)	(2.610)	(2.517)
Dependency ratio	0.484	0.496	0.566	0.514
	(0.245)	(0.228)	(0.212)	(0.232)
Total land holding (ha)	1.519	1.528	1.398	1.484
	(8.312)	(4.660)	(8.230)	(7.264)
Livestock holding (TLU)	2.296	2.665	2.756	2.565
	(3.792)	(3.665)	(3.560)	(3.682)
Access to credit (dummy)	0.235	0.276	0.251	0.254
	(0.424)	(0.447)	(0.434)	(0.435)
Market access (dummy)	0.426	0.452	0.549	0.474
	(0.495)	(0.498)	(0.498)	(0.499)
Free food aid (dummy)	0.0912	0.0753	0.182	0.115
	(0.288)	(0.264)	(0.386)	(0.319)
Prod. Safety Net Program participant (dummy)	0.0491	0.0547	0.0692	0.0573
	(0.216)	(0.228)	(0.254)	(0.232)
Outcome Variables				
Calorie consumption/aeu	3426.3	3265.6	2947.4	3221.4
	(1955.8)	(1910.8)	(1842.1)	(1915.4)
Food insecurity (dummy)	0.390	0.422	0.509	0.438
	(0.488)	(0.494)	(0.500)	(0.496)
Household Diet Diversity Score (HDDS)	5.424	5.633	5.833	5.623
	(1.818)	(1.797)	(1.796)	(1.811)
Calorie share of staples	0.819	0.805	0.818	0.814
	(0.142)	(0.153)	(0.149)	(0.148)
Food expenditure share	0.826	0.794	0.794	0.805
	(0.119)	(0.125)	(0.129)	(0.125)
N	3136	3014	2832	8982

Notes: Column [1]-[3] presents summary statistics for the years 2011/12, 2013/14, and 2015/16, respectively. Column [4] reports summary statistics of the whole sample.

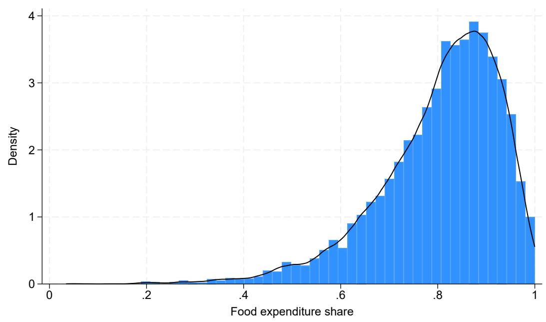
Where Y_{ivt} is the outcome variable of interest (calorie consumption per capita, household diet diversity score, and food share) of household i in village v at time (round) t. D_{vt-1} is the key explanatory variable of interest, drought in village v



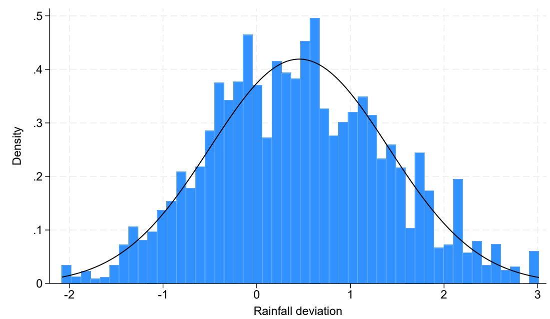
(a) Per capita calorie



(b) Household Diet Diversity Score



(c) Share of food expenditure



(d) Rainfall Deviation

Figure 2: Kernel Distribution of outcome variables and weather shock.

at time $t-1$. We use drought in the previous production season instead of the current season as agricultural income and consumption in the current year is largely determined by previous year's rainfall and harvest. X_{ivt} is a vector of control variables of household i in village v at time t, which in our specification includes household head variables (the age and gender of the household head; the maximum number of years of education in the household) and household-level socioeconomic variables (household size; dependency ratio; landholding; and livestock holding measured as tropical livestock unit, TLU)[3], access to credit, and market access. β_1 is the key coefficient of interest measuring the impact of drought on the outcome variable of interest, and ψ is the vector of coefficients for the control variables. In addition, we control for φ_i a term capturing time-invariant household unobserved heterogeneity, and η_t capturing time (round) fixed effects. ϵ_{it} represents an idiosyncratic error term. To account for correlations in outcome variables of households living in the same geographical areas, we cluster the standard errors at the village (enumeration

