Intraseasonal Variations in Time Use, Food Security, and Health Outcomes among Women in Rural Malawi*

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November 2025

Abstract

The sequential nature of agriculture poses significant challenges to rural women in sub-Saharan Africa, particularly in managing health and balancing farm and domestic work across different periods of the agricultural cycle. Despite its importance, empirical evidence on these intraseasonal dynamics remains limited. This study investigates intraseasonal variations in time use, food security, and anthropometric outcomes among female caregivers in 300 farm households in rural Malawi, using panel data collected at four points during the 2022/2023 agricultural season. Results show that women's work hours increase during the lean period, reducing leisure time. Food insecurity also worsens during this period, contributing to declines in women's nutritional status, particularly as measured by mid-upper arm circumference. Fluctuations in body weight further suggest community-wide structural dynamics within the agricultural season beyond individual health, labor supply, and household food insecurity. Overall, the findings underscore the need for policies that account for within-season variation—particularly the pre-harvest hunger period—to improve food security, nutritional outcomes, and, ultimately, women's welfare in rural Malawi.

Keywords: seasonality, gender, agricultural labor, food security, Malawi

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* The authors would like to thank Kana Miwa and the seminar participants at the Association for Regional Agricultural and Forestry Economics international workshop for their valuable comments and suggestions. We also extend our thanks to the supports of Limbikani Matumba at the Lilongwe University of Agriculture and Natural Resources for his logical arrangements. In addition, we would like to thank Madalitso Simon Chilembo, Chikondi Kamwaza, Pemphero Mtimuni, and Maureen Maseya for their excellent research assistant work. This work was supported by the JSPS RONPAKU (Dissertation Ph.D.) Program. The authors also acknowledge financial support from JSPS KAKENHI No. 20K22119. Any remaining errors are our own.
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1. Introduction

Agriculture is a crucial sector in most developing economies, playing a multifaceted role in the livelihoods of rural households. Globally, agri-food systems employ many women, and in several countries, women rely more heavily on these industries for their livelihoods than men do (FAO, 2023). A reassessment using nationally representative data from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) initiative reports that women contribute slightly more than 50% of agricultural labor to each activity domain (e.g., land preparation, planting/weeding, and harvesting) in Malawi, the country studied in this paper (Palacios-Lopez et al., 2017). The substantial role of women in agriculture has motivated empirical studies on gender to inform the design of future policies aimed at improving women's development outcomes (e.g., Melaku et al., 2024).

In rural African settings, women bear the primary responsibility for their families' health and face challenges in managing nutrition and balancing workloads between on-farm and domestic activities during the farming season (Johnston et al., 2018). Agricultural labor demand varies across seasons and genders, affecting household labor supply decisions and gender roles (Skoufias, 1993; Wodon & Beegle, 2006). In addition, intense farming periods from a production perspective correspond to the hunger period from a consumption perspective, with heightened food insecurity caused by seasonal food scarcity further complicating the link between work, nutrition, and health (Orr et al., 2009; Khandker, 2012; Anderson et al., 2018). Cross-sectional data miss these critical variations; therefore, the complex link between work, nutrition, and health emphasizes the need for a holistic approach to investigate intraseasonal variations in factors relevant to women's welfare by collecting data between the onset and end of agricultural production. Despite the significance of seasonality and its consequences as a fundamental challenge in rural Africa, even descriptive evidence remains scarce, as highlighted by Johnston et al. (2018) and Lentz et al. (2019) in their review. This scarcity is primarily due to the high data requirements of frequent panel surveys across several periods.

This study uses new household panel data collected four times within the same farming season from rural Malawi to investigate the intraseasonal variations in women's time-use patterns, household food security, and health outcomes among Malawian agricultural households.[1] As a unique feature of this study, female representatives (i.e., the spouses of the head or female household heads) aged 18 to 49 years were interviewed in the sampled households. During the 2022/2023 agricultural season, 300 randomly selected households were visited and interviewed four times: November 2022 (land preparation period), January 2023 (growing period), March 2023 (early harvest period), and June 2023 (post-harvest period). Based on field observations, we identify January to March as the lean period, a

[1] Although the term 'season' is sometimes used to denote a specific stage within a crop cycle (e.g., the harvesting season), it more commonly refers to an entire crop cycle. To maintain consistency, this study adopts the latter definition, using 'season' exclusively to refer to complete crop cycles. Then, we divide a crop cycle into four periods corresponding to distinct agricultural production stages for maize production: land preparation, growing, early harvest, and post-harvest periods. In addition, a lean period (or a hunger period) refers to the months preceding harvest.

classification supported by descriptive evidence on food insecurity indicators. As a welfare indicator, we measured body weight and left mid-upper arm circumference (MUAC) in female representatives to capture acute malnutrition in the short term.

Our empirical results indicate that women's agricultural work hours are inversely related to their leisure time, with a notable decrease in leisure time during periods of increased farm labor demands. In addition to the reduced time commitment to agricultural activities in March, women reduced the time spent on household chores. This decline in domestic work hours was primarily due to a reduction in cooking time. We also find that illness prevalence is highest during the lean period between January and February, coinciding with both heightened food insecurity and peak agricultural labor requirements. Illness episodes are associated with reductions in women's domestic work hours, even after controlling for period-specific effects, suggesting some degree of flexibility in the allocation of household tasks. However, we find no evidence of a comparable reduction in agricultural work hours when women report illness, indicating that time pressures during peak farming periods may compel women to prioritize farm labor even when they are unwell.

We also observed pronounced intraseasonal fluctuations in household food security and dietary quality. Households experience food insecurity and poor dietary diversity during the lean period before the main harvest. With a significant decrease in nutrient-dense foods, households rely on simple diets consisting primarily of staples (*Nsima*, a thick porridge made from maize flour) and vegetables. The Household Dietary Diversity Score (HDDS) reveals that households typically consume three or four food groups during the lean period. These variations observed in the descriptive analysis hold after controlling for household-fixed effects and household-specific health shocks in a regression analysis.

Finally, the data reveal that anthropometric outcomes (i.e., body weight and MUAC) also deteriorate during the hunger period but revert after harvest in June. Our regression analysis indicates that intraseasonal changes in household-level food security are associated with deteriorating nutritional outcomes, as measured by MUAC. Thus, acute malnutrition among women occurs within a cropping season, mainly due to limited access to food. In contrast, intraseasonal variations in women's body weight suggest additional influences beyond idiosyncratic factors such as time use, illness, and household food security, pointing instead to broader structural dynamics within the agricultural season.

This study contributes to the literature on agriculture-nutrition linkages from a gender perspective by offering empirical evidence based on high-frequency data collected over relatively short periods. Among the growing body of research exploring the relationship between women's time use and nutrition outcomes, Vemireddy and Pingali's (2021) study is a notable complementary work.[2] Using

[2] Most previous work on the gendered dimensions of agriculture–nutrition linkages has provided detailed insights but has typically relied on case studies with small sample sizes (e.g., Kinabo et al., 2003; Rao & Raju, 2020). In Section 2, we discuss these earlier studies to develop our conceptual framework.

monthly panel data from India over ten months and employing individual-level nutrient estimates, they find that women's intake of macro- and micronutrients declines during peak agricultural seasons. They attribute this decline to time trade-offs between market work and food preparation, reflecting the high opportunity cost of the latter, particularly among landless women engaged in agricultural wage labor. In contrast, we find that, in our study setting, increased agricultural labor by women is accommodated primarily through a reduction in leisure time rather than in food preparation. Indeed, cooking time is longer during peak farm labor periods compared to post-harvest periods. This contrast highlights the significance of context-dependent factors, including intrahousehold labor substitution, labor market structures, and food preparation practices, in shaping time-sensitive agriculture-nutrition links.

Komatsu et al. (2019), using nationally representative panel data from Tanzania, report no significant association between farm work hours and Body Mass Index (BMI) for women, in contrast to the negative association observed for men. Building on their work, we expand the discussion by examining other channels through which nutritional outcomes fluctuate across production stages in an agricultural season, including illness, household food security, and dietary quality.[3] Our findings suggest that household food insecurity, rather than shifts in time allocation, is the key driver behind the deterioration in women's anthropometric measures. By adopting a more comprehensive analytical framework, this study deepens our understanding of how women reallocate their time in response to period-specific farm labor demands and the broader welfare implications of these intraseasonal adjustments.

This study also contributes to the seasonality literature by providing empirical evidence that the hunger period remains a persistent threat in rural areas, particularly for women in Malawi. In this context, the study closest to ours is that of De Janvry et al. (2022), who investigated the empirical characterization of the seasonality of rural labor calendars in Malawi by connecting the labor requirements of crops to the labor supply reported by households. Their household-level analysis also examined the depth of the associations between seasonal labor calendars, employment opportunities, and low consumption. Given that family members may respond differently to environmental changes within an agricultural season, we conducted an individual-level analysis, focusing on women—often the most nutritionally vulnerable members of the household. Thus, we extend the work of De Janvry et al. (2022) by using anthropometric measures as welfare indicators and describing the impact of agricultural crop calendars on women's welfare in rural economies. In doing so, we offer a more granular understanding of how gendered welfare outcomes are shaped for each production stage.

[3] Other related studies are Waswa et al. (2021) and Hasan et al. (2023), which examine how seasonal variations in food availability and access contribute to inadequate nutrient intake among women and their children and the association between household food insecurity and child undernutrition. Unlike these studies, we explicitly incorporate intraseasonal changes in labor demand as another key driver and associate them with health and nutritional outcomes by collecting time-use data.

The remainder of this paper is organized as follows. Section 2 presents the conceptual framework that motivates the empirical analysis. Section 3 describes the study site and discusses the importance of studying intraseasonal variations in women's time use, health, and food security in this setting, followed by a description of the household survey conducted in Malawi's Mchinji district. Section 4 provides descriptive evidence on key empirical variables. Section 5 presents the regression analysis, exploring intraseasonal variations in time use, household food security, and nutritional outcomes, and discusses their welfare implications. Finally, Section 6 concludes the paper by outlining policy implications and future research directions.

2. Conceptual Framework

[Figure 1]

This section hypothesizes a chain of effects relevant to within-season sequential production processes, which will guide the subsequent empirical analysis. Building on previous literature from economics, nutrition, medicine, and gender studies, Figure 1 presents a conceptual framework that illustrates how intraseasonal changes within the agricultural season drive fluctuations in women's workload, time use, health, and household food security, collectively shaping women's nutritional outcomes. The conceptual framework identifies four pathways through which intraseasonal variations determine women's nutritional status. We discuss each pathway in detail below.

Pathway 1: Changing time allocation patterns reflecting period-specific farm labor demands

Agriculture has a sequential nature. In chronological order, typical cropping activities start with field preparation (clearing and plowing), followed by planting, weeding, scaring away animals, harvesting, and milling. Reflecting crops' agronomy, farm labor demands are seasonal. Because the timing of performing each agricultural practice is crucial for achieving yield potential, agricultural workloads are concentrated in specific periods within a farming season. According to the crop-level labor demand calendars for the average Malawian households constructed by De Janvry et al. (2022), within the main agricultural cycle, the November-December planting period is the peak of farm labor demand for family labor, followed by the harvesting period between mid-March and late April, for the cultivation of maize, the staple in the country. Labor requirements for each agricultural operation are also often gender-specific (Quisumbing, 1996; Gulati et al., 2024). To support this, Skoufias (1996) demonstrates that intertemporal substitution in labor supply to agricultural work is responsive to own-gender-specific village wage rates only for females in India. No evidence for cross-wage effects across genders indicates that male and female labor supply is determined independently in his research context.

Thus, reflecting the gender division of labor by task and period-specific workload in agricultural work, women's time allocations into farm work, domestic chores, and leisure differ across agricultural production stages within a cropping season (Arrow 1a: Farm labor demand in Figure 1). As evidence from Malawi, Wodon and Beegle (2006) report that based on the 2004 Second Integrated Household Survey (IHS) collected over 13 months, the average weekly total working hours peaked in December at 47.7 (36.2) hours for female (male) adults in rural samples within the 2004/05 agricultural season, corresponding to the peak period of farm labor demand (De Janvry et al., 2022). Women's leisure time is significantly less than men's throughout the year, reflecting their heavier burdens of household chores and tasks such as fetching firewood and water.

As another key observation, agricultural activities are generally physically demanding and thus require considerable physical exertion. In response to time-varying labor requirements, energy expenditures also differ within an agricultural season. For example, Kinabo et al. (2003) report varying energy expenditure among rural women in Tanzania, with 2775 kcal/day in April (when they spent eight hours in farming activities on average) amid the rainy season, which is higher than the average energy expenditure of men of 2400kcl/day in the same month and of women of 2020 kcal/day in October during the dry season. In addition, recent studies employing innovative approaches to measure energy expenditure have highlighted it as an understudied link in agriculture-nutrition pathways (Zanello et al., 2017; Srinivasan et al., 2020; Daum & Birner, 2022). In this regard, Komatsu et al. (2019) report a negative association between time spent in agricultural crop production and BMI, particularly for Tanzanian men, albeit of small magnitude.

The burgeoning literature reports on the mediating role of farm technologies (e.g., Daum & Birner, 2022, for mechanization; Komatsu et al., 2019, for sprayer) and household technologies (e.g., Dinkelman, 2011, for electric cookstoves) in mitigating the labor burden. Such labor-saving technologies can reduce both time spent and physical exertion. However, the take-up of these technologies is generally low, partly due to women's limited bargaining power in household technology adoption decisions (Miller & Mobarak, 2013; Gulati et al., 2024). Thus, increased work burdens would lead to period-specific energy deficiency—defined as the gap between energy intake and expenditure—and, in turn, result in weight loss for most rural women in developing countries (Higgins & Alderman, 1997).

As another possible channel, during peak agricultural periods, women's long working hours in farming may reduce the time available for domestic reproduction, leisure activities, or both (Johnston et al., 2018; Rao & Raju, 2020). In turn, such time constraints can adversely affect their nutritional status by limiting opportunities for adequate rest and food preparation.[4] Thus, increased work intensity and longer working hours in response to the timely involvement in agricultural activities may adversely affect their nutritional status due to high energy loss and squeezed time for chores and leisure. Overall,

[4] Particularly, the reduced time to prepare nutritious food can lower household nutrient intake and deteriorate the health status of everyone, including herself, within the family. We did not explicitly specify this important link in Figure 1 because, in our survey questionnaire, the reference periods for household food security and sickness questions precede that for time use.

the energy intensity of different activities (e.g., planting versus harvesting) and time allocation patterns (e.g., on-farm work versus domestic work) significantly influence women's nutritional status (Arrow 1b: Energy expenditure/domestic reproduction).[5]

Pathway 2: Changing health status reflecting period-specific disease risks

Arrow 2a: Disease risk in Figure 1 represents different disease exposure even within the main agricultural season for the following two reasons. First, epidemiological studies highlight seasonality in the frequency and severity of major diseases in Africa. For example, the significant role of climatic conditions such as precipitation and temperature in malaria transmission is confirmed by Egbendewe-Mondzozo et al. (2011) for 25 African countries in general and Lowe et al. (2013) for Malawi in particular, while Hajison et al. (2017) report the recently declining trend of inter-seasonal variations in malaria cases among children below five years old in Zomba district, Malawi. As another example, Kirolos et al. (2021) report that the peak of tuberculosis case notification rates occurs from January to March during the rainy season, as well as in September and October, in Blantyre, Malawi.

Second, seasonal changes in the household's economic environment influence health-seeking behavior (Sauerborn et al., 1996). Given the high opportunity cost of time during the peak period, farmers may allocate less time to seek care. Moreover, even if they become ill, they may spend less on healthcare by choosing lower-cost treatment options (e.g., home care) due to limited financial resources during the agricultural season. Certain illnesses—such as gastrointestinal ailments or conditions that impair the efficient conversion of food intake into nutrients—can directly affect nutritional outcomes, including body weight (Dercon & Krishnan, 2000) (Arrow 2c: Health status). In summary, exposure to increased disease risks, reduced time for seeking care due to high opportunity costs, and limited healthcare utilization resulting from insufficient financial resources all affect women's nutritional status.[6] The salience of this pathway is likely to be period-specific. For instance, during the hunger period, when food is scarce and less accessible, women may be particularly vulnerable to the adverse effects of illness due to their already weakened nutritional status (Matchado, 2019).

In addition to the direct pathway from sickness to women's nutritional status, sickness also mediates the influence of production stages on time use patterns (Arrow 2b: Time allocation changes). While their illness episodes and hence poor health status can restrict the amount and efficiency of labor supplied (e.g., Bhargava, 1997), women may also need to devote more time to treating sick family members or working more hours to compensate for the economic activities of the sick during periods

[5] Body mass may have important feedback on productivity, given the nutrition-productivity link proposed by the extensive literature (Bliss & Stern, 1978; Dasgupta & Ray, 1986; Strauss & Thomas, 1998). While taking into account the productivity implications of fluctuations in nutritional status is beyond the scope of this study, this possibility provides another motivation for using anthropometric measures as the study's outcome.

