Smallholder Farming Households Nutrition Under Extreme Heat: Vulnerabilities and Adaptation *

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Abstract

Climate change threatens food security in Sub-Saharan Africa, but the magnitude of its nutritional impacts and the household-level behaviors that mediate them remain understudied. I examine how extreme heat during the crop growing season affects the commercialization and consumption decisions of Nigerian smallholder farming households, and how these responses shape post-harvest nutrition. Using five waves of panel data (2010–2024) linked to high-resolution weather, I exploit within-household variation in growing-season temperatures. Results show that hotter seasons depress harvests and reduce diet quality while leaving total caloric intake unchanged. I estimate that a $+1°C$ warming would result in 1.62 and 0.63 million additional households with inadequate protein and iron intake, respectively. Less educated households and those with young children, who require protein and iron for growth, are more adversely affected. I demonstrate that households reduce crop commercialization to safeguard calories from own-produced staples and cut their purchases of nutritious and cash-intensive foods. This reflects a risk-minimizing behavior under incomplete food and labor markets and binding caloric constraints. In line with this, I find no evidence of adjustments in off-farm labor. Findings suggest that on-farm adaptation alone cannot maintain diet quality under climate change, underscoring the need for integrated policies that extend beyond calorie sufficiency and pair market participation and labor market development strategies with climate-risk mitigation.

Keywords: agriculture; climate change; extreme heat; Nigeria; nutrition.

JEL Codes: I15, O13, Q11, Q12, Q54.

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1 Introduction

Undernutrition undermines human capital formation (Glewwe et al., 2001; Maluccio et al., 2009), deteriorates long-run health (Hoynes et al., 2016), and reduces productivity (Case and Paxson, 2008). The associated aggregate economic burden resulting from lost productivity and direct healthcare costs is substantial, at roughly 2-3% of global GDP each year (FAO, 2013). Despite notable progress over recent decades, the burden remains pronounced in Sub-Saharan Africa: undernourishment affects more than 22% of the population (FAO, 2022), and micronutrient deficiencies are widespread (FAO et al., 2021; Passarelli et al., 2024). At the same time, the region is warming faster than the global average (WMO, 2024). The increased frequency and intensity of extreme heat events could slow or even reverse progress against malnutrition (Blom et al., 2022). This is a salient issue for Sub-Saharan Africa, where the majority of households are smallholder farmers, for whom a hot growing season poses a direct threat to their primary sources of food and income.

While the link between extreme heat and reduced agricultural productivity is well-established (Hultgren et al., 2025; Schlenker et al., 2006; Schlenker and Roberts, 2009), much less is known about the pathways through which these productivity shocks translate into household nutrition. The magnitude of the nutritional impact is also uncertain, shaped by households' capacity to adapt. Faced with a harvest shortfall, a farm household's food consumption and crop commercialization decisions are intertwined under incomplete food and labor markets, common in such developing settings (Dillon and Barrett, 2017; Dillon et al., 2019). Yet, much of the literature has focused on coarse nutritional outcomes, such as self-reported food security or dietary diversity indices, which capture the extensive margin of consumption, or total calorie intake (Dillon et al., 2015; Randell et al., 2022; Dasgupta and Robinson, 2022; Villacis et al., 2022; Kroeger, 2023). These metrics can mask important changes in dietary quality and obscure the commercialization–consumption nexus that mediates nutrition. Understanding household adaptation responses and achieving precision in assessing the magnitude of the nutritional impact are prerequisites for effective climate adaptation policy design.

This paper examines the impact of extreme heat on food consumption and nutrition among smallholder farm households. I focus on Nigeria, the most populous African nation, with over

70% of households engaged in farming, high poverty rates, and widespread food insecurity (National Bureau of Statistics, 2024; World Bank, 2025). I study adjustments to food consumption and crop commercialization patterns in response to temperature-induced crop losses and assess their implications for undernutrition, diet quality, and nutrient intake.

I use five waves of nationally representative panel data from the Nigeria Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA), spanning 2010–2024. The survey provides microdata on household-level agricultural production and livestock management, as well as comprehensive food consumption diaries. I convert the latter into calories and the intake of crucial nutrients to dietary health, including protein, iron, zinc, and vitamin A, and create nutrient adequacy indicators based on international requirement standards and household composition. I then match these data with high-resolution gridded weather data. I model the relationship between weather and agricultural productivity as a non-linear function of cumulative exposure to heat and precipitation during the growing season. My hypothesis is that high growing-season temperatures increase crop losses, and that this decline in agricultural output is subsequently transmitted to reduced household welfare after harvest. The empirical strategy exploits quasi-random within-household variation in growing-season temperatures to identify the impact of extreme heat on post-harvest nutrition.

I find that hotter growing seasons significantly reduce harvests. In the short term, however, this productivity loss does not translate into a reduction in total calorie intake. Instead, the shock's impact is on diet quality. Extreme heat leads to a decrease in household dietary diversity and an increase in the proportion of households with inadequate protein and iron intake. The magnitude is economically significant: a uniform $+1°C$ warming is associated with an additional 1.62 million and 0.63 million Nigerian households (4.04% and 1.56% of farm households) with inadequate protein and iron intake, respectively.

These adverse effects are not borne equally. The nutritional impacts are significantly larger for less educated households and those with young children, a concerning finding that aligns with evidence showing extreme heat increases the prevalence of child stunting (Blom et al., 2022). While closeness to markets and greater income diversity are associated with improved nutrition, they do not moderate the adverse effects of high growing-season temperatures. Livestock management, itself adversely affected by heat, does not buffer nutritional and income losses.

To understand the underlying mechanisms, I examine households' adjustments in market behavior. First, households sell a smaller share of their harvest. This adaptation allows them to maintain consumption of their own-produced foods, mainly cereals, roots, and tubers, thereby securing their caloric needs. Second, this decision, combined with the initial harvest loss, generates an income shock, reflected by a drop in total expenditure. Households cope by cutting spending on both food purchases and non-food items. The cuts to food purchases disproportionately affect cash-intensive and nutritious foods such as vegetables, pulses, and animal meat, which are essential components of a healthy diet and significant sources of protein and iron. Thus, this adaptation strategy ensures calorie sufficiency while degrading diet quality. Adverse nutritional effects worsen as time since harvest elapses and own-produced food stocks are depleted.

I demonstrate that this post-harvest market behavior adjustment is consistent with risk minimization under incomplete food and labor markets and binding caloric constraints. I find no statistically significant effects of extreme heat on post-harvest off-farm labor, suggesting that income shortfalls from harvest losses are not offset by increased off-farm labor. Additionally, findings indicate that post-harvest market-level prices are largely unresponsive to growing season temperatures, at least in the short run. This lack of measured effects lends support that the transmission of production shocks to post-harvest prices does not drive the documented households' crop commercialization and food purchase responses.

This paper makes three main contributions. First, it provides novel causal evidence on how heat shocks translate into malnutrition in low-income settings with agricultural-dependent livelihoods. It expands the literature on climate impacts and nutrition by moving beyond coarse metrics, such as experience-based food security indicators or calorie intake, to focus on the intensive margin of nutrient adequacy (Dillon et al., 2015; Malacarne and Paul, 2022; Amare et al., 2021; Wegenast et al., 2025). Specifically, by examining inadequacies in nutrient intake - most notably protein and iron - which are pervasive among Sub-Saharan African households but often overlooked in economic analyses,[1] this approach reveals significant deteriorations in diet quality that are otherwise masked by a focus solely on caloric sufficiency.

Second, by separating consumption into own-produced and purchased sources, which is absent from the climate-nutrition literature, I provide evidence on how heat-induced harvest losses trigger defensive post-harvest reallocation. Households retain a larger share of staple production for home use and cut back on market purchases of nutrient-dense foods, thereby preserving calories at the expense of diet quality. The latter aligns with Bennett's law and the literature on households' food purchase responses to macroeconomic shocks (Headey et al., 2014; Ecker and Hatzenbuehler, 2022). I rationalize this reallocation as a caloric risk–minimizing response under incomplete food and labor markets and binding caloric constraints.

Third, I reveal a post-harvest farm household adaptation response not previously documented. Following a heat shock in the growing season, households reduce commercialization and the share of harvest sold. The positive relationship between commercialization and smallholder farmers' nutrition is well-documented (Hazrana and Mishra, 2025; Chegere and Kauky, 2022; Ogutu et al., 2020). Increasing market participation through interventions that lower transaction costs, improve smallholders' access to markets and information, and strengthen rural infrastructure, is essential to escaping semi-subsistence poverty traps (Omiti et al., 2009; Barrett, 2008). My findings suggest that climate change may represent an additional constraint to such participation. This complements a rich literature focusing on productive responses to extreme weather shocks (Aragón et al., 2021; Mayorga et al., 2025; Costinot et al., 2016), the reallocation of economic activities (Rosenzweig and Stark, 1989; Kochar, 1999), and consumption smoothing techniques, such as asset sales and access to credit (Rosenzweig and Wolpin, 1993; Di Falco et al., 2011).

These findings are likely relevant in other smallholder farmer contexts with incomplete markets and highlight the limitations of on-farm strategies in mitigating nutritional risks under climate stress. Households' defensive adaptation preserves caloric intake in the short run but degrades nutrient adequacy, underscoring the need for policy approaches to extend beyond

[1] One notable exception is McCullough et al. (2024), which model consumer preferences across five Sub-Saharan African countries and examine how nutrient intake responds to changing food prices, total expenditures, and other demand determinants.

calorie sufficiency. To protect nutrition, interventions should integrate climate-risk mitigation with strategies that expand income diversification and foster market participation.

This paper is divided as follows. Section 2 develops a conceptual framework. Section 3 details the Nigerian context and the data sources, including the construction of the main variables used in this study and summary statistics. Section 4 describes the empirical strategy. Section 5 presents the main results, investigates household adaptation responses, explores heterogeneity and potential moderators, and discusses the effect of a uniform warming scenario. Finally, Section 6 concludes.

2 Conceptual framework

This section develops a post-harvest conceptual framework to examine how extreme heat affects the joint determination of commercialization, off-farm labor, and diet composition.

Without loss of generality, I assume a one-person farm household framework with a single output, s, harvested after the growing season. I call this output "staples" and it can represent any cereal, root, or tuber commonly cultivated by Nigerian smallholder farmers.[2] Harvest for s depends on A (with $s'(A) > 0$), a productivity shifter capturing the idea that farmers using identical inputs may obtain different output levels due to farming skills, soil quality, or exposure to weather shocks.[3] Consistent with the agricultural yields and temperature literature (Hultgren et al., 2025), extreme heat (H) has a detrimental effect on productivity, such that $A'(H) < 0$. Household utility is $U(c, n)$, where n denotes the consumption of non-staple "nutritious" foods (e.g., vegetables, fruits, animal-sourced foods) and c represents other market consumption. Staple consumption does not enter the utility directly: staples are treated as a cheap way to meet

[2]The National Bureau of Statistics (2024) shows that the most commonly cultivated crops among farming households (as a share of farming households growing crops) are maize (44.9%), sorghum (28.5%), millet (17.8%), and rice (16.2%) (cereals); cassava (44.9%) and yam (18.7%) (roots and tubers). Other crops, such as pulses or nuts, are less cultivated, e.g., beans (16.5%), groundnut (11.5%).

[3]I assume that capital is fixed, e.g., access to irrigation, which is low in Nigeria.

basic calorie requirements $\underline{K}$, with k_s the calorie content of one unit of s and k_n the calorie content of one unit of n. The household obtains income by selling a share $q \in [0, 1]$ of s and by supplying off-farm labor $l \in [0, \bar{L}]$ at a fixed wage $w > 0$.[4] I assume that the utility function is increasing and strictly concave and that $\frac{p_s}{k_s} < \frac{p_n}{k_n}$.[5]

After each harvest season, the household maximizes utility by choosing off-farm labor l, the commercialization share $q \in [0, 1]$, selling qs and retaining $(1 - q)s$ for home consumption, and the quantities purchased of nutritious foods n and staples s_b. In this simplified post-harvest setting, the farm household's problem is:

$$
\begin{aligned}
\max_{q,l,n,s_b,c} \quad & U(c, n) \\
\text{s.t.} \quad & p_s s_b + p_n n + c \leq p_s q s + wl, \\
& k_s\big[(1 - q)s + s_b\big] + k_n n \geq \underline{K}.
\end{aligned}
$$

If output and labor markets are complete and well functioning, harvest s can be costlessly converted into cash at price p_s, and off-farm labor can be supplied freely at wage w. In this complete-markets benchmark, the household's post-harvest problem reduces to a standard consumption–labor choice with exogenous income: commercialization is purely an accounting choice, and the household is indifferent between retaining own-produced staples for home consumption and selling them and re-purchasing staples at p_s. The buying and selling prices for staples coincide, $p_s^{buy} = p_s^{sell} = p_s$ (no wedge), and the internal shadow price of staples equals the market price. A temperature-induced harvest shortfall is a standard income shock that can be offset by supplying more off-farm labor $l \in [0, \bar{L}]$. There is no sharp prediction for n, but with ample earning capacity (high w or high $\bar{L}$ relative to initial l), nutritious food intake can be maintained.

This prediction changes when markets are incomplete. Under incomplete food markets but

[4] $\bar{L}$ represents a cap on the number of hours the household can work off-farm in the post-harvest period. Because utility is defined only over n and c, the model would otherwise push off-farm labor to infinity at any positive wage. $\bar{L}$ is the maximum feasible off-farm working hours given day length and other household and farm maintenance tasks.

[5] Globally, including in Sub-Saharan Africa, the price per kilocalorie is significantly lower for staples than nutritious foods (Masters et al., 2018; Bai et al., 2021).

complete labor markets, households face a buy–sell wedge on staples: the price at which they can buy staples exceeds the price at which they can sell them, $p_s^{buy} = p_s^{sell} + \upsilon_s$. Households face a buy-sell wedge on staples ($\upsilon_s > 0$). Selling and then repurchasing staples destroys value. In the household's problem, the relevant price is therefore not the observed selling price p_s^{sell} but an internal shadow price $\tilde{p}_s$, which captures the opportunity cost of consuming or selling one additional unit of s given the calorie requirement and the wedge. With complete markets and a slack calorie constraint, $\tilde{p}_s = p_s^{sell}$. With a positive wedge and a binding calorie requirement, $\tilde{p}_s$ exceeds p_s^{sell} and lies closer to p_s^{buy}, because selling an extra unit of s today may require buying back calories later at the higher price p_s^{buy} or cutting nutritious foods n. To meet calorie requirements cheaply after a harvest shortfall, the household avoids paying the wedge by retaining more of the smaller harvest. Cash needs for n are partially met by working more off-farm, and the net effect on n depends on earning capacity.

Under incomplete labor markets (e.g., due to limited local demand) but complete food markets, there is no wedge on staple prices, and calories can be purchased at p_s without additional loss, provided the household has cash. However, liquidity is tight because l cannot expand (or can expand only slightly). In this case, a negative productivity shock pushes the household to sell a larger share of the harvest to raise cash, reducing the resources available for nutritious foods, leading n to decline, particularly when the calorie constraint is binding.

Finally, when both food and labor markets are incomplete, the cheapest way to secure calories is to retain own-produced staples. The shadow price $\tilde{p}_s$ is high because of the buy–sell wedge and the binding calorie requirement, and the ability to earn additional cash is limited. As productivity falls due to extreme heat, commercialization declines, $\frac{dq}{dA} > 0$,[6] while off-farm labor adjusts little, $\frac{dl}{dA} \approx 0$. In such environments, extreme heat induces households to reduce both commercialization and the consumption of nutritious foods: households retain a larger share of the (smaller) harvest to secure calories and scale back cash-intensive purchases of n. They also face a risk of calorie shortfalls when $\underline{K}$ is high relative to s. This prediction is especially relevant where staple buy–sell wedges are large and local labor demand is limited, conditions that characterize many smallholder environments in Nigeria and similar developing

[6]Since extreme heat reduces productivity ($A'(H) < 0$), hotter seasons reduce commercialization.

settings (Dillon and Barrett, 2017; Dillon et al., 2019).

This framework also highlights forces that could confound a negative relation between extreme heat and commercialization. First, if extreme temperatures depress aggregate supply and raise output prices, higher prices would encourage sales, biasing the heat–commercialization coefficient toward zero or a positive value. I examine the role of prices in Section 5.6. Second, correlated productivity shocks can raise harvests and sales in periods that are also classified as hot, attenuating a negative effect. This could be the case with precipitations, thus I flexibly control for precipitation to net out correlated agronomic shocks.

Guided by this framework, the empirical analysis estimates the effect of extreme heat on home-grown consumption, commercialization, purchases, and subsequent dietary quality as measured both through dietary diversity and nutrient adequacy.

Several limitations are worth noting. I focus on *ex-post* household adaptation, i.e., after the weather shock occurred (Carleton et al., 2024). I build on agricultural producer–consumer household models in which, under incomplete markets, production and consumption decisions are generally non-separable (Benjamin, 1992; Janvry et al., 1991; Pitt and Rosenzweig, 1985). In my simplified framework, I treat harvest as predetermined at the time of commercialization and food consumption decisions, abstracting from *ex-ante* adaptation, such as production-stage adjustments. Post-harvest off-farm labor l does not affect production and thus enters only as an income-generation margin. The literature documents additional within-growing season responses, such as changes in input use (Mayorga et al., 2025; Aragón et al., 2021) and crop mix (Costinot et al., 2016), as well as consumption-smoothing strategies, including off-farm work and migration (Rosenzweig and Stark, 1989; Kochar, 1999). I examine these additional potential adaptation responses in Section 5.6.

3 Data

3.1 The Nigerian Context

Nigeria, the most populous nation in Sub-Saharan Africa with approximately 233 million people, serves as the setting for this analysis. The country faces considerable socioeconomic challenges, with 56% of its population living below the poverty line and over 30 million experiencing acute food insecurity (World Bank, 2025; World Food Programme and Food and Agriculture Organization of the United Nations, 2025). Agriculture is central to Nigeria's economy, involving over 70% of households (over 42 million). Major cultivated crops include maize, cassava, sorghum, yams, and millet (National Bureau of Statistics, 2024). Poverty is widespread among farm workers (World Bank, 2014). Agricultural productivity is hampered by several constraints, including limited market access, land degradation, insufficient infrastructure, and minimal irrigation (World Bank, 2025). Climate change intensifies these challenges and is projected to decrease agricultural productivity and worsen food insecurity, making Nigeria increasingly vulnerable (World Bank, 2021). Understanding farm household responses to rising temperatures is thus crucial and a key aspect of designing effective climate adaptation policies.

