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Drought Exposure and Food-Security Transitions in Sub-Saharan Africa: A Hidden Markov Approach

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Abstract

This paper examines food-security dynamics in Sub-Saharan Africa using a Hidden Markov Model and harmonized LSMS-ISA panel data for Ethiopia, Malawi, and Nigeria across four survey waves. We model household dietary diversity as an observed indicator of an underlying food-security regime and study how early drought exposure shapes transitions between latent states. Climate stress is measured using an early drought-warning indicator based on the 3-month Standardized Precipitation Evapotranspiration Index. Model selection identifies two regimes based on low and high dietary diversity. Transitions are strongly asymmetric: households in the high-diversity state show high persistence, with a probability of 0.92 of remaining there, whereas one in three food-insecure households fails to transition upward, pointing to a structurally disadvantaged subset requiring targeted intervention. Early drought exposure is associated with a 9.8 percentage-point lower probability of belonging to the high-diversity state. Female-headed households are 5.9 percentage points less likely to belong to that state, whereas urban households are 20.6 percentage points more likely. The results are robust to different estimators, alternative SPEI accumulation periods, a drought-onset indicator, crop-adjusted drought exposure, and an alternative binary HDDS outcome defined relative to the country-specific median. Subnational estimates reveal substantial spatial heterogeneity in drought effects. The findings support food policies that link early-warning systems to adaptive safety nets, rural market access, and geographically targeted interventions.

Keywords: Food security, Latent variable, Climate change, Drought, Africa
JEL classification: Q18, O1, I32, C33

1. Introduction

Food insecurity persists as one of the main structural barriers to development in Sub-Saharan Africa. Recent global evidence shows that progress in reducing hunger has slowed markedly, and the region continues to record the highest prevalence of undernutrition and moderate or severe food insecurity worldwide (FAO et al., 2024). In these settings, food insecurity is compounded by the interaction of climatic shocks, weak market integration, economic instability, and persistent structural inequalities. The effects of these vulnerabilities are most pronounced where households depend on rain-fed agriculture, spend a large share of their income on food, and have limited access to insurance or formal safety nets. As a result, transitory shocks can generate persistent welfare losses.[1]

Climate variability is especially important in this context. A growing literature shows that weather shocks affect food security through multiple channels, including lower agricultural production, higher food prices, declining labor income, and worsening health conditions (Kubik and May, 2018; Barrett, 2021). These effects are often strongest in low-income settings, where households spend a large share of income on food and are heavily dependent on rain-fed agriculture. Climate stress may therefore reduce both the quantity and the quality of food consumption, with potentially lasting consequences for vulnerable groups such as children and pregnant women (Cheah et al., 2025). At the same time, vulnerability is not uniform. Access to assets, livelihood diversification, local institutions, and gender constraints differentiate households' capacity to cope with adverse shocks (Acosta et al., 2021; Antonelli et al., 2022; Ranucci et al., 2025). Against this background, identifying how early climatic stress propagates into lasting food security deterioration — rather than merely correlating drought with observed dietary outcomes at a given point in time — requires an empirical framework capable of tracking latent household conditions over time. This is the central substantive question that motivates our analysis.

A fundamental challenge in food security research is that the phenomenon remains inherently latent and is only imperfectly observed. Although the concept is multidimensional, covering availability, access, utilization, and stability (FAO, 2006), most empirical analyses rely on indicators that cap-

[1] Recent debates have also emphasized the importance of broader conceptual extensions that account for agency and sustainability (Clapp et al., 2022).

ture only one dimension at a time. Dietary diversity, caloric intake, food expenditures, and experiential measures are all informative, but none fully identifies the underlying condition researchers seek to study (Carletto et al., 2013; Jones et al., 2013; Leroy et al., 2015). This measurement gap is particularly consequential in panel settings. Two households may exhibit identical dietary patterns in each period, despite differing substantially in their risk exposure, coping capacity, and vulnerability to future deterioration. Standard empirical approaches often struggle to recover these latent disparities or to characterize the dynamic transitions between security states over time.

Against this backdrop, this paper makes three contributions to food-policy research. First, it conceptualizes household food security as a dynamic latent process rather than a static observed outcome. This allows us to distinguish persistence, upward mobility, and downward risk across food-security regimes. Second, it shows that early drought exposure is robustly associated with a lower probability of reaching or remaining in the high dietary-diversity regime, even when water deficits are measured at relatively mild stages. Third, it documents how this vulnerability is structured by household and territorial characteristics. Specifically, female-headed households are less likely to occupy the high-diversity regime, urban households are substantially more likely to do so, and drought effects vary sharply across subnational regions. These findings point to the value of linking climate early-warning systems to geographically targeted food-security interventions.

We pursue these objectives through a latent variable framework based on a Hidden Markov Model. Rather than attempting to settle the debate on food security measurement (Manikas et al., 2023), our contribution provides an analytical framework to better understand the latent mechanisms and transitions that define the phenomenon. Using harmonized LSMS-ISA panel data for Ethiopia, Malawi, and Nigeria, we model the evolution of household food security over four survey waves and use the Household Dietary Diversity Score (HDDS) as the observed indicator of the latent state. Widely applied in developing-country contexts, the HDDS captures a key dimension of food access and diet quality while maintaining a strong association with nutritional adequacy (Fongar et al., 2019; Mehraban and Ickowitz, 2021). Although it does not encompass the full concept of food security, it provides a tractable and policy-relevant measure for longitudinal analysis.

We proxy climate variability using an early drought-warning indicator derived from the 3-month SPEI, coded as one when the index falls below -0.5. This threshold is intended to capture relatively early stages of water

stress that may already adversely affect agricultural production and food security. A series of robustness checks supports the choice of this cutoff. First, we implement falsification exercises to assess whether alternative time scales associated with meteorological drought and water storage alter the interpretation of the results. Second, we estimate an additional specification based on a traditional linear model to rule out the possibility of a basic inconsistency relative to the HMM estimates. Third, we extend the analysis of weather shocks based on the regional short-term SPEI indicator by constructing a drought-onset measure, which is assumed to have a smaller effect on HDDS. The empirical specification also includes controls for the gender of the head of household, urban residence, and fixed regional effects, thereby accounting for structural and territorial differences in access to food and exposure to vulnerability.

The paper relates to three strands of literature. First, it is related to work on climate variability and household welfare, which shows that drought and other weather shocks reduce agricultural output and worsen food consumption outcomes in low-income settings (d'Agostino et al., 2025), although recent setbacks, combined with the persistence of high levels of deprivation, have reinforced the vulnerability of populations already exposed to armed conflict, climate change, extreme weather conditions, and economic slowdowns (Brück and d'Errico, 2019; Martin-Shields and Stojetz, 2019; Wiebe et al., 2019). Second, it relates to the literature on food security measurement, which emphasizes both the usefulness and the limitations of standard indicators, including dietary diversity-based measures (Swindale and Bilinsky, 2006; Usman and Haile, 2022). Third, it contributes to a smaller set of studies using latent-variable methods to analyze food insecurity conditions that are only partially observed, including the analysis of food choice behavior (Alemu and Olsen, 2019), the experience and transitions of food insecurity (Waqo et al., 2025), and the dynamics of global food access (Bartolucci and Farcomeni, 2022). Compared to this literature, our focus is on the dynamic interaction between drought exposure and latent food security regimes in a comparative panel setting in Sub-Saharan Africa.

Our results point to a relatively simple but substantively meaningful latent structure. A two-state specification provides the best fit for the data, distinguishing between a low dietary diversity regime – associated with greater food insecurity – and a high dietary diversity regime – associated with more secure conditions. The estimated transition matrix reveals strongly asymmetric state dependence: households in the high-diversity state exhibit high per-

sistence, whereas those in the low-diversity state follow a less stable trajectory — with meaningful upward mobility for the majority, but a non-negligible share remaining persistently food-insecure. A central finding is that early drought exposure – measured through a mild SPEI threshold designed to capture the early stages of water deficit rather than full drought conditions – is associated with a substantially lower probability of belonging to the high dietary-diversity regime. This result is remarkably stable for alternative accumulation periods, threshold definitions, crop-specific specifications, and an alternative binary definition of HDDS. Furthermore, female-headed households are negatively associated with that probability of belonging to the dietary-secure regime, whereas urban residence exerts a substantial positive effect. Finally, spatial analysis reveals significant subnational heterogeneity in the magnitude of climatic shocks, suggesting that vulnerability is strongly mediated by local conditions.