[6] Given a possible energy imbalance in the peak period, a poor nutritional status may increase disease risks. This study limits its attention to short-run effects, assuming that the effects on disease incidence are lagged. Incorporating this important feedback is left for future research.

of disease epidemics (Dercon & Krishnan, 2000; Dureja & Negi, 2022). Health shocks would also affect women's nutritional status via worsened household-level food security (Arrow 2d: Forgone economic activities). The drivers of heightened food insecurity include increased medical spending, reduced time for food collection, and earnings losses due to forgone wage labor activities.[7]

Pathway 3: Changing household food security conditions due to period-specific food availability

As the production stage proceeds towards the period of food scarcity preceding harvest, the economic environment faced by the agricultural household becomes harsh. Specifically, food availability becomes restricted for the following reasons, thereby threatening household food security, especially during the months preceding the annual harvest (Arrow 3a: Food availability).

First, subsistence farmers generally store the crop harvests they receive as an annual lump sum at harvest time and rely on these grain inventories until the next harvest. Depending on the previous year's harvest and transactions, grain stocks may run out by the lean period up to a year later (Burke et al., 2019; Fink et al., 2020). Additionally, stored grain may be lost or wasted due to pests or mold. Despite its well-documented effectiveness, the take-up of technologies that prevent postharvest grain losses in storage (e.g., hermetic bags) remains low (Nakoma Ngoma et al., 2025). Thus, the lag between investments and returns when only one cropping season is possible throughout the year constrains food availability in the latter period.

Second, within-year variation in food prices is substantial. Gilbert et al. (2017) identify Malawi as the country that experiences the most pronounced seasonal differences in maize prices among the sub-Saharan African countries they studied. Specifically, February and March coincided with peak maize prices each year (Chiwaula et al., 2024). While it may be optimal to consume less in the lean period where food prices are high, such a response would be outweighed by the general incentive to avoid fluctuations in nutrition among farmers living at the subsistence level. Given that the majority are net buyers and maize is the primary source of calorie intake, systematic maize price fluctuations affect dietary choices, making ensuring sufficient calorie intake during the lean season difficult.[8]

Third, liquidity shortages due to limited access to consumption credit and informal borrowing arrangements significantly constrain farmers' consumption behavior during the lean period (Burke et al., 2019; Fink et al., 2020). For example, Behrman et al. (1997) estimate income effects on calories separately for the planting and harvesting stages of agricultural production. While the income-calorie relationship is negligible in the harvesting stage, characterized by high food availability at low cost,

[7] It is noteworthy that compensating intrahousehold labor supply responses and informal insurance arrangements may mitigate the latter two channels (e.g., Genoni, 2012; Dureja & Negi, 2022).

[8] Chiwaula et al. (2024) estimate that the average daily per capita caloric intake from maize alone amounts to approximately 1100 kcal. Based on the fifth Malawi IHS conducted in 2019/20 as part of the LSMS-ISA, they also report that maize consumption is lowest in February, about 10% below its peak levels observed in June and November.

they attribute their reported positive planting-stage wage-calorie elasticity to low consumption levels during the planting stage, reflecting the high food prices and limited access to credit. Thus, their overall results highlight the importance of stage-specific cash constraints in restricting food consumption decisions.

Fourth, time constraints imposed by agricultural activities during the peak period may have ripple effects on dietary choices and food consumption patterns. Particularly, increased labor demands can limit the time available for food preparation, potentially leading to less diverse and nutritious household diets and contributing to deficiencies in essential vitamins and minerals (Vemireddy & Pingali, 2021; Marivoet & Ulimwengu, 2022).

In consequence, food shortage and limited dietary choices may induce households to skip meals or consume less than usual in the months preceding the annual harvest, leading to periodic hunger evaluated by household-level welfare indicators such as consumption (Khandker et al., 2012).[9] As evidence of seasonal hunger from Malawi, Anderson et al. (2018) identify January and February as the months when hunger is prevalent among rural households. Given that the hunger period corresponds to the period when energy demands remain high, energy imbalances between food intake and energy expenditure can result in reduced body weight. Thus, period-specific stresses in food security would be reflected in individual welfare indicators, such as nutritional status (Arrow 3b: Food and nutrient intakes).

Pathway 4: Remaining pathways to women's nutritional status

Finally, Arrow 4: Other period-specific effects in Figure 1 represents the remaining period-specific effects on nutritional status beyond time allocations, disease, and household-level food security pathways. The candidates include period-specific consumption patterns and biological responses to climate variations in rainfall and temperature (Vemireddy & Pingali, 2021). As another intriguing possibility, reflecting food price fluctuations across periods and limited access to food, households may invest in the nutritional status of family members whose marginal returns to improving nutrition are high (Croppenstedt & Muller, 2000; Broussard, 2012).[10] In addition to such period-specific returns to nutrition, the allocation of limited food resources to women can be optimal when they engage in tasks that require high energy intensities. The conceptual framework in Figure 1 incorporates these

[9] Anderson et al. (2018) provide a review of ex-post responses to seasonal hunger.

[10] The significance of the nutrition-productivity link proposed by the extensive literature depends on context-specific factors. For example, Fafchamps and Quisumbing (1999) report a weak association between nutrition and productivity, as well as labor allocation in crop production, livestock raising, and market work for women in Pakistan, where a cultural system restricts their mobility. On the contrary, as Wodon and Beegle (2006) report, Malawian women devote a comparable amount of time to strenuous subsistence activities as men do. Given women's high contribution to physically demanding farm activities, we speculate that the nutrition-productivity link has important implications for women in our research context.

possibilities by allowing intraseasonal variations to directly affect women's nutritional status (e.g., body weight).

This section has outlined four interconnected causal pathways behind intraseasonal variations in women's nutritional status. The following section describes the empirical variables corresponding to each conceptual factor that determines nutritional outcomes.

3. Setting

3.1. Study Site

This study uses data from agricultural households in Mchinji district in the central region of Malawi. We selected Mchinji district as our survey area for three primary reasons. First, Mchinji district is located approximately 100 km northwest of Lilongwe. The proximity to the urban center in Lilongwe adds interesting variations in the time-use patterns of women, depending on how frequently men leave the village in search of seasonal employment in the city. Because Mchinji district also borders Zambia and Mozambique, the Zambia border district of Chipata (also the capital of the Eastern province of Zambia) and the Mozambique district bordering Mchinji offer seasonal labor for men and women from Mchinji district. This geographic feature generates another essential factor to consider when analyzing variations in women's time use, particularly when their husbands leave home in search of opportunities across these borders.

Second, Mchinji is an active tobacco-growing district, along with Kasungu, Lilongwe, and Dowa. Tobacco production is labor- and time-intensive, and commercial tobacco farms thus serve as a major source of seasonal rural employment for local farmers, locally known as *ganyu*. *Ganyu* in farming is also common during the rainy season, and its payment is typically made in cash or in-kind (Dimova et al., 2010). *Ganyu* can provide short-term relief by bridging seasonal gaps in food and income for rural households, albeit often insufficiently (Bouwman et al., 2021; Gono et al., 2023).[11] Thus, investigating its role in food security and nutritional stability is a meaningful exercise.

Third, the prevalence of malnutrition is salient in Mchinji district. According to the fifth Malawi IHS report in 2020, malnutrition levels persistently remain high in the central region, where Mchinji district is located, followed by the southern and northern regions (MNSO, 2020). Among the nine districts in the central region, Mchinji has the second-highest malnutrition rate, with stunting at 18% and underweight at 9%. Underlying this issue, food shortages are common despite Mchinji's good transport links to neighboring districts, which, in theory, could facilitate food access. The IHS 2020 food shortage data, which describe seasonal food availability, show that Mchinji was among the top 10 out of 32 districts in Malawi, where food stock shortages persisted in most months that year (MNSO, 2020).

[11] For example, De Janvry et al. (2022) demonstrated that low household consumption in rural areas is critically associated with a lack of work opportunities, indicating that *ganyu* is a key activity in nourishment and consumption smoothing for rural households in Malawi.

This pattern aligns with the findings of Mkondiwa and Apland (2022), identifying Mchinji as a maize-supplying district for Lilongwe. This contrast between food outflows and local shortages suggests that food access includes affordability as a core component.

[Figure 2]

Among the seven traditional authorities (TA) in Mchinji district, we selected TA Mkanda and Sub-chief (SC) Mavwere as the study sites to capture interesting contrasts in female labor demand. Figure 2 shows the locations of these two sites. TA Mkanda is adjacent to Chipata in Zambia and has a livelihood system influenced by the two countries' socioeconomic activities. In contrast, SC Mavwere is on the international border with Mozambique and is close to the Lilongwe urban center. Although TA Mkanda and SC Mavwere share similar agricultural production and demographic characteristics, women's livelihoods and time use could show remarkable differences because of variations in exposure to international borders and Malawi's capital city.

The main agricultural cycle at the study site is the rainy season, which spans from November to March.[12] At the survey time of this study, in the 2022/23 agricultural season, the primary crop in the survey area was maize (the staple food), followed by legumes, such as soybeans and groundnuts. Both men and women participated in maize production, with women dedicating comparable amounts of time to its cultivation, as observed in the fields. For context, the onset of the 2022/2023 rainy season was typical for Mchinji district, as the planting rains started in late November (DCCMS, 2023). Although floods occurred due to Tropical Cyclone Freddy in mid-March, no significant damage to crop production was observed because the crops had already matured. Overall, the study sites experienced normal to above-normal rainfall and slightly warmer conditions in the season (DCCMS, 2023). Given normal crop production from the 2022/2023 agricultural season, the Famine Early Warning Systems Network (FEWS NET) assessed that the Mchinji district faced minimal to no food security outcomes in June 2023 (FEWS NET, 2023). The adequate climate and crop conditions during the study period lend more credence to our results from this particular season, yielding a general takeaway about livelihoods across production stages among rural women in the study site.

3.2. Data

This study uses panel data from 300 households. For survey sampling, we obtained the latest list of households and villages in the district prepared by the planning division of the Mchinji district office in August 2022. The list includes approximately 7500 households in 47 villages in TA Mkanda and 20000 households in 161 villages in SC Mavwere. From the list, we randomly selected 12 villages

[12] De Janvry et al. (2022) report that only 10% of households plant during the dry season from October to June, and agriculture is the most cyclical source of work. Given the limited role of the dry season in farming in rural Malawian contexts, this study focuses its attention on periods within the rainy season.

from TA Mkanda and eight villages from SC Mavwere.[13] We excluded villages that were too small to cover a sufficient number of households or those that were not found during fieldwork.

The survey team consisted of four graduates from national universities in Malawi and the first author. A unique feature of the survey was that female household representatives were interviewed. In most cases, the survey team interviewed the spouses of the household heads or the female household heads. In each village, households were sampled from the official household roster, which was randomly sorted prior to selection. We set the following three inclusion conditions for households: (1) they had been in the village for the past two years consistently, (2) the female representative's age was verified to be between 18 and 49 years, and (3) they had at least one child under the age of five years. In the initial survey conducted in November 2022, we visited the first 15 households on the randomized list in each village to screen for eligibility. If a household did not meet the inclusion criteria, the next household on the list was visited, and this process continued down the list until 15 eligible households were selected per village. In this way, a total of 300 households were sampled across all villages.

[Figure 3]

Each household was interviewed four times during the main agricultural season using structured questionnaires. Figure 3 illustrates the timeline of the interviews throughout the survey, with the typical agricultural practices of maize production for each period. We conducted the first survey in early November 2022 to collect information on land preparation from 300 households.[14] The second survey was conducted with 290 households in mid-to-late January 2023 to follow up with the respondents and capture the time spent on planting activities and fertilizer applications. This period corresponded to the first weeding phase. We then conducted the third survey in mid-to-late March with 291 households and the fourth in mid-June with 271 households to collect information on harvesting activities.[15] Thus, the data form an unbalanced panel. In addition to details on agricultural activities, each survey collected the following information: family rosters, the health status of each member, participation in seasonal *ganyu* labor, household assets, food security, and the social groups in which the household participates.

We restricted the analysis sample by dropping 35 observations that failed to interview female representatives or collect outcome variables (3.0%, 35/1152). Thus, the total number of observations in the analysis sample is 1117, with 298 observations from November 2022, 281 from January 2023,

[13] We assigned more weights to TA Mkanda than SC Mavwere because, according to the list prepared by World Agroforestry (ICRAF), SC Mavwere has 400 villages and TA Mkanda has 603. Villages may be heterogeneous; thus, the number of villages is not necessarily proportional to population. However, the list from the district office may likely be incomplete. The ICRAF's list is available at http://landscapeportal.org/layers/geonode:villagesgeo.
[14] All eligible households agreed to participate in the survey. A likely reason for the high participation rate is that respondents received a bar of soap as a token of appreciation for their time and effort.
[15] The data collection in TA Mkanda covering 12 villages took 6–8 days on average, depending on the presence of social events like festivals and funerals. The survey took 4–6 days on average in SC Mavwere, covering eight villages.

278 from March 2023, and 260 from June 2023. The attrition rate between November 2022 and June 2023 is 12.8% ((298-260)/298).

3.3. Measurement and Construction of Key Variables

This subsection discusses how key variables are measured in the survey and how they are constructed for the subsequent empirical analysis.

Household food insecurity

[Table 1]

To gauge household-level food insecurity levels across the periods within the agricultural cycle, we adopted the Household Food Insecurity Access Scale (HFIAS) developed by the USAID-funded Food and Nutrition Technical Assistance project (Coates et al., 2007). After the pre-test in the field, we included seven occurrence questions regarding household food insecurity experiences in the previous 30 days, along with follow-up questions to inquire about the frequency of these occurrences during the same period. Table 1 presents the seven questions used in the survey. These experience-based food insecurity scales can capture household-level behavioral and psychological manifestations of insecure food access in three domains: 1) anxiety and uncertainty about household food access, 2) insufficient quality (variety, preferences, and social acceptability), and 3) insufficient food intake and its physical consequences (Swindale & Bilinsky, 2006). The questions are relatively straightforward, and this scale is validated in rural settings (e.g., Knueppel et al., 2010; Gebreyesus et al., 2015).[16]

While each measure is interesting, aggregating them into a summary index would benefit further analysis. To reflect the severity of the food insecurity condition for each question, we constructed the Household Food Insecurity Access Prevalence (HFIAP) Status indicator, following Coates et al. (2007). In this categorical indicator, households are classified into four levels based on the most severe condition experienced: food secure (= 1), mildly food insecure (= 2), moderately food insecure (= 3), or severely food insecure (= 4). Table 1 summarizes this classification scheme.

Household dietary quality

Nutritional outcomes depend not only on food quantity but also on dietary diversity and the intake of micronutrients (Korir et al., 2023). National food-based dietary guidelines for each country

[16] Despite their methodological appeal, self-reported food insecurity measures (e.g., HFIAS and HDDS) may suffer from response biases, including social and economic desirability, limited knowledge about other household members' food security conditions, and perceptions that are not necessarily representative of the entire household (Tadesse et al., 2020; Data4Diets, 2023). To mitigate these concerns, we restrict our analysis sample to households in which the main female household member responded to the survey and include household fixed effects in all the regressions to control for time-invariant reporting tendencies. Nonetheless, we acknowledge that response bias cannot be fully eliminated and highlight this as a limitation of the study. Exploring hybrid approaches that incorporate calculated indicators to minimize biases from misreporting, as recommended by Tadesse et al. (2020), is left for future work.

recommend the intake of safe, nutritious, and diverse foods after computing the nutritional needs of the average population to determine adequacy. The HDDS, defined as the total number of food groups consumed within a specific reference period, provides a household-level indicator for assessing the ability to access a diverse range of food. The literature has also validated the HDDS as a proxy for socioeconomic status.[17]

In this study, each survey recorded what the household had consumed in the previous 24 hours as the recall period. This study categorized food into the following 12 groups[18]: 1) cereals; 2) roots and tubers; 3) milk and milk products; 4) vegetables and tubers; 5) fruits; 6) meats; 7) eggs; 8) fish; 9) legumes, nuts, and seeds; 10) oils and fats; 11) sweets; and 12) spices, condiments, and beverages. We defined the number of food groups as the HDDS and used it in our analysis. Thus, our defined HDDS ranges from 0 to 12.