3.2 LSMS-ISA data

This study utilizes panel data from the Nigeria General Household Survey (GHS), part of the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). Specifically, it uses five waves collected in 2010/11 (wave 1), 2013/14 (wave 2), 2015/16 (wave 3), 2018/19 (wave 4), and 2023/24 (wave 5). The LSMS-ISA is a nationally representative and georeferenced household survey.[7] It captures detailed information on household demographics, socioeconomic characteristics, plot- and crop-level agricultural activities, livestock management, food prices, and food consumption. Demographic information is captured post-planting,

[7] A partial panel refresh was carried out in wave 4. Also, the representativeness of the GHS was impacted during wave 4 due to security issues, which prevented data collection in some locations. As a result, the wave 4 data is only representative of the areas that were safely accessible. The GHS does not track "split-off" households. I test the robustness of my results to the exclusion of the two latter waves 4 and 5 in Section 5.5.

while the other variables used in this analysis are derived from the post-harvest dataset collected between January and April.

A harmonised farm-to-fork micro panel dataset was constructed. Household-level agricultural output data were processed following the work of Bentze and Wollburg (2024). Only households engaged in crop cultivation, with available geolocation,[8] and observed for at least three waves were retained. Furthermore, households must have at least two waves with strictly positive agricultural output, plot area, and food consumption. This selection process yields a final sample of 9,006 observations from 2,832 unique households, distributed across 392 enumeration areas (clusters), representing 92.5% of the panel farm household-year observations from the five survey waves of the Nigeria LSMS-ISA (Table C1). Figure 1 displays the geographical distribution of these clusters, illustrating the survey's comprehensive coverage across Nigeria.

Household food consumption data were collected through a 7-day recall, which detailed the food items consumed and their sources (own production, purchase, gift/transfer). It is important to note that these data reflect household-level food availability rather than individual intake, as they do not account for waste or intra-household distribution. Household food consumption data were processed following the work of McCullough et al. (2024). To assess nutritional status, food consumption quantities were harmonised to kilograms based on reported standard units or converted from non-standard units. Nutritional content was assigned using African food composition tables, adjusted for edible portions and potential cooking losses. Assumed fortification rates for relevant staples were incorporated, as described in Appendix A. Household-level nutrient requirements - i.e., dietary energy, protein, iron, zinc, and vitamin A - were calculated based on the age and sex composition of the household, using estimated average requirements (EAR) from established sources and adult equivalence scales.[9] Adequacy percentages were constructed by dividing each household's total energy and nutrient availability by its EAR. Based on these percentages, dummy variables were created to indicate whether household-level caloric or nutri-

[8]Enumeration area coordinates are not publicly disclosed for wave 5. For this wave, I replaced missing coordinates with the enumeration area coordinates from the previous wave for the same enumeration area.

[9]For example, children and elderly members are counted as less than one full adult equivalent. See Appendix A for more details.

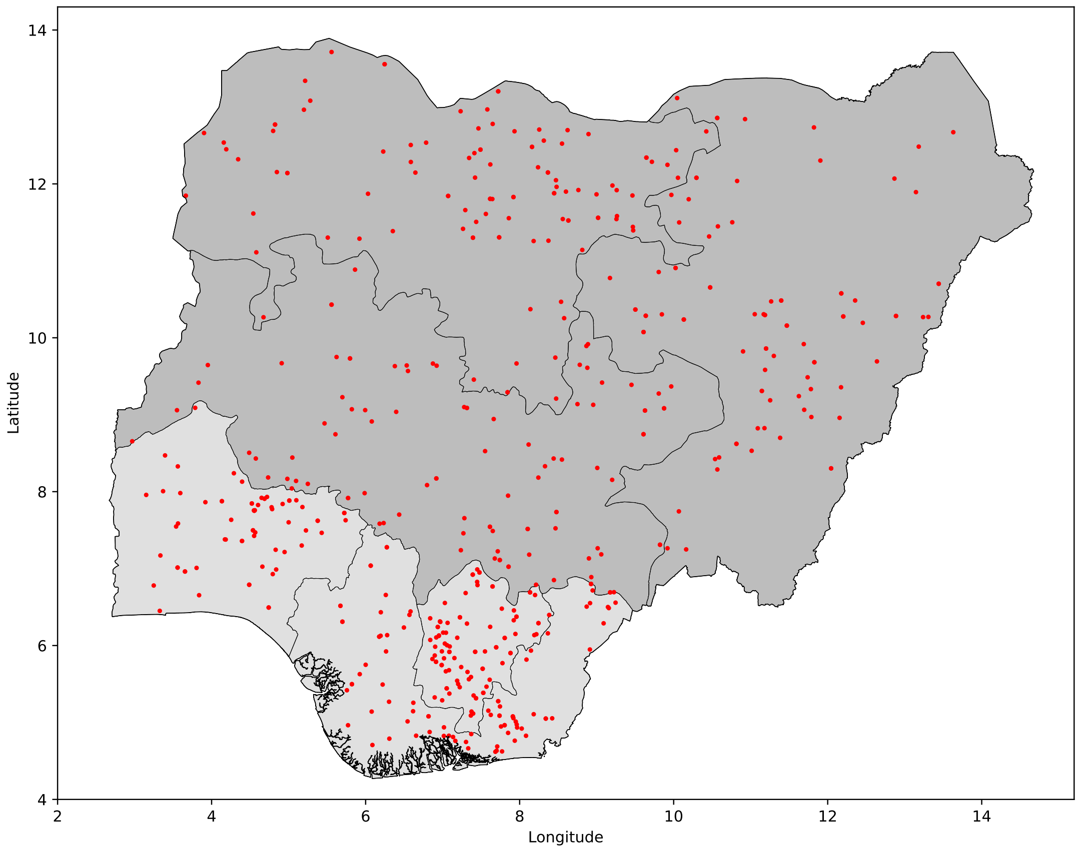

Figure 1. **Map of sample cluster locations.** Map of Nigeria, showing Northern (darker gray) and Southern (lighter gray) zones and regional borders. Cluster locations are represented by red dots. Based on 2,832 unique panel farm HH, within 392 enumeration areas (clusters).

ent consumption falls below 100, 80, or 60 percent of the recommended levels. The thresholds below 100% adequacy serve as a proxy to capture distributional impacts. Hereafter, I will refer to the 80% adequacy threshold as "suboptimal" intake and the 60% threshold as "insufficient" intake.

Finally, household dietary diversity is measured using the Household Dietary Diversity Score (HDDS), which reflects a household's economic access to varied food and its food security. The standard HDDS includes 12 food groups (FAO, 2011).[10] Following Nguyen and Qaim (2025), the oils/fats, sugar/honey, and miscellaneous food groups are excluded, as these are often considered less nutritious and may skew the HDDS as a measure of dietary quality

[10]The 12 food groups are: cereals; roots & tubers; vegetables; fruits; meat, poultry, and offal; eggs; fish and seafood; pulses, legumes, and nuts; milk and milk products; oil/fats; sugar/honey; miscellaneous (mostly spices, condiments, and beverages) (FAO, 2011).

	Mean	Median	SD	Min.	Max.
Head age (years)	52.87	52.00	14.62	16.00	100.00
Head formal education (1/0)	0.40	0.00	0.49	0.00	1.00
Head female (1/0)	0.14	0.00	0.35	0.00	1.00
Child < 5 yo (1/0)	0.47	0.00	0.50	0.00	1.00
Child < 15 yo (1/0)	0.79	1.00	0.41	0.00	1.00
HH size	6.06	6.00	3.25	1.00	31.00
Total yield (kg/ha)	8,224.58	3,063.20	12,837.06	0.00	56,497.18
Total harvest (kg)	3,181.84	1,500.00	6,255.99	0.00	161,000.00
Total area (ha)	1.00	0.51	1.64	0.00	42.57
Share of harvest sold	0.20	0.00	0.30	0.00	1.00
HH livestock under management (1/0)	0.69	1.00	0.46	0.00	1.00
HH annual total exp per capita (USD 2020)	671.77	490.24	956.84	43.97	38,805.34
HH dietary diversity score (HDDS)	5.58	6.00	1.61	1.00	9.00
HH own-production share of energy intake	0.46	0.49	0.28	0.00	1.00
Observations	9,006				

Table 1. **Household descriptive statistics.** Agricultural output values are winsorized at the 99th percentile. Annualized expenditure in USD 2020 (originally, food: last 7 days; non-food: last month or last 12 months). Expenditure information is missing for wave 5. Household dietary diversity score (HDDS) is defined as nine groups based on (Nguyen and Qaim, 2025). HH: household.

(Verger et al., 2019).

Table 1 provides descriptive statistics on household characteristics and agricultural output. On average, households have a total plot area of 1.0 hectare (ha). The majority of households do not participate in the commercialization of their harvest. Over two-thirds of the sample manage livestock. Average daily per capita expenditure is USD 1.84 (2020 USD), reflecting the high prevalence of extreme poverty among Nigerian farm households. The median household reports having consumed six out of the nine food groups that comprise the HDDS in the last seven days, with cereals and vegetables representing the two groups with the highest likelihood of consumption (over 97%) (Figure B1).

Figure 2 displays the average share of sample households with adequate dietary intake for energy, protein, and three micronutrients, including iron, zinc, and vitamin A. Protein is crucial for basic growth and tissue repair. The selected micronutrients are critical for vital physiological functions: iron for oxygen transport (preventing anemia), vitamin A for vision and immunity, and zinc for immune function and growth (Passarelli et al., 2024). Deficiencies in these areas lead to severe outcomes like stunted growth, weakened immunity, and cognitive impairment,

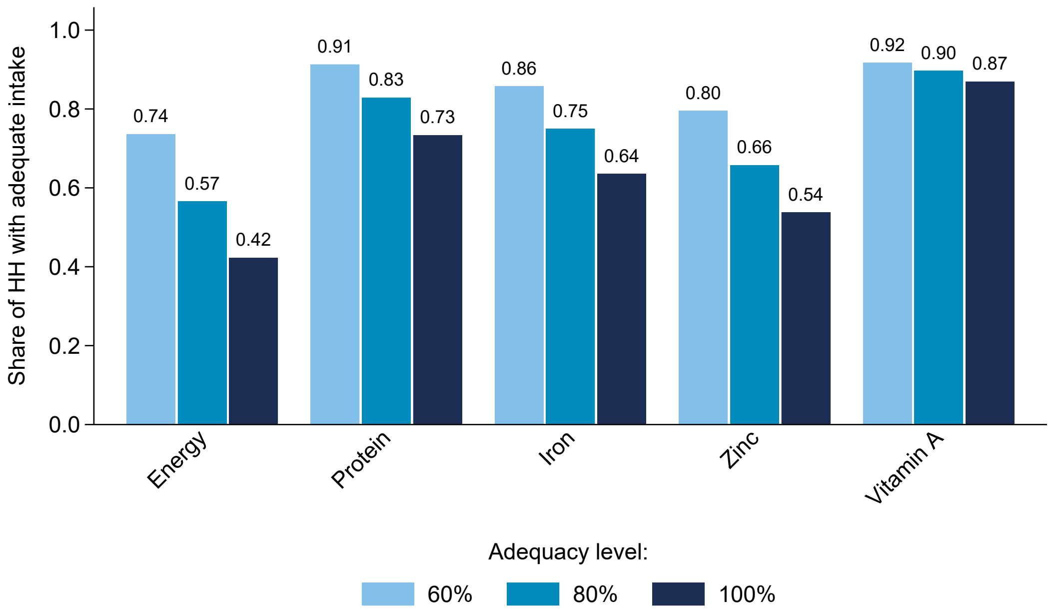

Figure 2. **Average energy and nutrient adequacy levels.** HH: household.

all of which hinder productivity and development (Black et al., 2013). The mean prevalence of household energy adequacy is 42%. Among nutrients, adequacy is highest for vitamin A (87%) and lowest for zinc (54%). As expected, the share of sample households with adequate dietary intake is higher for lower adequacy levels.

3.3 Weather data

Household locations (cluster centroids) were matched with high-resolution gridded weather data. Daily temperature data were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis dataset, which provides data at a $0.1° \times 0.1°$ resolution (approximately $10\text{km} \times 10\text{km}$) (Hersbach et al., 2020). Precipitation data were derived from the University of California, Santa Barbara Climate Hazards Center Infrared Precipitation with Station (CHIRPS) dataset (Funk et al., 2015). Originally at $0.05° \times 0.05°$ resolution, monthly precipitation data were reaggregated using means to match the $0.1° \times 0.1°$ ERA5 grid. The weather data for a specific grid square was assigned to an LSMS-ISA cluster if the cluster lay within that grid square.

The growing season is defined based on the Famine Early Warning Systems Network (FEWS-

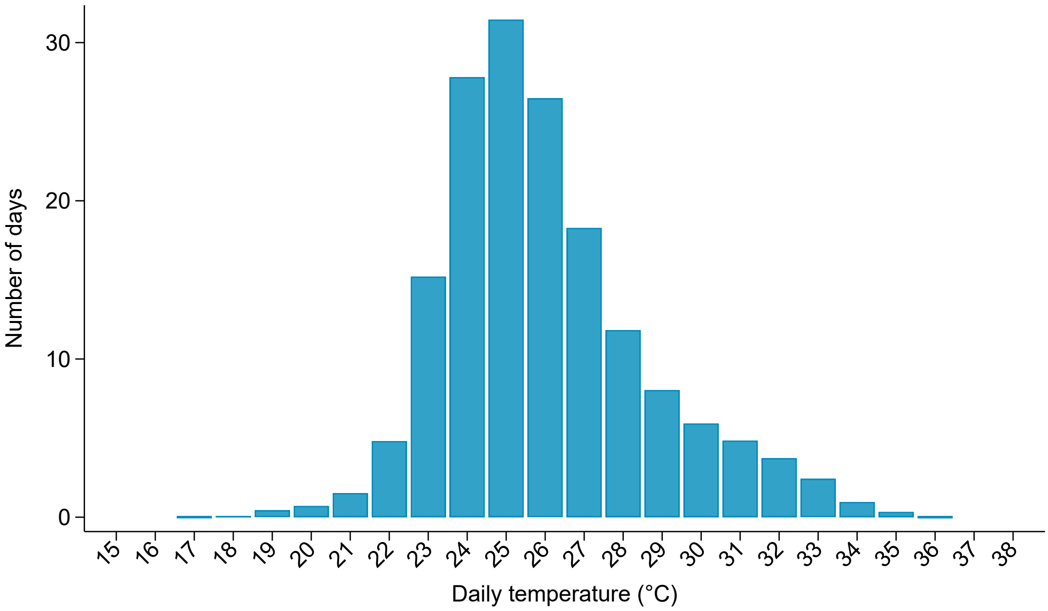

Figure 3. **Temperature distribution of growing season days.** Based on the sample farm panel households, i.e., 9,006 observations, 2,832 HH, within 392 enumeration areas (clusters), over 2010-2023.

NET) agricultural calendar for Nigeria (Figure B5).[11] It refers to the period during which crops are planted and grown. It is defined as March to August for the Southern region (including the South East, South South, and South West administrative regions) and May to September for the Northern region (including the North Central, North East, and North West administrative regions). This definition aligns with the distribution of the percentage of planted plots per month derived from the 39,030 plots cultivated by the sample farm households (Figure B6). Figure 3 shows the distribution of temperatures observed during the last completed growing season for the whole sample.[12]

[11] Source: Famine Early Warning Systems Network, Season Calendar (Accessed 10 April 2025).
[12] Figure B7 presents a similar distribution by region.

4 Empirical strategy

The empirical analysis aims to identify how households respond to extreme heat and its impact on household nutrition. The primary channel through which weather affects farm households is agricultural production. Assuming farm-level production in Nigeria can be represented by a Cobb-Douglas production function,[13] where $y_{i,t}$ denotes agricultural output (post-harvest) for household i following growing season t, weather conditions in the growing season affect output production through their effect on the productivity term $A_{i,t}$ (Aragón et al., 2021). I approximate the reduced-form nutritional impact of weather conditions during the last growing season using the following log-linear regression model:

$$y_{i,t} = g(\beta, \mathbf{w}_{i,t}) + \lambda_m + \mu_t + \eta_i + \varepsilon_{i,t} \tag{1}$$

where the y is post-harvest agricultural output or a nutritional outcome and $g(\beta, \mathbf{w}_{i,t})$ is a non-linear function of temperature and precipitation $\mathbf{w}_{i,t}$ during the last growing season. The parameter of interest is β, which represents the vector of reduced-form estimates of the effect of weather shocks on farm household nutrition. This multi-way panel fixed effects regression approach is common in the climate economics literature (Dell et al., 2014). The identification strategy leverages the quasi-random variation in weather exposure within-households across growing seasons. I include a comprehensive set of fixed effects to isolate this exogenous variation. The terms λ_m, μ_t, and η_i are respectively a set of month-of-interview fixed effects, growing season fixed effects, and household fixed effects. λ_m control for seasonality in nutrition, such as the depletion of food stocks as the interview date gets further from the last harvest. μ_t accounts for any country-wide changes in weather conditions or nutrition that may be spuriously correlated over time, as well as macro-level trends and systemic measurement error across survey waves. η_i controls for unobserved time-invariant household characteristics and heterogeneity.

Based on the seminal work of Schlenker et al. (2006), I model the nonlinear relationship between temperature and productivity using a degree-days approach. This method allows for

[13] $y_{i,t} = A_{i,t} K_{i,t}^{\alpha_1} L_{i,t}^{\alpha_2} X_{i,t}^{\alpha_3}$, where $A_{i,t}$ represents the productivity term, $K_{i,t}$ capital use (e.g., land area), $L_{i,t}$ labor use (e.g., family and hired labor), and $X_{i,t}$ input use (e.g., fertilizer).

temperature exposure effects to be cumulative, with temperature exposure being beneficial up to a certain point and harmful thereafter. Specifically, I construct two measures for each household i in growing season t: growing degree days ($GDD_{i,t}$) and harmful degree days ($HDD_{i,t}$). $GDD_{i,t}$ capture the cumulative exposure to temperatures between 8°C and a threshold τ,[14] while $HDD_{i,t}$ captures exposure to extreme heat, i.e., temperatures above τ. Formally:

$$\begin{aligned} \mathrm{GDD}_{i,t} &= \sum_{d=1}^{n} \big(\min\{\mathrm{h}_{i,d}, \tau\} - 8\big)\, \mathbf{1}\{\mathrm{h}_{i,d} \geq 8\}, \\ \mathrm{HDD}_{i,t} &= \sum_{d=1}^{n} \big(\mathrm{h}_{i,d} - \tau\big)\, \mathbf{1}\{\mathrm{h}_{i,d} > \tau\}. \end{aligned} \tag{2}$$

Here, h_d is the average temperature on day d and n is the total number of days in the growing season. A key empirical challenge is defining τ, the temperature threshold above which harm occurs. This threshold is likely crop- and context-specific. Estimates from studies in other settings may not be transferable due to differences in crop mix, agricultural technology, and climate. Therefore, I adopt a data-driven approach by estimating a series of regressions of log agricultural output on $GDD^{\tau}_{i,t}$ and $HDD^{\tau}_{i,t}$, iterating τ across a range of plausible temperatures, similar to the procedure used in Schlenker et al. (2006). I then select the optimal threshold, τ^*, that provides the best model fit (i.e., the highest R^2).