The findings have at least two broader implications. First, the persistence of latent food-security regimes suggests that one-off interventions are unlikely to be sufficient in contexts where structural disadvantage is self-reinforcing. In addition, the heterogeneity of the climatic effects implies that aggregate policy responses may not adequately identify and address the needs of the most vulnerable areas. Second, the robustness of the drought effect, even during the initial stages of water deficit, underscores the importance of early-warning systems and anticipatory action, rather than policy responses that are triggered only once drought conditions have fully materialized.

The rest of the paper proceeds as follows. Section 2 presents the empirical framework. Section 3 describes the data and key variables. Section 4 reports the main results. Section 5 presents robustness checks, and Section 6 concludes.

2. Hidden Markov to model food security

We explore the latent structures that shape the spatial and temporal evolution of food security across different contexts in Sub-Saharan Africa. We use household dietary diversity (HDDS) as the observed indicator of food security. Unlike a standard Markov chain estimated on observed HDDS categories, the HMM does not treat the dietary diversity score as an error-free measure of the underlying food-security condition. Instead, it models the observed score as a noisy signal of a latent state, allowing the model to recover household-specific food-security trajectories that account for measurement

error and unobserved heterogeneity in ways that observed transition matrices cannot. Let $\mathbf{Y}^{(t)}$ denote the vector of r categorical response variables observed at time t, with $t = 1, \ldots, T$ and $T = 4$, which are grouped following Vaitla et al. (2017) into three categories: 0 (severely food insecure), 1 (moderately food insecure), and 2 (food secure). Let $\mathbf{X}^{(t)}$ denote the vector of individual covariates observed at occasion t. When covariates are incorporated into the latent model, the observed responses are assumed to reflect an underlying individual characteristic of interest based on food security, that is not directly observable and may evolve over time. In this context, it is relevant modeling how covariates influence their latent distribution (Bartolucci et al., 2017).

A differential logit parameterization is adopted for the initial and transition probabilities. Under this formulation, the initial probability of belonging to latent state u and the probability of moving from state $\bar{u}$ at time $t-1$ to state u at time t are written as:

$$\log \frac{\pi^{(1)}_{u|x}}{\pi^{(1)}_{1|x}} = \beta_{0u} + \mathbf{x}^\top \beta_{1u}, \tag{1}$$

and

$$\log \frac{\pi^{(t)}_{u|\bar{u}x}}{\pi^{(t)}_{\bar{u}|\bar{u}x}} = \gamma_{0\bar{u}u} + \mathbf{x}^\top (\gamma_{1u} - \gamma_{1\bar{u}}). \tag{2}$$

Assuming conditional independence across individuals given the covariates, the log-likelihood of the model is:

$$\ell(\theta) = \sum_{i=1}^{n} \log P(\tilde{\mathbf{y}}_i \mid \tilde{\mathbf{x}}_i). \tag{3}$$

The parameter vector θ is estimated by maximum likelihood through the EM algorithm (Baum et al., 1970; Dempster et al., 1977). The expected complete-data log-likelihood can be written compactly as:

$$\begin{aligned}\ell^*(\theta) = &\sum_{j=1}^{r}\sum_{t=1}^{T}\sum_{u=1}^{k}\sum_{x}\sum_{y=0}^{c_j-1} a^{(t)}_{juxy} \log \phi^{(t)}_{jy|ux} + \sum_{u=1}^{k}\sum_{x} b^{(1)}_{ux} \log \pi^{(1)}_{u|x} \\ &+ \sum_{t=2}^{T}\sum_{\bar{u}=1}^{k}\sum_{u=1}^{k}\sum_{x} b^{(t)}_{\bar{u}ux} \log \pi^{(t)}_{u|\bar{u}x}.\end{aligned} \tag{4}$$

Here, $a_{juxy}^{(t)}$ denotes the number of individuals who, at occasion t and for covariate profile x, are in latent state u and report category y for response variable $Y_j^{(t)}$; $b_{ux}^{(1)}$ is the corresponding frequency of initial latent-state membership; and $b_{\bar{u}ux}^{(t)}$ is the number of transitions from state $\bar{u}$ to state u.

The EM algorithm alternates between two steps until convergence of $\ell^*(\theta)$. In the E-step, the expected sufficient statistics in the expression above are computed conditionally on the observed responses and the current parameter estimates. This step relies on forward and backward recursions. The forward recursion processes the panel sequentially and combines the initial probabilities, the transition structure, and the conditional response probabilities to evaluate, on each occasion, the likelihood of the observed history under each latent state. The backward recursion then exploits information from subsequent observations to recover smoothed posterior probabilities for state membership and for adjacent-state transitions. These posterior quantities deliver the expected counts required by the M-step. In the M-step, $\ell^*(\theta)$ is maximized with respect to θ, thereby updating the parameters. The detailed algebra of the forward-backward recursions is reported in Appendix A.1 in the Supplementary Materials.

A key issue in latent Markov models concerns the choice of the number of latent states. Among the available criteria, the Bayesian Information Criterion (BIC) is especially attractive because, under suitable regularity conditions, it provides a consistent estimate of the number of mixture components as the sample size increases (Keribin, 2000). We therefore select the model based on:

$$BIC = -2\hat{\ell} + p\log(n), \tag{5}$$

where $\hat{\ell}$ denotes the maximized log-likelihood and p the number of free parameters. Following standard practice, we estimate the model for increasing values of k and retain the specification that minimizes the BIC.

Once the model has been estimated, we also recover the most likely latent trajectory for each individual conditional on the full sequence of observed responses and covariates. To this end, we use a Viterbi-type decoding procedure adapted to ordered responses and covariate-dependent transition and probabilities (Viterbi, 1967; Juang and Rabiner, 1991). Whereas the forward-backward recursions employed in the E-step are used to compute smoothed posterior probabilities and expected sufficient statistics, the decoding step serves a different purpose, assigning each individual to the single most likely sequence of latent states over time. The algorithm evaluates, at each occa-

sion and for each candidate state, the probability of the best partial path ending in that state and stores the corresponding predecessor. Starting from the final period, the optimal latent sequence is then recovered by backward tracing. This procedure yields an interpretable subject-specific classification of food-security histories that is fully consistent with the estimated hidden Markov structure. For brevity, the decoding algorithm for the optimal latent path is reported in Appendix A.2 in the Supplementary Materials.

3. Data and variables

We primarily rely on the data provided by the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA)[2]. The dataset comprises information from approximately 59,000 households and is nationally representative of the countries surveyed. It also accurately reflects the agricultural sector of households and smallholders within these countries. The longitudinal design enables the tracking of households over time, providing valuable insights into changes and trends across survey rounds (Bentze and Wollburg, 2024). From this source, we retrieved harmonized data covering the period 2008-2019 and organized in four subsequent waves for Ethiopia, Malawi, and Nigeria.

The selection of countries is based on multiple criteria. Specifically, it required that each country had at least four waves of data collection to ensure a sufficient temporal span for the analysis. Furthermore, waves needed to be implemented over sufficiently comparable time periods to enhance the consistency and comparability of the data between countries. In addition, all data were collected with reference to the head of the household. Appendix B provides information on waves by country, survey years, and number of observations.

3.1. Household Dietary Diversity Score

The Household Dietary Diversity Score (HDDS) is employed to investigate the underlying structure and evolution of food security in the three selected African countries. HDDS primarily reflects food access (Jones et al.,

[2]The LSMS-ISA is a unique system of longitudinal surveys designed to improve the understanding of household and individual welfare, livelihoods and smallholder agriculture in Africa and implemented by the World bank. See: https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA.

Table 1: Descriptive statistics by country

	Observations	Mean	Std.Dev	Min	Max
Panel A - Full sample					
HDDS	42,380	1.7390	0.5185	0	2
Early drought warning	42,380	0.2006	0.4005	0	1
Gender	42,380	0.2453	0.4302	0	1
Urban	42,380	0.1515	0.3585	0	1
Panel B - Ethiopia					
HDDS	12,946	1.4630	0.6502	0	2
Early drought warning	12,946	0.2164	0.4118	0	1
Gender	12,946	0.2396	0.4269	0	1
Urban	12,946	0.0878	0.2831	0	1
Panel C - Malawi					
HDDS	13,459	1.9050	0.3237	0	2
Early drought warning	13,459	0.3023	0.4593	0	1
Gender	13,459	0.2939	0.4556	0	1
Urban	13,459	0.1876	0.3904	0	1
Panel D - Nigeria					
HDDS	15,975	1.8230	0.4361	0	2
Early drought warning	15,975	0.1022	0.3029	0	1
Gender	15,975	0.2088	0.4065	0	1
Urban	15,975	0.1726	0.3780	0	1

Notes: Household Dietary Diversity Score (HDDS) values range from 0 to 2 according to the following cutoff categories: 0–3 (severely food insecure), 4–5 (moderately food insecure), and 6–12 (food secure). For the dichotomous variables, a value of 1 indicates an SPEI value below -0.5 for early drought warning, a female household head for gender, and an urban settlement with at least 20,000 inhabitants for urban.