Time use

For each survey, female respondents were asked about their time-use patterns in the last 24 hours. To develop the time use module, we first compiled a comprehensive list of possible daily activities based on prior household surveys conducted in Malawi (e.g., LSMS-ISA). These activity categories were then adapted to reflect the local context and specific survey periods. The questionnaire was designed using the World Bank's Survey Solutions platform, which enabled automated checks to minimize data entry errors. For example, the questionnaire was programmed to flag unreported time based on identified gaps between recorded activities and to detect inconsistencies by calculating the duration of each activity, thereby helping to ensure internal consistency and data quality. Given that task synchronization is common in the local context, the time-use module allowed for multitasking and the reporting of up to two simultaneous activities within the same timeframe. The enumerators asked the respondents to recall their activities from 4:00 AM on the day before the interview until 3:59 AM on the interview day, covering a whole 24-hour period.[19] The enumerators then categorized the recorded activities. For each activity, respondents were asked to specify the start and end times, which were subsequently recorded. Based on these responses and the activity classifications, we grouped the reported activities into three broad categories: agricultural work, household chores, and leisure.[20]

[17] However, this indicator has not been validated as a proxy for the adequacy of specific macro- and micro-nutrients, and the minimum cutoff point for a sufficiently diverse diet has not been established in the literature. Refer to Data4Diets (2023) for a comprehensive introduction to the HDDS and other food security indicators.

[18] The survey asked questions on 16 more fine-grained categories. In calculating the HDDS, 1) vitamin A rich vegetables and tubers, 2) dark green leafy vegetables, and 3) other vegetables (e.g., tomatoes and onions) are aggregated into vegetables. 1) Vitamin A rich fruits (e.g., mangos) and 2) other fruits (e.g., bananas) are aggregated into fruits. Finally, 1) organ meats and 2) fresh meats are aggregated into meats.

[19] We adopted a 24-hour recall period for time use data collection to minimize retrospective recall bias (Masuda et al., 2014; Kilic et al., 2024). While averaging across multiple days could yield a smoother measure of time use, it would also increase both recall bias and respondent burden (Seymour et al., 2020). A potential limitation of the single-day recall approach is that time use patterns may vary by day of the week. To address this concern and ensure comparability across observations, we include day-of-week fixed effects in all regressions.

[20] The "Agricultural work" category aggregates the following subcategories: "food crop farming," "cash crop farming," "livestock raising," "fishing/fishpond culture," "work as employed," "own business work," and "commuting (to/from the

Our interviewer-assisted recall-based time use diary method may be prone to cognitive errors in activity recall (Seymour et al., 2020). For instance, based on randomized control trial results, Kilic et al. (2024) report lower participation but longer reported time spent on agricultural activities—and higher participation and longer duration for leisure—when time use is collected using a recall-based method, compared to data recorded with smartphone applications.[21] Nonetheless, the diary recall approach with face-to-face interviews may be a practical and realistic choice in contexts with lower literacy and numeracy, such as in our study setting (Lentz et al., 2019).[22]

Health status

Regarding health status, we asked the respondents whether each household member had been sick during the specified reference period and, if so, how many days they were unable to work due to illness.[23] The reference periods varied by survey round: two months (November-December) for the January 2023 survey, two months (January-February) for the March 2023 survey, and three months (March-May) for the June 2023 survey.[24] To account for these differences in reference duration, we report monthly averages when describing the intraseasonal pattern of illness in the next section.

Nutritional status

The survey also collected anthropometric data from women aged 18 to 49 years. Women's weights were recorded using a digital scale. Changes in body weight reflect short-term health status. The survey team used a tape measure to record women's left arm MUAC. MUAC is also used to determine short-term acute malnutrition due to undernutrition or disease.

4. Describing Intraseasonal Dynamics of Food Security, Time Use, and Health

workplace)." While the category includes some non-farm activities, such as wage employment and own business, these are infrequent in the sample and, when they do occur, are predominantly agriculture-related. Therefore, we retain the label "agricultural work" to reflect the dominant nature of these activities in the local context. The "Household chores" category includes: "shopping/getting services," "weaving and sowing," "cooking," "domestic work (e.g., fetching water and firewood)," "caring for children," "caring for adults (elderly and sick)," and "traveling (for consumption purposes)." We include commuting and travel times in their respective categories, as they represent time inputs necessary to complete the main productive or domestic task. This classification is consistent with standard practices in time-use surveys that count necessary travel as part of the primary activity. Finally, the "Leisure" category aggregates the following subcategories: "sleep and resting," "eating and drinking," "personal care," "watching TV/listening to the radio," "exercising," "social activities and hobbies," and "religious activities."

[21] This overestimation is partly attributed to the minimum activity duration of 15 minutes commonly used in recall-based diary methods. In contrast, our time-use module records the actual start and end times of each activity, allowing for finer resolution that may help reduce the risk of systematic overestimation of time use.

[22] The median years of education among sampled female respondents is five, with more than 10% having never attended school.

[23] No formal definition of "sick" was provided to respondents; thus, responses may reflect self-reported perceptions of illness and may be subject to measurement errors. To mitigate this concern, all regressions include individual fixed-effects for the main female respondent, which helps control for time-invariant differences in reporting behavior across respondents.

[24] The reference period for the illness questions in the November 2022 survey was the preceding two weeks.

This section describes the time-series patterns of the key empirical variables used in the analysis. To contextualize these patterns, we begin by outlining the agricultural calendar in the survey area. Figure 3 presents the timeline of major maize production activities alongside the survey months. The four survey rounds—November, January, March, and June—correspond to the land preparation, growing, early harvest, and post-harvest periods, respectively. Based on field observations, we identify the period from January to March as the lean period, during which food stocks are typically depleted. Because the food insecurity indicators refer to conditions in the previous 30 days, responses from the January and March survey rounds most clearly reflect the food security conditions during the lean period. We first verify this intraseasonal pattern using descriptive evidence.

[Figure 4]

Figure 4 depicts intraseasonal fluctuations in household food security in the rural Malawian context by presenting kernel density estimates of the distributions of answers to HFIAS questions for each survey. Each panel in Figure 4 represents a different facet of food security: food availability (FS1), household consumption capacity (FS2), dietary diversity (FS3), and food choice (FS4). For example, the Q1 panel captures food availability by reporting the number of days out of the last 30 when respondents worried that their household would not have sufficient food to eat. The kernel density plot indicates that household-level concerns about running out of food were most intense in January, providing evidence that January is part of the lean period. To a lesser extent, food concerns were also intense for most households in November, indicating that food insecurity had already begun at the onset of the rainy season. Although early harvests in March can mitigate food concerns, as noted by Anderson et al. (2018), most continued to face food security concerns until the post-harvest period in June in our research context.

The Q2 panel represents consumption capacity by reporting the number of days the respondent was unable to eat their preferred foods in the last 30 days. The Q3 panel captures dietary diversity by reporting the number of days the respondent had to eat a limited variety of foods in the last 30 days. These panels illustrate a greater capacity to eat favored foods and a more varied diet (including legumes and fish, as discussed in more detail later) in the post-harvest period than in other months when only food staples and vegetables are consumed. Conversely, these indicators showed discernible decreases throughout the pre-harvest periods, particularly in January. This pattern provides further evidence for the lean period, and families frequently turn to less preferred meal choices (Q4).

[Figure 5]

Figure 5 illustrates the severity and human cost of food insecurity in rural Malawi, particularly in extreme forms. Figure 5 focuses on three experiences that capture the essential characteristics of food insecurity: eating smaller meals than needed (Q5), having no food for an entire day (Q6), and going to bed hungry (Q7). A clear intraseasonal pattern emerges. In June, when households typically have greater food availability following the main harvest, these experiences are nearly absent. In contrast, each of the three indicators is reported by a non-negligible share of households in the other survey months. These patterns indicate that, for at least some households, severe food insecurity is a recurring reality prior to the harvest period.

[Figure 6]

Figure 6 further confirms these patterns by showing transitions in household food insecurity categories based on the HFIAP Status indicators across periods within the cropping season. While only a very few households achieve food security throughout the season, the proportion classified as severely food insecure peaked in March, consistent with the lean period. Notably, transitions from severe food insecurity occurred more frequently toward moderate food insecurity than towards full food security in June, suggesting that food insecurity remains a pressing concern even during the post-harvest period for about half of the sample households. Taken together with Figures 4 and 5, Figure 6 underscores the dynamic nature of food security and its close alignment with the seasonal agricultural cycle.

[Figure 7]

The intraseasonal pattern of dietary diversity exacerbates stress from the limited food intake during the lean period. Figure 7 illustrates the distribution of the HDDS by survey time, showing how the eating patterns and nutritional adequacies of rural Malawian families changed across periods within the agricultural season. The HDDS for the first two survey months was concentrated on three food groups. The distribution did not change significantly in March, although most field crops are maturing by this time, theoretically increasing household access to green maize and some field vegetables. These early harvests do not translate into dietary diversity because maize and vegetables are already part of the standard diet in January, as we will confirm later. Thus, the average HDDS remained low: 3.52 in November 2022, 3.23 in January 2023, and 3.21 in March 2023. In addition to highlighting the problem of food availability, the decline in dietary diversity during the lean period of January and March raises questions about nutritional sufficiency and its potential health effects. Figure 7 also shows a much flatter HDDS distribution during the post-harvest period, as some households transition towards more than five food groups. However, despite the observed improvement, the average HDDS remained below the recommended minimum of five food groups at 4.20.

[Figure 8]

To further examine intraseasonal variations in nutritional diversity among rural Malawian households, Figure 8 presents the fraction of food categories consumed by households in the last 24 hours by survey round to show how their food plates changed throughout the agricultural season. For instance, Figure 8 shows a decrease in the number of nutrient-dense foods (e.g., meats, fish, and milk) high in protein and micronutrients as a striking feature of the lean period in January and March: Diets during this period are primarily composed of vegetables and staples (*Nsima*) with salt, resulting in an average HDDS of 3.[25] In the post-harvest period, the data reveal a modest increase in the consumption of a few food groups (e.g., roots, fish, legumes, and oil). Despite this slight improvement, overall dietary diversity remains poorly represented, highlighting persistent challenges in achieving adequate nutrition even after harvest.

[Figure 9]

The lean period, characterized by reduced food intake and limited dietary diversity, also coincides with peaks in agricultural labor. Figure 9 illustrates how women allocate their time across activities during the active period of agricultural production, from the beginning of the crop season (November) to the end (June), emphasizing their roles and ability to adjust to the farming cycle. Thus, Figure 9 shows the flexibility with which women manage their time. A noteworthy pattern concerns the interaction between agricultural work and leisure. In November and January, which have more work hours for farming activities than in other months, and in March, which is marked by reduced farm labor demands, women devote fewer hours to work and more to leisure, with this pattern persisting in June. Therefore, work hours and leisure time are inversely related. On the contrary, the average time spent on household chores was stable across all periods.

[Figure 10]

The health problems that rural Malawian women face may also exhibit seasonal features, introducing an additional source of stress on their nutritional status beyond limited food access and heightened labor demands. Figure 10 illustrates the monthly averages of illness frequency and sick days among the main female respondents in each period. Notably, the proportion of women with illness is higher during the agricultural production period—when farm labor demand peaks between November and February—than between March and May, although the difference is not significant. Moreover, the average number of sick days was highest in the lean period between January and February, coinciding with both heightened food insecurity and intensive agricultural work.

[Figure 11]

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[25] While salt is not nutritionally categorized as a food group, it is recognized for its fortified iodine content, a micronutrient of public health importance.

Overall, the descriptive evidence suggests that the lean period—particularly January—is marked by heightened food insecurity, peaks in agricultural labor, and increased illness prevalence, all of which have significant implications for women's nutritional status. Figure 11 illustrates the physical health of the sampled women in rural Malawi based on weight and MUAC outcomes.[26] Compared to the beginning of the rainy season, these outcomes deteriorated during the growing period in January, primarily when farmers were engaged in planting, weeding, and other agricultural activities. Average weight reached its lowest point in March. Although mean MUAC values remained above the undernutrition cutoff of 24 cm for non-pregnant adult women throughout the agricultural season, the aggregate pattern in Figure 11 may obscure meaningful heterogeneity in MUAC fluctuations across periods among sampled women. Given that MUAC is a sensitive indicator of acute malnutrition, we further investigate this heterogeneity in the regression analysis below. By June, when agricultural activities are reduced and food security improves, weight and MUAC measurements returned to the levels recorded in November. We now turn to examining the pathways linking intraseasonal labor demands, health risks, and food access to women's nutritional status in a more rigorous way using regression analysis.

5. Econometric Analysis

5.1. Empirical Specifications

[Table 2]

While the descriptive evidence presented in Section 4 highlights intraseasonal variations in women's work patterns and health outcomes, the associations between the factors that determine women's welfare are complex, as illustrated by the conceptual framework in Figure 1. This study focuses on women's anthropometric outcomes (i.e., body weight and MUAC) as welfare indicators. This section disentangles the complex relationships among labor supply, food security, illness, and health by employing a regression framework to examine the determinants of across-period fluctuations in women's anthropometric outcomes. Table 2 presents the definitions and summary statistics of the variables used in the regression analyses.

Based on the assumed relationship depicted by the conceptual framework in Figure 1, we specify the fixed-effects model for women's time use as follows:

$$TimeUse_{ijt}^{k} = \beta_0 + \beta_1 Sick_{ijt} + \beta_2 Sick_{-ijt} + \beta_X X_{jt} + \alpha_i + \alpha_t + \varepsilon_{ijt} \quad (1)$$

where $TimeUse_{ijt}^{k}$ represents the hours spent on activity k by main female respondent i from household j at time t. We define two types of health shocks. $Sick_{ijt}$ is a dummy that equals one if main female respondent i became ill between the last survey time $t-1$ and the current survey time t. During the same reference period, $Sick_{-ijt}$ counted the number of family members, except for the main female

[26] Appendix Figures 1 and 2 display the distributions of body weight and MUAC, respectively, by survey round.

respondent, who became ill. X_{jt} represents household-level controls including household size.[27,28] To control for day-of-week lifestyle differences, X_{jt} includes six dummies for the day of the week to which the time use measured by the survey at time *t* refers. α_i is an individual fixed-effect for main female respondent *i*. α_t is a time fixed-effect for survey time *t* to capture the direct effect of seasonality. November 2022 is the reference category. Finally, ε_{ijt} is an error term. Errors are clustered by female respondent to account for the possible correlations of errors across survey rounds.

Using similar notations, we model household-level food security as follows:

$$FoodInsecurity_{jt} = \gamma_0 + \gamma_1 Sick_{ijt} + \gamma_2 Sick_{-ijt} + \gamma_3 X_{jt} + \mu_j + \mu_t + \epsilon_{ijt} \quad (2)$$

where $FoodInsecurity_{jt}$ is a food insecurity measure for household *j* at time *t*. The aggregated food insecurity index based on the HFIAP Status indicator (1-4) and HDDS separately is used as the outcome variable. μ_j is a household fixed-effect, and μ_t is a time fixed-effect for survey time *t*. ϵ_{ijt} is a random error term. Robust standard errors with household clustering are reported to allow for arbitrary correlation over time. Despite the ordinal nature, we run OLS for the food insecurity indicator to avoid biased estimates from non-linear models due to the incidental parameters problem associated with household fixed effects. Nevertheless, we also present ordered probit results in Appendix Table 1 to check the robustness of applying OLS to the categorical outcome variable.

The probability of becoming ill is high when food intake is insufficient; therefore, sickness variables can be endogenous because of potential reverse causality. Although incomplete, this study uses sickness variables measured during the reference period (i.e., the one or two months preceding the reference period of food security questions) to circumvent endogeneity concerns.

Finally, we use women's anthropometric measures as welfare indicators and specify their determinants as follows:

$$Y_{ijt} = \delta_0 + \delta_T TimeUse^k_{ijt} + \delta_F FoodInsecurity_{jt} + \delta_1 Sick_{ijt} + \delta_2 Sick_{-ijt} + \gamma_3 X_{jt} + \theta_i + \theta_t + u_{ijt} \quad (3)$$

where Y_{ijt} is the anthropometric outcome (either log-transformed body weight or MUAC) of main female respondent i from household j measured at time *t*. θ_i is a fixed-effect for main female respondent *i*, and θ_t is a time fixed-effect for survey time *t*. Finally, u_{ijt} is an error term.

[27] Other potential candidates for confounding factors include household assets (particularly livestock), off-farm income, and the use of hired labor, all of which may help cushion the adverse effects of period-specific labor demand on time use patterns, food security, and hence nutritional outcomes. However, we adopt a parsimonious specification, as the remaining variation after controlling for individual fixed effects would reflect net changes in these factors (e.g., livestock sales or acquisitions), which are likely to be endogenous. For this reason, we use the current, simpler model specification.