I control for total growing season precipitation ($P_{i,t}$) and its square to account for the cumulative non-linear effects of rainfall and avoid omitted-variable bias.[15] This leads to the following parametrization of the function $g(\beta, \mathbf{w}_{i,t})$:

$$g(\beta, \mathbf{w}_{i,t}) = \beta_1 GDD^{\tau^*}_{i,t} + \beta_2 HDD^{\tau^*}_{i,t} + \beta_3 P_{g,y} + \beta_4 P^2_{g,y} \tag{3}$$

The dependent variable in Equation 1 is transformed into logarithms for continuous variables. This is problematic for the food group-level analysis for a subset of households that reported zero consumption for specific food groups (Figure B1). To avoid the issue of an un-

[14] 8°C is a common lower bound for growing degree days in the literature (Aragón et al., 2021; Schlenker et al., 2006; Schlenker and Roberts, 2009).

[15] The main practical risk is multicollinearity, as temperatures and precipitations can move together at seasonal scales (e.g., during the growing season), which can inflate standard errors and make the separate coefficients less precise. However, this impacts precision, not consistency.

defined variable, I adopt the solution proposed by Blakeslee and Fishman (2018) and Carpena (2019). Specifically, zero-consumption observations are handled by setting the dependent variable to zero and simultaneously including a dummy variable to account for this data adjustment in the regression.[16]

Lastly, I account for potential spatial and temporal correlation in the error terms ($\varepsilon_{i,t}$) by estimating spatial heteroskedasticity and autocorrelation Consistent (HAC) standard errors based on Conley (1999), using a distance parameter of 100 km and a temporal lag parameter of 5 years.[17]

5 Main results

5.1 Temperatures and agricultural production

This section presents my main empirical results on the effect of extreme heat on farmers' productivity, as measured by total harvest (in kilograms). First, Figure 4 documents the outcomes from the iterative procedure consisting of nine regressions with different threshold τ ranging from 26°C to 34°C and the comparison of model fit. This procedure yields an optimal threshold of $\tau^* = 31$°C.[18] I use GDD and HDD calculated with this threshold in all subsequent regressions.

Table C3 presents the results obtained from estimating Equation 1 on total yield, harvest, and land area. Consistent with previous findings in other contexts (Schlenker and Roberts, 2009; Hultgren et al., 2025; Burke and Emerick, 2016), the estimates suggest that extreme heat has a negative effect on agricultural productivity and output. Each additional HDD in the last completed growing season results in a 1.54% decrease in total harvested quantities. To put this

[16] I provide a robustness check measuring household energy intake at the food group level in levels rather than logarithms in Section 5.5.

[17] Given that my choice of distance and temporal lag parameters of the spatial HAC standard errors is arbitrary, I assess the sensitivity of my main findings to variations in these parameters in Section 5.5.

[18] Figure B8 presents the results for a similar iterative procedure using total yield (kg/ha) as outcome, yielding the same threshold $\tau^* = 31$°C.

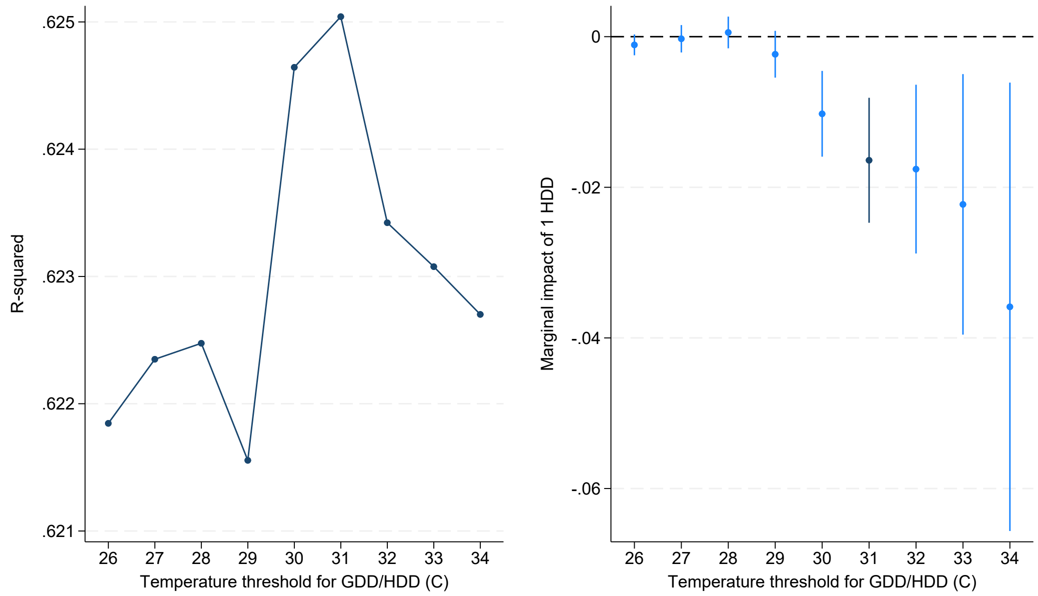

Figure 4. **Optimal GDD/HDD threshold using an iterative regression approach and effect on total harvest.** The left panel compares model fit (measured as R^2) between nine regressions, one for each GDD/HDD threshold between 26°C to 34°C. The right panel compares the marginal impact of one HDD for each of the nine regressions. Total harvest is measured in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional growing season HDD. Conley spatial HAC standard errors (in parentheses).

figure in perspective, note that under a uniform +1°C warming scenario, Section 5.7 projects that the average number of HDD during the growing season could increase by 12.95.

5.2 Temperatures, dietary diversity, and the intake of energy and nutrients

I estimate Equation 1 to test how extreme heat impacts the intake of energy and nutrients. Despite the extreme heat's impact on total harvested quantities, it does not have a statistically significant impact on average energy and nutrient intake.[19] However, I find that extreme heat during the last completed growing season decreases household dietary diversity, with statistical significance at the 10% level (Table 2), in line with Dillon et al. (2015)'s findings using cross-sectional data from wave 1 of the Nigeria LSMS-ISA panel. This effect is driven by a reduced likelihood of consuming nutritious foods, including fruits, meat, and eggs (Figure B9). These

[19] Table C4 shows similar results considering the effect of extreme heat on the average intake of the macronutrient components of total energy, namely carbohydrates, protein, and fat.

	HDDS	Energy	Protein	Iron	Zinc	Vitamin A
GDD	-0.0005	0.0001	0.0001	0.0002	0.0003	0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
HDD	-0.0053*	-0.0002	-0.0005	0.0004	0.0007	0.0016
	(0.0028)	(0.0015)	(0.0015)	(0.0017)	(0.0016)	(0.0021)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.597	0.554	0.605	0.620	0.516	0.455
Observations	9,006	9,006	9,006	9,006	9,006	9,006

Table 2. **Temperatures, dietary diversity, and the intake of energy and nutrients.** The household dietary diversity score (HDDS) is defined as nine food groups based on Nguyen and Qaim (2025). Coefficients on HDDS can be interpreted as the absolute change in the HDDS for one additional HDD (sample mean: 5.58). Total energy, protein, iron, zinc, and vitamin A are measured in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Conley spatial HAC standard errors (in parentheses). FE: fixed effects.

food categories, which represent essential components of a diverse diet and rich sources of the nutrients under study, are also among the least frequently consumed by sample households (Figure B1).

Next, I test if extreme heat affects the number of households with adequate energy intake. Figure 5 presents the estimates for the marginal effect of one additional HDD in the last growing season on the percentage of households with energy intake above 100%, 80%, and 60% adequacy. It shows that there is no statistically significant effect of extreme heat on the percentage of households that consume 100% or 80% of their energy requirements. In contrast, I find that an additional HDD in the last growing season increases the percentage of households with insufficient caloric intake - defined as not meeting at least 60% of their energy requirements - by 0.16 percentage points, however, this increase is not statistically significant at conventional levels ($p = 0.112$). These results suggest that extreme heat could exacerbate undernutrition for households already experiencing it at extreme levels.

Figure 5 shows the impact of extreme heat on household nutrient adequacy. Hot growing seasons negatively affect protein and iron adequacy among sample households. For protein, one additional HDD in the prior growing season increases the percentage of households below the 100% and 80% adequacy thresholds by 0.26 and 0.22 percentage points, respectively. For

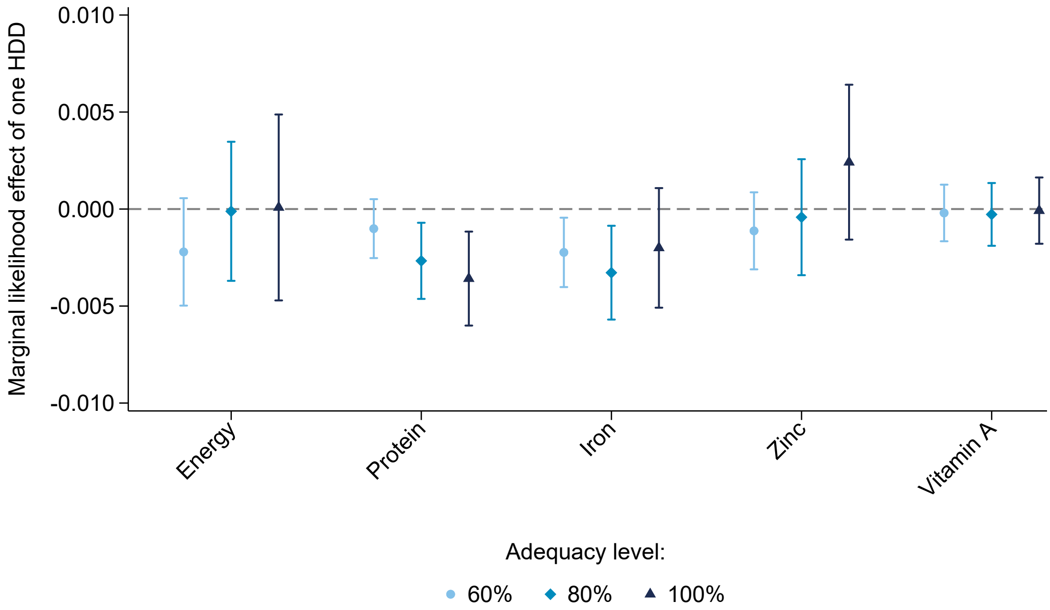

Figure 5. **Effect of HDD on nutrient adequacy.** Each nutrient adequacy represents a dummy equal to one if a household meets the intake requirement at various thresholds (60%, 80%, and 100%). Coefficients have been divided by the respective dependent variable sample mean, and can be interpreted as the relative percentage change in the likelihood of meeting the requirement for one additional HDD. Conley spatial HAC standard errors are used to build the 95% confidence intervals.

iron, it increases the percentage of households below the 80% and 60% adequacy thresholds by 0.25 and 0.19 percentage points, respectively. The effect sizes are smaller for the 60% nutrient adequacy threshold. This can be explained in part by the smaller share of households near or below this threshold (Figure 2). Lastly, I find no evidence that extreme heat in the last growing season pushes households below nutrient adequacy levels for zinc and vitamin A intake, at any of the considered levels.

In Figure B10, I examine what is driving these nutrient adequacy results by estimating the effect of extreme heat on energy intake by food group. The post-harvest intake of staple foods, including cereals, roots and tubers, and oil/fats, is not affected by extreme heat in the growing season. These food groups represent the three most important sources of energy for the average Nigerian farm household, with 54.8% for cereals, 17.1% for root & tubers, and 12.3% for oil/fats (Figure B2). This participates in explaining the null effect of extreme heat on total energy intake in Table 2. On the other hand, an additional HDD in the last growing season reduces the post-harvest intake of more nutritious foods, which are important sources of protein and iron, such as vegetables (-0.68%), meat (-0.33%), and pulses (-0.38%), as well as fruits (-0.30%).

5.3 Farm household response: commercialization and food purchase

As shown in Figure 4 and Table C3, farm households experience a negative shock to their harvest following extreme heat during the growing season. I am interested in examining their *ex-post* (i.e., post-harvest) adaptation responses and test the hypothesis laid out in Section 2. First, in Table C5, I examine changes in total energy intake, by source of consumption, i.e., purchased, own-produced, or gifted. Purchased foods represent approximately half of the total energy intake for the average household in the sample (49.5%), while own-produced foods represent 46.4%, and the rest is received as assistance or gift (4.1%) (Table 1). Extreme heat has no statistically significant effects on total energy intake from any consumption source, with a negative sign for the impact of one additional HDD on total energy purchased. Second, in Figure 6, I examine changes in purchased and own-produced calorie intake separately for each food group. Extreme heat has no statistically significant effects on energy intake from own-produced food, except for fruits. On the other hand, an additional HDD in the last growing season reduces energy intake from purchased vegetables (-0.75%), meat (-0.30%), and pulses (-0.49%).[20] These results suggest an adjustment toward meeting energy sufficiency through own production, mainly composed of staple cereals, roots, and tubers, rather than purchasing more nutritious foods, thereby worsening dietary quality.

Two pathways can support an increased post-harvest reliance on own-produced food following a negative agricultural shock. First, households could reduce commercialization. Second, households could modify their own-produced food consumption smoothing behavior by prioritizing own-produced food intake immediately post-harvest, thereby risking the faster depletion of these resources.

Table 3 reports the effect of extreme heat on commercialization and household expenditure. In line with the hypothesis in Section 2 and the above-mentioned first potential pathway behind

[20] Purchased energy represents the majority of total energy intake from vegetables (84.2%), meat (88.0%), and pulses (66.5%) (Figure B4).

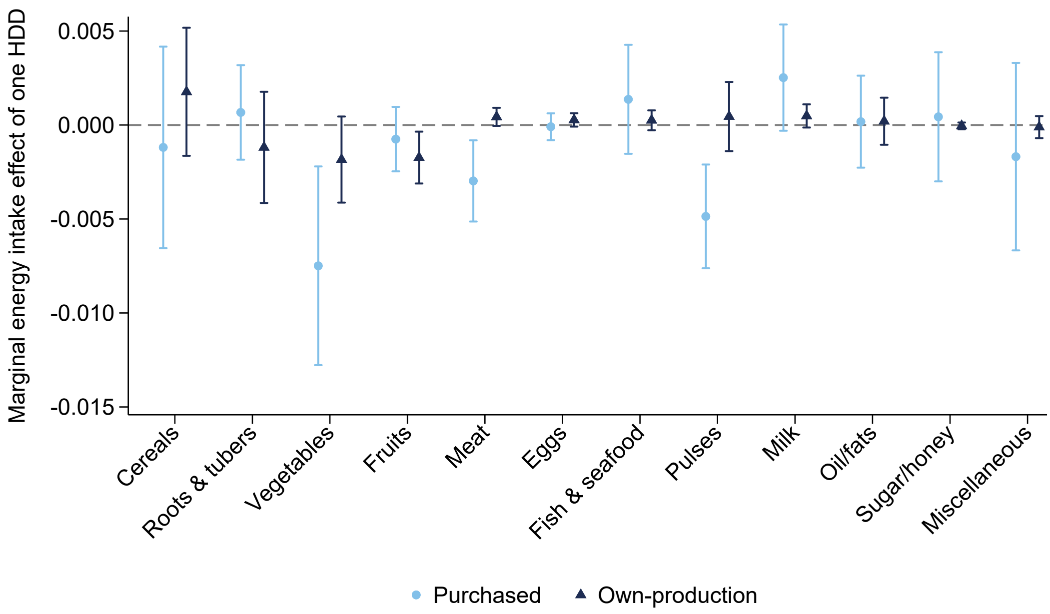

Figure 6. **Effect of HDD on energy intake, by food group and source of consumption.** Each food group is expressed as the logarithm of total energy intake, thus coefficients can be interpreted as the relative percentage change for one additional HDD. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors are used to build the 95% confidence intervals.

increased reliance on own-produced food post-harvest, I find that one additional HDD in the last growing season has a negative impact on both the extensive and intensive margins of commercialization. It decreases the likelihood of selling at least some harvested quantities by 0.40 percentage points (or relatively by 0.99%) and the share of total harvest sold by 0.18 percentage points (relatively by 0.90%).

In line with findings by others in the literature (Carpena, 2019; Dillon et al., 2015), Table 3 also shows that the drop in crop production is accompanied by lower household spending, likely aggravated by reduced commercialization as a share of total harvest. Indeed, all HDD coefficients are negative and statistically significant. Total expenditure, a proxy for income in the development economics literature (Carletto et al., 2021), decreases by 0.74% for each additional growing season HDD.[21] Extreme heat also decreases food purchases. The higher income

[21]Total expenditure includes a valuation of own-produced consumption, reducing classical measurement error and capturing resources actually available for nutrition.

	Total exp	Food exp	Non-food exp	Seller	Share sold
GDD in growing season	-0.0008***	-0.0001	-0.0006***	-0.0004***	-0.0002***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
HDD in growing season	-0.0074***	-0.0034**	-0.0075***	-0.0040***	-0.0018***
	(0.0017)	(0.0016)	(0.0014)	(0.0011)	(0.0006)
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes
R^2	0.661	0.591	0.749	0.471	0.470
Observations	8,146	8,146	8,146	8,150	8,150
Mean Y	.	.	.	0.508	0.199

Table 3. **Temperatures, expenditure, and commercialization.** Expenditure is expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Annualized expenditure in USD 2020 (originally, food: last 7 days; non-food: last month or last 12 months). Food expenditure represents purchased food. Total expenditure includes a valuation of own-produced consumption. Expenditure information is missing for wave 5. Seller is a dummy variable equal to one if a household is selling any harvested quantities. Information on sold harvested quantities is missing for some households (either missing or set to missing because it is higher than harvested quantities or negative). I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors (in parentheses). exp: expenditure. FE: fixed effects.

elasticity of the demand for more nutritious foods, particularly vegetables and meat, compared to staples (Colen et al., 2018), explains the targeted cuts in purchases for these foods (Figure 6). This pattern is consistent with Bennett's law operating in reverse: when resources contract, diets de-diversify away from purchased nutritious foods toward staples (Headey et al., 2014; Ecker and Hatzenbuehler, 2022).

Additionally, it is important to understand how extreme heat impacts non-food expenditures. Non-food spending is often a reliable indicator of a household's economic well-being (Deaton, 1997). It also has consequences for a household's food budget. This relationship could go in two directions. Households might cut back on non-food items to protect food purchases, or, alternatively, non-food purchases could end up limiting the funds available for food purchases. I show that one additional growing season HDD leads to a 0.75% decrease in non-food expenditure, supporting the former. As can be seen in Table C6, extreme heat affects most types of non-food spending, including housing, communication and transport, and clothing. The largest negative effects are observed for housing, where one additional HDD in the previous growing season results in a 0.94% decrease in expenditure. Housing includes expenses on utilities (water, electricity, gas, fuels, and refuse collection), maintenance, domestic household services, and rent. Although the HDD coefficient is negative for education, it is not statistically significant at conventional levels.