2013), as the consumption of a wider variety of foods generally implies greater economic or physical access to food (Swindale and Bilinsky, 2006), and to a lesser extent serves as a proxy for food utilization by capturing dimensions of dietary quality and the nutritional adequacy of the household's food basket (Kennedy et al., 2011).

More specifically, HDDS reflects a household's economic capacity to access a diverse diet and is widely employed as an indicator of the food access dimension of food security (Leroy et al., 2015). It is based on the concept of dietary diversity, measured by counting the number of different food groups consumed over a specific reference period, typically using self-reported data on the consumption of 12 food groups in the previous 24 hours[3]. Although dietary diversity scores have been formally validated as measures of nutrient adequacy and food security mainly for 24-hour recall periods among women and children (Verger et al., 2019), existing evidence suggests that longer recall periods at the household level remain informative. For example, 7-day HDDS measures are significantly correlated with individual 24-hour recall scores (Fongar et al., 2019), and are widely used in the literature as proxies for dietary quality and food access (e.g., Sibhatu et al. (2015); Mehraban and Ickowitz (2021); Usman and Haile (2022); Nguyen and Qaim (2025)). Given the computational requirements of our analytical methodology and following Vaitla et al. (2017), we recoded HDDS into three ordered categories of progressively increasing values, each corresponding to a higher level of dietary diversity and, accordingly, to a higher level of food security[4]. Table 1 reports the descriptive statistics for HDDS in each country as well as for the covariates of the model. As a robustness check, we also construct an alternative binary HDDS outcome. For each country, we calculate the median of the country-specific HDDS distribution and define a dichotomous indicator equal to one when the household's HDDS lies above that median and zero otherwise. This alternative specification serves two purposes. First, it verifies that the main results are not driven by the three-category classifica-

[3]The following 12 food groups are used to calculate the HDDS indicator: cereals, roots and tubers (considered staple foods); vegetables, fruits, meat, eggs, fish and seafood, pulses, legumes, and nuts, and milk and milk products (considered micronutrient-rich foods); oils and fats, and sugar and honey (considered energy-dense foods); and miscellaneous foods. For each of the 12 food groups, households receive a score of 1 if the food group was consumed in the preceding 24 hours, and 0 if it was not. The overall HDDS is then calculated by summing these values, resulting in a score ranging from 0 to 12, corresponding to the total number of different food groups consumed by the household during the reference period. See https://inddex.nutrition.tufts.edu/data4diets/indicator/household-dietary-diversity-score-hdds

[4]HDDS values between 0 and 3 were grouped into Category 0 (severely food insecure); values between 4 and 5 into Category 1 (moderately food insecure); values between 6 and 12 into Category 2 (food secure).

tion adopted in the benchmark model. Second, it allows the latent Markov framework to be re-estimated using a simpler country-specific threshold that is less dependent on externally imposed cut-offs.

Now, we contextualize the observed HDDS values against the existing empirical literature on dietary patterns in each of the three countries. Ethiopia recorded one of the lowest mean HDDS scores (1.46 on average). This pattern aligns with empirical evidence from national surveys showing that, in many Ethiopian households, diets are heavily dominated by cereals and legumes and feature relatively low consumption frequencies of nutrient-rich foods such as lean meats, fruits, and vegetables (Workicho et al., 2016), resulting in widespread and severe micronutrient deficiencies (Mekonnen et al., 2020). A distinctive feature of the Ethiopian context is the strong seasonal character of dietary vulnerability, with significant fluctuations in both diet composition and caloric intake across agricultural seasons (Hirvonen et al., 2016). Household income, market proximity, and access to services are consistently identified as the main structural determinants of dietary diversity (Mekonnen et al., 2020; Usman and Haile, 2022).

Malawi displays a similarly monotonous dietary pattern, with the food system heavily centered on maize – accounting for approximately half of total plant-based caloric intake – and with micronutrient-rich foods remaining severely under-consumed (Jones et al., 2014; Schneider et al., 2022). As in Ethiopia, households' ability to diversify their food basket is tightly linked to income levels, market access, and farm production diversity (Koppmair et al., 2017).

Nigeria presents a more heterogeneous picture, reflecting the country's pronounced urban–rural divide. Despite a comparatively higher mean HDDS, fruits and animal-source foods remain the least consumed food groups across the country, with rural households – particularly in the north – facing the most acute nutritional deficiencies (Mekonnen et al., 2021). Food expenditure, asset ownership, and location are consistently identified as the key structural determinants of dietary diversity (Akerele et al., 2023).

The use of harmonized HDDS data from the LSMS-ISA offers several advantages that are particularly relevant to our analytical framework. The data are collected using consistent methodologies across countries and survey rounds, thereby enabling reliable cross-sectional and longitudinal comparisons (Carletto and Gourlay, 2019). The survey is nationally representative and tracks households over time, making it possible to analyze the dynamics of dietary patterns and the factors driving changes in food security. Finally,

the integration of agricultural and socioeconomic variables in LSMS-ISA provides a more comprehensive basis for understanding the determinants of dietary diversity.

3.2. Climate variability and other controls

Building on the food security patterns documented above, we now turn to the covariates included in the model. Among these, climate variability – and drought in particular – represents the key control variable of interest, given its well-established role as a structural driver of food insecurity in sub-Saharan Africa (Wheeler and von Braun, 2013; Deschênes and Greenstone, 2007). Drought is a slow-onset and often insidious climatic hazard that arises from sustained deviations in precipitation from long-term norms. When such deficits persist, they generate water shortages that adversely affect both human activities and ecological systems (Wilhite and Pulwarty, 2017).

To capture these dynamics, we employ the Standardized Precipitation Evapotranspiration Index (SPEI), derived from the Global Drought Crop Monitoring (GDCM) dataset, which provides near real-time global information on drought conditions at a 0.5° spatial resolution with weekly updates since 1979. A major advantage of the SPEI is its multiscale nature, as it combines precipitation and potential evapotranspiration, reflecting the climatic water balance and accounting for temperature-driven evaporative demand (Vicente-Serrano et al., 2023, 2010). This feature makes the index particularly suitable for assessing climate stress in agricultural systems, where both water availability and heat conditions jointly shape crop productivity. Consistent with the literature, negative SPEI values, which indicate drought conditions, have been associated with lower agricultural yields, greater price volatility, and increased food insecurity, especially in rain-fed systems such as those prevalent in Sub-Saharan Africa (Lobell et al., 2011).

In the empirical analysis, we construct an early drought-warning indicator based on the short-term SPEI, using a three-month accumulation period and assigning a value of one when the index falls below -0.5. By adopting a threshold that is considerably milder than conventional SPEI-based drought classifications (Vicente-Serrano et al., 2010), the indicator is intended to capture the early stages of hydro-climatic imbalance, in which water availability begins to deviate from long-term norms, but has not yet reached the severity typically associated with drought. The rationale for this choice is

that, in rain-fed agricultural systems such as those examined here, even relatively modest precipitation deficits may be sufficient to induce soil-moisture stress, affect crop development, and ultimately reduce household dietary diversity. Waiting until conditions deteriorate to conventional drought thresholds would risk overlooking the initial phase of agricultural stress through which drought begins to translate into food insecurity. Within this framework, the use of relatively mild SPEI thresholds has received increasing support in the recent literature (Wang et al., 2025). This specification is also consistent with previous research suggesting that shorter accumulation windows are more appropriate for capturing meteorological and agricultural drought dynamics (Vicente-Serrano et al., 2012). Nevertheless, because alternative accumulation periods may reflect different hydrological processes, we also conduct robustness checks using SPEI measures computed over 6-, 9-, and 12-month horizons. To account for local agricultural heterogeneity, the binary early drought indicator is further matched to the predominant crop in each region, while maintaining the same temporal aggregation as in the baseline specification. This allows us to capture crop-specific exposure to climatic stress and to assess the sensitivity of the estimated relationship between drought and food security to the underlying agricultural context.

We complement the climate variable including additional controls drawn from the LSMS-ISA database. Specifically, we control for the gender of the household head and for urban residence. The gender variable takes the value of one if the household head is female. From the sample, 24.5% of households are female-headed (Table 1), widely documented in the literature as facing a systematically higher exposure to food insecurity, due to more limited access to land, credit and productive resources (Doss, 2018). The urban variable equal to one for households located in settlements with at least 20,000 inhabitants and serves as a proxy for the potential advantages associated with urban residence, particularly in terms of market access, income opportunities, and dietary diversity (Headey et al., 2019). Finally, fixed regional effects are included to account for unobserved heterogeneity related to structural, socioeconomic, and environmental differences across regions.