[3]Total livestock holdings have been aggregated using Tropical Livestock Unit (TLU) used by FAO for intentional comparison. TLU is equivalent to 250 kg live weight of standardized live animals by species mean live weight. We used TLU equivalent coefficients from FAO (2011); camel = 0.7, cattle = 0.5, horse = 0.5, mule = 0.6, and donkey = 0.3, goat and sheep = 0.1, and chicken = 0.01.

area level).

4.2. Regression Results

We begin with estimating the impact of drought on households' log of per capita calorie intake using a fixed effects estimator and report the results in Table 2. Column 1 presents estimates of the impact of drought on per capita calories from all foods consumed. Columns 2 - 6 present estimates of the impact of drought on calorie consumption from the different types of foods - vegetables, fruits and pulses, animal sources, staples, oils, and other food items. We applied the inverse hyperbolic sine (HIS) transformation to the dependent variables to account for households with zero values in some food groups. Decomposing the impact of drought on calorie consumption by food groups is important to understand the key mechanisms that explain the impact on total calorie consumption. In all regressions, the first regression controls for drought only, and the second regression controls for all covariates. We cluster the standard errors at the enumeration area level in all specifications.

Results in column 1 suggest that drought has a positive and statistically significant effect on households' per capita calorie intake—specifically, a one standard deviation decrease in rainfall increases per capita calorie consumption by approximately 5.5%. At first, the results seem contrary to the expectation. However, a careful look at the results in columns 2 and 4 suggests that an increase in staple food consumption primarily drives the increase in total calorie consumption during drought conditions. A one standard deviation decrease in rainfall decreases per capita calorie consumption from vegetables, fruits, and pulses by 18.9% (column 2) and increases per capita calorie consumption from staples by 8.1% (column 4). Therefore, the results suggest that households keep their calorie consumption during covariate shocks by substituting relatively expensive food items (e.g., vegetables, fruits, and pulses) with inexpensive food items (e.g., staples).

The results are consistent with Hou (2010), which uses panel data from rural Mexico collected under the PROGRESA safety net program to examine the impact of drought on food consumption and the mitigating effects of participating in PROGRESA. The author finds that while drought reduces total food expenditures, it paradoxically increases total calorie availability by shifting consumption toward cheaper staple grains. It also shows that having access to the conditional cash transfer program reduced the impact of drought on the nutritional intake of rural Mexican households.

Next, we estimate the impact of drought on household food utilization and economic vulnerability captured by the household diet diversity score (HDDS) and

Table 2: Impact of Drought on Calorie Intake

Variables	1		2		3		4		5		6	
	Total calorie		Vegetable fruit & pulse		Animal source		Staples		Oil		Others	
$Drought_{t-1}$	0.057**	0.055**	-0.186*	-0.189*	-0.019	-0.018	0.082**	0.081**	0.075	0.072	-0.098	-0.095
	(0.027)	(0.027)	(0.106)	(0.105)	(0.114)	(0.114)	(0.036)	(0.035)	(0.056)	(0.056)	(0.087)	(0.087)
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,982	8,982	8,982	8,982	8,982	8,982	8,982	8,982	8,982	8,982	8,982	8,982

Note: This Table presents fixed effects regression results on the impact of drought on households' log of per capita calorie consumption. Column [1] presents the impact of drought on households' total calorie consumption. Column [2] presents the impact of drought on calories from vegetables, fruits, and pulses. Columns [3] and [4] report the impact of drought on calories from staple and animal food sources. Columns [5] and [6] describe the impact of drought on calories from oil and other food sources, respectively. The control variables include household head and socioeconomic characteristics reported in Table 1. Standard errors (in parenthesis) are clustered at the enumeration area level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

the share of food expenditure in total household expenditure. The results are reported in columns 1 - 6 of Table 3. We control for drought in columns 1, 3, and 5. We control for drought and other covariates in columns 2, 4, and 6. We cluster standard errors at the enumeration area level in all specifications.