Next, I examine the impact of the uncovered post-harvest household risk-minimizing strategy, which consists of prioritizing own-produced food intake post-harvest to ensure energy sufficiency, on consumption smoothing. For this, I estimate the heterogeneous effect of one additional HDD by survey months. Interviews for the Nigeria LSMS-ISA post-harvest household questionnaire are conducted between January and April, with the majority taking place in February and March.[22] Table 4 shows that the negative impact of extreme heat on dietary diversity, as well as protein and iron suboptimal adequacy (80%), intensifies with time since harvest.[23] This is likely driven by both the depletion of the income collected from the sale of harvest, as illustrated by a stronger reduction in food purchases in March-April compared to January-February, and the depletion of home-grown food reserves with a decline in own-produced food intake in March-April (Table C7). The latter is caused by a lesser energy intake from own-produced cereals, vegetables, and pulses (Table C8). This results in a more adverse impact on insufficient energy adequacy (60%), however, non-statistically significant at conventional levels (Figure B12).

5.4 Heterogeneity and potential moderators

I explore heterogeneity in the effect of the last growing season temperatures on household nutrition to identify the most vulnerable populations. Table 5 presents heterogeneity by head sex and education, as well as the presence of children below five years old in the household. Results suggest that the effect of HDD on dietary diversity and nutrient adequacy is weaker among households with heads with formal education. On the other hand, the impact of extreme heat on malnutrition is qualitatively similar between households with and without a female head. Formal education could be correlated with a higher ability to participate in non-farm

[22] Only the post-harvest household questionnaire for wave 4 is collected in January (Table C2). Thus, I conduct a robustness check omitting wave 4 (Table C9), finding similar results.

[23] Figure B12 presents the results for this heterogeneity analysis by adequacy threshold for each nutrient.

	HDDS	Adq prot	Adq iron	Food exp	Non-food exp	Share sold
GDD	-0.0003	0.0001	0.0001	0.0001	-0.0006***	-0.0002**
	(0.0004)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
GDD × Mar-Apr	-0.0002	-0.0002***	-0.0002***	-0.0003***	-0.0000	-0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
HDD	-0.0017	-0.0012	-0.0015	-0.0024	-0.0074***	-0.0017***
	(0.0030)	(0.0009)	(0.0009)	(0.0016)	(0.0013)	(0.0006)
HDD × Mar-Apr	-0.0047***	-0.0011***	-0.0011**	-0.0016**	0.0004	0.0001
	(0.0015)	(0.0004)	(0.0004)	(0.0007)	(0.0006)	(0.0003)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.598	0.484	0.493	0.620	0.749	0.471
Observations	9,006	9,006	9,006	8,146	8,146	8,150
Mean Y	5.576	0.829	0.750	.	.	0.199

Table 4. **Temperatures, dietary diversity, nutrient adequacy, expenditure, and commercialization, by survey months.** Adequacy indicators are set to 80% adequacy levels. Coefficients on HDDS can be interpreted as the absolute change in the HDDS for one additional HDD. Coefficients on adequacy indicators can be interpreted as percentage-point change in the likelihood for one additional HDD. Expenditure is expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Annualized expenditure in USD 2020 (originally, food: last 7 days; non-food: last month or last 12 months). Food expenditure represents purchased food. Expenditure information is missing for wave 5. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Information on sold harvested quantities is missing for some households (either missing or set to missing because it exceeds the harvested quantities or is negative). Conley spatial HAC standard errors (in parentheses). Adq: Adequacy. FE: fixed effects. HDDS: Household dietary diversity score.

employment. However, incomplete labor markets may limit the availability of such non-farm opportunities (Dillon et al., 2019). I investigate this further in Section 5.6. A complementary, compositional channel is that education is positively associated with household diet quality net of resources (Rashid et al., 2011). Mechanistically, schooling could attenuate the impact of shocks by enhancing nutritional knowledge, inventory management, or financial planning to smooth consumption when extreme heat tightens resource constraints. Lastly, the nutrition of farm households with young children, who require protein and iron for growth (Black et al., 2013), is the most adversely impacted. This finding is concerning, given that over 30% of children below five years old remain stunted in Nigeria (Akombi et al., 2017).

It is interesting to investigate potential moderators of the adverse effects of extreme heat on dietary diversity and nutrient adequacy to inform strategies for improving resilience to cli-

	HDDS	Adq prot	Adq iron	Food exp	Non-food exp	Share sold
HDD	-0.0050*	-0.0021***	-0.0023***	-0.0039**	-0.0067***	-0.0018***
	(0.0028)	(0.0008)	(0.0008)	(0.0016)	(0.0014)	(0.0006)
HDD $\times$ Head formal edu	0.0038***	0.0010***	0.0011***	0.0021***	-0.0003	0.0003
	(0.0014)	(0.0003)	(0.0004)	(0.0006)	(0.0006)	(0.0003)
HDD	-0.0053*	-0.0022***	-0.0024***	-0.0042***	-0.0075***	-0.0017***
	(0.0028)	(0.0008)	(0.0009)	(0.0016)	(0.0014)	(0.0006)
HDD $\times$ Head female	0.0041	0.0004	-0.0004	0.0034**	0.0011	0.0000
	(0.0027)	(0.0007)	(0.0007)	(0.0015)	(0.0014)	(0.0007)
HDD	-0.0025	-0.0019**	-0.0019**	-0.0025	-0.0080***	-0.0014**
	(0.0028)	(0.0008)	(0.0009)	(0.0017)	(0.0014)	(0.0006)
HDD $\times$ Age $<$ 5 yo	-0.0044***	-0.0005*	-0.0010**	-0.0024***	0.0006	-0.0006*
	(0.0013)	(0.0003)	(0.0004)	(0.0007)	(0.0006)	(0.0003)
Mean Y	5.576	0.829	0.750	.	.	0.199

Table 5. **Effect of HDD on dietary diversity, nutrient adequacy, expenditure, and commercialization, by household characteristics.** This table displays the results from 16 regressions, under the main specification. Adequacy indicators are set to 80% adequacy levels. Coefficients on HDDS can be interpreted as the absolute change in the HDDS for one additional HDD. Coefficients on adequacy indicators can be interpreted as percentage-point change in the likelihood for one additional HDD. Expenditure is expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Annualized expenditure in USD 2020 (originally, food: last 7 days; non-food: last month or last 12 months). Food expenditure represents purchased food. Expenditure information is missing for wave 5. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Information on sold harvested quantities is missing for some households (either missing or set to missing because it is higher than harvested quantities or negative). Conley spatial HAC standard errors (in parentheses). Adq: Adequacy. edu: education. HDDS: Household dietary diversity score.

mate change. Closeness to markets, livestock management, and income diversity have all been found to be correlated with improved nutrition in Sub-Saharan Africa (Babatunde and Qaim, 2010; Nguyen and Qaim, 2025; Headey et al., 2018). I examine these potential moderators by estimating heterogeneous responses to extreme heat. I interact HDD with the logarithm of the distance in kilometers to the nearest population center with more than 20,000 inhabitants. This represents a proxy for access to food markets in the literature, both for selling harvest and purchasing food (Nguyen and Qaim, 2025). I conduct similar interactions with three dummy variables: one equal to one if the household managed at least one livestock head in the last 12 months, one equal to one if the household ran at least one non-farm entreprise in last 12 months, and one equal to one if the household head was employed in a wage job in the last seven days before the post-harvest interview. Results suggest no moderating effects on nutritional indicators for livestock management and non-farm enterprise. A higher distance to the closest population center is negatively associated with the effect of an additional HDD on the likelihood of a household meeting suboptimal iron adequacy (80%), although this association is only statistically significant at the 10% level. A post-harvest wage job is positively associated with the effect of an additional HDD on the likelihood of a household meeting suboptimal iron adequacy and on the share of harvest sold, suggesting that off-farm employment may play a buffering role, reducing the need for households to pursue the risk-minimization strategy highlighted in Section 5.3 (Table C10).

I investigate the non-moderating role of livestock management further. Managing livestock could serve as both a nutritional buffer, as animal-sourced foods represent a source of quality protein among farm households, and an income buffer through the sale of livestock and their products (Headey et al., 2018; Rosenzweig and Wolpin, 1993). First, I estimate the effect of extreme heat on the number of livestock heads managed by panel farm households involved in livestock over the last 12 months.[24] Given the year-round exposure of livestock and the lack of a well-defined 'growing temperature range' for animals, I adopt a binned temperature approach rather than HDD. This allows me to flexibly estimate the nonlinear effects of discrete temperature extremes on herd outcomes over the last 12 months.[25] Replacing a day with an average temperature $< 31°$C by a day $> 35°$C in the last 12 months reduces the number of large ruminant heads under management (bulls, cows, steers, heifers, calves, or ox) by 7.22%, with no statistically significant effects on the number of small ruminant heads under management

[24] I follow the same data processing criteria as for panel farm households, as described in Section 3. Only households engaged in livestock management and observed for at least three waves were retained. Furthermore, households must have at least two waves with strictly positive livestock heads. This selection process yields a final sample of 5,627 observations from 1,949 unique households, accounting for 62.48% of the panel farm household-year observations across the five survey waves of the Nigeria LSMS-ISA.

[25] I depart from the degree-days specification used elsewhere in the paper and instead use temperature bins for the livestock analysis for two reasons. First, the outcome variable (i.e., number of livestock heads) is measured as an annual stock, not tied to a growing season. A 12-month exposure window, combined with livestock's physiological response to extreme heat, is likely to exhibit nonlinear effects at extreme temperatures. Second, unlike crops, livestock lack a defined "growing" temperature range. Using temperature bins allows for easier interpretation of high-heat exposure episodes across the full year, rather than relying on cumulative heat intensity as in HDD, which is better suited to crop yield modeling.

(goats or sheep). Days with average temperature between 31°C and 35°C have no statistically significant effects (Figure 7).

Figure B11 shows that this result is driven by increased death or losses of large ruminants, with an additional day with an average temperature > 35°C in the last 12 months increasing the number of dead or lost large ruminants by 40.04%. This high magnitude is explained by the rare occurrence of such days in the sample, with the mean number of days with an average temperature > 35°C being 0.78 per year. Thus, the effect being modelled represents a 128% increase in such days. I find no evidence that these results are driven by increased slaughter, either for sale or own-consumption.[26] This finding, where extreme heat reduces large but not small ruminant herds, is directly supported by the biological literature. Large ruminants, particularly high-production cattle, generate significant internal (metabolic) heat to stay alive, grow, or produce milk. Their large body mass, relative to their skin's surface area, makes it physically difficult for them to shed this internal heat. Small ruminants, in contrast, generate less metabolic heat and have a larger surface-area-to-mass ratio, allowing them to cool down more efficiently and be more resilient to heat shocks (Kadzere et al., 2002; Silanikove, 2000). Finally, I find that the purchase of small ruminants declines by 9.28% for each additional day with an average temperature > 35°C. This suggests that the income shock imposed by extreme heat prevents households from making such types of asset purchases.

5.5 Robustness checks

Table 6 presents several checks on the robustness of my main results to alternative model specifications. I only report the estimate associated with HDD, with each row representing a different specification.

Row 1 shows robustness to a less parsimonious model that includes household-level controls, which may be time-varying and thus not captured by household fixed effects, as well as a soil fertility index constructed by Bentze and Wollburg (2024). This index is a composite measure of soil quality, built using principal component analysis to aggregate seven binary

[26] Results are available upon request.

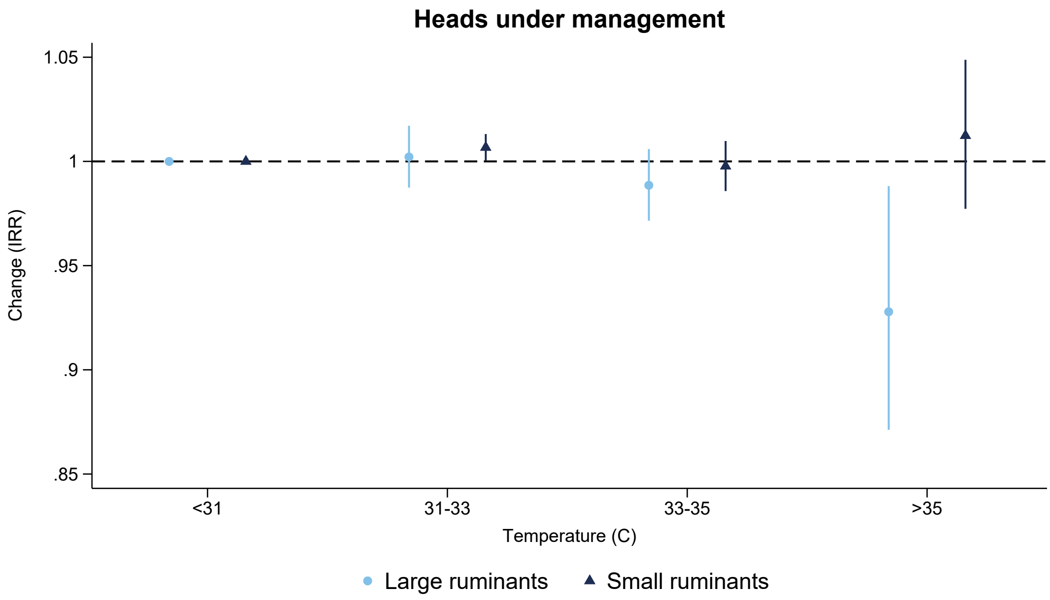

Figure 7. **Temperatures and livestock heads under management.** Poisson pseudo-maximum likelihood estimations using the computationally efficient estimator for Poisson regressions using high-dimensional fixed effects developed by Correia (2016). Coefficients are exponentiated and presented as incidence rate ratios (IRR). Coefficients are presented as incidence rate ratios. Reference bin < 31C. Weather over the last 12 months (number of days in each bin). Mean number of annual days with average temperature > 35C: 0.6. 95% confidence intervals are built using robust clustered standard errors at the household level.

indicators of soil constraints.[27] Row 2 estimates the main specification with robust clustered standard errors at the household level instead of spatial HAC standard errors. The statistical significance of my results remains unchanged under this alternative (and arguably simpler) assumption about the error structure. A partial refresh of the panel sample was undertaken in wave 4 (Table C1). Additionally, the representativeness of the survey was compromised during wave 4 due to security issues, which prevented data collection in certain locations. In row 3, I show the robustness of my findings to the exclusion of the latter waves 4 and 5. These later waves include only a subsample of panel households and rely on a long consumption recall period (30 days). Lastly, in row 4, I allow for different HDD thresholds for the Southern and Northern

[27]The binary indicators are: nutrient availability, nutrient retention, rooting conditions, oxygen availability, excess salts, toxicity, and workability. These indicators are provided with the LSMS-ISA microdata.

	Harvest (kg)	HDDS	Adq prot	Adq iron
1. HH & soil char controls	-0.0154***	-0.0050*	-0.0019**	-0.0020**
	(0.0047)	(0.0028)	(0.0008)	(0.0009)
2. Clustered SE at HH level	-0.0154***	-0.0053**	-0.0022***	-0.0025***
	(0.0020)	(0.0022)	(0.0005)	(0.0006)
3. Excluding waves 4 and 5	-0.0140***	-0.0069**	-0.0027***	-0.0029***
	(0.0051)	(0.0032)	(0.0010)	(0.0011)
4. Different HDD thr by region	-0.0117**	-0.0055*	-0.0034***	-0.0044***
	(0.0049)	(0.0029)	(0.0009)	(0.0011)

Table 6. **Robustness checks.** This table displays the results from 16 regressions, under the main specification. HH and soil characteristics added: head age, head age squared, head sex, head education, log of HH size, and weighted average soil fertility index (plot level). Regional HDD thresholds: Southern 30°C, Northern 31°C. Adequacy indicators are set to 80% adequacy levels. Total harvest is measured in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional growing season HDD. Coefficients on HDDS can be interpreted as the absolute change in the HDDS for one additional HDD. Coefficients on nutrient adequacy can be interpreted as percentage-point change in the likelihood for one additional HDD. Conley spatial HAC standard errors (in parentheses, except if otherwise stated). Adq: Adequacy. HDDS: Household dietary diversity score. Adq: adequacy. HH: households. prot: protein. SE: standard errors. thr: threshold.

zones.[28] Results are similar to the baseline specification, with a slightly lower coefficient for total harvest and higher coefficients for protein and iron adequacy (in absolute terms).

My identification hinges on the absence of unobserved factors that could plausibly explain the estimated effects. To probe the assumption and verify that high growing season temperatures truly drive the documented effects, I carry out similar falsification exercises as in Mayorga et al. (2025). I randomly reassign temperatures and precipitations across clusters, generate 1,000 such placebo weather datasets, and re-estimate my main specification. Because this permutation breaks the spatial link between actual weather and outcomes, I expect no systematic relationship between heat exposure and changes in the dependent variables. Figure B13 plots the sampling distribution of the placebo estimates of the HDD coefficients, alongside the corresponding point estimate from Table C3, Table 2, and Figure 5. The placebo distributions are approximately

[28]These zone-specific thresholds were chosen by replicating the analysis shown in Figure 4 in the Southern and Northern zones separately. HDD thresholds with the best model fit were respectively 30°C and 31°C. The results from this exercise are available upon request.

normal and centered at zero. In contrast, my main results coefficients (vertical dotted lines) lie far from the tails of the placebo distributions, indicating that the observed effects are unlikely to be due to random assignment.

Because several related outcomes are analyzed in parallel, I assess the sensitivity of statistical significance to multiple-hypothesis testing. I compute Benjamini and Hochberg (1995)'s false discovery rate (FDR) q-values within each family of tests using the Conley spatial-HAC p-values from the corresponding regressions. This adjustment does not affect point estimates or the Conley-based confidence intervals shown in the figures (which remain pointwise), but it provides a more conservative criterion for declaring statistical significance when many hypotheses are tested simultaneously. I perform this robustness for the nutrient adequacy results in Figure 5, where effects are reported across multiple nutrients and adequacy thresholds, for the likelihood of consumption (extensive margin) results in Figure B9, where effects are reported across multiple food groups, and for the energy intake by food group and consumption source results in Figure 6, where effects are reported across multiple food groups and consumption sources. The main patterns remain qualitatively unchanged under FDR control: the most robust effects continue to be concentrated in the dimensions highlighted in the baseline results, whereas marginal findings (especially those significant only at the 10% level) are more sensitive to the multiple-testing correction (Table C16, Table C17, and Table C18).