4. Results

We begin the empirical analysis by determining the number of latent states that most appropriately characterizes the observed dynamics in dietary diversity of the household. As reported in Table 2, the log-likelihood

improves monotonically as the number of latent classes increases from one to four. However, the Bayesian Information Criterion (BIC) reaches its minimum under the two-class specification. This result suggests that the longitudinal evolution of food security can be summarized by a latent structure composed of two distinct regimes, pointing to the existence of persistent and structurally differentiated states of food security that are not directly observable from the raw HDDS distributions alone (Carletto et al., 2013; Jones et al., 2013).

Table 2: Data analysis results for number of latent classes = 1,...,4

Latent class	Log Likelihood	AIC	BIC
1	-44787.26	89578.51	89594.13
2	-21770.51	43791.01	**44766.79**
3	-21454.26	43408.51	45360.06
4	-21383.73	43521.45	46464.39

Notes: The coefficient written in bold highlights the model with the optimal number of latent classes according to the BIC criterion.

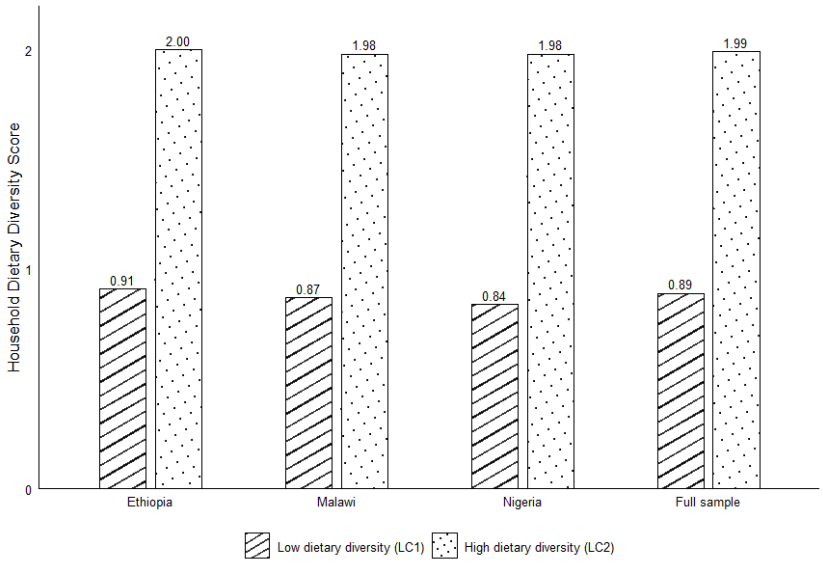
The interpretation of these two latent states is clarified by the conditional response probabilities reported in Table 3. The first latent class is associated with a low profile of dietary diversity. Conditional on a household being in this class, the probability of being moderately food insecure is 0.649, while the probabilities of being severely food insecure and food secure are 0.151 and 0.199, respectively. This pattern identifies a vulnerable regime in which households are concentrated primarily in the intermediate category of food insecurity yet remain exposed to a non-negligible risk of severe deprivation. By contrast, the second latent class corresponds to a high profile of dietary diversity. For households in this class, the probability of being food secure is 0.971, whereas the probabilities of being moderately or severely food insecure are close to zero. The estimated conditional probabilities reveal a sharp separation between the two latent regimes, supporting the interpretation of the hidden process as a distinction between structurally disadvantaged and relatively resilient food security conditions, a dichotomy that, as shown below, proves remarkably persistent over time and whose determinants vary substantially across household characteristics and subnational contexts.

Figure 1 provides further validation of this interpretation by mapping the latent classes back to the original HDDS scale. Across all three countries,

Table 3: Conditional response probabilities (latent classes = 2)

Variety diet	Low dietary diversity (LC1)	High dietary diversity (LC2)
Category		
Severely food insecure	0.1515	0.0000
Moderately food insecure	0.6490	0.0290
Food secure	0.1995	0.9710

Figure 1: Average Household Dietary Diversity Score (HDDS) according to each latent class



Notes: The values of the Household Dietary Score on the y-axis refer to our response variable and take the following values: 0 (severely food insecure), 1 (moderately food insecure), 2 (food secure).

the mean HDDS associated with the low dietary diversity class is slightly below one, whereas the corresponding mean for the high dietary diversity class is consistently close to two. These differences are substantial and indicate that the latent classification is not merely a statistical artifact, but reflects meaningful and geographically consistent variation in actual food consumption patterns, lending support to the cross-national comparability

of the estimated regimes

Table 4: Initial and transition probabilities (latent classes = 2)

	Low dietary diversity (LC1)	High dietary diversity (LC2)
Initial probabilities		
	0.2656	0.7344
Transition probabilities		
Low dietary diversity (LC1)	0.3440	0.6560
High dietary diversity (LC2)	0.0800	0.9200

The dynamic features of the model are summarized in Table 4, which reports both the initial probabilities and the transition matrix. At the beginning of the observation period, 26.6% of households are assigned to the low dietary diversity class, while 73.4% belong to the high dietary diversity class, indicating that the more favorable latent condition is the most prevalent in the pooled sample. The transition probabilities reveal that food security dynamic is far from static. Households initially in low dietary diversity state have a probability of 34.4% of remaining there and a probability of 65.6% of moving upward. By contrast, households in the high dietary diversity state exhibit much stronger persistence, with a probability of 92% of remaining there and only a 8% probability of moving downward.

These transition patterns point to an asymmetric dynamic structure with substantive implications. On the one hand, the probability of exiting the disadvantaged state is not only far from negligible but exceeds the probability of remaining trapped within it. This suggests the existence of meaningful pathways to improved food security, potentially linked to changes in income opportunities, agricultural performance, market access, or household coping capacity. However, once households attain the high dietary diversity state, they tend to remain there with a high degree of persistence, making the more favorable regime substantially more stable than the disadvantaged one. This asymmetry indicates that food security trajectories are path dependent: upward mobility is possible, but once a more secure condition is achieved, it becomes considerably easier to maintain than to lose (Antman and McKenzie, 2007; Jalan and Ravallion, 1998). In this sense, the results reinforce

the broader argument that food insecurity should not be interpreted solely through static observed results, since such measures may obscure the deeper persistence and transition mechanisms underlying the dynamics of household welfare (Jones et al., 2013).

Table 5: Parameters affecting the transition probability of belonging to the high dietary diversity latent class

	Coefficient	Odds-ratio	Average Marginal Effect
Early drought warning	-0.5337***	0.5864	-9.8
	(0.0627)		
Gender	-0.3232***	0.7238	-5.9
	(0.0548)		
Urban	1.1793***	3.2520	+20.6
	(0.0945)		

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are reported in parentheses. For the dichotomous variables, a value of 1 indicates an SPEI value below -0.5 for early drought warning, a female household head for gender, and an urban settlement with at least 20,000 inhabitants for urban.

We next examine how the selected covariates affect the probability of belonging to the high dietary diversity latent class. Table 5 shows that all three covariates included in the transition equation are statistically significant and economically meaningful. The coefficient associated with the early drought warning indicator based on the SPEI is negative and highly significant (-0.533). The corresponding odds ratio, equal to 0.586, indicates that drought conditions are associated with a marked reduction in the odds of transitioning to, or remaining in, the high dietary diversity state. In marginal terms, drought exposure lowers the probability of belonging to the favorable latent class by 9.8 percentage points. This result supports the view that climatic stress undermines households' ability to maintain diversified diets (Dillon et al., 2015; Maggio et al., 2019).