Fixed effects regression results in column 1 suggest drought has a statistically significant negative effect on household diet diversity score (HDDS). Column 1 suggests that a one standard deviation decline in rainfall leads to a 3.1% reduction in HDDS. The statistical significance and magnitude of the drought remains the same when we include controls in column 2. Still, drought significantly reduces the diversity of the household food consumption basket.

Table 3: Impact of Drought on Nutrition and Economic Vulnerability

Variables	1	2	3	4	5	6
	log(HDDS)		Food expenditure share		Non-food expenditure share	
$Drought_{t-1}$	-0.031*	-0.031*	0.020***	0.019***	-0.020***	-0.019***
	(0.018)	(0.018)	(0.006)	(0.006)	(0.006)	(0.006)
Control variables	No	Yes	No	Yes	No	Yes
Village fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,982	8,982	8,982	8,982	8,982	8,982

Note: This Table reports fixed effects regression results on the impact of drought on household nutrition and economic vulnerability indicators. Column [1] displays the impact of drought on the log of HDDS. Columns [2] and [3] present the impact of drought on households' food and non-food budget share, respectively. The control variables include household head and socioeconomic characteristics reported in Table 1. Standard errors (in parenthesis) are clustered at the enumeration area level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Consistent with the expectation, drought has a positive and statistically significant impact on households' economic vulnerability to food insecurity. A one standard deviation decrease in the previous year's rainfall raises the share of food expenditure of households to total expenditure by about 2% (Columns 3 & 4). One possible explanation is that when there is shock, households are more likely to compromise the quantity and/or quality of their diets or cut back on basic non-food expenditures, further undermining their food security status. To test this, we divided household spending into food and non-food expenditure categories and ran the fixed effects regressions. The results suggest that a standard deviation decrease in the previous year's rainfall results in the same amount (about 2%) decrease in non-food expenditure (Columns 5 & 6). Thus, the increase in food expenditure in response to drought comes at the expense of basic non-food expenditures, such as health and education, which will likely affect the long-term welfare of households.

Taken together, the results suggest that drought increases households' per capita calorie intake. However, one cannot consider this finding a positive phenomenon because it comes at the expense of dietary diversity, which is crucial for maintaining a healthy and balanced diet. Adequate nutrient intake is essential to lead a healthy life by improving the immune system Calder (2013), gut health Heiman and Greenway (2016), and cognitive functioning Prado and Dewey (2014), and reducing the risk of chronic diseases Ruel (2003b).

4.3. Food Price Shocks and Urban Households Food Consumption

Is increasing calorie consumption and reducing diet diversity in response to drought a rural household phenomenon or a possible phenomenon in other covariate shocks-affected setups? To shed light on this question, we analyzed data from two rounds of the urban sample of the same data (the Ethiopian Socioeconomic Survey ESS) conducted in 2013/14 and 2015/16. A notable covariate shock in urban areas of developing countries is food price inflation (Dessus et al., 2008; Alem and Söderbom, 2012; Headey and Martin, 2016). Urban Ethiopian households are particularly vulnerable to food price shocks because Ethiopia experienced rapid food price inflation in the past decade and urban households are net food buyers. For example, in April 2022, food inflation in Ethiopia reached almost 43% compared to April 2021, and a large part of it was driven by inflation in major food items (World Bank, 2024).