I also probe how sensitive the results are to alternative choices of the distance and temporal lag parameters used for Conley (1999)'s spatial-HAC standard errors. Table C11 shows that my main results remain stable across distance cutoffs from 50 to 200 km and temporal lags from 1 to 10 years. Using lower distance cut-offs leads to higher statistical significance for the HDDS estimate. However, given the likely significant spatial autocorrelation in both the independent variable and dependent variables, a wider distance cutoff is justified.

In this study, I express the continuous outcomes (mainly energy and nutrient intake) in logarithms because the data are very unevenly distributed (positively skewed) (Figure B3). Taking the natural log reduces skewness and stabilizes variance. This transformation also yields elasticities in interpretation. I provide a robustness check measuring household energy intake at the food group level in levels rather than logarithms (i.e., in kilocalories). I then divide the effect by the mean intake to express results as a marginal change for one additional HDD in the last growing season. The results of this sensitivity analysis in Figure B14 show that the direction and significance of coefficients are similar to Figure B10.

5.6 Additional pathways

Prices as omitted variables

A potential concern is that my results might be influenced by changes in relative prices. Extreme heat shocks can reduce aggregate supply and increase crop and food prices. A crop price increase may create incentives to increase harvest sales. On the other hand, a price increase in nutritious foods may incentivize reliance on staples and own-produced foods to ensure energy sufficiency, potentially leading to a reduction in commercialization. The main specification includes growing season fixed effects. If agricultural and food markets are well integrated nationally, this approach would control for such price effects. However, this is unlikely to be the case in Nigeria, where evidence points to incomplete or uneven market integration (Dillon and Barrett, 2016; Amare et al., 2024). Thus, I test the impact of extreme heat in the growing season on post-harvest community-level (i.e., enumeration area or cluster) food prices using the main specification. Prices are collected during the same survey month as for food expenditure and consumption information in a given enumeration area. I have selected the following food items because of their highest coverage in the data and to represent each of the nine HDDS food groups used in this analysis: millet, potato, onion, banana, beef, egg, fish, groundnut, and milk. Current (nominal) retail prices in local currency (Naira) are harmonised per kilogram and converted to 2015 constant (real) prices using the food consumer price index from the UN Food and Agriculture Organization (FAO) (FAO, 2025).

I follow the main specification as detailed in Equation 1. For the majority of food items, Table C12 shows that there is no statistically significant relationship between growing season heat and post-harvest local prices. There are some exceptions. An additional HDD in the last growing season decreases the price of onion and banana by 2.44% and 2.38%, respectively, and increases the price of groundnut by 1.19% ($p < 0.1$). However, the number of observations is limited for many food items. This is due to missing data and a restriction of the sample to food markets observed at least during three waves and with at least two non-missing prices for a given item. Also, only the effect on onion remain statistically significant ($q < 0.1$) when using Benjamini and Hochberg (1995)'s false discovery rate (FDR) q-values to account for multiple hypothesis testing (Table C19).

As a sensitivity analysis, I test the impact of growing season heat on post-harvest prices using monthly panel data from the World Bank Real Time Food Prices (Andrée, 2021), which contains historical monthly food price estimates by product and market in developing countries. In Nigeria, the sample covers the years 2014 to 2024, 17 food items, and 64 markets. I test the impact on food prices in January, February, March, and April, matching the months of data collection for household consumption in the LSMS-ISA in Nigeria. Across food items, Figure B15 confirms a limited impact on food prices in the short-run post-harvest. The overall food price index, built by the World Bank using consumption weights, increases by 0.13% in January with each additional HDD in the growing season (no statistically significant effects in the following months). While this short-term increase could have an effect on food expenditure, it is not substantial enough to explain the magnitude observed in Table 3, given mostly price-inelastic demand in Nigeria (McCullough et al., 2024).

The overall lack of a price response (or minor response) is consistent with findings from a previous cross-sectional analysis in Nigeria (Dillon et al., 2015). These results likely reflect my focus on the immediate post-harvest period, whereas price adjustments may take several months to materialize as stocks deplete and markets clear. For instance, evidence from Niger shows that drought-induced price increases emerge only around six months after harvest (Kakpo et al., 2022).

The role of post-harvest off-farm employment

I consider the effects of extreme heat on *ex-post* labor activity, which could impact income and thus purchasing power. High temperatures can negatively impact employment by either impairing worker health or reducing overall labor demand. Households can also seek additional employment as an adaptation response to compensate for the negative effects of extreme heat on agricultural income (Colmer, 2021). Table 7 shows that point estimates are near zero and that heat in the growing season has no statistically significant effects on post-harvest small-own business or wage employment, either on the extensive or intensive margin. Given the low baseline engagement in wage employment (7.3%) and modest participation in small own-business (18.1%), scope to expand off-farm hours appears limited. This pattern is consistent with binding time and market frictions: households do not substantially reallocate from farm to non-farm work, nor do they add net hours off-farm, even after experiencing adverse heat. These findings are consistent with thin and incomplete labor markets (Rosenzweig, 1988). The labor-income smoothing margin remains muted, helping explain why expenditure falls (Table 3).

	Extensive margin			Intensive margin			Last 12m
	Farm	SOB	Wage	Farm	SOB	Wage	NFB
GDD in growing season	-0.0002	0.0000	0.0000	-0.0004*	-0.0000	0.0000	0.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0002)	(0.0001)	(0.0000)	(0.0001)
HDD in growing season	-0.0007	0.0002	0.0001	-0.0018	-0.0001	0.0004	0.0003
	(0.0007)	(0.0005)	(0.0003)	(0.0017)	(0.0009)	(0.0004)	(0.0007)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.552	0.539	0.583	0.746	0.865	0.917	0.634
Observations	8,937	8,937	8,931	8,930	8,938	8,938	9,006
Mean Y	0.509	0.181	0.073	.	.	.	0.519

Table 7. **Effect of HDD on post-harvest labor activity.** Labor activity in the last 7 days before interview. Conley spatial HAC standard errors (in parentheses). FE: fixed effects. NFB: Non-farm business. SOB: small-own business.

Changes in household composition

Extreme heat during the growing season may reshape household composition. This could have consequences on the farm's productive capacity, for example, if it changes the number of working-age household members. It could also change the total amount of food necessary for the household. Three effects may be at play: fertility, migration, and mortality. I test these channels by estimating regressions from my main specification with the number of children, the number of working-age adults, and the number of elderly in the household as the outcome. Results are shown in Table C13. No coefficient is statistically significant at any conventional level. As expected from the climate-health literature, the sign of the coefficient on HDD is negative for young children and the elderly. The latter are more likely to die from heat shocks (Carleton et al., 2022), whereas for the former, fertility may be negatively impacted, for example, by increasing the risk of delivery complications for pregnant women (Barreca and Schaller, 2020). On the other hand, the coefficient on HDD is positive for the number of working-age adults in the household. Interpreted through a liquidity-constraint lens in poor rural settings, hot growing seasons may temporarily inhibit out-migration and induce short-run co-residence or even return migration (Hirvonen, 2016; Cattaneo and Peri, 2016), increasing the number of working-age adults at home, even in the absence of a higher farm labor demand (Table C15).

Other coping mechanisms

My main results suggest that farm households respond to temperature-induced crop losses (*ex-post*) by selling a smaller share of harvested crops to maintain calories, which consequently tightens cash and reduces purchases of nutrient-dense foods, thereby degrading dietary quality. In this section, I examine other coping mechanisms that have been previously documented.

First, I examine *ex-ante* productive adaptation responses in terms of input use and crop mix. Consistent with previous studies (Mayorga et al., 2025; Jagnani et al., 2019), I find that households reduce the use of productivity boosting inputs, such as fertilizers. However, I do not find evidence of increased use of pesticides as protective inputs. While mixed cropping, as opposed to monocropping, may allow farmers to dilute their risk from adverse productive shocks (Shaffril et al., 2018), I find no evidence of increased mixed cropping in hotter seasons (Table C14).

Second, I study the effect of growing season heat on farm labor allocation during the agricultural season. Table C15 shows no direct relationship between extreme heat and farm labor inputs. This is consistent with previous results in Nigeria (Mayorga et al., 2025). From a consumption-smoothing perspective, the relevant margin is off-farm earnings. Unfortunately, the LSMS-ISA does not record within-agricultural-season off-farm labor. Prior work in other contexts find that extreme weather increases off-farm labor supply as households seek liquidity (Branco and Féres, 2021; Kochar, 1999). If households face a binding time constraint, holding on-farm work fixed leaves little slack to expand off-farm work, implying a limited scope for within-agricultural-season labor reallocation toward cash income. Lastly, I find no effect of extreme heat in the growing season on the likelihood of a household owning a non-farm business (Table 7).

5.7 Back-of-the-envelope uniform warming projections

I provide a projection exercise in which I simulate changes in harvest, dietary diversity, and protein and iron adequacy under a uniform $+1°C$ warming scenario. This approximately corresponds to the projected warming in Nigeria under the SSP2-4.5 "intermediate" greenhouse gas emissions scenario by 2050 based on the Coupled Model Intercomparison Project Phase 6 (CMIP6) (World Bank, 2024).[29] I calculate the expected change in GDD and HDD and then estimate the expected effect on the outcomes of interest by multiplying the variations by the corresponding estimates from my main specification (Table C3, Table 2, and Figure 5). This exercise deliberately isolates the impact of temperature, employing a ceteris paribus assumption. It does not endogenize other complex phenomena associated with climate change, such as biophysical shifts or broader socioeconomic adaptations. Consequently, the findings should not be interpreted as a comprehensive forecast.

Results are reported in Table 8. I find that a uniform $+1°C$ warming scenario would decrease harvest by 27.38% and subsequently dietary diversity by 0.29%, protein adequacy by 4.04 percentage points (3.18 p.p. for 80% adequacy), and iron adequacy by 1.56 percentage points (3.54 p.p. for 80% adequacy). These percentage changes correspond to an increase of around 1.62 million and 0.63 million households with inadequate protein and iron intake (1.28 and 1.42 million households for 80% adequacy), respectively, out of Nigeria's 2022 farm household population of 42 million households (National Bureau of Statistics, 2024).

The projected yield impact is larger than the latest -10.8% estimate for Africa by 2050 under RCP4.5 from Hultgren et al. (2025). The latter is based on subnational aggregate agricultural production data. Nevertheless, the results from my projection exercise are in line with those of Wollburg et al. (2024), who found that climate shocks reduced crop production among small-

[29]Mean annual surface temperature in Nigeria was 27.7°C in 2014 (last year of the historical reference period 1950-2014, used to train the CMIP6) and is expected to be 28.65°C by 2050 under SSP2-4.5 "moderate" scenario by 2050 based on CMIP6 (World Bank, 2024).

	Effect of uniform $+1°C$ temperature increase
Δ GDD	43.601
Δ HDD	12.951
Δ Harvest (%)	-27.378
Δ HDDS (%)	-0.288
Δ Protein 100% adequacy (p.p.)	-4.038
Δ Protein 80% adequacy (p.p.)	-3.183
Δ Iron 100% adequacy (p.p.)	-1.556
Δ Iron 80% adequacy (p.p.)	-3.538

Table 8. **Predicted effects of a uniform $+1°C$ warming scenario.** HDDS: household dietary diversity score. p.p.: percentage points.

holder farmers by 29% in Sub-Saharan Africa between 2008 and 2019, using LSMS-ISA data. While smallholder farmers represent the majority of crop production in Sub-Saharan Africa, the commercial farm sector is rapidly increasing (Jayne et al., 2022). Commercial farming may be more resilient to climate shocks, with larger farm sizes and better access to agricultural inputs.

6 Discussion

This paper set out to identify how extreme heat during the growing season affects post-harvest nutrition outcomes for smallholder farm households in Nigeria, extending beyond energy sufficiency to focus on nutrient adequacy. A central objective was to shed light on household adaptation responses to temperature-induced crop losses in terms of consumption, commercialization, and purchases. Using panel microdata and exploiting quasi-random within-household variations in weather across growing seasons, I demonstrate that extreme heat reduces harvested quantities but has no immediate impact on post-harvest energy intake, while exacerbating nutrient shortfalls.

I document a behavioral response to the production shock. Households increase reliance on own-produced foods and retain a larger share of their harvest, mainly composed of cereals and tubers, to preserve calorie intake. Combined with the temperature-induced harvest shortfall, the decreased share of harvested crops sold reduces cash income and food purchases, with cuts falling disproportionately on cash-intensive and nutrient-dense items, such as vegetables, pulses, and meat. While safeguarding energy intake, this *ex-post* adaptation strategy degrades diet quality. This is consistent with predictions from a post-harvest farm household model in the presence of incomplete food and labor markets and binding caloric constraints.

A uniform $+1°$C warming is associated with an additional 1.62 million and 0.63 million Nigerian households with inadequate protein and iron intake. The nutritional impacts are significantly larger for households with children under five years old, a concerning finding given the crucial role of these nutrients in linear growth, cognitive development, and immune function during early childhood (Black et al., 2013). Moreover, these estimates are likely lower bounds. Climate change may further erode dietary quality by lowering the nutrient content of foods, thereby amplifying nutrient inadequacies (IPCC, 2019). Although my estimates capture only responses up to four months post-harvest, I show that adverse nutritional effects worsen as time since harvest elapses. As stocks deplete, the ex-post strategy that initially safeguards calories may also fail to maintain energy sufficiency; a transition that future work could track with high-frequency panel survey data.

To my knowledge, Stainier et al. (2025) represents the only other study that separates own-produced from purchased foods when mapping climate shocks to diets. Both studies document diet-quality losses following hot growing seasons; however, the direction of the market response differs. In rural India, Stainier et al. (2025) find households purchase more to offset own-production shortfalls, enabled by a labor reallocation into non-agricultural work. In Nigeria, I find no post-harvest expansion of off-farm labor and, consequently, no compensating rise in food purchases; instead, households sell less and buy less. This may be explained by relatively more complete rural labor markets in India.[30] The absence of an operative labor channel in Nigeria maps into a defensive autarkic behavior and opposite purchase responses.

I acknowledge a number of limitations to my analysis. First, food consumption is recorded with a 7-day recall in the first three waves and a 30-day recall in the last two. Shorter windows tend to overstate mean intake (Mukherjee and Chaudhury, 2020). While this primarily

[30] Also, Stainier et al. (2025) do not examine the impact on commercialization and include rural non-farm households in their sample.

affects levels, bias could arise if recall behavior covaries with heat. Nevertheless, Villacis et al. (2023) show that both recall periods perform as well in identifying food-insecure households in Nigeria. I mitigate this by including growing-season (survey-wave) fixed effects that absorb recall-window differences and common shocks. I also show the robustness of my results to excluding the last two waves. Second, because food may not be distributed equally within households (D'Souza and Tandon, 2019), the effects of extreme heat on undernutrition may be attenuated or masked for vulnerable subgroups, particularly if allocation shifts under financial stress (Hazrana et al., 2025). I partly address this by examining heterogeneity by household composition. However, a more comprehensive assessment would require individual-level consumption data. Lastly, although my analysis accounts for zone-specific growing season calendars and degree days thresholds (i.e., Southern vs. Northern), a more granular approach, tailoring season timing and temperature cut-offs to crop-specific phenology and local climate, would likely improve precision. Future work with finer seasonal data could reduce timing mismatches and strengthen inference across heterogeneous agro-climatic contexts.

Despite these shortcomings, this paper makes significant contributions to our understanding of the consequences of extreme temperatures for household food utilization and nutrition, an issue that remains understudied in the literature. Shifting from coarse indices to nutrient-specific intake and adequacy measures reveals declines in diet quality that were previously obscured by aggregate calorie intake metrics. Designing climate adaptation policy requires understanding household responses to heat. Crucially, all core variables in this analysis (agricultural production, livestock management, prices, consumption, and nutrition) are measured within the same household-panel architecture, improving the internal consistency of estimated pathways and reducing the scope for ecological fallacy.

Prior work shows that commercialization generally improves diet quality (Chegere and Kauky, 2022; Ogutu et al., 2020), yet its nutrition gains are attenuated in the presence of climate shocks (Hazrana et al., 2025). However, the behavioral channel through which weather shocks attenuate these gains has remained underexplored. By separating own-produced from purchased intake and investigating the commercialization–consumption trade-off, this paper reveals a margin of adjustment not previously documented: households reduce the share of harvest sold and secure energy intake through home-grown staple consumption, while cutting purchases of nutrient-dense foods. Thus, climate shocks not only dampen the returns to commercialization but also reduce commercialization itself, tightening cash constraints and transmitting the shock into diet-quality losses. This immediate post-harvest response erodes the commercialization pathway out of poverty (Barrett, 2008) and is likely relevant in other smallholder contexts with incomplete markets.

Safeguarding nutrition under climate change necessitates moving beyond caloric sufficiency to target nutrient-adequate diets that support healthy and active lives. It requires integrating climate-risk mitigation with measures that keep smallholders engaged in markets and improve their access to non-farm labor opportunities. Direct financial support could also help mitigate nutritional losses (Premand and Stoeffler, 2022).

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Appendix

A. Appendix Data Details

LSMS-ISA geographical offset

In the LSMS-ISA data, household confidentiality was preserved by applying a geographic offset process to the location data. Initially, coordinates were aggregated to the enumeration area (EA) level by calculating the mean location of each EA. These aggregate points were then randomly displaced by up to 2 km in urban areas and up to 5 km in rural areas, with the latter receiving a larger offset due to a higher disclosure risk in less dense settings. To further mask the data, a small subset of rural clusters (1% in most samples) was subjected to a larger displacement of up to 10 km. The maximum potential offset for any rural point is 10 km.

Weather data

I extract minimum and maximum daily temperatures from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 climate reanalysis dataset at the 0.1° resolution, or about 10×10km close to the equator (Hersbach et al., 2020). I estimate the average daily temperature as the average of the daily maximum and daily minimum temperatures. Total precipitation data are extracted from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) database, which combines observations from real-time meteorological stations with infra-red data at the 0.05° resolution, or about 5×5km close to the equator (Funk et al., 2015). Total precipitation data is reaggregated using means to match ERA5's resolution. The weather data for a specific 0.1° resolution grid square is assigned to an LSMS-ISA cluster if the cluster lies within that grid square. The low resolution of the weather data ($\approx 10\times10$km) is larger than the random geographic offsets applied to the coordinates. Therefore, the process of altering the coordinates is not expected to meaningfully affect the effect of the weather variables on the outcome variables.

Agricultural output data

Agricultural output data initially provided by the LSMS-ISA surveys at the plot level are aggregated, i.e., summed up, at the household level, while the maximum values of indicator variables (e.g., intercropped or not) are retained. Plots for which output amounts or size (area) are missing or not strictly positive are dropped. Agricultural output values are winsorised at the 99th percentile. Harvest is valued using median prices per enumeration area. If there are fewer than 10 observed sales in the area, prices are calculated at a higher geographical level. Prices are calculated independently for each crop type (Bentze and Wollburg, 2024). Harvest values are converted to current USD and deflated to 2020 USD, using exchange rates and a deflator from the World Bank. The same transformation is performed for household expenditure.