A similarly adverse effect emerges for the gender variable. The estimated coefficient is negative (-0.323) and statistically significant, with an odds ratio of 0.723 and an average marginal effect of -5.9 percentage points. This suggests that female-headed households are associated with a systematically lower probability of being in the high dietary diversity state. Although the specific transmission mechanisms cannot be identified within the present

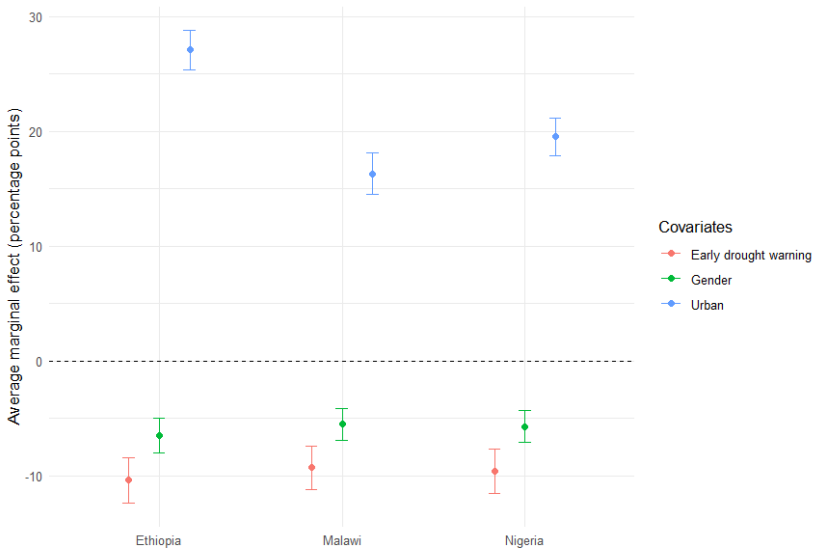
framework, this pattern is consistent with the broader literature emphasizing how labor market segmentation and structural inequalities in access to productive assets (Doss et al., 2018) interact with a heightened gendered vulnerability to environmental shocks to shape food security outcomes (Flatø et al., 2017; Arora, 2023). Hence, latent food security dynamics appear to be influenced not only by environmental shocks, but also by persistent social and demographic disparities.

By contrast, urban residence is associated with a strongly positive effect on the probability of belonging to the high dietary diversity class. The estimated coefficient is 1.179, the odds ratio is 3.252, and the average marginal effect reaches +20.6 percentage points. This finding suggests that households located in urban areas enjoy a substantial advantage in access to more diversified diets, a result consistent with large-scale evidence on the primary drivers of food availability in sub-Saharan Africa (Frelat et al., 2016). Such an effect likely reflects closer proximity to markets, more stable food supply chains, greater income diversification, and broader access to non-farm employment opportunities. At the same time, the magnitude of the urban effect may reveal a clear territorial divide in food security conditions, pointing to the persistent disadvantages and market isolation faced by rural households (Stifel and Minten, 2017).

Figure 2 reports the average marginal effects by country. The negative effect of drought on food security appears to be strongest in Ethiopia (-10.4 percentage points), compared with -9.3 and -9.6 percentage points in Malawi and Nigeria, respectively. Likewise, being female in Ethiopia reduces the probability of transitioning to the latent class associated with higher dietary diversity by approximately -6.5 percentage points, compared with -5.5 and -5.7 percentage points in Malawi and Nigeria. The largest cross-country differences, although uniformly positive, are observed for urban residence: in this case, the probability of belonging to the more favorable latent class increases by 27.1 percentage points in Ethiopia, 16.3 in Malawi, and 19.6 in Nigeria. These results underscore the importance of country-specific conditions in shaping food security dynamics, although the effects of structural covariates appear to be more heterogeneous across countries than those of the climatic covariate.

Figure 3 complements the national-level estimates by showing that climate-related food insecurity operates through place-specific mechanisms. The quartile classification highlights where the drought penalty is most severe within each country, suggesting that food-policy responses should be sen-

Figure 2: Parameters affecting the transition probability to belong to high dietary diversity latent class for each country



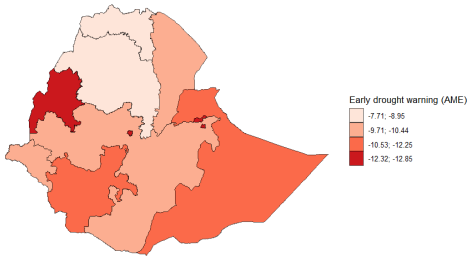
Notes: Values on the y-axis represent average marginal effects. The light-red bar corresponds to the early drought warning variable, which takes the value of 1 when the SPEI is below −0.5. The green bar corresponds to the gender variable, which is equal to 1 if the household head is female. The light blue bar represents the urban variable, which takes the value of 1 if the household resides in an urban area (defined as a settlement with at least 20,000 inhabitants). The horizontal dashed line corresponds to the zero value.

sitive to territorial heterogeneity. This evidence also echoes the broader methodological concern that standard aggregate indicators may overlook hidden structures and context-specific dynamics that are central to understanding food insecurity in fragile settings (Carletto et al., 2013).

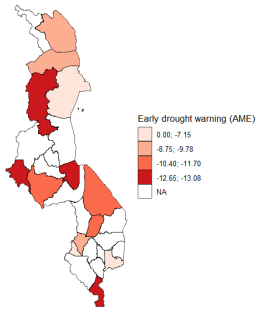
5. Robustness

This section evaluates the stability of the main findings along four dimensions. First, we compare the latent Markov estimates with conventional OLS regressions. Second, we test whether the drought effect depends on the SPEI accumulation window by using 6-, 9-, and 12-month alternatives. Third, we replace the benchmark early drought-warning indicator with a drought-onset measure based on continuously negative SPEI values. Fourth,

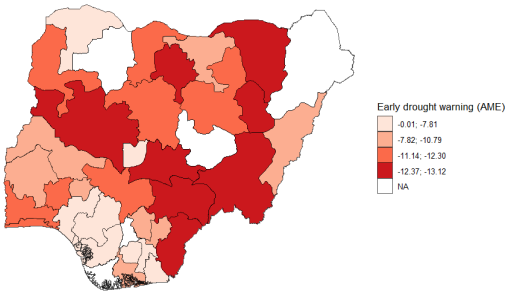
Figure 3: Early drought warning by region, quartiles distribution by national context (Average Marginal Effect)



(a) Ethiopia



(b) Malawi



(c) Nigeria

we assess whether the results depend on the three-category HDDS coding by re-estimating the model with a binary HDDS outcome defined relative to the country-specific median. Together, these exercises assess the sensitivity of the findings to modeling strategy, climate measurement, and food-security measurement.

5.1. OLS estimates

The OLS estimates reported in Table 6 provide a useful robustness check and are broadly consistent with the results obtained from the latent Markov specification in Table 5. In particular, the coefficient associated with early drought (SPEI) remains negative and statistically significant across all sam-

ples, except for Nigeria, confirming that adverse climatic conditions systematically reduce dietary diversity and, consequently, food security.

Similarly, the urban residence variable retains a positive and highly significant coefficient in all specifications, aligning with the strong positive marginal effect estimated in the latent model and reinforcing the evidence of a structural urban advantage in access to diversified diets. The gender variable also displays a negative association in most cases, in line with the latent model result; however, its statistical significance weakens in the Nigerian subsample, further suggesting the presence of cross-country heterogeneity.

Table 6: Robustness: food insecurity estimates by OLS

	Full sample	Ethiopia	Malawi	Nigeria
Early drought warning	-0.0548***	-0.1269***	-0.0158*	0.0069
	(0.0055)	(0.0116)	(0.0066)	(0.0092)
Gender	-0.0661***	-0.1426***	-0.0503***	-0.0163
	(0.0054)	(0.0130)	(0.0060)	(0.0085)
Urban	0.1312***	0.3072***	0.0913***	0.0796***
	(0.0067)	(0.0198)	(0.0073)	(0.0094)
Observations	42,380	12,946	13,459	15,975
Regional FE	Yes	Yes	Yes	Yes
R^2	0.1722	0.0552	0.0367	0.0726

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are reported in parentheses. For the dichotomous variables, a value of 1 indicates an SPEI value below -0.5 for early drought warning, a female household head for gender, and an urban settlement with at least 20,000 inhabitants for urban.

Although the magnitude of the coefficients differs across empirical approaches, the direction and statistical significance of the effects remain remarkably stable, thereby strengthening the overall validity of the main findings. At the same time, the relatively low explanatory power of the OLS models highlights their limited ability to capture the dynamic and latent structure of food security, thus further supporting the adoption of the Hidden Markov framework as a more appropriate tool for modeling persistence and transitions in household dietary outcomes.[5]

[5]The latent state captures both structural conditions and the cumulative effects of drought over time, whereas an OLS model assumes a static and contemporaneous rela-

5.2. Robustness to alternative SPEI accumulation periods

Because drought processes unfold over varying temporal horizons, the choice of the accumulation period for the SPEI may critically affect the interpretation of climatic stress. Incorporating multiple timescales enables a distinction between different forms of drought exposure across hydro-climatic systems. Shorter accumulation periods are typically associated with meteorological and agricultural drought, as they capture relatively immediate precipitation deficits and soil moisture stress affecting crop production. By contrast, longer timescales are more informative regarding hydrological drought and broader changes in water storage, which tend to operate through more gradual transmission mechanisms (Vicente-Serrano et al., 2010).

To assess the sensitivity of the benchmark results to the temporal aggregation of the drought indicator, we re-estimate the model using early drought-warning measures based on SPEI accumulation periods of 6, 9, and 12 months. This exercise verifies whether the negative relationship between climatic stress and food security is driven by short-term shocks or remains detectable when drought is measured over longer horizons.