[28] The presence of alternative labor within the household may help reduce women's workload, particularly in the domain of domestic tasks. While child labor outside the household is uncommon in our sample, children and other female household members may share the burden of household responsibilities. We will explore the role of these family members in intrahousehold labor substitution, particularly in relation to cooking, in a later section. It is also worth noting that polygamous households were not observed in our study sites, in contrast to some regions of northern Malawi.

The current specification relates women's time use, measured for the 24 hours preceding the interview, to their anthropometric measures collected on the interview day. One concern is that time use over a single day may not immediately influence nutritional status. For instance, the physical strain associated with agricultural work is likely to accumulate over time. As such, it may be a better specification to assume that anthropometric measures reflect conditions shaped by a longer prior period, which time-use data cannot capture with a 24-hour recall period. A related concern is potential reverse causality reflecting potential nutrition-productivity links: current nutritional status may itself affect the amount of labor women can supply, given the proximity between the reference periods of the two variables.

Our rationale for using contemporaneous time-use measures is that time-use data collected over the last 24 hours are intended to represent average period-specific time allocation patterns within the agricultural season, rather than to capture short-run relationships. Nonetheless, to address concerns regarding the appropriate temporal link between time use and nutritional status, we conduct robustness checks using lagged time-use variables in place of contemporaneous ones. These exercises help assess whether our main empirical findings are sensitive to potential misspecification of the timing assumed in Equation (3).

5.2. Regression Results

5.2.1. Time Use by Women

[Table 3]

Table 3 presents the factors influencing women's time by reporting OLS regression results for Equation (1). The results show that one's own illness has a statistically positive association with time spent on agricultural work (Column 1). However, because illness may be period-specific, this relationship could reflect spurious correlations. After considering this possibility by adding period dummies, the estimated coefficient on own illness remains positive and is marginally significant (p-value = 0.13; Column 2).[29] While this result does not reach conventional significance levels, the direction of the association (Arrow 2b: Time allocation changes in Figure 1) is noteworthy given the contrasting relationship with domestic work hours that we discuss below. One explanation for this unexpected positive correlation between farm work hours and illness is reduced labor productivity due to sickness. If the workload must be completed on time and alternative labor is difficult to find, those who are ill should also work.[30] However, women's labor productivity would be lower than normal, and farm work

[29] One possible reason for the reduced significance is multicollinearity between own illness and the number of sick household members, which are moderately correlated with the coefficient of correlation of 0.35 for the analysis sample. This correlation may reduce the independent variation available to estimate the effect of one's own illness. To assess this, we re-estimated the same regression in Column 2 after excluding the number of sick family members. The point estimate for own sickness increased to 0.508, and the p-value decreased to 0.09. Nevertheless, we prefer the full specification with family member illness, as it allows us to examine potential intrahousehold labor substitution effects.

[30] Sinha (2010) made a similar observation by highlighting the working conditions of farmers in India. He found that many agricultural workers remain engaged in agricultural practices despite hunger, pregnancy, and unpleasant health states.

would take longer. These results suggest that, even when experiencing illness, women cannot easily adjust farm labor due to binding agronomic constraints (e.g., narrow planting windows and time-sensitive weeding) and workforce shortages. In this context, women have little flexibility to reduce farm labor in response to health shocks in an agricultural season.

Columns (3) and (4) show that an increase in work hours in response to illness correlates with a decrease in domestic work hours. This contrast may indicate greater flexibility in household chores than in farm work.[31] Regarding the consequences of illness in leisure time, the estimated coefficient is not statistically significant at any conventional level (Columns 5 and 6). The coefficients of the number of sick family members are insignificant across the specifications, providing no evidence of the consequences of health externalities on time use, at least in our dataset.

The period dummies in the even-numbered columns capture variations in time use across different stages of the agricultural production cycle, corresponding to Arrow 1a: Farm labor demand in Figure 1. Women's time-use patterns remained comparable between November 2022 and January 2023. This important empirical regularity can have implications for the gender division of labor, particularly in agriculture, which may account for changes in working hours across different periods. While different agricultural activities may demand disproportionate hours from other family members based on comparative advantage, our results illustrate women's consistent engagement in farming during the pre-harvest periods.

The results also show that women devoted less time to agricultural work and, in turn, increased leisure time in March 2023 (Columns 2 and 6). This pattern can be attributed to the sequential nature of agricultural practices, whereby the most time-consuming activities are land preparation in November and planting, weeding, and fertilizer application in January. March is a relaxed time for farmers because it is the pre-harvest time when their time commitment to their farm is minimal. Thus, the reduced time commitment to agricultural activities allows for more leisure time. Females' time commitment to agricultural work in June is still minimal, although farming households have harvested and sold their produce to agricultural traders by this time.

In contrast to the stable pattern of the average time spent on household chores across all periods, as depicted in the descriptive time series in Figure 9, women spent over 30 minutes less per day on chores

[31] The flexibility in household chores can be seen in the results based on the day of the week. Compared to Monday, which serves as the reference category, women work longer hours on Wednesday, Thursday, and Friday. This pattern can be linked to the standard practice of days dedicated to work. In contrast, the time spent on household chores is shorter on these days. This may be explained by how women consider work a higher priority (including farm work) than household chores, which can be delegated to other family members, such as children. We also find that women spend less time at work and more time on leisure on Saturdays and Sundays. This empirical pattern is consistent with the standard practice of locals attending festivals and community mobile markets on Saturdays. In contrast, Sunday is a day of rest for attending religious activities and visiting family members.

in March. Although this decline became less pronounced, the trend persisted into June 2023. As Wodon and Beegle (2006) demonstrate using time-use data over 13 months from Malawi, household chores are predominantly the responsibility of women in this context. If the volume of domestic tasks remains constant throughout the year and women consistently bear responsibility for this domain of work, one would expect the time spent on chores to remain stable, regardless of the periods within the agricultural season.

[Table 4]

To further investigate this unexpected pattern, we run the same regression separately for three sub-categories of domestic work: cooking, water and fuelwood collection, and other household chores (e.g., childcare). The estimation results presented in Table 4 indicate that the decline in time spent on household chores in March and June is primarily driven by a reduction in cooking time. One plausible explanation for the reduced cooking time is the availability of fresh vegetables from fields and gardens, which require shorter cooking times compared to dry maize and legumes. Another potential mechanism is intrahousehold labor substitution: with reduced farm labor demand in March, other female household members or children may help with food preparation.

Appendix Table 1 tests these hypotheses by interacting period dummies with indicators for the consumption of “other vegetables” (e.g., tomatoes and onions), the number of female adults aged 19-40, and the number of female children aged 6-18. The estimation results support the interpretation that improved access to fresh vegetables for self-consumption during the post-harvest periods contributes to reduced cooking time. Specifically, the interaction terms between the vegetable consumption dummy and the March and June period dummies are negative and statistically significant, while the period dummies themselves become insignificant once these interactions are included (Columns 1 and 4).[32] By contrast, we find no supporting evidence that intrahousehold labor shifts drive reduced cooking time after the early harvest period (Columns 2-4 in Appendix Table 1).

5.2.2. Household Food Security

[Table 5]

Table 5 presents the regression results for the factors influencing household food insecurity and the HDDS. Regarding the pathway corresponding to Arrow 2d: Forgone economic activities in Figure 1, Column (1) shows that the illness of the main female household representative is associated with a deterioration in household food security. However, this association becomes statistically insignificant once period dummies are included in Column (2), suggesting that seasonal patterns in disease

[32] While we also examine the potential role of the early harvest of green maize in reducing cooking time, the estimation results do not provide supporting evidence (results not shown).

prevalence may drive the relationship. In contrast, women who experienced illness between the survey periods reported a higher HDDS (Column 4). One possible explanation is that when the female representative becomes ill, the family increases her access to food as a way of helping her obtain better nutrition to recover quickly from the illness. A common practice is to source special foods for patients, such as snacks, fruits, and other nutritious foods, during their illness. Another prevalent coping strategy for sick days involves adjusting food consumption patterns (Ansah et al., 2021). During the sick period, households may shift to diets that require less labor to prepare, thereby conserving time and energy while enabling family members to meet their labor obligations without compromising the patient's nutritional intake. Despite these plausible mechanisms, the relatively small magnitude of the estimated coefficient suggests that the economic significance of this pathway appears limited.

We now turn our discussion to intraseasonal variations in household-level food security, corresponding to Arrow 3a: Food availability in Figure 1. Compared to November 2022, household food security deteriorated in January 2023, as evidenced by a higher food insecurity score and a lower HDDS (Columns 2 and 4 in Table 6). This downward trend worsens further in March.[33] Low HDDS in these months indicate limited household access to diverse diets. January and early March correspond to the hunger period, a time characterized by depleted household food stocks, reduced food availability in rural markets, and rising food prices. Additionally, limited cash flow during this period often constrains household purchasing power, preventing individuals and families from consuming a diverse and nutritious diet (Benson & De Weerdt, 2023).[34]

Households typically have access to green maize and some field vegetables by March. Nevertheless, the regression results suggest that these early harvests do not ease food insecurity or translate into dietary diversity because maize and vegetables are already part of the standard diet in January. The

[33] We conducted three robustness checks to assess the sensitivity of our findings. First, given that our food insecurity index is ordinal, we estimated ordered probit regressions despite concerns related to the incidental parameters problem. Columns (1) and (2) in Appendix Table 2 report coefficient estimates from the ordered probit model. The qualitative results remain consistent with those obtained from the main specification. As expected, the calculation of marginal probabilities was unsuccessful due to issues with perfect prediction. Second, to address concerns about limited variations in the food insecurity score, we constructed an alternative measure using principal component analysis (PCA) applied to the seven food security questions. PCA was selected because it is a data-driven approach to constructing a composite index that captures the underlying variation across potentially correlated answers. We then used the first principal component to determine the weighting factors for each answer for gauging food insecurity and defining the index. By definition, a higher score implies greater food insecurity. Appendix Figure 1 illustrates the changes in the PCA-based food insecurity measure across survey rounds, with the highest scores observed in January 2023. Using the PCA-based index as the dependent variable, Columns (3) and (4) in Appendix Table 2 replicate the specifications from Columns (1) and (2) of Table 6. The results remain qualitatively similar. Finally, Appendix Table 3 reports regression results for each of the original food security questions. The results provide direct evidence that severe food insecurity situations peaked in March, as reflected in responses to FQs 6 and 7. Overall, these robustness checks suggest that our main findings are not sensitive to the choice of regression model or the aggregation method used to construct the food insecurity index.

[34] We also examine the role of *ganyu* labor in stabilizing food security by including a dummy variable equal to one if any household member engaged in *ganyu* work in the past two months. The estimation results show a statistically significant positive coefficient in the regression for the food insecurity score (results not shown), suggesting potential reverse causality: *ganyu* labor is likely a coping response to food insecurity. Given this endogeneity concern, we refrain from further interpretations of the role of *ganyu* labor in this paper.

breakdown of the HDDS in March, shown in Figure 10, confirms that most households consumed staples, vegetables, and spices (particularly salt), with only a few households consuming oil, legumes, or sweets. On average, dietary diversity remained very poor, with an average HDDS of 3.21. Moreover, green maize harvested early differs from the kind that could fetch the money they would receive when selling dry maize. As a result, the income generated from the sale of green maize may not provide sufficient resources for the family to afford an adequate and nutritious diet, contributing little to purchasing other foods and changing dietary diversity (Benson & De Weerdt, 2023). Overall, poor food access, limited purchasing power, and low food availability in rural markets contribute to inadequate diets during the hunger period.

The situation improved in June 2023, with both food security indicators and HDDS showing positive changes. This result aligns with expectations: By June, households begin to sell their farm produce and use the proceeds to supplement their diets, alongside harvested crops retained for self-consumption. The increases in food stocks from the harvest contribute to greater food availability and improved meal quality (Adekunle et al., 2020). During this period, local markets are also more responsive to rising demand from farmers who now have cash on hand. These markets often source food items from outside the community, thereby expanding dietary options. As we have seen in the HDDS breakdown in Figure 10, households increased their consumption of legumes, fish, and oils in June. We formally test this pattern using regression analysis. Appendix Table 4 reports regression results for each food group. The estimation results find significant increases in the consumption of roots, nuts, oils, and sweets in June relative to March. There are also modest increases in vegetables, meat, fish, and spices. Since certain food items, such as fish and oil, are market-sourced foods in these communities, this pattern suggests that the observed increase in dietary diversity during the post-harvest period is driven by improved cash flow.[35]

Overall, our descriptive and regression results highlight the persistent threat of the hunger period in rural Malawi, characterized by heightened food insecurity and low levels of dietary diversity at the household level prior to the main harvest. These findings suggest that food scarcity during this period is sufficiently severe to lead to hunger and missed meals in some households, consistent with evidence from other contexts (e.g., Khandker et al., 2012). The observed intraseasonal variations in food security further underscore the direct link between agricultural production and food access in terms of quality and quantity, corresponding to Arrow 3a: Food availability in Figure 1. This relationship has also been documented in similar settings, such as in Ethiopia (Aweke et al., 2022). Our descriptive analysis in the previous section revealed a similar pattern of fluctuations in women's weight and MUAC measurements across agricultural production stages, suggesting a cyclical dynamic in household food

[35] Household income in rural Malawi is closely linked to the success of the harvest and prevailing agricultural market prices. When harvest outcomes are poor or market prices are low, households may see little to no improvement in their ability to diversify diets, even after harvest. This may explain why, despite the end of the hunger period, more than 50% of surveyed households did not consume protein-rich foods (e.g., fish and legumes) during the post-harvest period.

security that may contribute to variations in women's nutritional status in rural Malawi. The following subsection statistically tests this hypothesis using a regression framework.

5.2.3. Women's Nutritional Status

[Table 6]

Finally, the regression analysis examines the factors contributing to intraseasonal variations in women's welfare by focusing on anthropometric measures. Table 6 presents the regression results for the determinants of body weight and MUAC of the main female household member. The number of observations in this analysis differs from that in the previous analysis. These health outcomes are missing for 51 observations, partially because some respondents rejected the measurement. Additionally, we excluded 11 observations with implausible values when the first differences in body weight and MUAC were 10 kg or 5 cm, respectively. Thus, the analysis includes 1055 observations in total.

First, we discuss the determinants of log-transformed body weight, as reported in Columns (1)–(4) of Table 6. Columns (1)-(2) include the food insecurity index based on the HFIAP Status indicator as a continuous variable, while Columns (3)-(4) replace this with dummies for each food insecurity category. In both specifications, the food insecurity score and HDDS are significantly associated in the expected direction in Columns (1) and (3). However, these associations lose statistical significance after controlling for period dummies (Columns 2 and 4). Additionally, we find no statistical significance for other channels, such as illness and time spent on agricultural work. In contrast, the results for period dummies suggest that women's body weight in January and March 2023 was 2.9% and 3.5% lower, respectively, compared to November 2022. These findings suggest that once individual fixed effects are controlled for, the regression captures only the direct effect of the agricultural production calendar on women's weight (Arrow 4: Other period-specific effects in Figure 1), while the indirect pathways via illness, time use, and food access (Arrows 1b: Energy expenditure/domestic reproduction, 2c: Health status, and 3b: Food and nutrient intakes) play a minor role. The observed intraseasonal variations in women's body weight thus suggest that influences beyond individual health, labor supply patterns, and household-level food insecurity are at play, pointing instead to broader structural dynamics within the agricultural season.

One empirical concern is the potential mismatch in timing between women's time use and their nutritional outcomes in our baseline specification, where time use is measured over the 24 hours preceding the interview, while anthropometric outcomes are recorded on the interview day. To assess the sensitivity of our results to this timing assumption, Appendix Table A5 re-estimates Equation (3) using lagged time-use variables in place of current time use. While the estimated coefficients on lagged hours spent in agricultural work are slightly larger in magnitude and retain the expected negative sign, none of the associations are statistically significant across specifications. These findings suggest that our main null results are not driven by the use of the 24-hour reference period for the time-use data.[36]

The negligible association between working time and body weight may reflect the interplay between two competing effects (Johnston et al., 2018). Longer work hours could contribute to weight loss due to increased energy expenditure (Higgins & Alderman, 1997). However, women engaged in paid work (e.g., *ganyu*) may have more financial resources to purchase food and potentially more nutritious options using their cash income, even in the peak period. This could have positive nutritional implications and counterbalance the adverse effects of energy consumption on body weight. Consequently, if these opposing effects cancel each other out, the relationship between women's working hours and body weight may become insignificant.

Given that the associations between household-level food security and dietary quality and women's body weight lose statistical significance once period dummies are included, intraseasonal variation—captured by the period dummies—plays a dominant role in driving body weight fluctuations among women. In this context, food access constraints may operate as covariate phenomena that affect entire communities during the hunger period (particularly in January and March) rather than as household-specific idiosyncratic phenomena (Columns 2 and 4). This interpretation underscores the hunger period as a widespread and recurring challenge in rural Malawi, suggesting that existing individual- or household-level coping mechanisms may be insufficient to address food insecurity in the face of period-specific community-wide scarcity.