Food and nutrient consumption data

Households report food items consumed at home over the seven full days preceding the interview date. Food consumption is categorized into three types: purchased, own-produced, and gifted (including transfers). Food items are grouped according to the Household Dietary Diversity Score (HDDS) food grouping (FAO, 2011), including: A. Cereals; B. Roots and tubers; C. Vegetables; D. Fruits; E. Meat, poultry, offal; F. Eggs; G. Fish and seafood; H. Pulses, legumes, nuts; I. Milk and milk products; J. Oil/fats; K. Sugar/honey; and L. Miscellaneous.

Food and nutrient consumption data cleaning follows McCullough et al. (2024). Units of consumption are harmonised to kilograms (kg) using conversion factors provided with the survey microdata. The interquartile range method is used to clean outliers of consumption per adult equivalent at the household-item level for each country. The nutritional content of food items is determined using published food composition tables from Africa (Lukmanji et al., 2008; Vincent et al., 2020; Stadlmayr et al., 2012; Hotz et al., 2012; University of California, Berkeley, 2006), and completed with data from the United States Department of Agriculture (USDA) (U.S. Department of Agriculture, Agricultural Research Service, 2019). For staple foods, I incorporate assumed fortification rates based on data from the Global Fortification Data Exchange (Global Fortification Data Exchange, 2023). Further adjustments were made to account for edible portions and nutrient losses during cooking, using information from the USDA (Matthews and Garrison, 1975; U.S. Department of Agriculture, Agricultural Research Service, 2007). As in McCullough et al. (2024), food away from home consumption is not included due to a lack of information about the items consumed to match them with nutrient content information.

I also follow McCullough et al. (2024) in constructing household-level estimated average requirements (EAR) for energy and each nutrient. EAR per adult equivalent is based on the age and sex composition of each household, assuming adults are of average weight and engage in moderate activity levels. Dietary energy (DE) and protein requirements are taken from FAO/WHO/UNU (2004). I establish EAR for vitamin A, total folate, and iron using the work of the Institute of Medicine (2006), for zinc based on the International Zinc Nutrition Consultative Group et al. (2004), and for iron from the Institute of Medicine (2002). I assume low bioavailability for both zinc and iron. For zinc, this is due to diets relying heavily on unrefined cereals, and for iron, it is because diets are high in phytate and low in animal-sourced foods.

To measure adequacy, I calculate the ratio of a household's intake to its EAR. A ratio greater than one indicates sufficient intake, while a ratio lower than one shows the fraction of the EAR being consumed. I then create a binary variable for energy and each nutrient that equals one if a household's intake exceeds its EAR and zero otherwise.

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B. Appendix Figures

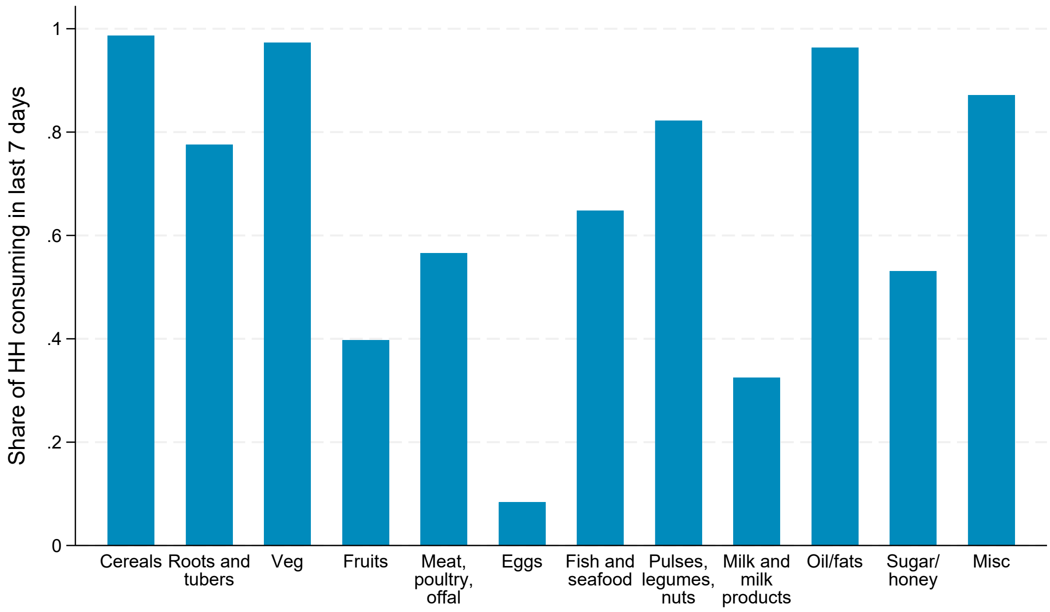

Figure B1. **Likelihood of consumption, by food group.** HH: household.
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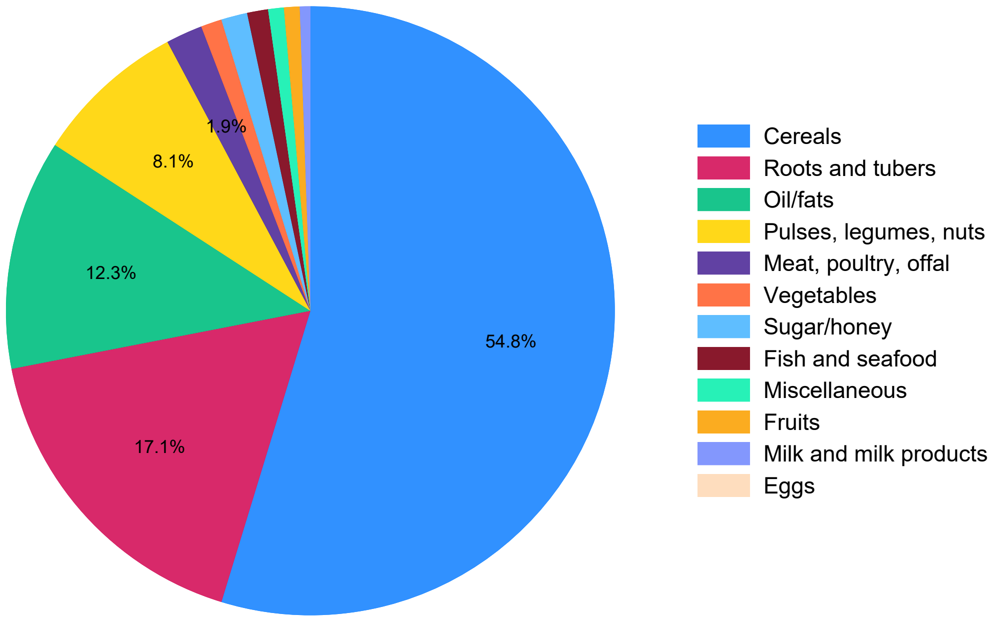

Figure B2. **Average share of total energy intake, by food group.**
Back to Section 5.

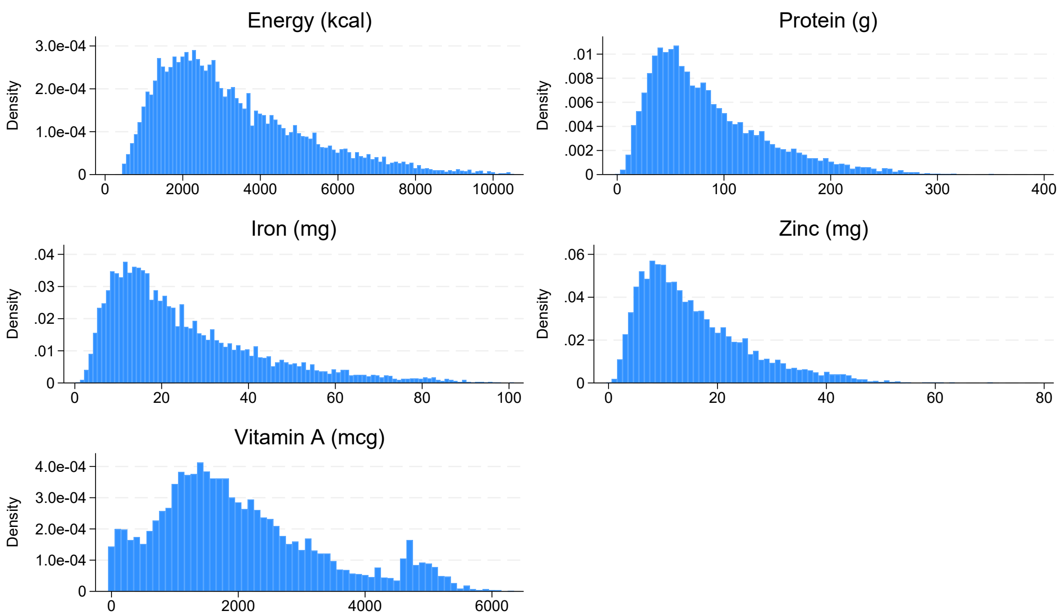

Figure B3. **Distribution of the intake of energy and nutrients.** Daily intake per adult equivalent unit.
Back to Section 5.

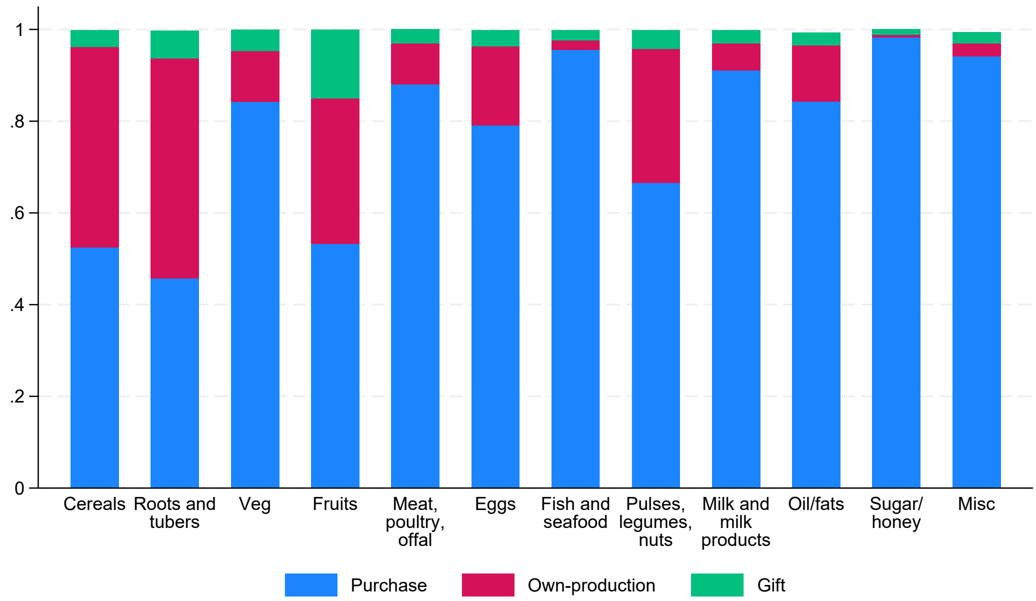

Figure B4. **Average share of total energy intake, by food group and source of consumption.**
Back to Section 5.

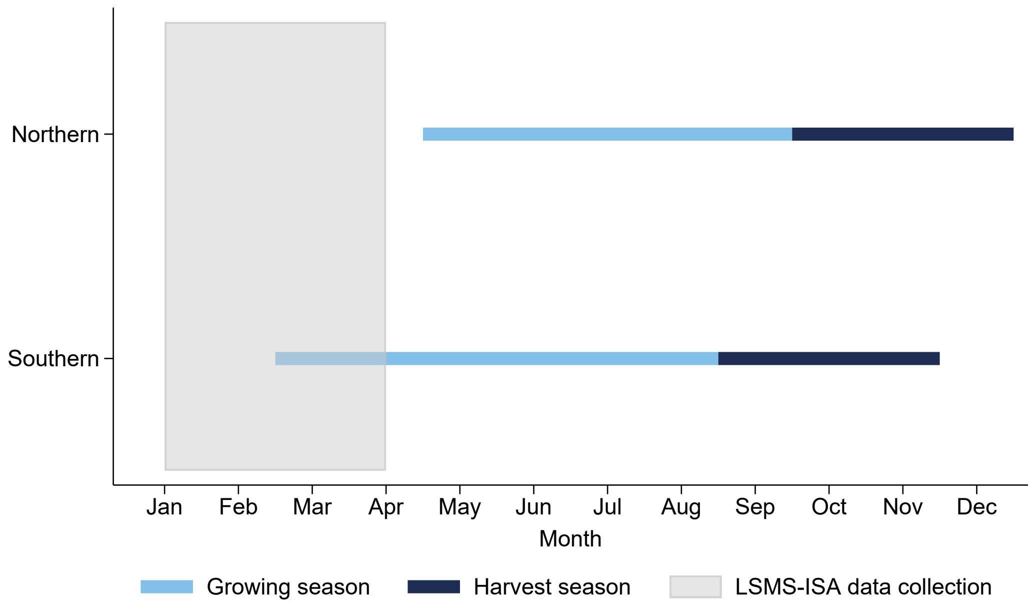

Figure B5. **Agricultural season calendar.** Based on Famine Early Warning Systems Network (FEWSNET). The growing season includes both planting and growing.
Back to Section 3.

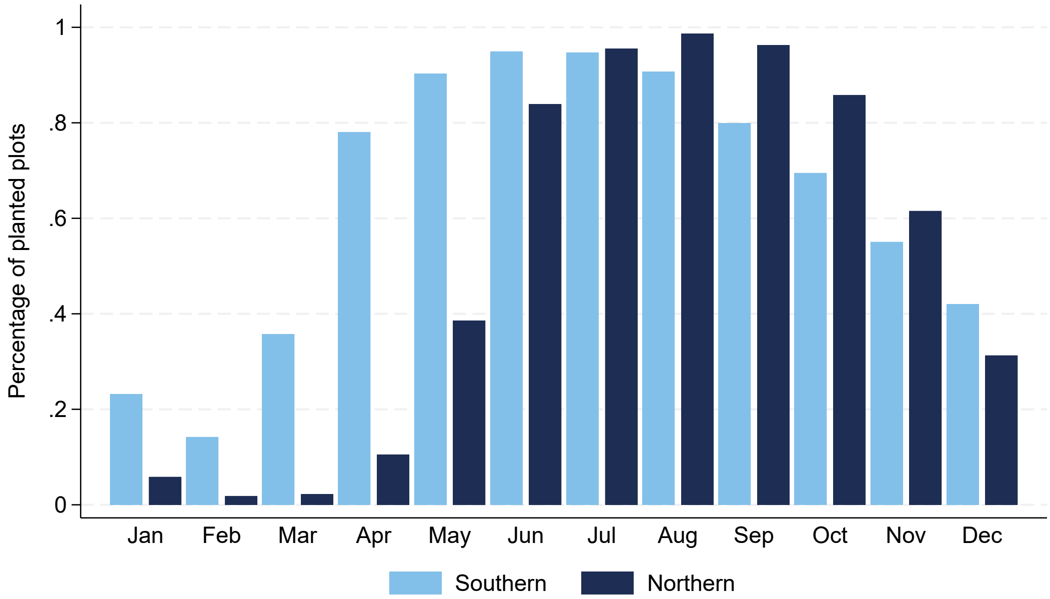

Figure B6. **Percentage of planted plots by month.** Based on 39,030 plots from sample panel farm HH. Representing all months between the reported planting start date and the reported harvest start date for each plot.
Back to Section 3.

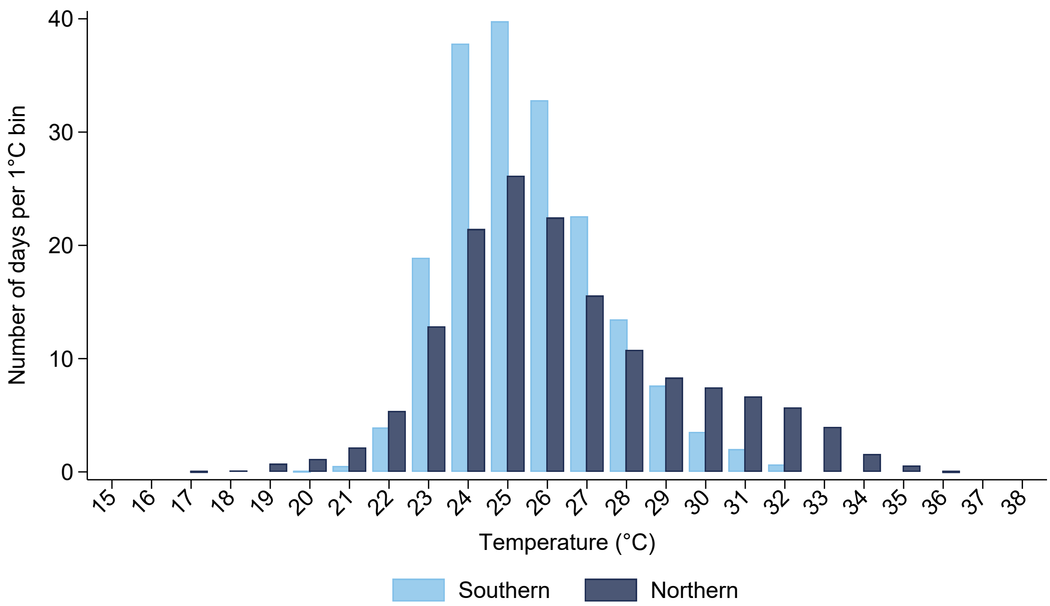

Figure B7. **Temperature distribution of growing season days, by region.** Based on the sample farm panel households, i.e., 9,006 observations, 2,832 HH, within 392 enumeration areas (clusters), over 2010-2023.
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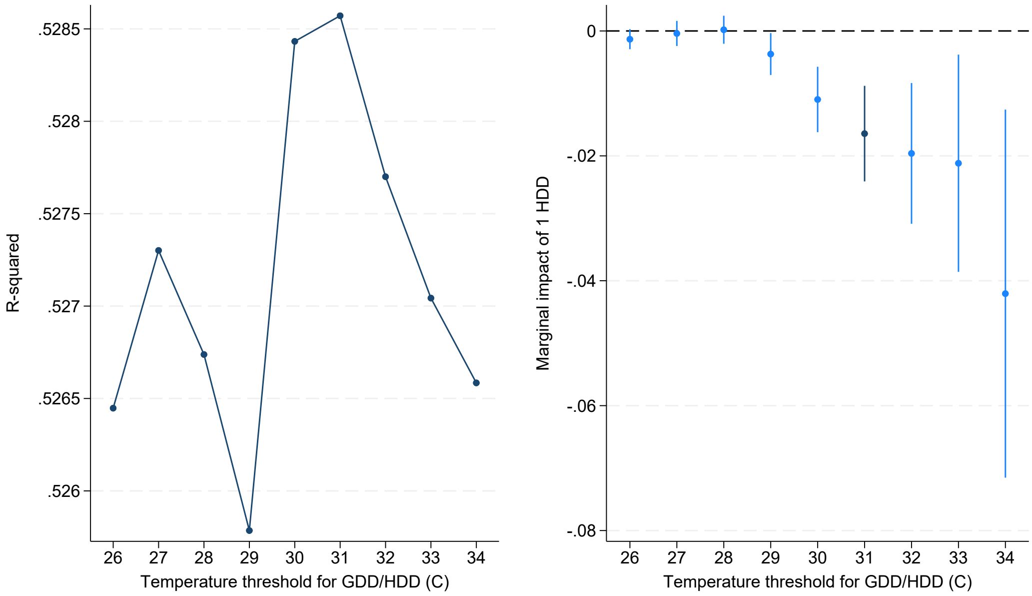