The estimated average marginal effects reported in Table 7 indicate that drought retains a negative and statistically significant effect across all alternative timescales considered, confirming the robustness of the main result. Although the magnitude of the estimated effect varies somewhat across specifications, the qualitative conclusion is unchanged: drought exposure systematically reduces the probability of belonging to the high dietary diversity latent class. More specifically, the estimated average marginal effect is -7.1 percentage points when the indicator is constructed using the 6-month SPEI, -7.2 percentage points using the 9-month SPEI, and -6.4 percentage points using the 12-month SPEI.

A first noteworthy implication is that the adverse effect of drought appears slightly stronger at the shorter and intermediate horizons. This pattern is consistent with the idea that food security, as proxied by dietary diversity, is especially sensitive to relatively recent climatic conditions, which are more likely to affect agricultural production, local food availability, and household purchasing capacity in the short run. By contrast, longer accumulation periods may capture more persistent but also more diffuse forms of climatic

tionship. For this reason, in the regression analysis the SPEI data used to construct the early drought indicator were lagged by one period.

Table 7: Parameters affecting the transition probability of belonging to the high dietary diversity latent class according to different time scales of climate variability

	Coefficient	Odds-ratio	Average Marginal Effect
Panel A: 6 months			
Early drought warning	-0.3838***	0.6812	-7.1
	(0.0598)		
Gender	-0.3251***	0.7224	-5.9
	(0.0562)		
Urban	1.1735***	3.2332	+20.8
	(0.0961)		
Panel B: 9 months			
Early drought warning	-0.3928***	0.6744	-7.2
	(0.0610)		
Gender	-0.3228***	0.7241	-5.9
	(0.0564)		
Urban	1.1650***	3.2059	+20.6
	(0.0965)		
Panel C: 12 months			
Early drought warning	-0.3490***	0.7053	-6.4
	(0.0592)		
Gender	-0.3259***	0.7218	-5.9
	(0.0561)		
Urban	1.1687***	3.2178	+20.6
	(0.0960)		

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are reported in parentheses. For the dichotomous variables, a value of 1 indicates an SPEI value below -0.5 for early drought warning, a female household head for gender, and an urban settlement with at least 20,000 inhabitants for urban.

stress, whose effects on food consumption can be partially attenuated by adjustment mechanisms, such as intertemporal smoothing and local coping strategies (Dercon and Krishnan, 2000), as well as livelihood diversification (Barrett et al., 2001) and market-based food access (Frelat et al., 2016).

At the same time, the fact that the coefficient remains statistically significant even at the 12-month horizon suggests that the effects of drought are not purely transitory. Rather, they may also reflect more persistent constraints on household welfare and access to diversified diets. The robustness of the climatic effect across different SPEI windows strengthens the interpretation

that drought is an important and systematic determinant of latent food security conditions, rather than an artifact of a specific operationalization of the climate variable.

The estimated effects of the additional covariates are also remarkably stable across alternative specifications. This result indicates that the negative association linked to the gender variable and the strong positive association linked to urban residence are not sensitive to the temporal scale used to define drought exposure. More generally, the overall stability of the model across alternative timescales supports the empirical validity of the benchmark specification based on the 3-month SPEI. Consistent with the model selection results reported in Appendix C, the two-state latent structure remains the preferred specification in all cases according to the BIC criterion.

5.3. Robustness to an alternative climate-shock indicator: drought onset

A further robustness exercise concerns the identification of drought through an alternative measure designed to capture the onset of water stress. Although drought may be broadly understood as a prolonged period of insufficient water availability, its empirical identification is complex. Drought is a slow-onset phenomenon, and the precise point at which climatic conditions become sufficiently severe to qualify as drought is often difficult to establish. This ambiguity is especially relevant in empirical analyses of food security since different thresholds may capture different stages of climatic stress and may have different implications for household welfare. More generally, drought is among the most consequential natural hazards worldwide, with effects that extend well beyond agricultural output and may include income losses, nutritional deterioration, and, in extreme cases, severe food crises (Funk and Shukla, 2020; Delforge et al., 2026).

To address this issue, we use an alternative indicator labeled *drought onset*, based on the short-term 3-month SPEI. This variable takes the value of one when the accumulated water deficit is characterized by SPEI values that remain continuously below zero, capturing the beginning of a drought episode rather than relying on the benchmark threshold of -0.5. This alternative measure is intended to identify an earlier and potentially less severe stage of climatic stress. As such, it provides a useful test of whether the main results depend on the specific threshold adopted in the baseline specification (Pei et al., 2020).

The estimates reported in Table 8 are fully consistent with the benchmark results (see, Table 5). The coefficient associated with drought onset is

Table 8: Parameters affecting the transition probability of belonging to the high dietary diversity latent class

	Coefficient	Odds-ratio	Average Marginal Effect
Drought onset	-0.5149***	0.5975	-9.3
	(0.0579)		
Gender	-0.3204***	0.7258	-5.8
	(0.0558)		
Urban	1.1850***	3.2706	+20.9
	(0.0964)		

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are reported in parentheses. For the dichotomous variables, a value of 1 indicates an SPEI value below zero for drought onset, a female household head for gender, and an urban settlement with at least 20,000 inhabitants for urban.

negative and highly statistically significant, and the corresponding average marginal effect indicates a reduction of 9.3 percentage points in the probability of belonging to the high dietary diversity latent class. This estimate is only slightly smaller than the benchmark effect obtained for the early drought-warning indicator reported in Table 5.

The somewhat smaller magnitude of the drought-onset effect is also substantively plausible. Because this alternative indicator is likely to include milder or earlier episodes of water deficit, it captures a broader set of climatic disturbances, not all of which necessarily translate into equally severe food security consequences. For this reason, the estimated effect may be expected to be slightly attenuated relative to the benchmark specification. Nonetheless, the persistence of a strong and statistically significant negative effect confirms that even the early phases of drought are sufficient to reduce the probability that households remain in, or transition into, the more favorable latent food-security regime.

The estimates for the additional covariates remain essentially unchanged. The average marginal effects associated with the gender and urban variables are -5.8 and $+20.9$ percentage points, respectively, which are almost identical to those obtained in the benchmark model. This stability further reinforces the interpretation that the main empirical findings are not driven by a specific definition of drought, but instead reflect more general and systematic relationships between climatic exposure, structural disadvantage, and

household food security.

5.4. Robustness to an alternative binary HDDS outcome

A further concern is that the benchmark results may depend on the three-category classification of the Household Dietary Diversity Score. Although this classification follows established practice and provides an interpretable ordering from severe food insecurity to food security, it may still impose cut-offs that affect the estimated latent structure. To address this issue, we re-estimate the latent Markov model using an alternative binary HDDS outcome.

For each country, we calculate the median of the country specific HDDS distribution and construct a dichotomous indicator equal to one when the household's HDDS lies above the national median and zero otherwise. This country-specific definition is useful because the distribution of dietary diversity differs across Ethiopia, Malawi, and Nigeria. Therefore, the binary specification provides a robustness check based on relative dietary diversity within each national context, rather than on the three benchmark categories used in the main analysis.

Table 9: Robustness to a binary HDDS outcome: parameters affecting the probability of belonging to the high dietary diversity latent class

	Coefficient	Odds-ratio	Average Marginal Effect
Early drought warning	-0.7140***	0.4896	-9.7
	(0.1067)		
Gender	-0.4046***	0.6672	-5.8
	(0.0655)		
Urban	1.8042***	6.0751	+34.3
	(0.1174)		

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are reported in parentheses. The dependent indicator is based on a binary HDDS outcome equal to 1 when the household's HDDS is above the country-specific median of the HDDS distribution and 0 otherwise. For the dichotomous variables, a value of 1 indicates an SPEI value below -0.5 for early drought warning, a female household head for gender, and an urban settlement for urban.

The results, reported in Table 9, closely support the benchmark findings. Early drought exposure remains negatively and significantly associated with

the probability of belonging to the high dietary-diversity latent class. The estimated coefficient is −0.714, corresponding to an odds ratio of 0.490 and an average marginal effect of −9.7 percentage points. This magnitude is almost identical to the benchmark estimate of −9.8 percentage points reported in Table 5. The gender variable also remains negative and statistically significant, with an average marginal effect of −5.8 percentage points, again closely matching the baseline result. Urban residence remains strongly positive, with an average marginal effect of +34.3 percentage points.

These findings indicate that the main results are not an artifact of the three-category HDDS coding. Even when dietary diversity is represented through a simpler country-specific binary outcome, early drought exposure is associated with a substantially lower probability of belonging to the more favorable latent food-security state. The robustness of the drought and gender effects across the two measurement strategies strengthens the interpretation that the latent Markov model is capturing meaningful food-security dynamics rather than mechanically reproducing a particular HDDS classification.