We, therefore, investigate the impact of food price shocks on food and nutrition security indicators in urban Ethiopian households. Because food price shocks are spatially invariant, we use self-reported food price shocks and estimate their effect on the same outcome variables - the log of calorie consumption, household dietary diversity score (HDDS), and the share of food expenditure. The questions on food price shocks were asked: "During the last 12 months, was your household affected by a food price shock?" for which the respondent answered "yes" or "no".[4]

Table 4 presents the regression results on the impact of food price shocks on the calorie intakes of urban households. Consistent with the results we document for rural households on the impact of drought on calorie intakes, the results here suggest that an increase in food prices has a positive and statistically significant effect on the calorie consumption of urban households. More specifically, an increase in food prices is associated with a 6.2% increase in daily per capita calorie consumption

[4] While using self-reported measures of food price shock is an option when there is no spatial variation in objective price shocks, self-reported measures in general may suffer from reporting bias. The results should therefore be taken with caution.

(Column 1). The plausible explanation is that during periods of price shocks, urban households are more likely to substitute relatively expensive food items with cheaper alternatives that are likely more calorie-dense.

Table 4: Impact of Food Price on Calorie Intake of Urban Households

Variables	1 Total calorie	2 Fruit, Veg. & Pulses	3 Animal source	4 Staples	5 Oil source	6 Other foods
Food price shock	0.062*	-0.079	-0.105	0.183***	-0.208**	0.008
	(0.035)	(0.069)	(0.211)	(0.067)	(0.081)	(0.090)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,148	3,148	3,148	3,148	3,148	3,148

Note: This table presents fixed effects regression results on the impact of food price shocks on the calorie intake of urban households. Column [1] describes the impact on households' total per capita calorie intake. Column [2] presents the impact on calories from vegetables, fruits, and pulses. Columns [3] and [4] report the impact on calories from animal and staple source foods, respectively. Columns [5] and [6] report the impact of calories from oil and other food sources, respectively. Price shock is measured by whether or not the household reported to have been affected by a food price shock in the previous year. The control variables include the head's age and gender, maximum education in the household, household size, dependency ratio, and access to credit. Standard errors (in parenthesis) are clustered at the enumeration area level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To investigate if the substitution of expensive but nutritious food items with cheap but relatively calorie-dense items explains the increase in the per capita calorie intake of urban households, we decomposed the total calories consumed by the five food sources (fruits, vegetables, and pulses; animal sources; staples, oil sources, and other food) and ran the regressions. The results reported in Table 4 suggest that urban households increase the consumption of staple foods and decrease the consumption of oil-source foods in response to a food price shock. A food price shock leads to an 18.3% increase in per capita calorie consumption from staple foods (Column 4) and a 20.8% reduction in per capita calorie consumption from oil-source foods (column 5). These effects are both statistically and economically significant. On the other hand, a food price shock increases calories from other sources and decreases calories from vegetables, fruits, pulses, and calories from animal sources. However, these effects are not statistically significant.

Finally, we investigate the impact of food price shocks on nutritional security and vulnerability of urban households as measured by HDDS and food expenditure share and report the results in Table 5. The results suggest a food price shock reduces household diet diversity by about 0.9 percent (Column 1). However, the

Table 5: Impact of Food Price on Nutrition and Economic Vulnerability of Urban Households

Variables	1	2	3
	log(HDDS)	Calorie from non-staple	Food expenditure share
Food price shock	-0.009	-0.032***	0.014
	(0.018)	(0.012)	(0.011)
Controls No	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	3,148	3,148	3,148

Note: This Table reports fixed effects regression results on the impact of food price inflation on household nutrition and economic vulnerability indicators. Column [1] displays the impact on the HDDS log. Column [2] presents the impact of non-staple foods on calories. Column [3] presents the impact on food expenditure share. The control variables include the head's age and gender, maximum education in the household, household size, dependency ratio, and access to credit. Standard errors (in parenthesis) are clustered at the enumeration area level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

effect is not statistically significant at conventional levels. On the other hand, a food price shock negatively impacts the share of calories from non-staple food sources - an alternative nutritional indicator and the effect is significant at 1%. A food price shock reduces the calorie share of non-staple foods by about 3.2% (Column 2), suggesting a corresponding increase in calorie consumption from staple foods. Column 3 suggests that a food price shock increases households' share of food expenditure by about 1.4%. However, the effect is not statistically significant at conventional levels.