Figure B8. **Optimal GDD/HDD threshold using an iterative regression approach and effect on total yield.** Total yield is measured in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional growing season HDD. Conley spatial HAC standard errors (in parentheses).
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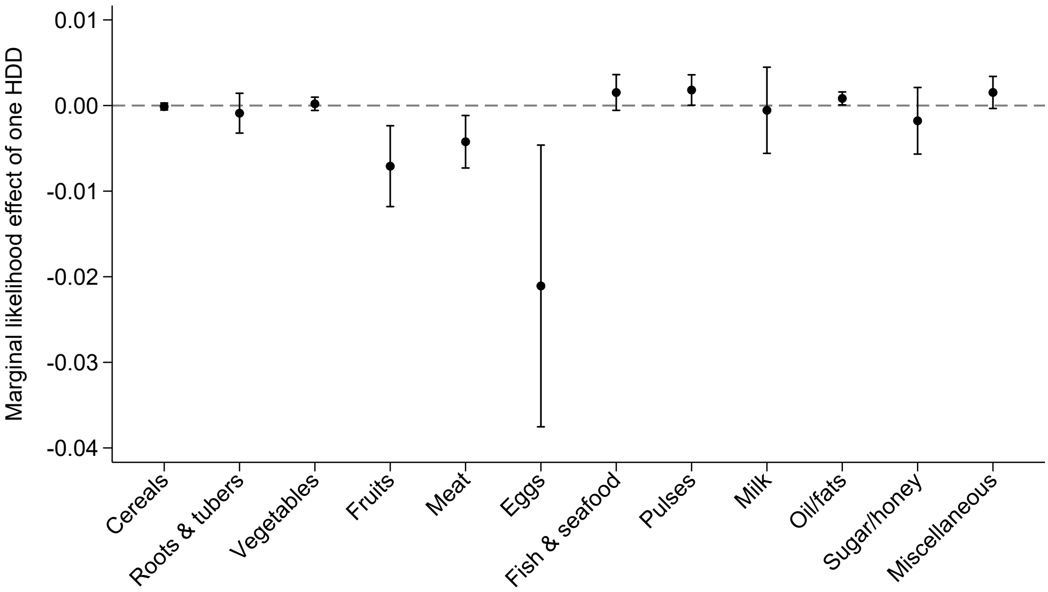

Figure B9. **Effect of HDD on consumption likelihood, by food group.** Each food group represents a dummy for household consumption in the last 7 days, but coefficients have been divided by the respective sample means, thus coefficients can be interpreted as the relative percentage change in the likelihood of consumption for one additional HDD. Conley spatial HAC standard errors are used to build the 95% confidence intervals.

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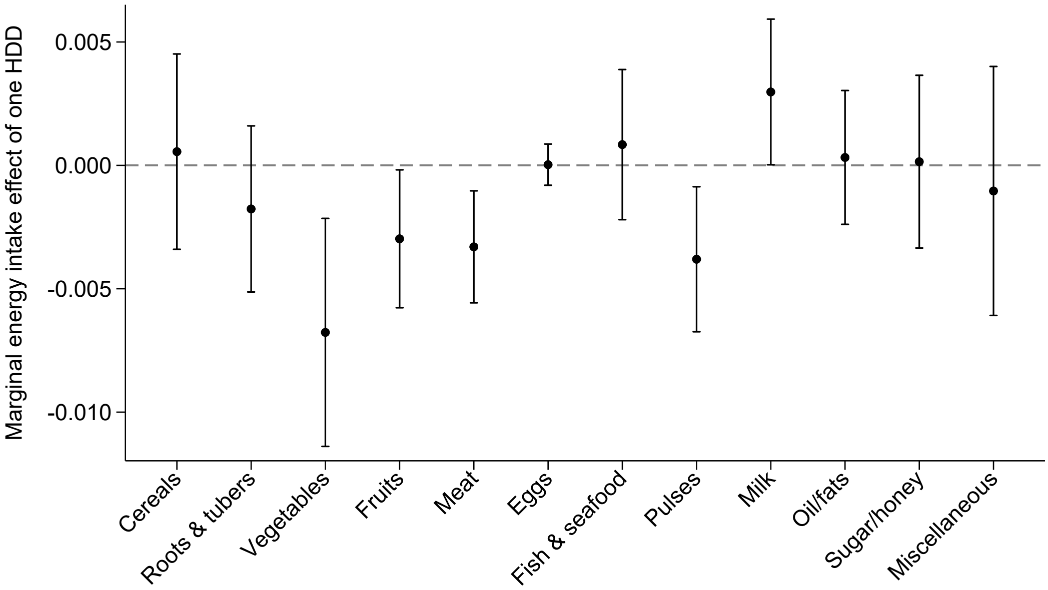

Figure B10. **Effect of HDD on energy intake, by food group.** Each food group is expressed as the logarithm of total energy intake, thus coefficients can be interpreted as the relative percentage change for one additional HDD. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors are used to build the 95% confidence intervals.

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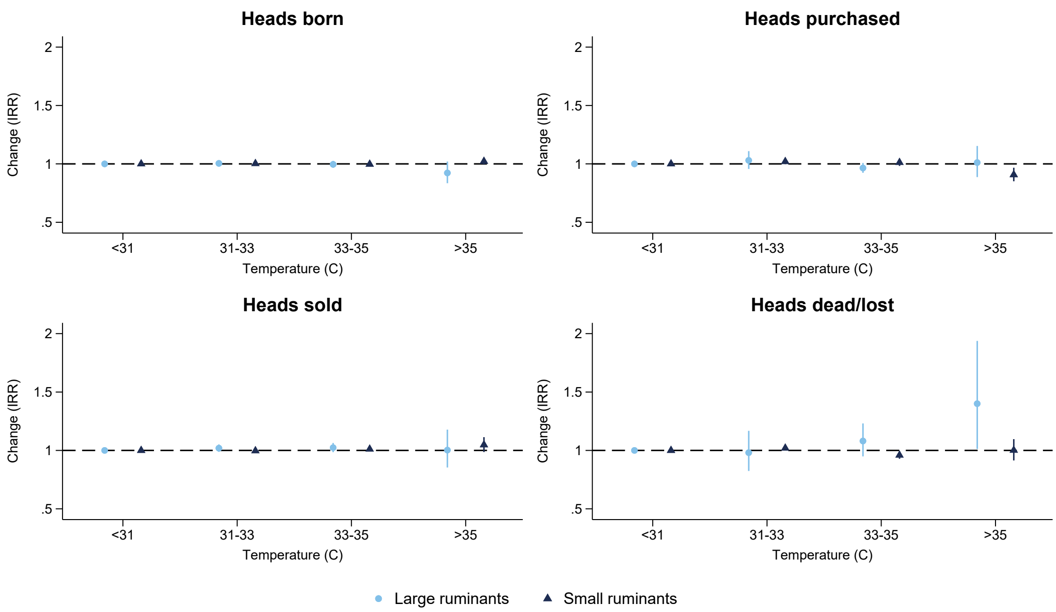

Figure B11. **Temperatures and livestock birth, purchase, sale, and death.** Poisson pseudo-maximum likelihood estimations using the computationally efficient estimator for Poisson regressions using high-dimensional fixed effects developed by Correia (2016). Coefficients are exponentiated and presented as incidence rate ratios (IRR). Reference bin < 31C. Weather over the last 12 months (number of days in each bin). Mean number of annual days with average temperature > 35C: 0.6. 95% confidence intervals are built using robust clustered standard errors at the households level.
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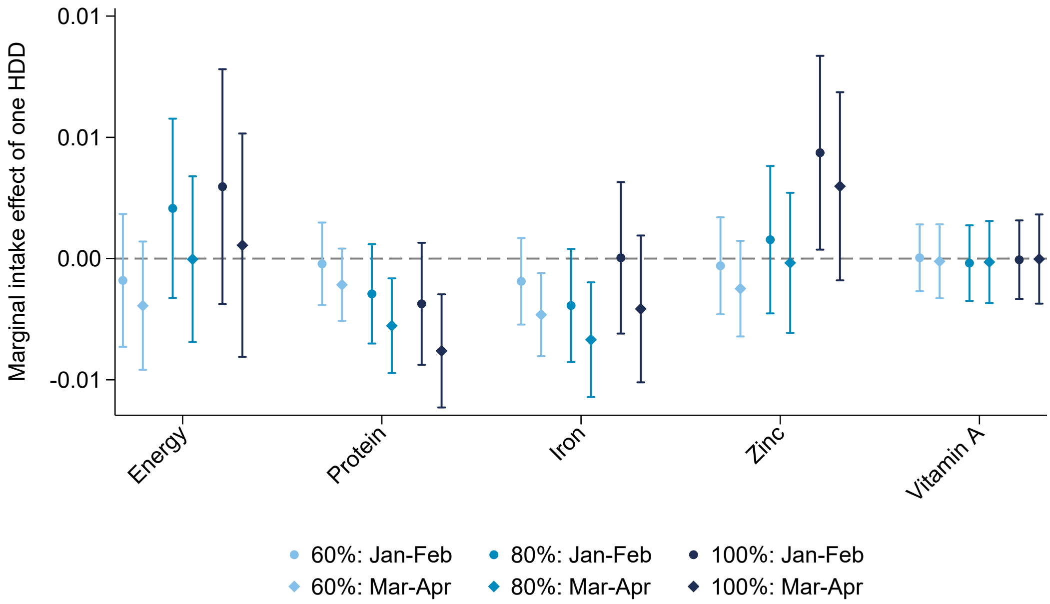

Figure B12. **Effect of HDD on household nutrient adequacy, by survey months.** Each nutrient adequacy represents a dummy equal to one if a household meets the intake requirement at various thresholds (60%, 80%, and 100%). Coefficients have been divided by the respective dependent variable sample mean, and can be interpreted as the relative percentage change in the likelihood of meeting the requirement for one additional HDD. Conley spatial HAC standard errors are used to build the 95% confidence intervals.
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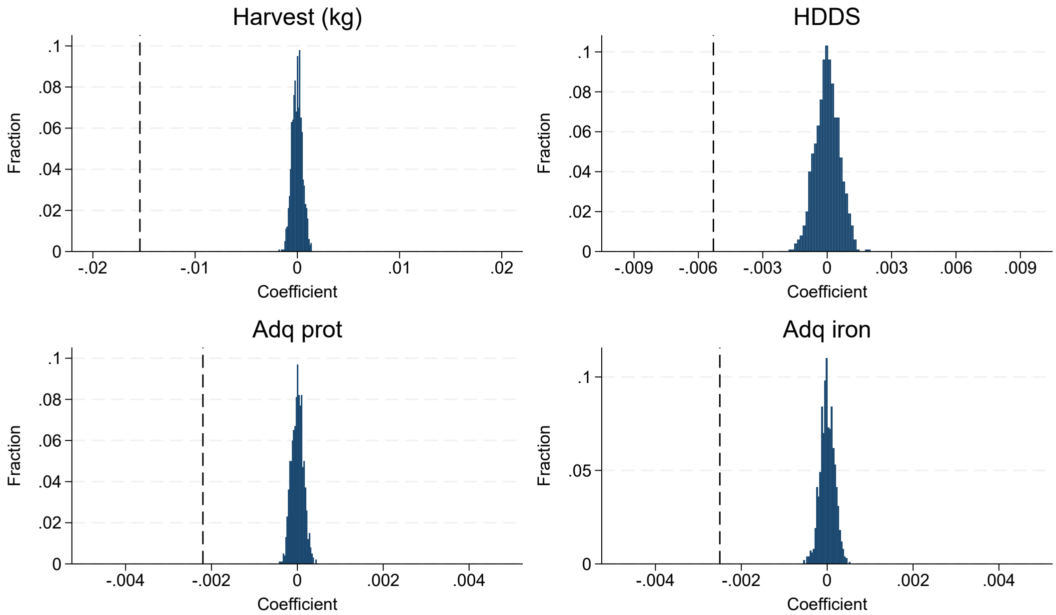

Figure B13. **Falsification tests.** Adequacy indicators are set to 80% adequacy levels. Distribution of the estimated coefficients resulting from the falsification tests using random weather allocation. The vertical dotted line in each subplot reflects the respective coefficient estimate of HDD for the main specification. Adq: adequacy. HDDS: Household dietary diversity score. prot: protein.

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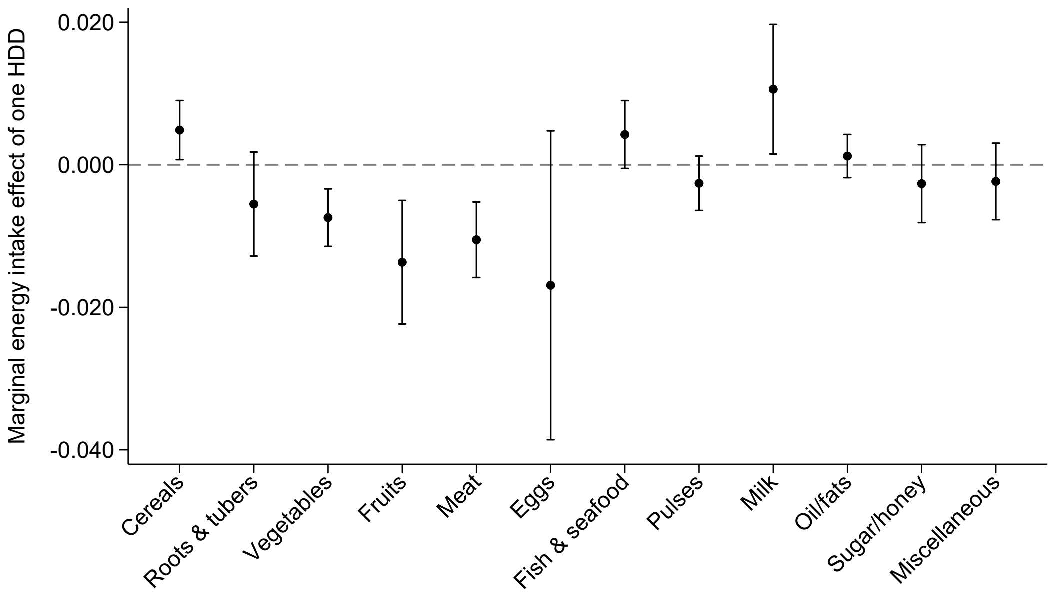

Figure B14. **Robustness: Effect of HDD on energy intake, by food group.** Total energy intake is expressed in kilocalories and the coefficient is divided by the mean energy intake, thus coefficients in this figure can be interpreted as the relative percentage change for one additional HDD. This provides a robustness to Figure B10, where the outcome variable is expressed as logarithms. Conley spatial HAC standard errors are used to build the 95% confidence intervals. Back to Section 5.

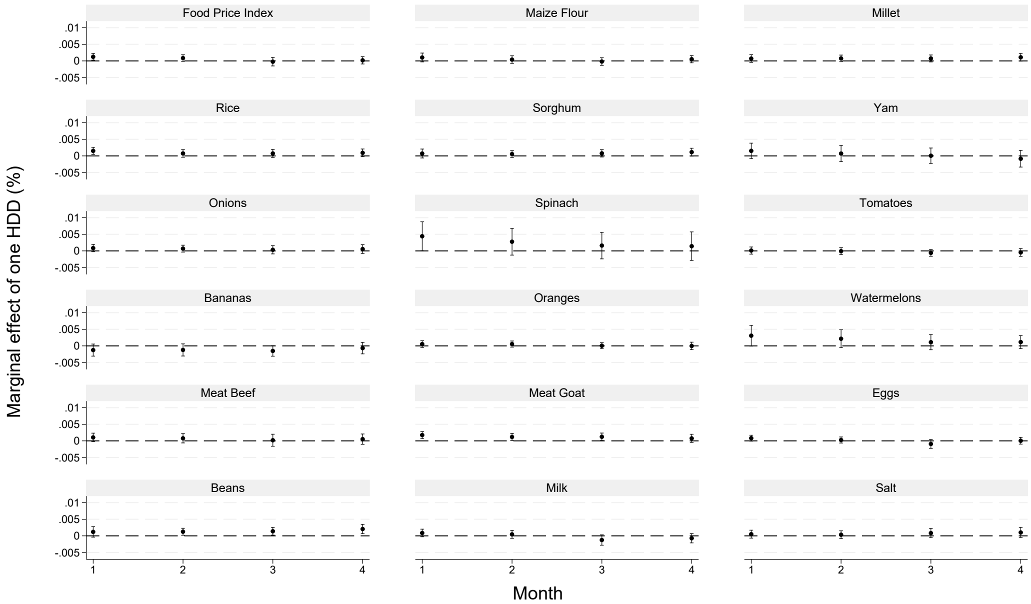

Figure B15. **Effect of HDD on post-harvest food prices, by food item and month.** Using monthly panel data from the World Bank Real Time Food Prices (Andrée, 2021), which contains historical monthly food price estimates by product and market in developing countries. In Nigeria, the sample covers the years 2014 to 2024, 17 food items, and 64 markets. The overall food price index is built by the World Bank using consumption weights. Variables are expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Months are: 1) January, 2) February, 3) March, and 4) April. Conley spatial HAC standard errors are used to build the 95% confidence intervals.
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C. Appendix Tables

	2010	2012	2015	2018	2023	All
Panel farm HH ($\geq$ 3 waves)	2,609	2,599	2,628	968	935	9,739
Strictly positive ag output & area	2,472	2,517	2,530	928	876	9,323
Strictly positive total energy intake	2,398	2,343	2,489	916	860	9,006
Final sample	**2,398**	**2,343**	**2,489**	**916**	**860**	**9,006**
% of panel sample	(91.9%)	(90.2%)	(94.7%)	(94.6%)	(92.0%)	(92.5%)

Table C1. **Sample selection.** A partial refresh of the panel sample was undertaken in wave 4. The representativeness of the survey was impacted during wave 4 due to security issues, which prevented data collection in some locations. The survey does not track "split-off" households. HH: household.
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	January	February	March	April	Total
Wave 1	0	41	2,296	61	2,398
Wave 2	0	373	1,964	6	2,343
Wave 3	0	597	1,879	13	2,489
Wave 4	902	14	0	0	916
Wave 5	0	797	63	0	860
Total	902	1,822	6,202	80	9,006