The natural question to ask is what else the significant period dummies capture in addition to aggregate-level intraseasonal food access constraints—namely, the mechanisms underlying Arrow 4: Other period-specific effects in Figure 1. Two omitted variables provide some possibilities. The first is that the period dummies capture intraseasonal fluctuations in the quantity of food consumed. While the regressions controlled for general household food security and dietary diversity, they do not account for food quantity due to data limitations. The sources of variation in food consumption amounts could include grain stock depletion and food price volatility. The severity of fluctuations in food prices and their impact on consumption are key considerations. Gilbert et al. (2017) examined seasonal patterns in food market performance among selected African countries and found that in Malawi, maize prices were the most acutely affected by seasonality. Such price shifts reduce consumer purchasing power and can significantly impact household food consumption. Incorporating the quantitative aspects of

[36] The same concern regarding potential timing mismatch and reverse causality also applies to the food insecurity measures. Appendix Table A6 examines this issue by re-estimating the specification using lagged measures of household food insecurity and HDDS, instead of those referring to the past 30 days. Using lagged indicators yields statistically insignificant coefficients with inconsistent signs, suggesting that they are less informative for explaining current nutritional outcomes. These results suggest that using food insecurity measures based on the most recent 30-day reference period provides a more suitable temporal framework for examining the relationship between household food insecurity and women's nutritional status.

consumption into the survey design in future work would help provide a clearer picture of seasonal variations in women's body weight. The second possibility is that the period dummies capture biological responses to climate variations in general and intraseasonal fluctuations in energy consumption, particularly linked to changing agricultural labor demands. Although hours spent on farm work are included in the model, they may not fully capture the energy cost of physically demanding work, especially if the relationship between work hours and energy consumption is nonlinear. The absence of direct measures of caloric loss due to drudgery means that such variation is likely absorbed by the period dummies.

Finally, family size was negatively associated with women's body weight, suggesting that resource constraints may be more pronounced in larger households during the agricultural season. However, we should interpret this result with caution because the migration decisions behind short-run changes in household structure are endogenous.

Our analysis used MUAC to determine acute malnutrition in the short term. Columns (5)-(8) in Table 6 present the regression results for MUAC. Several findings emerged. First, the number of household members, excluding the main female, who fell ill during the survey period was negatively associated with her MUAC. This interesting finding suggests that illness within the household, functioning as a shock, places an additional caregiving burden on women. As the primary caregivers, women may be forced to balance care responsibilities with existing labor demand for farm and domestic work. While the previous regression results in Table 3 did not find any impacts on time use patterns, the added strain may lead to less attention to their own nutritional needs. Moreover, intrahousehold food allocation may shift toward the ill family members, potentially reducing the dietary intake of the main female representatives and resulting in compromised nutritional outcomes.

Second, household-level food insecurity is also negatively associated with women's MUAC, even after controlling for period dummies (Columns 6 and 8). This finding suggests that acute shortfalls in household food access can have a rapid impact on women's nutritional status. Together, these results highlight the sensitivity of MUAC as a short-term indicator of nutritional stress stemming from caregiving burdens and household-specific food insecurity.

In contrast, the regression results show a direct association between agricultural production stages and MUAC only in January, reflecting the high energy requirements due to drudgery work (e.g., weeding) during this growing period. Additionally, earlier results suggest that heightened food insecurity during the lean period is widespread across communities, which may also be reflected in the January dummy. Taken together with the significant effects of household-level food insecurity on MUAC, these findings indicate that food insecurity is a primary channel through which the agricultural production calendar drives fluctuations in women's short-term nutritional status. Given that the food insecurity index captures relatively severe situations, these results underscore the need for timely policy interventions aimed at stabilizing food security throughout the agricultural season to prevent deteriorations in women's welfare.

6. **Conclusion and Policy Implications**

This study highlights the critical role of the agricultural production cycle in shaping women's labor allocation, household food security, dietary quality, and nutritional outcomes in rural Malawi. The three key findings of our analysis are summarized below.

1. Intraseasonal Farm Work and Leisure Imbalance among Women: During peak agricultural months (November to January), women's hours spent on farm work increase significantly, leading to a marked reduction in their leisure time. Despite these period-specific shifts, time spent on household chores remains relatively stable throughout the agricultural season, except for a decline in cooking time following the early harvest in March. This reduction is likely driven by the availability of fresh vegetables (e.g., tomatoes and onions) from fields and gardens, which require less preparation time than dry staples, rather than intrahousehold labor substitution.
2. Health Shocks and Time Use among Women: Women experience a higher incidence of illness and more sick days during the peak farming period in January and February compared to the post-harvest period. Illness episodes reduce women's domestic work hours, suggesting that household chores are more flexible and more easily adjusted than farm work in response to health shocks during an agricultural season.
3. Household Food Security and Women's Nutritional Declines: The hunger period, which precedes the main harvest, is characterized by acute food scarcity and limited dietary diversity. Households mainly consume staples with limited access to nutrient-dense foods in the hunger period, contributing to short-term nutritional deficits among women, as reflected in MUAC measurements. Household food security, dietary diversity, and women's nutritional outcomes improve significantly by June, following the main harvest.

These findings have profound implications for policy design and community-level interventions. The stark contrasts across agricultural production stages underscore the need to account for within-season variation in the formulation of policies aimed at improving food security, nutritional outcomes, and, ultimately, women's welfare in rural Malawi. Based on our empirical evidence, we highlight two promising areas for intervention.

First, we find that food access constraints act as covariate phenomena, affecting entire communities throughout the agricultural season. These intraseasonal variations are the primary drivers of body weight fluctuations among women. Therefore, ensuring year-round access to food—particularly during the lean season—is essential to mitigate short-term nutritional deficits. Potentially effective approaches are the timely implementation of community-level lean-season food transfers (Gelli et al., 2017) and expanding access to better food storage technologies (e.g., hermetic bags) (Nakoma Ngoma et al., 2025). Moreover, as our results indicate that household-specific food security conditions also influence acute malnutrition, it is crucial to target period-specific safety nets to food-insecure households during crucial periods within the agricultural cycle. Our findings further suggest that the design of food transfers should consider not only the quantity provided but also the nutritional quality and diversity of foods made accessible throughout the cropping season.

Second, we find that women's long work hours in both agricultural activities and household chores during the peak farming periods (November to February) come at the expense of reduced leisure time. While the burden of domestic work may decline slightly in the early harvest period due to the availability of fresh harvests that reduce cooking time, we find no evidence of intrahousehold labor substitution for domestic chores during peak agricultural periods. Moreover, the limited adjustment in agricultural work hours among women who report illness underscores a lack of alternative labor sources. If leisure is considered a component of welfare, then limited intrahousehold substitution and thin labor markets for hired agricultural work contribute to women's time poverty.

One potential policy response to reduce the strain of labor demands during periods of illness is the promotion of community-based labor-sharing schemes, in which local farmers collaborate to support households facing temporary labor shortages by substituting labor in time-sensitive agricultural tasks. These arrangements do not reduce total labor requirements at the community level; instead, they help redistribute labor during periods when illness constrains a household's capacity to meet period-specific workloads.[37] While labor sharing arrangements are not yet widespread in our study sites—unlike other sub-Saharan African countries (e.g., Mekonnen & Dorfman, 2017)—they have the potential to enhance households' ability to cope with illness-related labor disruptions by securing secure substitute labor.

A complementary approach, particularly for women with young children, is the introduction of community-based childcare institutions, which can reduce women's domestic care burdens during peak labor periods, in addition to their contributions to early childhood development (Neuman et al., 2014). Together, these community-level interventions can help buffer the effects of health shocks and intraseasonal labor peaks, thereby easing women's time constraints in both agricultural and domestic spheres. In this way, community-level institutional support for flexible labor redistribution has the potential to significantly alleviate the disproportionate time burden placed on women, especially when illness constrains their capacity to work or labor demands are high.

[37] Such systems are most feasible during less intensive labor periods, when households have excess labor available to contribute. Their effectiveness also depends on the presence of equitable social norms and reciprocal expectations at the local level. In settings where social hierarchies are pronounced, less powerful households may bear disproportionate obligations to contribute labor or be unable to receive equivalent support when they themselves face labor shortages due to family illness. These considerations underscore the importance of carefully designing institutions when promoting labor-sharing as a coping mechanism.

A more transformative and longer-term strategy for reducing women's agricultural workloads and alleviating time poverty is the adoption of scale-appropriate mechanization. Relatively simple technologies (e.g., hand-held planters and threshers) can reduce the time women spend on labor-intensive tasks, thereby addressing some of the root causes of time constraints. However, realizing these benefits through their adoption requires supporting institutions, including affordable financing mechanisms, reliable maintenance and repair services, and extension systems that are responsive to women's needs. Moreover, policies to facilitate mechanization must account for intrahousehold power dynamics to ensure that women have decision-making authority over the adoption and use of these technologies intended to benefit them (Miller & Mobarak, 2013; Gulati et al., 2024). Without attention to these institutional and social factors, mechanization initiatives may fail to reduce women's workloads—or could even inadvertently reinforce existing gender inequalities.

Future research should focus on collecting longitudinal data to assess the long-term implications of these intraseasonal variations in food security, labor, and health. Moreover, understanding the role of communities in protecting households from cyclical phenomena may provide valuable insights into sustainable, locally grounded interventions. Lastly, although the adoption of mechanized tools for planting and weeding remains rare in our study sites, examining the gender-differentiated welfare implications of such labor-saving technologies—particularly through reductions in both work hours and physical exertion—represents a promising avenue for future work. Our findings underscore the importance of a comprehensive approach to addressing the challenges women face in balancing their nutrition, workload, and health during periods of intense agricultural activity. Addressing these issues is crucial for fostering the resilience and overall well-being of women and their families in rural Malawi and similar agrarian contexts.

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Figures

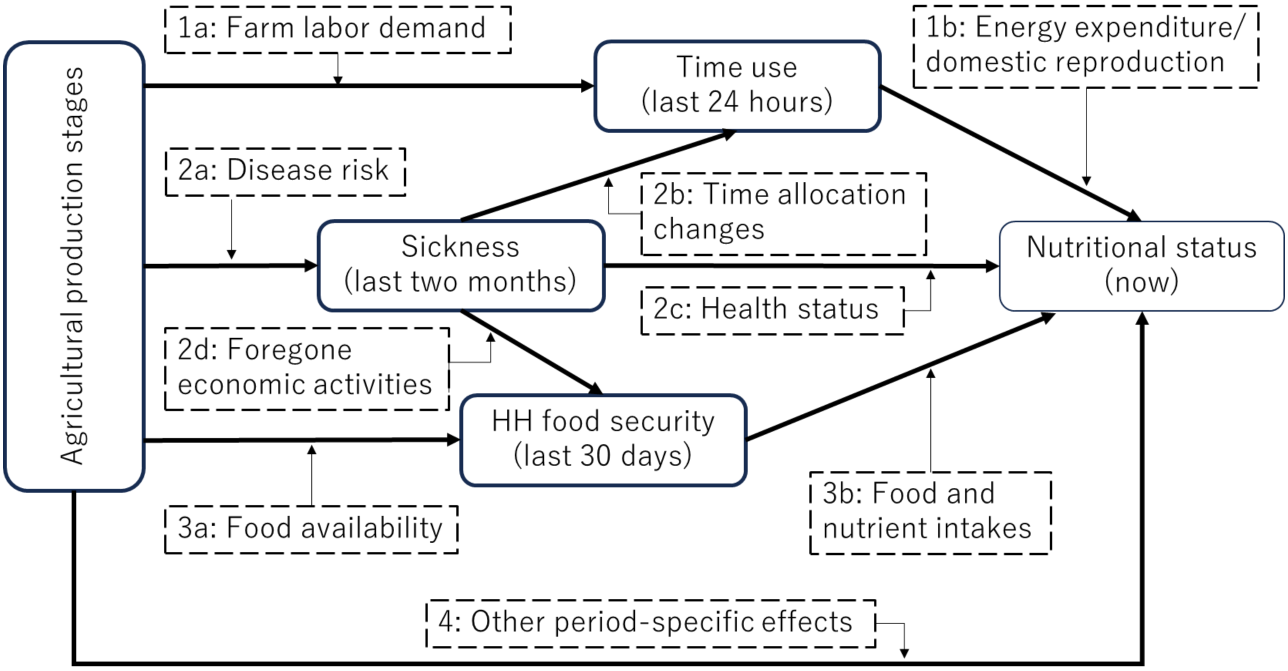


Figure 1. Graphical representation of the conceptual framework

Note: Numbers on the arrows correspond to the pathways described in the text. Arrows 1a and 1b represent *Pathway 1: Changing time allocation patterns reflecting period-specific farm labor demands*. Arrows 2a, 2b, 2c, and 2d represent *Pathway 2: Changing health status reflecting period-specific disease risks*. Arrows 3a and 3b represent *Pathway 3: Changing household food security conditions due to period-specific food availability*. Arrow 4 represents *Pathway 4: Remaining pathways to women's nutritional status*. Periods in parentheses indicate the reference period for each empirical variable collected in the household survey.

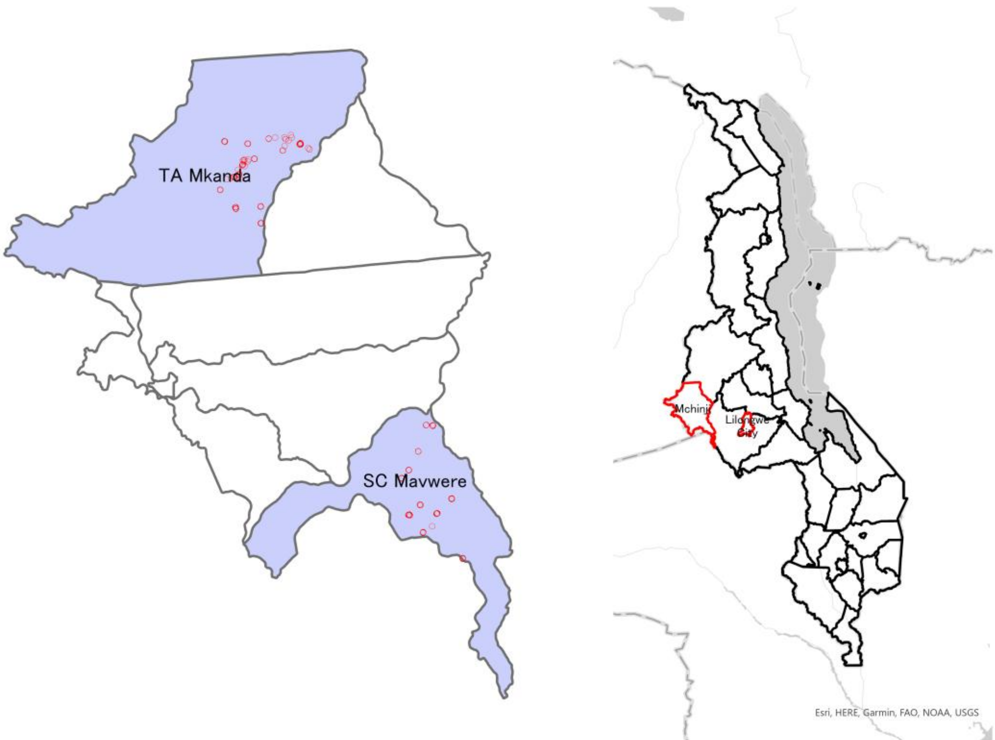


Figure 2. Location of survey villages in Mchinji district

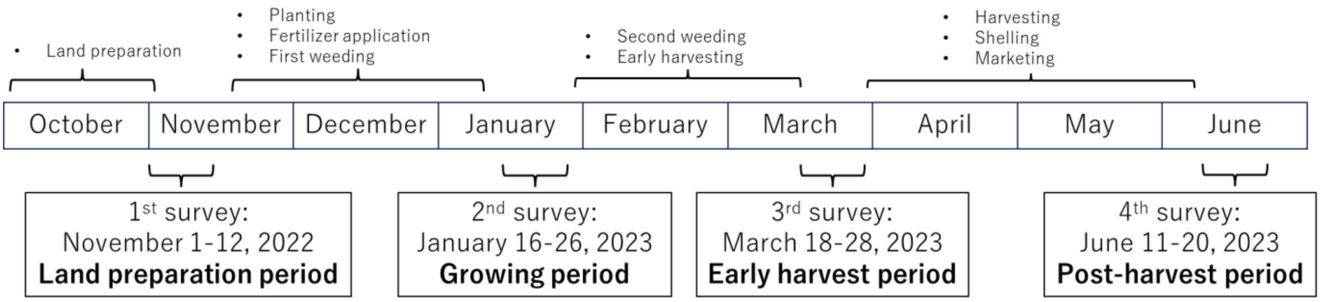


Figure 3. Agricultural activity calendar for maize production and timeline of the household surveys

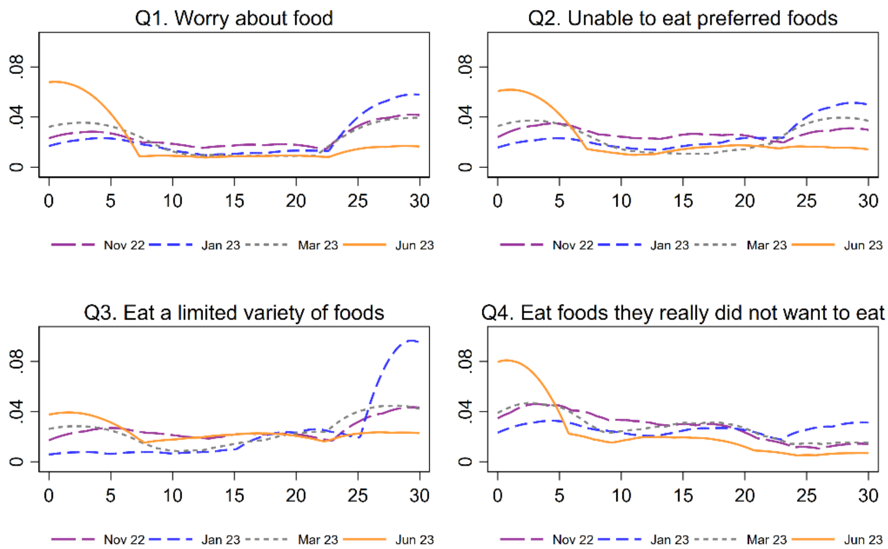


Figure 4. Household food security by survey round: Q1–Q4

Note**:** Each panel shows kernel density estimates of the distributions of answers to the frequency questions related to food security by survey round. The Epanechnikov kernel was used in estimating these densities. The Q1 panel shows the number of days the respondent worried that the household would not have sufficient food in the last 30 days on the X-axis. The Q2 panel indicates the number of days the respondent could not eat foods they preferred in the last 30 days on the X-axis. The Q3 panel shows the number of days the respondent had to eat a limited variety of foods in the last 30 days on the X-axis. The Q4 panel indicates the number of days the respondent had to eat some foods they did not want to eat in the last 30 days on the X-axis. The Y-axes show the estimated densities for all panels.