4.4. Heterogeneous Impact of Drought

Does drought affect all households uniformly, or does its effect differ based on socioeconomic characteristics? To shed light on this question, we conducted a heterogeneous impact analysis by interacting drought with the gender of the head of the household and participation in two safety net programs—food aid and productive safety net programs. We also investigate the impact of drought based on consumption (a proxy for income) quartiles.

We chose the gender of the household head because previous studies (Bardhan and Udry, 1999; Dercon, 2002; Alem et al., 2010) suggest that households headed by women are more susceptible to adverse events, have limited access to modern technologies, and frequently encounter challenges in navigating input and product markets. We chose participation in safety nets for the heterogenous analysis because Ethiopia is a drought-prone country, and the Ethiopian government invested significant resources to improve its disaster preparedness capacity to respond to major natural shocks. The most notable initiatives are the multi-donor-supported Productive Safety Net Programme - PSNP (World Bank, 2013) and the food-for-work and free food distributions (Gilligan and Hoddinott, 2007; Alem and Broussard, 2018). Launched in 2005, the PSNP aimed to transition millions of chronically food-insecure rural households from relying on emergency food aid to a more stable and predictable form of social protection (World Bank, 2013).

We present the results on the heterogeneous impacts of drought on the three key outcome variables - the log of household per capita calorie intake, HDDS, and food expenditure share - by the selected characteristics in Table 6. The results in rows 1 and 2 suggest that drought doesn't have a heterogeneous impact on any of the outcome variables based on the gender of the household head and receiving food aid. However, row 3 suggests that the impact of drought on the log of per capita calorie intake varies by households' involvement in the productive safety net program (PSNP). Specifically, experiencing a rainfall shock increases per capita calorie intake of PSNP participant households by 17.7% compared to non-PSNP recipients. The result is expected because PSNP is mostly implemented in drought-prone areas and compensates households that could use it to purchase staple foods. However, the overall impact of drought on the outcome variables of interest we document is unlikely driven by PSNP participant households because these households represent only 5.7% of the sample.

Finally, we investigate the differential impact of drought on our outcome variables by household economic status. We follow the literature and use consumption expenditure as a proxy for economic status. We divided the sample of rural households into four quartiles based on consumption per adult equivalent units (aeu) and ran the outcome variables on drought and control variables using fixed-effects regressions.

The results presented in Table 7 suggest that the impact of drought on all outcome variables of interest differs by consumption quartile. For example, the impact of a drought on per capita calorie consumption for the poorest households (lowest quartile) is negative and statistically significant at 10% (Column 1). A rainfall shock in the previous year reduces calorie consumption by approximately 9.1% for the poorest 25% households. This indicates that even if the overall effect of a weather shock on calorie consumption is positive, poor households still face calorie cuts during drought. One plausible explanation is that many low-income households largely consume staple foods and they don't have the option to

Table 6: Heterogeneous Effects of Drought by Gender of Head and Safety Net

	1	2	3
Variables	log(calorie)	log(HDDS)	Food expenditure share
$Drought_{t-1}$ x Gender	-0.015	-0.005	-0.012
	(0.038)	(0.020)	(0.008)
$Drought_{t-1}$ x Food aid	-0.000	-0.038	0.003
	(0.068)	(0.038)	(0.015)
$Drought_{t-1}$ x PSNP	0.177**	-0.015	-0.013
	(0.078)	(0.058)	(0.019)
Controls	Yes	Yes	Yes
Village FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	8,982	8,982	8,982

Note: This table reports fixed effects regression results on the heterogeneous impacts of drought on the outcome variables by the gender of the household head, food aid, and PSNP participation. Columns (1), (2), and (3) report the heterogeneous impact on the log of per capita calorie intake, HDDS, and food expenditure share, respectively. Standard errors (in parenthesis) are clustered at the enumeration area level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: Heterogeneous Effects of Drought by Per Capita Consumption Quartile