Table C2. **Distribution of interview months, by survey wave.**
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	Total yield (kg/ha)	Total harvest (kg)	Total area (ha)
GDD in growing season	-0.0018***	-0.0017***	0.0000
	(0.0004)	(0.0005)	(0.0004)
HDD in growing season	-0.0174***	-0.0154***	0.0020
	(0.0041)	(0.0047)	(0.0030)
Precipitations	0.0077**	0.0055**	-0.0022
	(0.0035)	(0.0028)	(0.0024)
Precipitations^2 ($\times 10^{-3}$)	-0.0157**	-0.0137**	0.0021
	(0.0077)	(0.0059)	(0.0055)
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes
R^2	0.506	0.602	0.727
Observations	9,006	9,006	9,006

Table C3. **Growing season weather, agricultural productivity, output, and land area.** Total yield, harvest, and land area are measured in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional growing season HDD. Conley spatial HAC standard errors (in parentheses). FE: fixed effects.
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	Energy	Fat	Carbs	Protein
GDD	0.0001	0.0000	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
HDD	-0.0002	0.0002	-0.0004	-0.0005
	(0.0015)	(0.0012)	(0.0017)	(0.0015)
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes
R^2	0.554	0.517	0.530	0.605
Observations	9,006	9,006	9,006	9,006

Table C4. **Temperatures and energy and macronutrient intake.** Expressed as logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Conley spatial HAC standard errors (in parentheses). FE: fixed effects.
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	Total	Purchased	Own-prod	Gifted
GDD in growing season	0.0001	-0.0001	0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
HDD in growing season	-0.0002	-0.0015	0.0002	-0.0020
	(0.0008)	(0.0013)	(0.0016)	(0.0015)
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes
R^2	0.554	0.558	0.905	0.895
Observations	9,006	9,006	9,006	9,006

Table C5. **Temperatures and energy intake, by source of consumption.** Expressed as logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors (in parentheses). FE: fixed effects. prod: production.
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	Education	Housing	Comm & transport	Clothing	Recreation
GDD in growing season	-0.0003*	-0.0008***	-0.0005**	-0.0006**	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
HDD in growing season	-0.0013	-0.0094***	-0.0065***	-0.0063***	0.0004
	(0.0017)	(0.0017)	(0.0017)	(0.0021)	(0.0025)
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes
R^2	0.808	0.728	0.863	0.570	0.662
Observations	8,146	8,146	8,146	8,146	8,146

Table C6. **Temperatures and non-food expenditure.** Housing includes utilities and household services. Comm: communication. Clothing includes housing goods. Recreation includes other miscellaneous expenses. Expenditure is expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Annualized expenditure in USD 2020 (originally, food: last 7 days; non-food: last month or last 12 months). Expenditure information is missing for wave 5. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors (in parentheses). FE: fixed effects. HDDS: Household dietary diversity score.
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	Total	Purchased	Own-prod	Gifted
GDD	0.0004*	0.0001	0.0005	0.0000
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
GDD × Mar-Apr	-0.0004***	-0.0003***	-0.0005***	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HDD	0.0015	-0.0007	0.0026	-0.0015
	(0.0015)	(0.0022)	(0.0026)	(0.0019)
HDD × Mar-Apr	-0.0015**	0.0002	-0.0034**	-0.0009
	(0.0007)	(0.0010)	(0.0013)	(0.0008)
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes
R^2	0.563	0.561	0.905	0.895
Observations	9,006	9,006	9,006	9,006

Table C7. **Temperatures and energy intake, by source of consumption and survey months.** Variables are expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors (in parentheses). FE: fixed effects.
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	Cereals	Roots	Veg	Fruits	Pulses
GDD	0.0004**	0.0001	0.0001	-0.0001	0.0001
	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
GDD × Mar-Apr	-0.0003***	0.0000	-0.0003***	0.0000	-0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
HDD	0.0033*	-0.0009	-0.0011	-0.0019**	0.0011
	(0.0018)	(0.0018)	(0.0013)	(0.0007)	(0.0010)
HDD × Mar-Apr	-0.0021**	0.0000	-0.0012*	0.0000	-0.0010*
	(0.0009)	(0.0006)	(0.0006)	(0.0002)	(0.0005)
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes
R^2	0.982	0.974	0.851	0.961	0.984
Observations	8,090	8,090	8,090	8,090	8,090

Table C8. **Temperatures and energy intake from main own-produced foods, by survey months.** Variables are expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors (in parentheses). FE: fixed effects.
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	HDDS	Adq prot	Adq iron	Food exp	Non-food exp	Share sold
GDD	-0.0004	0.0000	0.0000	0.0000	-0.0006***	-0.0001
	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0001)
GDD × Mar-Apr	-0.0001	-0.0001***	-0.0002***	-0.0002*	-0.0000	-0.0000
	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
HDD	-0.0028	-0.0014	-0.0016*	-0.0030*	-0.0088***	-0.0014**
	(0.0031)	(0.0010)	(0.0010)	(0.0018)	(0.0013)	(0.0006)
HDD × Mar-Apr	-0.0030**	-0.0010**	-0.0009*	-0.0007	0.0017**	0.0001
	(0.0015)	(0.0004)	(0.0005)	(0.0010)	(0.0008)	(0.0004)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.621	0.518	0.522	0.627	0.766	0.512
Observations	8,090	8,090	8,090	7,230	7,230	7,281
Mean Y	5.521	0.826	0.752	.	.	0.197

Table C9. **Robustness: Temperatures and dietary diversity, nutrient adequacy, expenditure, and commercialization, by survey months.** This table is a robustness analysis for Table 4, excluding wave 4. Adequacy indicators are set to 80% adequacy levels. Coefficients on HDDS can be interpreted as the absolute change in the HDDS for one additional HDD. Coefficients on adequacy indicators can be interpreted as percentage-point change in the likelihood for one additional HDD. Expenditure is expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Annualized expenditure in USD 2020 (originally, food: last 7 days; non-food: last month or last 12 months). Food expenditure represents purchased food. Expenditure information is missing for wave 5. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Information on sold harvested quantities is missing for some households (either missing or set to missing because it is higher than harvested quantities or negative). Conley spatial HAC standard errors (in parentheses). Adq: Adequacy. FE: fixed effects. HDDS: Household dietary diversity score. Back to Section 5.

	HDDS	Adq prot	Adq iron	Food exp	Non-food exp	Share sold
HDD	-0.0053*	-0.0020**	-0.0025***	-0.0036**	-0.0069***	-0.0011*
	(0.0031)	(0.0008)	(0.0009)	(0.0017)	(0.0015)	(0.0006)
HDD × HH livestock	-0.0003	-0.0003	-0.0001	-0.0003	-0.0009	-0.0008***
	(0.0015)	(0.0003)	(0.0004)	(0.0007)	(0.0006)	(0.0003)
HDD	-0.0065*	-0.0016	-0.0014	-0.0041**	-0.0077***	-0.0018**
	(0.0035)	(0.0010)	(0.0011)	(0.0019)	(0.0016)	(0.0007)
HDD × ln(dist pop center)	0.0004	-0.0001	-0.0002*	0.0001	0.0000	0.0001
	(0.0005)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
HDD	-0.0064**	-0.0021**	-0.0023**	-0.0036**	-0.0075***	-0.0017***
	(0.0030)	(0.0008)	(0.0010)	(0.0017)	(0.0014)	(0.0006)
HDD × HH non-farm enterprise	0.0019	-0.0003	-0.0003	-0.0003	-0.0001	-0.0001
	(0.0014)	(0.0003)	(0.0004)	(0.0008)	(0.0006)	(0.0003)
HDD	-0.0051*	-0.0022***	-0.0026***	-0.0040**	-0.0076***	-0.0020***
	(0.0028)	(0.0008)	(0.0009)	(0.0016)	(0.0014)	(0.0006)
HDD × Head wage job (last 7 days)	0.0001	0.0002	0.0011**	-0.0006	0.0007	0.0012***
	(0.0019)	(0.0004)	(0.0005)	(0.0010)	(0.0011)	(0.0004)
Mean Y	5.576	0.829	0.750	.	.	0.199

Table C10. **Effect of HDD on dietary diversity, nutrient adequacy, expenditure, and commercialization, by potential moderators.** This table displays the results from 24 regressions, under the main specification. Adequacy indicators are set to 80% adequacy levels. Coefficients on HDDS can be interpreted as the absolute change in the HDDS for one additional HDD. Coefficients on adequacy indicators can be interpreted as percentage-point change in the likelihood for one additional HDD. Expenditure is expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Annualized expenditure in USD 2020 (originally, food: last 7 days; non-food: last month or last 12 months). Food expenditure represents purchased food. Expenditure information is missing for wave 5. Information on sold harvested quantities is missing for some households (either missing or set to missing because it is higher than harvested quantities or negative). HH livestock, HH non-farm enterprise, and head wage job are dummy variables equal to one if the household manages at least one livestock head, ran at least one non-farm entreprise in last 12 months, was employed in a wage job in the last 7 days. The distance to the nearest population center with more than 20,000 inhabitants is in log kilometers. Conley spatial HAC standard errors (in parentheses). Adq: Adequacy. dist: distance. edu: education. HDDS: Household dietary diversity score. H: household. pop: population. prot: protein.
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	Harvest (kg)	HDDS	Adq prot	Adq iron
Distance 50km, time lag 1 year	(0.0038)***	(0.0025)**	(0.0007)***	(0.0008)***
Distance 50km, time lag 5 years	(0.0038)***	(0.0026)**	(0.0007)***	(0.0008)***
Distance 50km, time lag 10 years	(0.0039)***	(0.0027)*	(0.0007)***	(0.0009)***
Distance 100km, time lag 1 year	(0.0046)***	(0.0028)*	(0.0008)***	(0.0009)***
Distance 100km, time lag 5 years	(0.0047)***	(0.0028)*	(0.0008)***	(0.0009)***
Distance 100km, time lag 10 years	(0.0047)***	(0.0029)*	(0.0008)***	(0.0009)***
Distance 200km, time lag 1 year	(0.0056)***	(0.0030)*	(0.0008)***	(0.0009)***
Distance 200km, time lag 5 years	(0.0056)***	(0.0031)*	(0.0009)***	(0.0009)***
Distance 200km, time lag 10 years	(0.0057)***	(0.0032)*	(0.0009)**	(0.0009)***

Table C11. **Spatial-HAC standard errors sensitivity.** Adequacy indicators are set to 80% adequacy levels. Conley spatial HAC standard errors on the HDD coefficient for the main specification. Adq: Adequacy. HDDS: Household dietary diversity score. prot: protein.
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	Millet	Potato	Onion	Banana	Beef	Egg	Fish	Groundnut	Milk
GDD in growing season	0.0003	0.0004	-0.0030***	-0.0011	0.0006	0.0021	0.0004	0.0019***	0.0000
	(0.0003)	(0.0012)	(0.0011)	(0.0014)	(0.0012)	(0.0020)	(0.0009)	(0.0007)	(0.0022)
HDD in growing season	-0.0028	0.0182	-0.0244***	-0.0238**	-0.0019	0.0219	-0.0041	0.0119*	-0.0168
	(0.0026)	(0.0131)	(0.0090)	(0.0117)	(0.0102)	(0.0196)	(0.0086)	(0.0064)	(0.0172)
Cluster FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.454	0.586	0.398	0.607	0.450	0.718	0.510	0.521	0.545
Clusters	266	80	157	145	427	100	355	185	41
Observations	861	183	457	396	1,383	248	1,113	447	98

Table C12. **Temperatures and food prices.** Sample for each item contains enumeration areas observed for at least three waves and with at least two periods with non-missing information. Variables are expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Conley spatial HAC standard errors (in parentheses).

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	< 5 yo	15-65 yo	> 65 yo
GDD in growing season	-0.0001	0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0000)
HDD in growing season	-0.0005	0.0010	-0.0001
	(0.0006)	(0.0007)	(0.0001)
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes
R^2	0.622	0.792	0.578
Observations	8,949	8,941	8,949

Table C13. **Temperatures and household composition.** Each age group is expressed as the logarithm of total household member in that age range, thus coefficients can be interpreted as the relative percentage change for one additional HDD. I set the dependent variable (logarithm) to zero for all zero values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors (in parentheses).
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	Share of total area (ext. margin)				Intensive margin (kg)
	Mixed cropping	Pesticides	Organic fert.	Inorganic fert.	Inorganic fert.
GDD in growing season	0.0001	-0.0001	-0.0003***	0.0002	-0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
HDD in growing season	0.0006	0.0004	-0.0000	0.0008	-0.0046***
	(0.0007)	(0.0008)	(0.0010)	(0.0011)	(0.0017)
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes
R^2	0.550	0.529	0.509	0.598	0.853
Observations	9,006	9,006	9,006	9,006	9,006
Mean Y	0.678	0.180	0.116	0.380	.

Table C14. **Temperatures and farm household productive response.** Conley spatial HAC standard errors (in parentheses). Ext.: extensive margin. FE: fixed effects. Int.: intensive margin.
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	Total	Family		Hired	
	Int.	Ext.	Int.	Ext.	Int.
GDD in growing season	0.0009	-0.0001**	0.0010	0.0001	0.0005*
	(0.0009)	(0.0000)	(0.0009)	(0.0002)	(0.0003)
HDD in growing season	0.0048	-0.0004	0.0059	-0.0006	0.0016
	(0.0057)	(0.0002)	(0.0059)	(0.0013)	(0.0020)
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month-of-int FE	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes
R^2	0.690	0.391	0.704	0.537	0.844
Observations	9,006	9,006	9,006	9,006	9,006
Mean Y	.	0.985	.	0.679	.

Table C15. **Temperatures and farm labor during the agricultural season.** Conley spatial HAC standard errors (in parentheses). Ext.: extensive margin. FE: fixed effects. Int.: intensive margin. SOB: small-own business.
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	Energy	Protein	Iron	Zinc	Vitamin A
60%	-0.0022 (0.112) [0.335]	-0.0010 (0.189) [0.416]	-0.0022 (0.013) [0.047]	-0.0011 (0.256) [0.427]	-0.0002 (0.783) [0.972]
80%	-0.0001 (0.948) [0.972]	-0.0027 (0.007) [0.034]	-0.0033 (0.007) [0.034]	-0.0004 (0.778) [0.972]	-0.0003 (0.732) [0.972]
100%	0.0001 (0.972) [0.972]	-0.0036 (0.003) [0.034]	-0.0020 (0.194) [0.416]	0.0024 (0.225) [0.422]	-0.0001 (0.926) [0.972]

Table C16. **Robustness: Multiple hypothesis testing - Effect of HDD on nutrient adequacy.** This table is a robustness analysis for Figure 5. Each nutrient adequacy represents a dummy equal to one if a household meets the intake requirement at various thresholds (60%, 80%, and 100%). Coefficients have been divided by the respective dependent variable sample mean, and can be interpreted as the relative percentage change in the likelihood of meeting the requirement for one additional HDD. p-values built using Conley spatial HAC standard errors are in parentheses. Benjamini and Hochberg (1995)'s false discovery rate q-values are in squared brackets.
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	Estimate	p-value	q-value
Cereals	-0.0001	0.571	0.661
Roots & tubers	-0.0009	0.442	0.589
Vegetables	0.0002	0.606	0.661
Fruits	-0.0071	0.003	0.032
Meat	-0.0042	0.006	0.033
Eggs	-0.0211	0.011	0.042
Fish & seafood	0.0015	0.142	0.244
Pulses	0.0018	0.040	0.095
Milk	-0.0006	0.824	0.824
Oil/fats	0.0008	0.028	0.085
Sugar/honey	-0.0018	0.360	0.540
Miscellaneous	0.0015	0.104	0.208

Table C17. **Robustness: Multiple hypothesis testing - Effect of HDD on consumption likelihood, by food group.** This table is a robustness analysis for Figure B9. Each food group represents a dummy for household consumption in the last 7 days, but coefficients have been divided by the respective sample means, thus coefficients can be interpreted as the relative percentage change in the likelihood of consumption for one additional HDD. Conley spatial HAC standard errors are used to build the p-values. Benjamini and Hochberg (1995)'s false discovery rate q-values are presented in the last column.
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	Purchased			Own-production		
	Estimate	p-value	q-value	Estimate	p-value	q-value
Cereals	-0.0012	0.659	0.830	0.0018	0.302	0.679
Roots & tubers	0.0007	0.585	0.830	-0.0012	0.423	0.725
Vegetables	-0.0075	0.005	0.045	-0.0018	0.111	0.325
Fruits	-0.0008	0.368	0.679	-0.0017	0.012	0.072
Meat	-0.0030	0.006	0.045	0.0004	0.067	0.292
Eggs	-0.0001	0.797	0.833	0.0003	0.122	0.325
Fish & seafood	0.0014	0.345	0.679	0.0003	0.333	0.679
Pulses	-0.0049	0.000	0.009	0.0005	0.622	0.830
Milk	0.0025	0.073	0.292	0.0005	0.116	0.325
Oil/fats	0.0002	0.884	0.884	0.0002	0.749	0.833
Sugar/honey	0.0004	0.799	0.833	-0.0000	0.604	0.830
Miscellaneous	-0.0017	0.499	0.799	-0.0001	0.691	0.830

Table C18. **Robustness: Multiple hypothesis testing - Effect of HDD on energy intake, by food group and source of consumption.** This table is a robustness analysis for Figure 6. Each food group is expressed as the logarithm of total energy intake, thus coefficients can be interpreted as the relative percentage change for one additional HDD. I set the dependent variable (logarithm) to zero for all zero consumption values and include a dummy variable in the regression to account for this data transformation. Conley spatial HAC standard errors are used to build the p-values. Benjamini and Hochberg (1995)'s false discovery rate q-values are presented in the last column for each source of consumption.
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	Estimate	p-value	q-value
Millet	-0.0028	0.276	0.415
Potato	0.0182	0.166	0.373
Onion	-0.0244	0.007	0.063
Banana	-0.0238	0.043	0.190
Beef	-0.0019	0.853	0.853
Egg	0.0219	0.266	0.415
Fish	-0.0041	0.638	0.718
Groundnut	0.0119	0.063	0.190
Milk	-0.0168	0.334	0.429

Table C19. **Robustness: Multiple hypothesis testing - Effect of HDD on food prices.** This table is a robustness analysis for Table C12. Sample for each item contains enumeration areas observed for at least three waves and with at least two periods with non-missing information. Variables are expressed in logarithms, thus coefficients can be interpreted as the relative percentage change for one additional HDD. Conley spatial HAC standard errors are used to build the p-values. Benjamini and Hochberg (1995)'s false discovery rate q-values are presented in the last column.
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