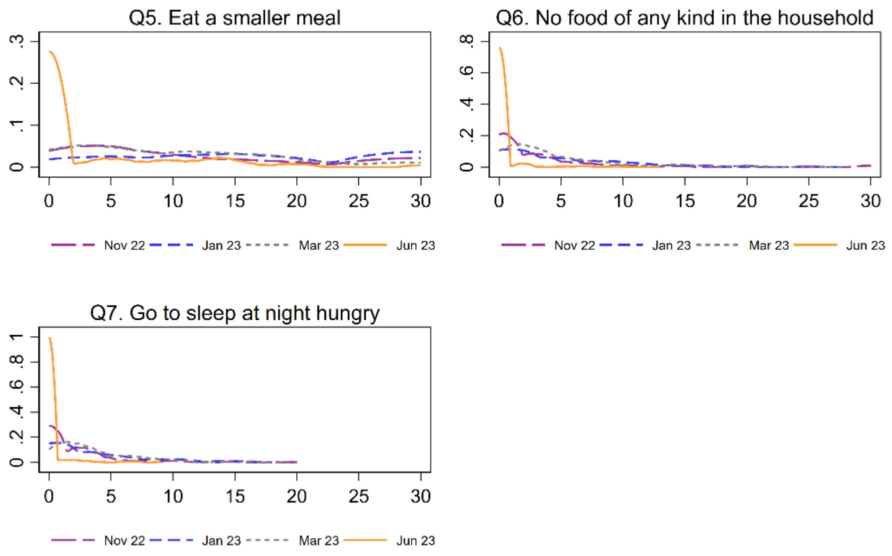


Figure 5. Household food security by survey round: Q5–Q7

Note: Each panel shows kernel density estimates of the distributions of answers to the frequency questions related to food security by survey round. The Epanechnikov kernel was used in estimating these densities. The Q5 panel shows the number of days the respondent had to eat a smaller meal than needed in the last 30 days on the X-axis. The Q6 panel indicates the number of days the respondent had no food in the last 30 days on the X-axis. The Q7 panel shows the number of days the respondent went to sleep at night hungry in the last 30 days on the X-axis. The Y-axes show the estimated densities for all panels.

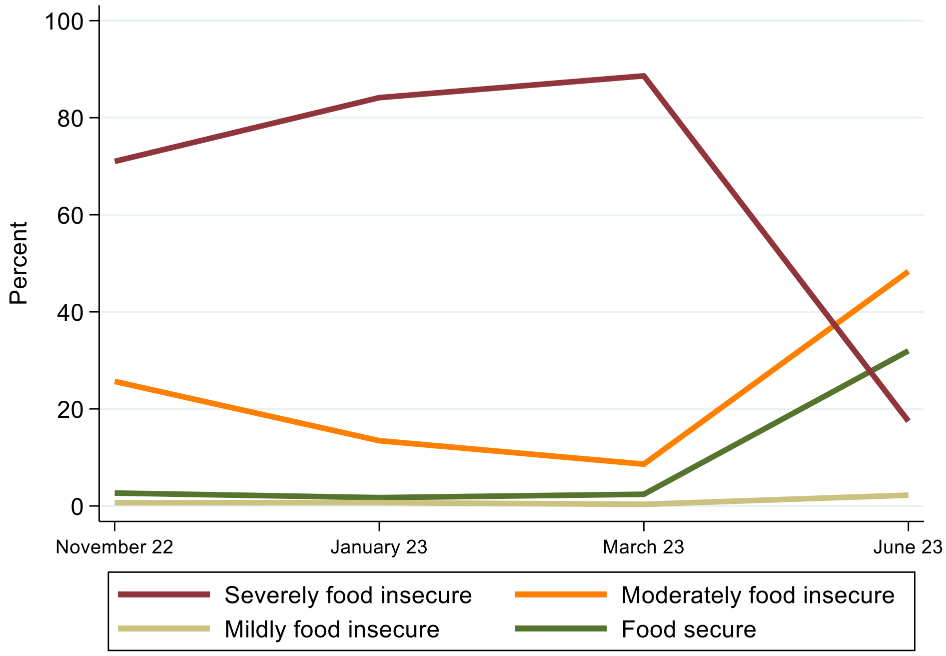


Figure 6. Household food insecurity category by survey round

Note: The figure shows the percentage distribution of households across food insecurity categories for each survey round. November, January, March, and June correspond to the land preparation, growing, early harvest, and post-harvest periods, respectively.

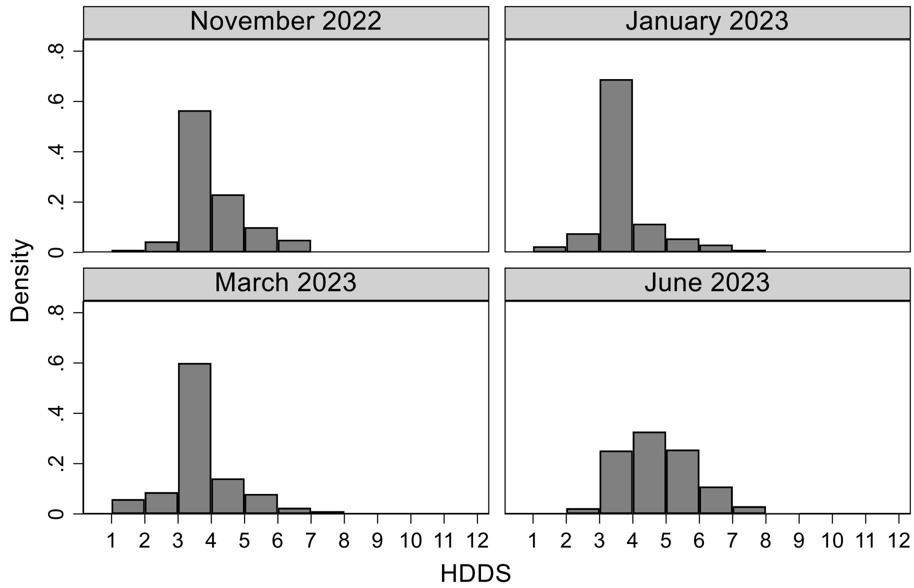


Figure 7. Household Dietary Diversity Scores (HDDS) by survey round

Note: November, January, March, and June correspond to the land preparation, growing, early harvest, and post-harvest periods, respectively.

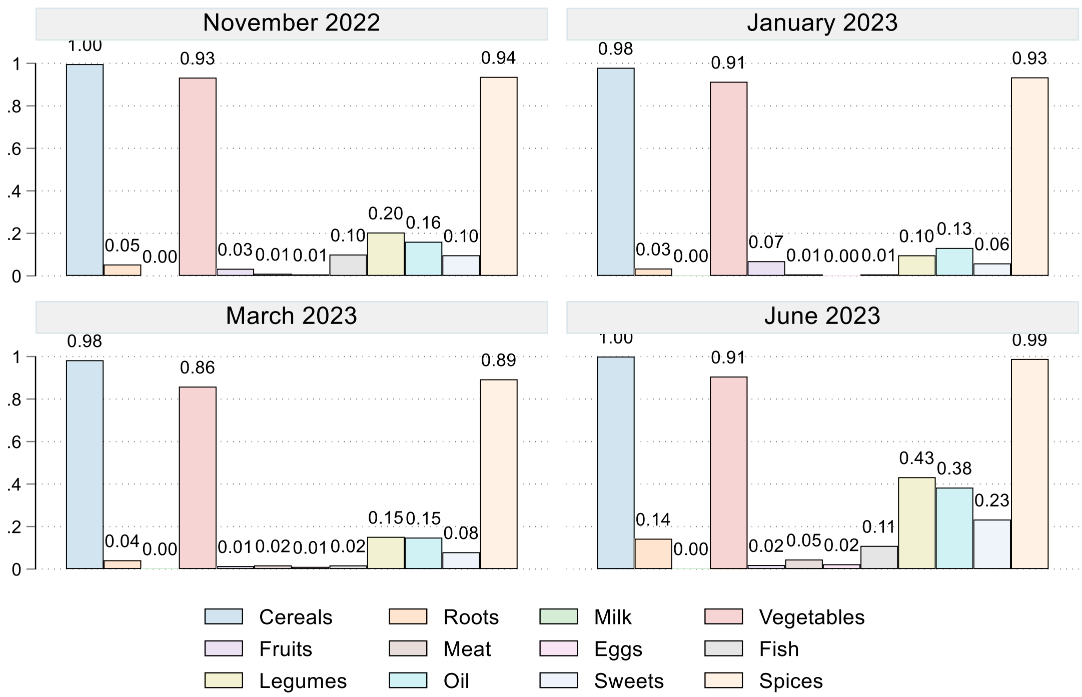


Figure 8. Breakdown of HDDS by survey round

Note: November, January, March, and June correspond to the land preparation, growing, early harvest, and post-harvest periods, respectively.

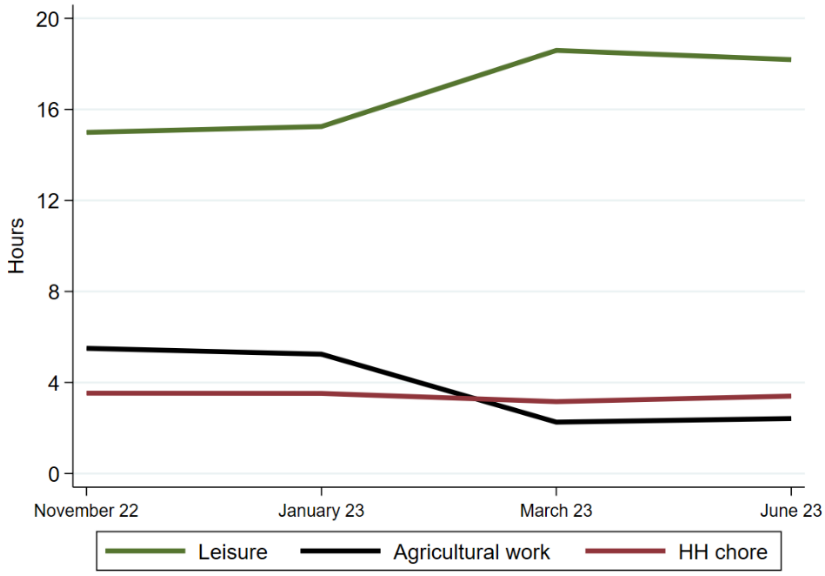


Figure 9. Time use by women across periods within the crop cycle

Note: November, January, March, and June correspond to the land preparation, growing, early harvest, and post-harvest periods, respectively.

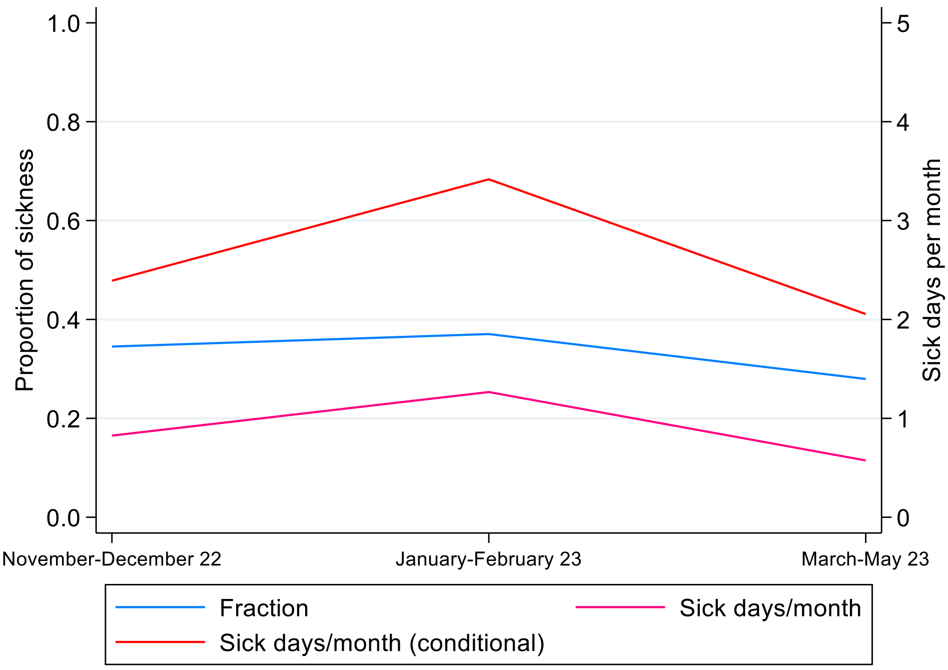


Figure 10. Illness incidence and the number of sick days among women by period

Note: November, January, March, and June correspond to the land preparation, growing, early harvest, and post-harvest periods, respectively. The red line shows the monthly average number of days the main female respondents were unable to work due to illness, among those who reported being sick.

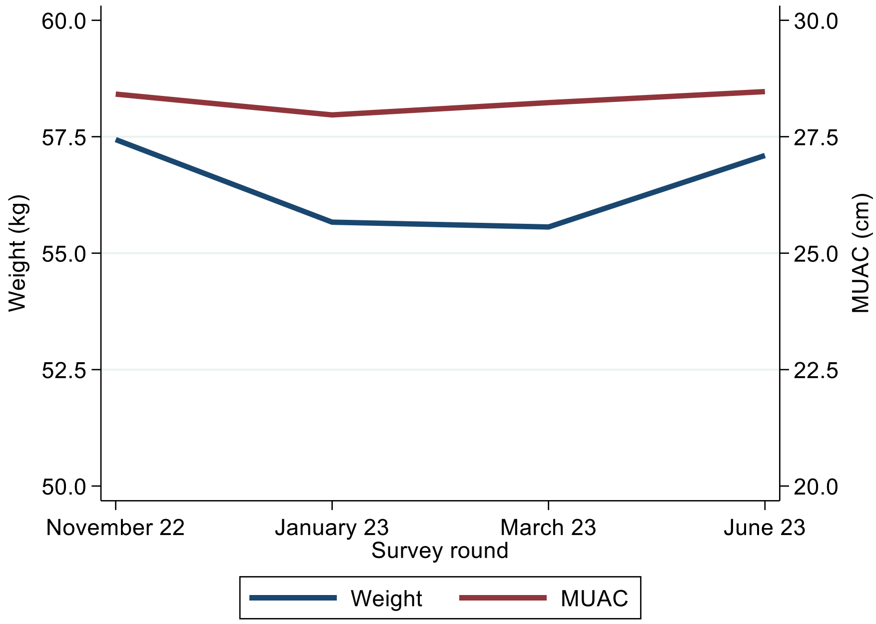


Figure 11. Women's weight and MUAC by survey round

Note: November, January, March, and June correspond to the land preparation, growing, early harvest, and post-harvest periods, respectively.