	1	2	3	4
Variables	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Calorie Consumption	-0.091*	0.043	0.043	0.068*
	(0.053)	(0.048)	(0.035)	(0.037)
HDDS	0.023	-0.076**	-0.067*	0.023
	(0.046)	(0.030)	(0.038)	(0.037)
Share of Food Expenditure	0.019	0.014	0.019*	0.034***
	(0.014)	(0.013)	(0.011)	(0.011)
Controls	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	2,246	2,245	2,246	2,245

Note: This table reports fixed effects regression results on the heterogeneous impacts of drought on the outcome variables by per capita consumption quartiles. Rows (1), (2), and (3) report the heterogenous impact on the log of per capita calorie consumption, log HDDS, and food expenditure share, respectively. The control variables include household head and socioeconomic characteristics reported in Table 1. Standard errors (in parenthesis) are clustered at the enumeration area level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

substitute away from staples during droughts (Jensen and Miller, 2008).

Table 7 also shows that the effect on calorie consumption for middle and higher-income households is positive. However, the effect is statistically significant for the highest-income households. Experiencing drought increases the per capita calorie consumption and the share of food expenditure of the richest 25% households by about 6.8% and 3.4%, respectively. This suggests that only the richest households have the ability to substitute food items and divert non-food expenditures to food expenditures during times of covariate shocks. The results in Table 7 also suggest that the effect of drought on HDDS of low and middle-income households is negative, but it is only statistically significant for middle-income households.

4.5. Robustness Checks

To verify that the key results we documented on the impact of drought on the nutritional outcomes of rural households are robust, we conducted several robustness checks. First, we estimate the regression results using the Conley standard errors (Conley, 1999), which are recommended to account for spatial correlation in the data. We estimated the standard errors accounting for spatial correlation of household variables within 100 km and presented the results in Table 8. The results suggest that the drought still has statistically and economically significant effects on all three outcome variables. In all cases, the coefficients are larger than those we documented in Tables 2 and 3.

Table 8: Impact of Drought on Food and Nutrition Security- Spatial Correlation

	(1)	(2)	(3)
	log(Calorie)	log(HDDS)	Share of Food expenditure
$Drought_{t-1}$	0.0546**	-0.0306**	0.0194***
	(0.0263)	(0.0139)	(0.00516)
Control variables	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Observations	8,982	8,982	8,982

Note: This Table reports fixed effects regression results on the impact of drought on the outcome variables with Conley standard errors. Column (1) reports the effects of drought on the log of calorie consumption. Column (2) presents the effect of drought on the log of HDDS. Column (3) reports the effect of drought on the share of food expenditure. The control variables include household head and socioeconomic characteristics reported in Table 1. Standard errors (in parenthesis) are clustered at the enumeration area level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Second, we conduct a falsification test to investigate if time-varying unobservables confound the effects of weather shocks on the outcome variables of focus. We specifically followed (Burke et al., 2015) and re-estimate our main specification using future drought (one year ahead) instead of lagged drought. Suppose mismatched weather data cannot explain food and nutrition security indicators. In that case, it implies that unobserved factors are unlikely to confound the effect of lagged drought, which was reported in our main result. All three regression results presented in Table 9 suggest that future drought doesn't affect the three outcome variables, which implies that time-invariant unobserved heterogeneity does not confound the drought effect we documented.