5.5. Crop-adjusted drought exposure and agricultural transmission

A plausible mechanism through which early drought exposure affects household dietary diversity is a shock to agricultural production. Climatic stress can reduce yields, lower harvest volumes, and weaken both own-consumption and the marketed surplus available to rural households (Lobell et al., 2011; Lesk et al., 2016; Dillon et al., 2015). In predominantly rain-fed agricultural systems such as those examined in this paper, even relatively early stages of water deficit may adversely affect food access by reducing the local availability of staple crops, increasing market dependence, and placing upward pressure on food prices (Barnett et al., 2008). Under these conditions, the effect of drought on dietary diversity is likely to operate not only through direct production losses, but also through broader disruptions to local food supply and household purchasing power.

However, household responses to production shocks are unlikely to be uniform across contexts. as they depend on the structure of local agricultural systems, the degree of crop specialization, the importance of market integration, and the capacity of households to smooth consumption or substitute across food sources. A growing body of evidence shows that the same climatic signal can generate markedly different food-security outcomes depending on the crop composition of local economies (Costinot et al., 2016; Maggio et al., 2019). For this reason, the same climatic signal may generate

different food-security outcomes depending on the predominant crop and the productive characteristics of each region. To better account for this source of heterogeneity, we complement the benchmark analysis by constructing a crop-adjusted drought indicator that matches early drought exposure to the main crop cultivated in each region, while maintaining the same temporal aggregation as in the baseline specification.

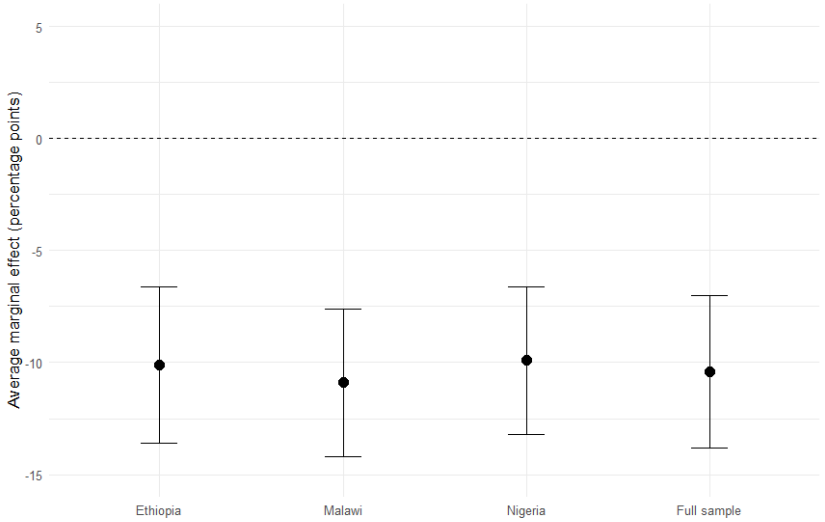
This extension is motivated by the idea that the same climatic shock may have different food-security implications depending on the crop composition of local agricultural systems. In Ethiopia and Malawi, maize is identified as the dominant crop in most regions and represents a key component of local food systems. In Nigeria, by contrast, tubers constitute the predominant crop in much of the country, although maize remains relevant in some regional contexts. The maps reported in Appendix D illustrate this spatial distribution of dominant crops and provide the basis for interpreting cross-country differences in the estimated effects of crop-specific drought exposure.

The results are summarized in Figure 4 and are broadly consistent with the benchmark findings. The statistical analysis based on the crop-adjusted drought indicator continues to support a two-state latent structure, distinguishing between low and high dietary diversity regimes. More importantly, the estimated effects confirm that early drought exposure reduces the probability of belonging to the high dietary diversity latent class, although the magnitude of this effect varies substantially across countries once the agricultural composition of each region is considered.

The strongest adverse effect is observed in Malawi, where the average marginal effect is large and statistically significant (-10.9 percentage points). Ethiopia and Nigeria also display a negative and statistically significant effect, equal to -10.1 and -9.9 percentage points, respectively. These differences suggest that the relationship between drought and food security is mediated not only by climatic exposure itself, but also by the interaction between drought conditions and the crop profile of the local economy.

This finding is substantively important for at least two reasons. First, it indicates that vulnerability to climatic stress is shaped by the composition of agricultural production: where the dominant crop is especially sensitive to short-term water deficits, drought is more likely to translate into reductions in food availability and dietary diversity. Second, the cross-country variation in the estimated effects suggests that households' exposure to drought cannot be fully understood without considering the crop-specific structure of local livelihoods and food systems. In this respect, the benchmark effect of early

Figure 4: Probability to belong to high dietary diversity latent class according to drought indicator for main crop



Notes: Values on y-axis measure the average marginal effect of early drought warning indicator according to main crop. Horizontal dashed line corresponds to the zero value.

drought should be interpreted as an average climatic penalty, whereas the crop-adjusted specification helps uncover one of the mechanisms through which that penalty is transmitted[6].

6. Conclusions

This paper has examined the dynamics of food security in three Sub-Saharan African countries through a latent variable framework based on a Hidden Markov model. A key motivation for this approach is that food security is inherently unobservable, with standard indicators capturing individual dimensions of a multidimensional phenomenon, while conventional

[6]When early drought is measured using the crop-adjusted indicator, the reduction in the probability of belonging to the high dietary diversity class increases from -9.8 to approximately -10.4 percentage points in the full sample. Although modest in absolute terms, this difference suggests that accounting explicitly for the dominant crop improves the measurement of effective exposure to agricultural stress.

empirical methods treat observed outcomes as direct measures of the underlying condition rather than as imperfect signals of a latent state. By modeling household dietary diversity as an observed indicator of an unobservable food security regime, and by explicitly characterizing the transitions between regimes over time, the HMM framework allows us to recover persistent latent structures and dynamic trajectories that would remain hidden under standard approaches. The results show that a two-state specification provides the most appropriate characterization of the data, distinguishing between a low dietary diversity regime associated with greater food insecurity and a high dietary diversity regime associated with more food-secure conditions.

The empirical findings convey three main messages. First, food security is characterized by strong state dependence. Households in the high dietary diversity state are very likely to remain there over time, whereas those in the low dietary diversity state face a more uncertain trajectory, although transitions towards better conditions remain possible. This indicates that food security is not a purely transitory outcome, but rather a dynamic process shaped by persistence and by the cumulative effects of previous conditions. Second, adverse climatic conditions are associated with a significantly lower probability of reaching or maintaining the more favorable latent state, confirming that drought exposure emerges as an important risk factor for households' dietary quality and, more broadly, on their food security prospects. Third, social and local characteristics also exert substantial effects: the negative association linked to female-headed households and the large positive effect of urban residence point to the relevance of structural inequalities in shaping households' ability to secure diversified diets.

The robustness of these findings is supported across multiple alternative specifications. OLS estimates are broadly consistent with the main specification in both direction and statistical significance, though their limited ability to capture latent dynamics reinforces the appropriateness of the HMM framework. The negative association between drought exposure and the high dietary-diversity latent class remains stable using alternative SPEI accumulation periods, and a similar result emerges when drought is identified through an alternative drought-onset indicator. Finally, the main findings are also robust to an alternative binary HDDS outcome.

The spatial dimension of the analysis further shows that climatic vulnerability is not uniform within countries. The quartile maps of region-specific marginal effects reveal substantial territorial heterogeneity in the drought penalty. Even when the overall association between early drought exposure

and dietary diversity is consistently negative, its magnitude varies markedly across subnational areas. Differences in agroecological conditions, market integration, infrastructure, irrigation, livelihood diversification, and institutional capacity are all likely to mediate the extent to which climatic shocks translate into lower dietary diversity. For food policy, this implies that national early-warning systems should be connected to subnational targeting rules rather than implemented only through uniform country-level interventions.

From a policy perspective, the results highlight the need for interventions that combine climate adaptation with measures aimed at reducing structural and territorial inequalities. Strengthening drought early warning systems, expanding adaptive safety nets, improving agricultural risk management, investing in irrigation and rural infrastructure, and protecting rural livelihoods are all likely to be important for preventing downward movements in food security. At the same time, the strong positive role of urban residence suggests that improving rural market access, transport infrastructure, and opportunities for income diversification may help narrow the gap between rural and urban households. Policies targeted at vulnerable groups and lagging regions are likely to be more effective than aggregate interventions that do not differentiate across contexts.