Tables

Table 1. HFIAS questions and food insecurity categories

		Frequency	
HFIAS questions	Rarely	Sometimes	Often
Q1. Worried about food	Food secure	Mildly FI	Mildly FI
Q2. Unable to eat preferred foods	Mildly FI	Mildly FI	Mildly FI
Q3. Ate a limited variety of foods	Mildly FI	Moderately FI	Moderately FI
Q4. Ate foods they really did not want to eat	Mildly FI	Moderately FI	Moderately FI
Q5. Ate a smaller meal than needed	Moderately FI	Moderately FI	Severely FI
Q6. No food of any kind in the household	Severely FI	Severely FI	Severely FI
Q7. Went to sleep at night hungry	Severely FI	Severely FI	Severely FI

Source: Adapted from Coates et al. (2007), with modifications.

Notes: Rarely indicates below twice in the past 30 days. Sometimes indicates three to ten days in the past 30 days. Often indicates more than 10 days in the past 30 days. FI stands for Food Insecure.

Table 2. Summary statistics of empirical variables

Variable	Definition	N	Mean	SD
Outcome variables				
Agricultural work	Time spent on agricultural work (hours)	1117	3.91	3.57
HH chore	Time spent on domestic work (hours)	1117	3.41	2.16
Cooking	Time spent on cooking (hours)	1117	1.54	0.99
Collection	Time spent on water and fuelwood collection (hours)	1117	0.29	0.46
Other chores	Time spent on other chores (hours)	1117	1.58	1.82
Leisure	Time spent on leisure activities (hours)	1117	16.70	3.36
Food insecurity score	Household Food Insecurity Access Prevalence (HFIAP) Status indicator (1-4)	1117	3.47	0.91
HDDS	Household Dietary Diversity Score (0-12)	1117	3.54	1.13
Body weight	Body weight of female respondent (kg)	1055	56.45	10.07
MUAC	Left mid-upper arm circumference of female respondent (cm)	1055	28.27	3.38
Control variables				
Own sick dummy	=1 if female respondent became ill during the reference period[1] (dummy)	1117	0.33	0.47
No. of sick family members	Number of family members, except for female respondent, who became ill during the reference period	1117	0.93	1.12
Family size	Number of individuals who normally live and eat their meals together, irrespective of blood ties[2]	1117	4.93	1.78

Notes:

[1] The reference periods are the preceding two weeks for the November 2022 survey, two months (November-December) for the January 2023 survey, two months (January-February) for the March 2023 survey, and three months (March-May) for the June 2023 survey.

[2] Individuals studying or staying elsewhere and temporary visitors who maintain a household elsewhere are excluded.

Table 3. Determinants of women's time use

	(1) Ag work	(2) Ag work	(3) HH chore	(4) HH chore	(5) Leisure	(6) Leisure
Own sick dummy	0.612*	0.482	-0.441*	-0.459**	-0.170	-0.022
	(0.343)	(0.314)	(0.231)	(0.230)	(0.307)	(0.274)
No. of sick family members	0.148	0.038	0.029	0.022	-0.179	-0.062
	(0.131)	(0.114)	(0.096)	(0.098)	(0.123)	(0.105)
Family size	0.403	0.258	-0.136	-0.176	-0.253	-0.070
	(0.269)	(0.268)	(0.171)	(0.173)	(0.243)	(0.236)
Tue	1.007**	0.250	-0.483*	-0.596**	-0.520	0.347
	(0.440)	(0.401)	(0.278)	(0.281)	(0.454)	(0.392)
Wed	1.449***	0.912**	-0.627**	-0.719**	-0.827*	-0.202
	(0.451)	(0.393)	(0.285)	(0.284)	(0.453)	(0.365)
Thu	2.304***	1.486***	-0.764**	-0.927***	-1.535***	-0.561
	(0.562)	(0.441)	(0.307)	(0.313)	(0.572)	(0.419)
Fri	0.519	0.826*	-0.494	-0.429	0.006	-0.365
	(0.563)	(0.470)	(0.345)	(0.336)	(0.565)	(0.436)
Sat	-1.090**	-0.238	-0.534*	-0.439	1.629***	0.685*
	(0.493)	(0.396)	(0.292)	(0.299)	(0.476)	(0.377)
Sun	-2.433***	-1.952***	-0.052	0.062	2.504***	1.914***
	(0.407)	(0.367)	(0.277)	(0.282)	(0.420)	(0.358)
January 2023		0.282		-0.172		-0.122
		(0.306)		(0.190)		(0.278)
March 2023		-2.585***		-0.563**		3.130***
		(0.303)		(0.222)		(0.257)
June 2023		-2.333***		-0.381*		2.694***
		(0.326)		(0.212)		(0.302)
Individual FE	YES	YES	YES	YES	YES	YES
Mean Y	5.50	5.50	3.53	3.53	14.99	14.99
R squared	0.42	0.53	0.35	0.36	0.39	0.55
N	1117	1117	1117	1117	1117	1117

Notes: Robust standard errors clustered by female respondent are reported in parentheses. Monday is the reference category for the day of the week. Mean Y represents the averages of the outcome variables in November 2022. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Determinants of women's time for domestic work

	(1)	(2)	(3)	(4)	(5)	(6)
	Cooking	Cooking	Collection	Collection	Other chores	Other chores
Own sick dummy	-0.100	-0.126	0.057	0.056	-0.398*	-0.388*
	(0.096)	(0.097)	(0.041)	(0.042)	(0.210)	(0.207)
No. of sick family members	-0.092**	-0.109***	0.020	0.025	0.101	0.105
	(0.038)	(0.039)	(0.017)	(0.017)	(0.084)	(0.086)
Family size	0.059	0.026	-0.023	-0.035	-0.172	-0.167
	(0.069)	(0.068)	(0.030)	(0.031)	(0.163)	(0.164)
Tue	-0.077	-0.169	-0.031	-0.026	-0.375*	-0.400*
	(0.150)	(0.148)	(0.058)	(0.058)	(0.219)	(0.226)
Wed	-0.017	-0.089	-0.063	-0.068	-0.547**	-0.563**
	(0.128)	(0.120)	(0.055)	(0.055)	(0.246)	(0.251)
Thu	0.069	-0.043	0.056	0.037	-0.889***	-0.921***
	(0.138)	(0.130)	(0.069)	(0.067)	(0.276)	(0.286)
Fri	-0.029	-0.025	-0.055	-0.056	-0.410	-0.347
	(0.139)	(0.136)	(0.065)	(0.065)	(0.271)	(0.263)
Sat	-0.215*	-0.120	0.011	-0.012	-0.330	-0.307
	(0.122)	(0.123)	(0.065)	(0.066)	(0.255)	(0.253)
Sun	-0.232*	-0.170	-0.041	-0.023	0.221	0.255
	(0.132)	(0.131)	(0.055)	(0.056)	(0.243)	(0.246)
January 2023		-0.017		-0.120***		-0.035
		(0.092)		(0.037)		(0.161)
March 2023		-0.263**		-0.057		-0.243
		(0.107)		(0.043)		(0.174)
June 2023		-0.402***		-0.036		0.057
		(0.083)		(0.045)		(0.188)
Individual FE	YES	YES	YES	YES	YES	YES
Mean Y	1.72	1.72	0.35	0.35	1.47	1.47
R squared	0.39	0.41	0.41	0.42	0.34	0.34
N	1117	1117	1117	1117	1117	1117

Notes: The outcome variables in columns (3) and (4) are the time spent on the collection of water and fuelwood. Robust standard errors clustered by female respondent are reported in parentheses. Monday is the reference category for the day of the week. Mean Y represents the averages of the outcome variables in November 2022. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Determinants of household food insecurity and HDDS

	(1)	(2)	(3)	(4)
	Food insecurity score	Food insecurity score	HDDS	HDDS
Own sick dummy	0.153**	0.055	0.083	0.152*
	(0.076)	(0.066)	(0.100)	(0.090)
No. of sick family members	0.085**	0.027	-0.009	0.038
	(0.036)	(0.025)	(0.048)	(0.043)
Family size	0.041	-0.034	-0.031	0.005
	(0.072)	(0.052)	(0.071)	(0.071)
January 23		0.108*		-0.254***
		(0.057)		(0.091)
March 23		0.178***		-0.295***
		(0.060)		(0.096)
June 23		-1.158***		0.765***
		(0.090)		(0.109)
HH FE	YES	YES	YES	YES
Mean Y	3.65	3.65	3.52	3.52
R squared	0.28	0.59	0.39	0.52
N	1117	1117	1117	1117

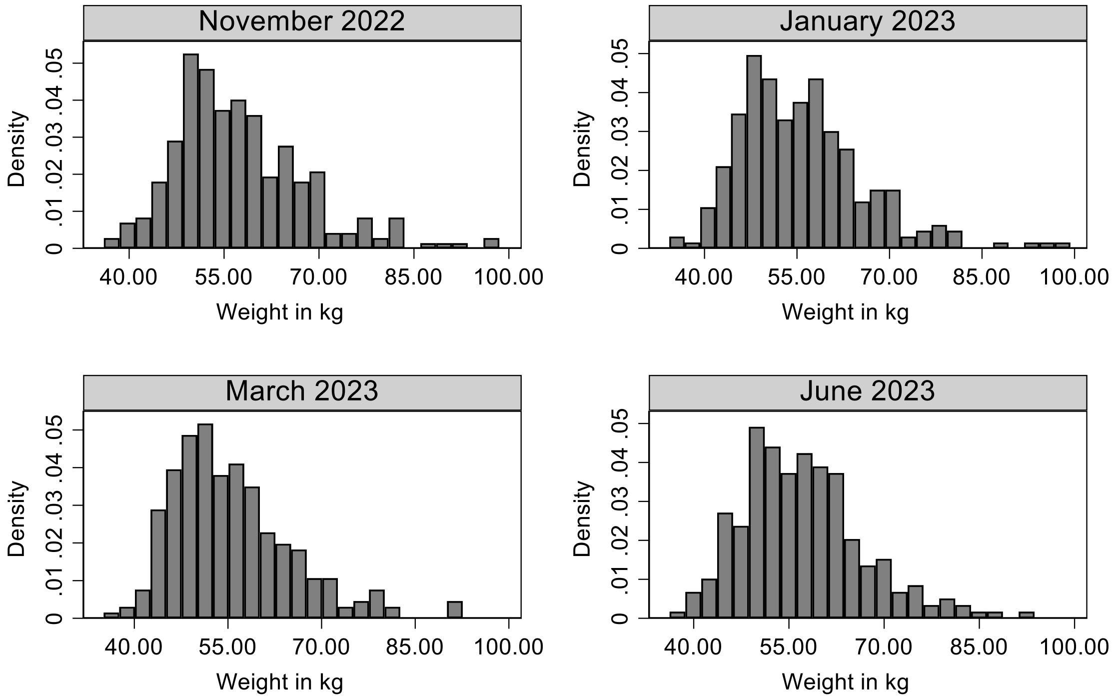
Notes: Robust standard errors clustered by household are reported in parentheses. Household fixed-effects are included. Six dummy variables indicating the day of the week for the last 24 hours reference period are included with Monday as the reference but not reported. Mean Y represents the averages of the outcome variables in November 2022. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Determinants of women's nutritional status

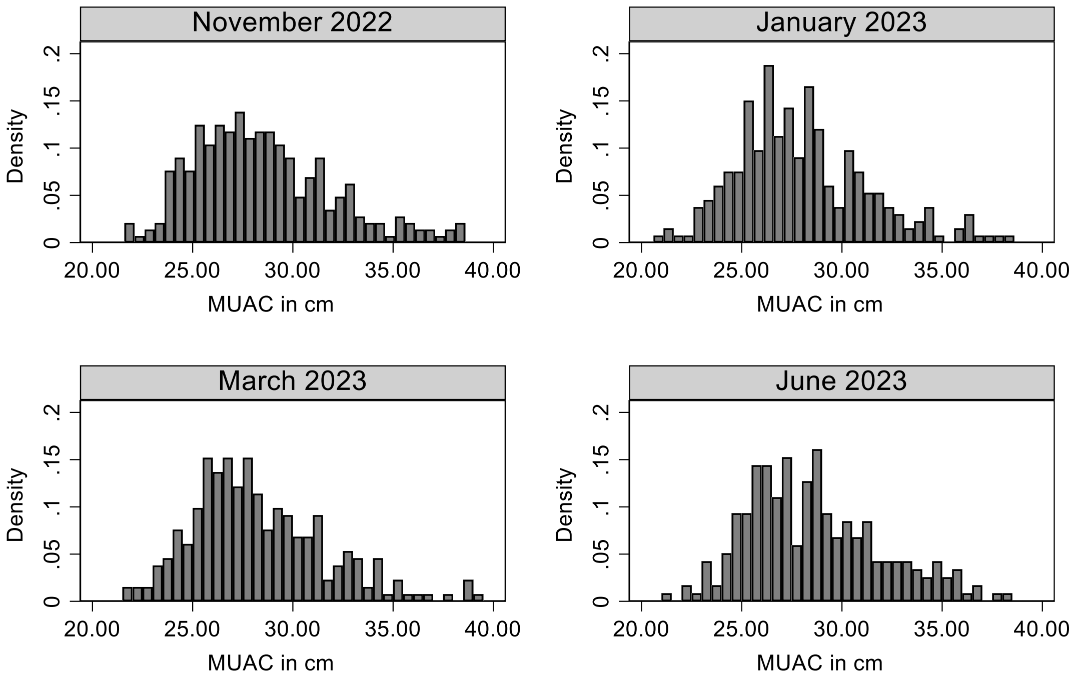
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lnWeight	lnWeight	lnWeight	lnWeight	MUAC	MUAC	MUAC	MUAC
Own sick dummy	0.000	-0.000	0.001	0.000	0.037	0.028	0.024	0.012
	(0.004)	(0.003)	(0.004)	(0.003)	(0.098)	(0.096)	(0.098)	(0.096)
No. of sick family members	-0.002	-0.001	-0.001	-0.001	-0.087**	-0.076*	-0.090**	-0.078*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.041)	(0.040)	(0.041)	(0.040)
Food insecurity score	-0.006***	0.002			-0.168***	-0.157**		
	(0.002)	(0.002)			(0.060)	(0.067)		
Mildly FI			-0.017	-0.014			-0.172	-0.116
			(0.021)	(0.022)			(0.394)	(0.402)
Moderately FI			0.001	0.006			-0.569***	-0.562***
			(0.006)	(0.006)			(0.190)	(0.199)
Severely FI			-0.015**	0.006			-0.565***	-0.485**
			(0.006)	(0.006)			(0.186)	(0.207)
HDDS	0.006***	0.002	0.005***	0.001	-0.007	-0.023	0.007	-0.014
	(0.002)	(0.002)	(0.002)	(0.002)	(0.043)	(0.048)	(0.045)	(0.049)
Family size	-0.004	-0.007**	-0.003	-0.006**	0.002	-0.039	-0.010	-0.053
	(0.003)	(0.003)	(0.003)	(0.003)	(0.071)	(0.073)	(0.072)	(0.074)
Agricultural work	0.000	0.000	0.000	0.000	-0.014	-0.010	-0.014	-0.010
	(0.001)	(0.001)	(0.001)	(0.001)	(0.023)	(0.024)	(0.023)	(0.023)
Leisure	-0.001	0.000	-0.001	0.000	0.008	0.005	0.007	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.024)	(0.026)	(0.024)	(0.026)
January 23		-0.029***		-0.029***		-0.320***		-0.346***
		(0.003)		(0.003)		(0.091)		(0.092)
March 23		-0.035***		-0.035***		-0.093		-0.126
		(0.004)		(0.004)		(0.130)		(0.130)
June 23		-0.000		-0.001		-0.094		-0.049
		(0.005)		(0.005)		(0.149)		(0.147)
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Mean Y	4.04	4.04	4.04	4.04	28.42	28.42	28.42	28.42
R squared	0.97	0.97	0.97	0.97	0.93	0.93	0.93	0.94
N	1055	1055	1055	1055	1055	1055	1055	1055

Notes: The outcome variables for Columns 1–4 are women's body weight after log transformation. Robust standard errors clustered by female respondent are reported in parentheses. Fixed effects for each female respondent are included. Six dummy variables indicating the day of the week for the last 24 hours reference period are included with Monday as the reference but not reported. Mean Y represents the averages of the outcome variables in November 2022. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