Table 9: Impact of Drought on Food and Nutrition Security- Falsification Test

	1	2	3
Variables	log(calorie)	log(HDDS)	Share of food expenditure
$Drought_{t+1}$	-0.048	0.017	-0.008
	(0.031)	(0.014)	(0.006)
Control variables	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Observations	8,982	8,982	8,982

Note: This Table reports fixed effects results for the falsification test. Column 1 reports the impact of future drought on the log of per capita calorie consumption. Column 2 presents the impact of future drought on the log of HDDS. Column 3 reports the impact of future drought on the share of food expenditure. The control variables include the household head and socioeconomic characteristics reported in Table 1. Standard errors (in parenthesis) are clustered at the enumeration area level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Finally, we use two alternative measures to define drought—the absolute deviation of the previous year's rainfall from the long-term mean and a dummy variable indicating drought when rainfall is below the 20^{th} percentile of the long-term mean—and re-estimate the key empirical specifications. As shown in Tables A.1 - A.2, the results remain largely consistent with our main findings. In all alternative definitions, drought increases calorie consumption and the food expenditure share but decreases household diet diversity.

5. Conclusion

Most previous studies show that drought in rain-fed agricultural setups of developing countries leads to a reduction in the consumption of food and, thus, calorie consumption. Using three rounds of rich nationally representative panel data from Ethiopia (the Ethiopian Socioeconomic Survey - ESS) matched with 35 years of rainfall data; we show that drought rather increases the calorie consumption of the affected households. We use the urban sample of the ESS data and investigate if the increase in calorie consumption by rural households in response to a covariate shock (drought) we document is a rural phenomenon or if other covariate shocks affect food consumption the same way. We also leverage the richness of the data and tease out the mechanisms through which covariate shocks lead to an increase in calorie consumption, which is the key contribution of our paper.

We find that drought has a positive and statistically significant effect on calorie consumption. A one standard deviation decrease in lagged rainfall leads to a 5.5% increase in per capita calorie consumption. The key mechanism through which drought increases calorie consumption is the increase in staple food consumption and the reduction in the consumption of other expensive food items, more importantly, fruits, vegetables, and pulses. We confirmed this mechanism by decomposing the source of calories by food type. Using fixed effects regressions, we show that a one standard deviation decrease in lagged rainfall leads to an 18.9% reduction in per capita calorie consumption from vegetables, fruits, and pulses and an 8.1% increase in per capita calorie consumption from staple foods. Consistent with this finding, we show that drought reduces the variety of food items consumed as measured by the household diet diversity score (HDDS). A one standard deviation decrease in lagged rainfall leads to a 3.1% reduction in HDDS.

We find a similar effect of food price shocks (the key covariate shocks in an urban context) using the urban sample of the data. A food price shock in the previous year leads to a 6.2% increase in per capita calorie consumption. Food price shocks increase per capita calorie consumption from staples by 18.3% and reduce per capita calorie consumption from oil foods by 20.8%. We also note that rural and urban households reduce expenditure on the consumption of non-food items (e.g., health and education) to increase their spending on food in response to covariate shocks. Taken together, the results suggest that during large-scale covariate shocks, households substitute relatively expensive food items (e.g., vegetables, fruits, and pulses) with cheaper food items (e.g., staples), leading to an increase in total calorie consumption.

Our findings have significant implications on policies related to mitigating the impact of shocks, more importantly, drought. In many parts of the global south, climate change results in more prevalent and intense droughts (IPCC, 2014, 2021). FAO (2016) and Wang et al. (2019) show that climate change is also making

El-Niños - the tropical Pacific's unusual warming of sea surface temperatures happening every 2 - 7 years and resulting in heavy rain, flooding, and drought - more frequent and intense. Our findings highlight interventions in two important areas. First, given these stylized facts, strengthening the capacity to forecast rainfall shocks and inform farm households is critical. Recent studies, e.g., Udry et al. (2019) in Ghana, Yegbemey et al. (2023) in Benin, and Burlig et al. (2024) in India, show that farmers who receive weather forecast information can adjust production and reduce the damage. Second, we highlight that disaster response programs often offer emergency food assistance, mostly staples. Given the documented effect of drought in pushing households to shift away from important nutritional food items, such as vegetables, fruits, and dairy products, the distribution of nutritional supplements, particularly to vulnerable groups such as children, that make up for the nutritional loss, is important to reduce future health effects. Investigating the impact and cost-effectiveness of these interventions is left for future research.

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