The paper also points to limitations that may guide future research. While the robustness checks provide substantial support for the empirical strategy, the framework does not allow for a fully causal identification of the mechanisms through which climatic stress affects food security. The use of a climatic water balance index as the key climate variable mitigates concerns about reverse causality, since precipitation deficits are determined independently of household behavior. However, spatial sorting — whereby households in drought-prone regions may differ systematically from others in unobserved dimensions such as soil quality, infrastructure, or social capital — cannot be fully ruled out despite the inclusion of regional fixed effects. To the extent that such sorting is correlated with lower dietary diversity, our estimates of the early drought penalty may reflect in part these unobserved structural disadvantages rather than the effect of climatic stress alone. Future work could extend the latent approach by incorporating additional food security indicators, explicitly modeling other relevant shocks such as conflict and price volatility, and investigating more directly the role of crop composition, market transmission, and household adaptation strategies in mediating the effects of drought. Notwithstanding these limitations, the evidence pre-

sented here shows that latent variable approaches offer a valuable tool for studying food security as a dynamic and multidimensional phenomenon. By recovering persistent latent structures and asymmetric transition dynamics that remain hidden under conventional empirical methods, the HMM framework provides a richer empirical basis for understanding how persistent forms of vulnerability shape household food security trajectories, and for designing interventions that are sensitive to the heterogeneity of exposure and disadvantage across regions and household types.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Forward-backward recursions and path decoding

This appendix presents the recursions used in the E-step of the EM algorithm and in the decoding of the most likely latent-state sequence.

Appendix A.1. Forward-backward recursions for the E-step

For an individual with observed responses $\mathbf{y} = (y^{(1)}, \ldots, y^{(T)})$ and covariates $\mathbf{x} = (x^{(1)}, \ldots, x^{(T)})$, define the forward variable

$$\alpha_1(u) = \pi^{(1)}_{u|x^{(1)}}\, p\big(y^{(1)} \mid U^{(1)} = u, x^{(1)}\big), \tag{A.1}$$

and, for $t = 2, \ldots, T$,

$$\alpha_t(v) = \left[\sum_{u=1}^{k} \alpha_{t-1}(u)\, \pi^{(t)}_{v|ux^{(t)}}\right] p\big(y^{(t)} \mid U^{(t)} = v, x^{(t)}\big). \tag{A.2}$$

The corresponding backward variable is initialized as

$$\beta_T(u) = 1, \tag{A.3}$$

and, for $t = T-1, \ldots, 1$,

$$\beta_t(u) = \sum_{v=1}^{k} \pi^{(t+1)}_{v|ux^{(t+1)}}\, p\big(y^{(t+1)} \mid U^{(t+1)} = v, x^{(t+1)}\big)\, \beta_{t+1}(v). \tag{A.4}$$

These quantities imply the posterior probability of state membership,

$$\tau_t(u) = P\big(U^{(t)} = u \mid \mathbf{y}, \mathbf{x}\big) = \frac{\alpha_t(u)\beta_t(u)}{\sum_{w=1}^{k} \alpha_t(w)\beta_t(w)}, \tag{A.5}$$

and the posterior probability of a transition from u to v between $t-1$ and t,

$$\xi_t(u,v) = P\big(U^{(t-1)} = u, U^{(t)} = v \mid \mathbf{y}, \mathbf{x}\big) = \frac{\alpha_{t-1}(u)\pi^{(t)}_{v|ux^{(t)}} p\big(y^{(t)} \mid U^{(t)} = v, x^{(t)}\big)\beta_t(v)}{\sum_{\bar{u}=1}^{k}\sum_{\bar{v}=1}^{k} \alpha_{t-1}(\bar{u})\pi^{(t)}_{\bar{v}|\bar{u}x^{(t)}} p\big(y^{(t)} \mid U^{(t)} = \bar{v}, x^{(t)}\big)\beta_t(\bar{v})}. \tag{A.6}$$

The expected counts entering the E-step are obtained by summing $\tau_t(u)$ and $\xi_t(u,v)$ over individuals with the relevant response categories and covariate profiles.

Appendix A.2. Decoding the optimal latent path

To recover the most likely latent path, we use a Viterbi-type recursion. Let $\delta_t(v)$ denote the highest probability of any partial path ending in state v at time t, and let $\psi_t(v)$ be the corresponding back-pointer. Initialization is given by

$$\delta_1(u) = \pi^{(1)}_{u|x^{(1)}}\, p\big(y^{(1)} \mid U^{(1)} = u, x^{(1)}\big), \qquad \psi_1(u) = 0. \tag{A.7}$$

For $t = 2, \ldots, T$,

$$\delta_t(v) = \max_{u \in \{1,\ldots,k\}} \Big\{ \delta_{t-1}(u)\, \pi^{(t)}_{v|ux^{(t)}} \Big\}\, p\big(y^{(t)} \mid U^{(t)} = v, x^{(t)}\big), \tag{A.8}$$

$$\psi_t(v) = \arg \max_{u \in \{1,\ldots,k\}} \Big\{ \delta_{t-1}(u)\, \pi^{(t)}_{v|ux^{(t)}} \Big\}. \tag{A.9}$$

The final state is selected as

$$u^*_T = \arg \max_{u \in \{1,\ldots,k\}} \delta_T(u), \tag{A.10}$$

and the remaining states are obtained recursively for $t = T-1, \ldots, 1$ by

$$u^*_t = \psi_{t+1}\big(u^*_{t+1}\big). \tag{A.11}$$

The sequence $\big(u^*_1, \ldots, u^*_T\big)$ is therefore the most probable latent trajectory conditional on the observed responses and covariates.

Appendix B. Waves by country, survey years and number of observations

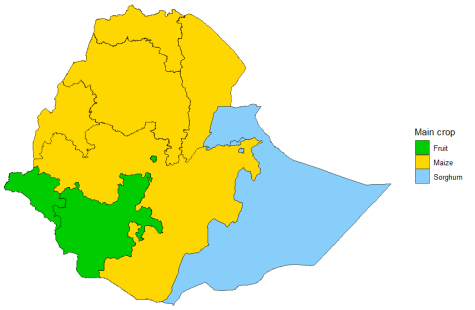
	Country	Survey years	Observations
Wave 1			
	Ethiopia	2010/2011	3429
	Malawi	2009/2010	3474
	Nigeria	2010/2011	3984
Wave 2			
	Ethiopia	2012/2013	3504
	Malawi	2012/2013	4081
	Nigeria	2012/2013	3919
Wave 3			
	Ethiopia	2014/2015	3458
	Malawi	2015/2016	2764
	Nigeria	2015/2016	3830
Wave 4			
	Ethiopia	2017/2018	2555
	Malawi	2018/2019	3140
	Nigeria	2018/2019	4242
Total			
	Ethiopia	2010/2018	12,946
	Malawi	2009/2019	13,459
	Nigeria	2010/2019	15,975
Full sample			42,380

Appendix C. Selection model according to different SPEI timescales

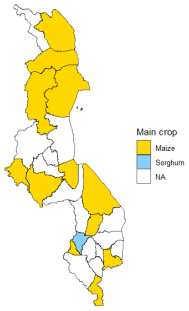
	Latent class	Log Likelihood	AIC	BIC
Panel A: 6-month timescale				
	1	-44787.26	89578.51	89594.13
	2	-21785.46	43820.92	**44796.70**
	3	-21453.83	43407.67	45359.22
	4	-21391.44	43356.87	46479.81
Panel B: 9-month timescale				
	1	-44787.26	89578.51	89594.13
	2	-21785.13	43820.25	**44796.03**
	3	-21434.44	43368.88	45320.43
	4	-21373.85	43501.69	46444.63
Panel C: 12-month timescale				
	1	-44787.26	89578.51	89594.13
	2	-21787.18	43824.35	**44800.13**
	3	-21458.87	43417.73	45369.28
	4	-21385.11	43524.22	46467.16

Notes: Values written in bold highlight the optimal model selection based on the BIC criterion.

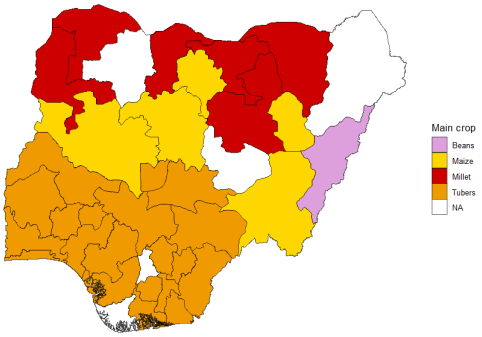
Appendix D. Main crop by countries



(a) Ethiopia



(b) Malawi



(c) Nigeria

Notes: purple = beans; green = fruit; yellow = maize; red = millet; light blue = sorghum; orange = tubers.

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