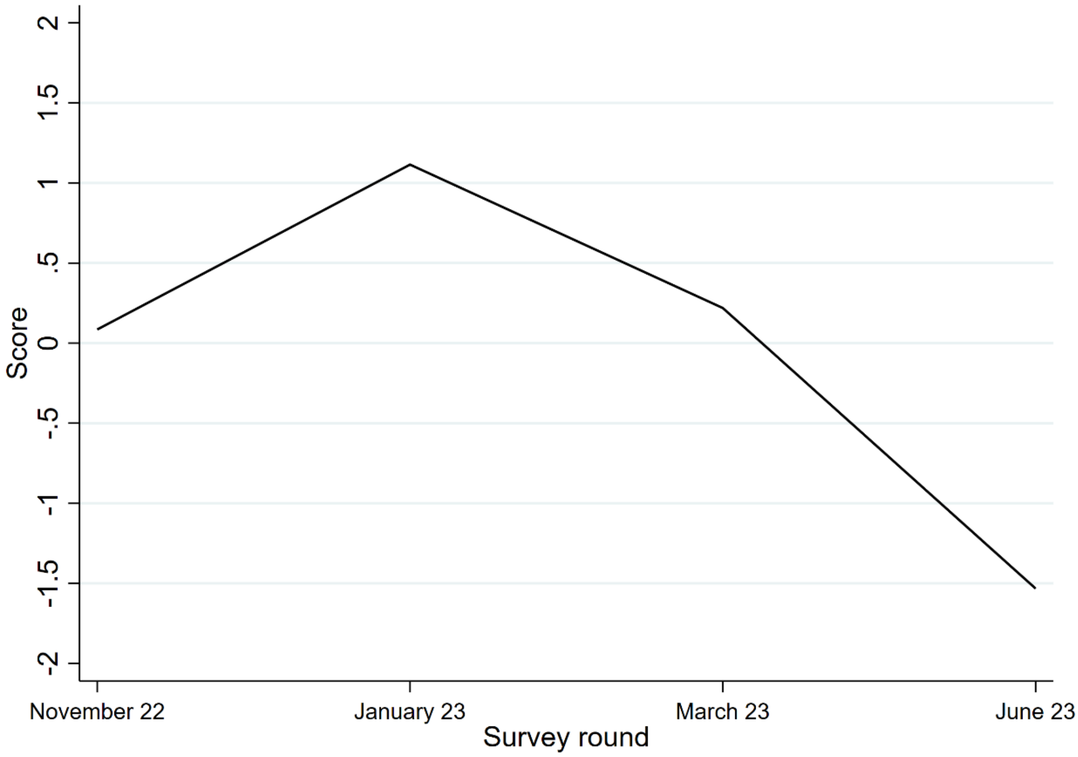
Appendix Figures



Appendix Figure 1. Distribution of weight by survey round



Appendix Figure 2. Distribution of MUAC by survey round



Appendix Figure 3. Household food insecurity scores

Note: November, January, March, and June correspond to the land preparation, growing, early harvest, and post-harvest periods, respectively.

Appendix Tables

Appendix Table 1. Determinants of women's cooking time

	(1)	(2)	(3)	(4)
January 23	0.165	-0.004	0.020	0.229
	(0.129)	(0.096)	(0.124)	(0.158)
March 23	-0.025	-0.231**	-0.290**	-0.016
	(0.148)	(0.111)	(0.136)	(0.179)
June 23	-0.165	-0.405***	-0.294***	-0.035
	(0.145)	(0.082)	(0.114)	(0.167)
Consumed other vegetables	0.282*			0.295**
	(0.148)			(0.149)
× January 23	-0.284			-0.295
	(0.194)			(0.194)
× March 23	-0.403**			-0.394*
	(0.200)			(0.202)
× June 23	-0.376*			-0.396**
	(0.200)			(0.201)
Number of female adults		0.339		0.314
		(0.271)		(0.277)
× January 23		-0.157		-0.142
		(0.293)		(0.303)
× March 23		-0.332		-0.322
		(0.335)		(0.336)
× June 23		-0.112		-0.121
		(0.299)		(0.301)
Number of female children			-0.101	-0.076
			(0.142)	(0.142)
× January 23			-0.047	-0.057
			(0.094)	(0.097)
× March 23			0.031	0.021
			(0.100)	(0.102)
× June 23			-0.100	-0.114
			(0.080)	(0.082)
Individual FE	YES	YES	YES	YES
Mean Y	1.72	1.72	1.72	1.72
R squared	0.42	0.41	0.42	0.42
N	1117	1117	1117	1117

Notes: The outcome variables are women's time spent on cooking. All the columns report the coefficients estimated by OLS. Robust standard errors clustered by female respondent are reported in parentheses. The same control variables as in Table 5 are included but not reported. Mean Y represents the averages of the outcome variables in November 2022. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 2. Determinants of household food insecurity and HDDS

	(1)	(2)	(3)	(4)
	Food Insecurity	Food Insecurity	PCA-based FI	PCA-based FI
Own sick dummy	0.340**	0.170	0.040	-0.095
	(0.134)	(0.203)	(0.169)	(0.151)
No. of sick family members	0.173***	0.100	0.108	-0.010
	(0.067)	(0.075)	(0.072)	(0.060)
Family size	0.149	0.046	-0.131	-0.164
	(0.123)	(0.149)	(0.157)	(0.116)
January 23		0.653***		0.976***
		(0.173)		(0.145)
March 23		0.957***		0.204
		(0.222)		(0.187)
June 23		-2.423***		-1.593***
		(0.200)		(0.155)
Model	Ordered Probit	Ordered Probit	OLS	OLS
HH FE	YES	YES	YES	YES
Mean Y	3.65	3.65	0.09	0.09
N	1117	1117	1117	1117

Notes: The outcome variables are food insecurity index for columns 1 and 2 and PCA-based food insecurity index for columns 3 and 4, respectively. Columns 1 and 2 report the coefficients estimated by the ordered probit model. Columns 3 and 4 report the coefficients estimated by OLS. Robust standard errors clustered by household are reported in parentheses. Household fixed-effects are included. Six dummy variables indicating the day of the week for the last 24 hours reference period are included with Monday as the reference but not reported. Mean Y represents the averages of the outcome variables in November 2022. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 3. Determinants of each food insecurity component

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FQ1	FQ2	FQ3	FQ4	FQ5	FQ6	FQ7
Own sick dummy	-0.664	-1.280	-0.653	-0.568	-0.650	0.326	0.309
	(1.067)	(1.048)	(1.002)	(0.910)	(0.917)	(0.419)	(0.273)
No. of sick family members	0.069	-1.095**	0.624	-0.477	-0.229	0.321*	0.205**
	(0.439)	(0.429)	(0.436)	(0.360)	(0.353)	(0.184)	(0.101)
Family size	-1.257	-0.945	-1.843***	-0.793	-0.724	0.214	0.248
	(0.838)	(0.840)	(0.652)	(0.692)	(0.790)	(0.260)	(0.201)
January 2023	2.498**	4.047***	5.869***	4.467***	5.214***	1.072**	1.419***
	(1.023)	(1.018)	(0.962)	(0.979)	(1.027)	(0.532)	(0.304)
March 2023	-1.174	0.755	0.020	0.819	-1.066	1.120*	2.000***
	(1.221)	(1.171)	(1.138)	(0.998)	(0.967)	(0.578)	(0.339)
June 2023	-10.516***	-6.948***	-5.325***	-5.548***	-8.460***	-2.704***	-1.411***
	(1.155)	(1.107)	(1.083)	(0.949)	(0.884)	(0.434)	(0.234)
HH FE	YES	YES	YES	YES	YES	YES	YES
Mean Y	17.80	15.64	18.41	11.48	11.47	3.27	1.85
R squared	0.49	0.43	0.45	0.41	0.49	0.43	0.52
N	1117	1117	1117	1117	1117	1117	1117

Notes: Robust standard errors clustered by household are reported in parentheses. Household fixed effects are included. Six dummy variables indicating the day of the week for the last 24 hours reference period are included with Monday as the reference but not reported. Mean Y represents the averages of the outcome variables in November 2022. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 4. Determinants of each food group intake

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cereals	Roots	Vegetables	Fruits	Milk	Meat	Eggs	Fish	Nuts	Oil	Sweets	Spices
Own sick dummy	0.007	-0.012	0.054*	0.005	0.005	0.013	0.004	-0.001	0.010	0.025	0.031	0.010
	(0.012)	(0.023)	(0.030)	(0.019)	(0.005)	(0.016)	(0.010)	(0.019)	(0.037)	(0.036)	(0.029)	(0.024)
No. of sick family members	-0.004	0.015	-0.026*	0.007	0.001	0.000	0.003	0.011	0.018	0.013	0.003	-0.002
	(0.006)	(0.014)	(0.015)	(0.008)	(0.001)	(0.006)	(0.004)	(0.010)	(0.017)	(0.016)	(0.011)	(0.011)
Family size	-0.010	0.013	-0.013	-0.005	0.003	0.013	0.001	-0.007	-0.028	0.029	0.018	-0.010
	(0.008)	(0.014)	(0.020)	(0.009)	(0.003)	(0.009)	(0.011)	(0.016)	(0.028)	(0.022)	(0.022)	(0.016)
November 2022	0.012	0.030	0.068**	0.021	-0.007	-0.003	-0.005	0.081***	0.052	0.016	0.010	0.020
	(0.013)	(0.022)	(0.034)	(0.016)	(0.007)	(0.012)	(0.009)	(0.025)	(0.037)	(0.035)	(0.030)	(0.028)
January 2023	-0.007	0.006	0.065**	0.055***	-0.002	-0.001	-0.007	-0.013	-0.060*	0.001	-0.023	0.027
	(0.015)	(0.021)	(0.032)	(0.017)	(0.005)	(0.011)	(0.008)	(0.015)	(0.034)	(0.035)	(0.026)	(0.026)
June 2023	0.011	0.115***	0.061*	0.009	-0.001	0.030*	0.012	0.084***	0.268***	0.236***	0.156***	0.079***
	(0.010)	(0.029)	(0.033)	(0.014)	(0.001)	(0.016)	(0.013)	(0.024)	(0.044)	(0.040)	(0.036)	(0.024)
HH FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mean Y	0.99	0.05	0.93	0.03	0.00	0.01	0.01	0.10	0.20	0.16	0.10	0.93
R squared	0.28	0.29	0.32	0.30	0.45	0.29	0.28	0.34	0.38	0.44	0.37	0.35
N	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117

Notes: Robust standard errors clustered by household are reported in parentheses. Household fixed effects are included. The reference category for time periods is March 2023. Six dummy variables indicating the day of the week for the last 24 hours reference period are included with Monday as the reference but not reported. Mean Y represents the averages of the outcome variables in November 2022. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 5. Robustness check: lagged time use and women's nutritional status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lnWeight	lnWeight	lnWeight	lnWeight	MUAC	MUAC	MUAC	MUAC
Own sick dummy	-0.005	-0.005	-0.005	-0.005	-0.115	-0.104	-0.129	-0.118
	(0.004)	(0.004)	(0.004)	(0.004)	(0.136)	(0.135)	(0.137)	(0.136)
No. of sick family members	-0.001	-0.001	-0.001	-0.001	-0.072	-0.072	-0.071	-0.072
	(0.001)	(0.001)	(0.001)	(0.001)	(0.051)	(0.052)	(0.052)	(0.052)
Food insecurity score	0.001	0.001			-0.191**	-0.191**		
	(0.003)	(0.003)			(0.084)	(0.083)		
Mildly FI			0.004	0.004			-0.412	-0.426
			(0.016)	(0.016)			(0.421)	(0.431)
Moderately FI			0.007	0.007			-0.514**	-0.513**
			(0.007)	(0.007)			(0.203)	(0.201)
Severely FI			0.003	0.003			-0.547**	-0.547**
			(0.008)	(0.008)			(0.255)	(0.253)
HDDS	0.004*	0.004*	0.004*	0.004*	0.048	0.052	0.053	0.057
	(0.002)	(0.002)	(0.002)	(0.002)	(0.057)	(0.057)	(0.057)	(0.057)
Family size	-0.005	-0.005	-0.004	-0.004	0.022	0.021	0.011	0.010
	(0.003)	(0.003)	(0.003)	(0.003)	(0.106)	(0.107)	(0.108)	(0.109)
Agricultural work, t-1	-0.001	-0.001	-0.001	-0.001	-0.031	-0.039	-0.029	-0.037
	(0.001)	(0.001)	(0.001)	(0.001)	(0.026)	(0.029)	(0.026)	(0.029)
Leisure, t-1	-0.001	-0.001	-0.001	-0.001	0.000	-0.004	0.003	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.028)	(0.031)	(0.029)	(0.031)
Agricultural work, t		0.000		0.000		-0.021		-0.022
		(0.001)		(0.001)		(0.027)		(0.027)
Leisure, t		0.000		0.000		-0.011		-0.011
		(0.001)		(0.001)		(0.034)		(0.033)
March 23	-0.009**	-0.009**	-0.008**	-0.009**	0.259**	0.234	0.250**	0.226
	(0.003)	(0.004)	(0.003)	(0.004)	(0.124)	(0.147)	(0.125)	(0.148)
June 23	0.023***	0.022***	0.021***	0.021***	0.061	0.022	0.119	0.081
	(0.005)	(0.006)	(0.006)	(0.007)	(0.176)	(0.204)	(0.188)	(0.214)
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Mean Y	4.00	4.00	4.00	4.00	27.96	27.96	27.96	27.96
R squared	0.98	0.98	0.98	0.98	0.95	0.95	0.95	0.95
N	730	730	730	730	730	730	730	730

Notes: The outcome variables for Columns 1–4 are women's body weight after log transformation. Robust standard errors clustered by female respondent are reported in parentheses. Fixed effects for each female respondent are included. Six dummy variables indicating the day of the week for the last 24 hours reference period are included with Monday as the reference but not reported. Mean Y represents the averages of the outcome variables in January 2023. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 6. Robustness check: lagged household food insecurity and women's nutritional status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lnWeight	lnWeight	lnWeight	lnWeight	MUAC	MUAC	MUAC	MUAC
Own sick dummy	-0.008	-0.006	-0.008	-0.006	-0.177	-0.153	-0.176	-0.155
	(0.005)	(0.004)	(0.005)	(0.004)	(0.132)	(0.134)	(0.133)	(0.136)
No. of sick family members	-0.002	-0.001	-0.002	-0.001	-0.105*	-0.079	-0.105*	-0.078
	(0.002)	(0.002)	(0.002)	(0.002)	(0.058)	(0.053)	(0.058)	(0.053)
Food insecurity score, t-1	0.002	0.000			0.087	0.035		
	(0.003)	(0.003)			(0.096)	(0.087)		
Mildly FI, t-1			-0.044	-0.028			-0.191	-0.144
			(0.041)	(0.036)			(1.010)	(0.947)
Moderately FI, t-1			-0.001	0.005			0.068	0.079
			(0.009)	(0.008)			(0.332)	(0.298)
Severely FI, t-1			0.001	0.003			0.188	0.103
			(0.009)	(0.008)			(0.305)	(0.265)
HDDS, t-1	-0.004*	-0.003	-0.003	-0.003	-0.097*	-0.071	-0.095*	-0.071
	(0.002)	(0.002)	(0.002)	(0.002)	(0.055)	(0.057)	(0.055)	(0.057)
Family size	-0.007*	-0.005	-0.007*	-0.005	0.036	0.036	0.036	0.035
	(0.004)	(0.004)	(0.004)	(0.004)	(0.120)	(0.114)	(0.121)	(0.114)
Agricultural work	0.001	0.001	0.001	0.001	-0.010	-0.004	-0.009	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.024)	(0.025)	(0.024)	(0.025)
Leisure	0.001	0.001	0.001	0.001	0.013	-0.007	0.013	-0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.028)	(0.031)	(0.027)	(0.031)
March 23		-0.009**		-0.008*		0.247		0.248
		(0.004)		(0.004)		(0.153)		(0.153)
June 23		0.025***		0.025***		0.449***		0.450***
		(0.004)		(0.004)		(0.132)		(0.132)
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Mean Y	4.00	4.00	4.00	4.00	27.98	27.98	27.98	27.98
R squared	0.98	0.98	0.98	0.98	0.95	0.95	0.95	0.95
N	732	732	732	732	732	732	732	732

Notes: The outcome variables for Columns 1–4 are women's body weight after log transformation. Robust standard errors clustered by female respondent are reported in parentheses. Fixed effects for each female respondent are included. Six dummy variables indicating the day of the week for the last 24 hours reference period are included with Monday as the reference but not reported. Mean Y represents the averages of the outcome variables in January 2023. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.